Learning on the Go: Understanding How Gig Economy Workers Learn with Recommendation Algorithms

SHUNAN JIANG, College of Engineering, University of California, USA
WICHINPONG PARK SINCHAISRI, Haas School of Business, University of California, USA

As gig economy platforms increasingly rely on algorithms to manage workers, understanding how algorithmic recommendations influence worker behavior is critical for both optimizing platform design and worker welfare. In this paper, we investigate the dynamic interactions between gig workers and platform algorithms, focusing on workers' learning processes and strategy development. Using a mixed-methods approach, including descriptive analysis, two-way fixed-effects regression, and multinomial logit modeling, we analyze over one million orders completed by gig workers on a retail delivery platform. Our results uncover a clear learning curve, with workers progressively improving efficiency and on-time delivery performance as they gain experience. We also discovered that workers new to the platform rely more on algorithmic recommendation for task selection, while experienced workers deviate from it and develop their own strategies. This shift away from algorithmic recommendations indicates that these workers might perceive platform suggestions as less beneficial or aligned with their evolved needs, pointing to the need for adaptive recommendation algorithm which takes worker feedback and provides greater flexibility for experienced workers to align task selections with their personal strategies. Our research suggest that platforms should design human-centric recommendation systems that adapt to workers' learning trajectories and experience levels to enhance collaborative dynamics and improve outcomes for both workers and platforms.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**.

Additional Key Words and Phrases: gig economy, worker performance, worker learning, task bundling, recommendation algorithms, empirical analysis

ACM Reference Format:
Shunan Jiang and Wichinpong Park Sinchaisri. 2025. Learning on the Go: Understanding How Gig Economy Workers Learn with Recommendation Algorithms. In *Proceedings of ACM Conference on Computer-Supported Cooperative Work and Social Computing (CSCW '25).* ACM, New York, NY, USA, 21 pages. https://doi.org/XXXXXXX.XXXXXXX

1 Introduction

As technology-mediated work continues to reshape the labor landscape, gig economy platforms, such as grocery delivery, ride-hailing, and freelancing, have become crucial sources of flexible, task-based employment. These platforms offer workers independence in task selection but also present them with complex decision-making challenges, especially as the volume and diversity of tasks grow. Without the traditional support networks of coworkers, supervisors, or mentors, gig workers must independently navigate these challenges, often learning through trial and error [39].

Authors' Contact Information: Shunan Jiang, College of Engineering, University of California, Berkeley, California, USA, shunan_jiang@berkeley.edu; Wichinpong Park Sinchaisri, Haas School of Business, University of California, Berkeley, California, USA, parksinchaisri@berkeley.edu.

CSCW '25, Oct 18–22, 2025, Bergen, Norway

ACM ISBN 978-1-4503-XXXX-X/18/06
https://doi.org/XXXXXXX.XXXXXXX

To enhance operational efficiency, many platforms now rely on algorithmic recommendation systems to support workers' decision-making. In grocery delivery, for example, platforms frequently suggest bundling multiple orders into a single trip to streamline routes, reduce idle time, and boost earnings. However, these algorithmic recommendations introduce new layers of complexity, requiring workers to integrate automated suggestions with their own personal strategies. Navigating this balance can be difficult, leading to misaligned decisions that may reduce performance or result in suboptimal outcomes. For example, [19] highlighted the difficulty of batched orders on food delivery platforms and found gig workers often rejected to bundle orders.

When workers have the autonomy to create their own task bundles, they may overestimate their capacity or fail to account for the logistical challenges of complex deliveries, resulting in delayed orders, missed service windows, or customer dissatisfaction. The cognitive load imposed by the vast number of available tasks further complicates decision-making, forcing workers to juggle multiple, often competing, priorities. These priorities include maximizing earnings, minimizing effort, and meeting performance benchmarks imposed by the platform.

Our research explores the dynamic interplay between algorithmic recommendations and worker decision-making, with a focus on how workers engage with platform-suggested tasks and bundling strategies, and how these recommendations shape learning and performance over time. Through this investigation, we seek to inform the design of effective human-centered recommendation systems that align platform goals with worker needs. Our findings will provide insights into how these systems can better support worker autonomy and performance while fostering more effective collaboration between platform algorithms and worker strategies.

We adopt a mixed-method approach to investigate how gig workers engage in learning and decision-making on an on-demand retail delivery platform. Using a dataset of 1.2 million orders from 5,000 gig workers over 364 days in New York City, we apply a two-way fixed-effects regression model, controlling for external variables such as weather conditions and traffic patterns, to assess how workers learn to perform better through experience. We then perform a descriptive analysis to uncover how workers learn to bundle tasks with platform recommendation and how the interaction influences their performances. Additionally, to analyze workers' task selection behaviors, we employ a multinomial logit model that captures how workers respond to platform recommendations and explore new stores as they accumulate experience. This methodological framework offers a comprehensive view of worker strategies, shedding light on how workers co-adapt with platform algorithms to optimize performance over time.

Our findings reveal several key insights into worker adaptation to algorithmic systems. First, workers demonstrate a clear learning curve, with significant improvements in efficiency and on-time delivery as they gain experience. The regression analysis shows that store-specific experience plays a crucial role in enhancing performance, while skills acquired from other stores also contribute to improvement. These transferable skills, such as navigating store layouts and managing customer expectations, enable workers to adapt more efficiently across different contexts, highlighting the importance of cross-context learning.

When choosing which orders to accept, workers can decide whether to follow platform recommendations or select from a pool of non-recommended orders. Our findings indicate that newer workers are more inclined to rely on platform suggestions, while more experienced workers develop their own strategies, increasingly deviating from algorithmic recommendations. This progression highlights how workers gradually build confidence and optimize their task selection strategies, ultimately improving both performance and earnings. Our results suggest that as workers gain proficiency, platforms should adapt their algorithms to offer greater flexibility, enabling experienced workers to align task selection with their evolving strategies. Additionally, incorporating worker feedback mechanisms can further personalize recommendations, ensuring suggestions remain relevant and responsive to workers' changing needs.

The results also underscore the importance of balancing exploration and exploitation behaviors. While excessive exploration, such as accepting unfamiliar orders or exploring new stores, can initially hinder performance and increase dropout risk, moderate exploration proves essential for long-term success. Platforms could tailor recommendations to promote familiarity early on, fostering stability and learning, and then gradually introduce a mix of familiar and novel tasks to encourage growth and sustained engagement as workers accumulate experience.

These findings highlight the value of human-centric recommendation systems that evolve in tandem with workers' learning trajectories and preferences. By aligning algorithmic recommendations with workers' strategies and experience levels, platforms can improve collaborative interactions, enhance performance outcomes, and foster long-term engagement within the gig economy. This adaptive approach can empower workers while ensuring platform systems remain both efficient and supportive of worker autonomy and development.

Our paper is organized as follows: Section 2 reviews related work and outlines our contributions. Section 3 introduces the context of our study and describes the dataset. In Section 4, we provide empirical evidence on how workers learn to improve performance through experience. Section 5 explores how workers adapt to the platform's recommendations for bundling tasks. Section 6 examines how workers learn to select tasks with the platform's recommendation algorithms and discusses implications for recommendation algorithm design. Finally, Section 7 presents our concluding remarks.

2 Related Works and Contributions

Our work relates to two major streams of literature: the interactions between humans and algorithms or computer-supported platforms and worker learning and performance improvement in operations management.

2.1 Human-Algorithm Interactions at Work

Our paper contributes to the ongoing discussion on how digital platforms can enhance worker performance and how workers interact with these new technologies. Researchers have explored various mechanisms for performance improvement. For example, [27] found gig workers working in the high quality of platforms are more likely to have greater job autonomy and satisfaction. [37] demonstrated a dedicated feedback communication space could enhance the cooperation between gig workers and restaurants on food delivery platforms. [17] explored how structured feedback can guide online crowd workers toward improved performance. [36] studied how gig workers interact with food delivery platforms and underscored the importance of addressing worker well-being in platform design. [13] explored the use of customizable and evolving avatars to improve worker engagement.

Further contributions examine how new technologies like AI systems can empower gig workers. [28] showed that AI-guided systems can enhance service quality among gig workers, particularly for novices, although these systems can also extend task completion times due to reliance on AI consultations. [41] and [40] emphasized the importance of stakeholder-centered AI design, co-creating worker tools through data probes that address worker needs directly, aiming to align algorithmic management with worker well-being and engagement. [11, 12] highlighted the nuanced dynamics of AI adoption for worker well-being, noting that workers may resist AI tools like passive sensing systems due to perceived invasiveness and control, despite potential performance benefits. [16] proposed surveillance tools, designed to enable gig workers to monitor and track their performance, giving them more autonomy over their work processes. [31, 34] discussed how

AI-driven collective action and advanced design methods can empower gig workers, facilitating a more worker-centric future in platform economies. [25] discussed how algorithmic management shapes power dynamics between workers and managers, impacts worker autonomy, and requires new algorithmic competencies. Similarly, [26] examined how gig workers develop the skills to navigate algorithmic management systems, emphasizing the importance of algorithmic literacy for improving worker performance. [29] explored how workers perceive algorithmic decisions, focusing on fairness, trust, and emotional responses to algorithmic management, which are critical factors influencing worker performance. [30] examined the broader impact of algorithmic management on human workers, highlighting how data-driven systems affect job satisfaction and autonomy, thus influencing performance outcomes. However, offering algorithmic recommendations could lead to unintended negative consequences. For example, humans may exhibit *algorithm aversion*, biased perception against algorithmic advice [14, 15], or even if they are open to such recommendation they may not be able to effectively incorporate it into their workflow [5].

Our research aims to fill the gap in understanding how gig workers learn and adapt to algorithmic systems over time. While prior studies have explored the role of AI in improving worker performance, there is still limited understanding of how workers develop strategies for engaging with these systems in the long term. Specifically, we investigate how workers respond to algorithmic recommendations during their early interactions with the platform and how their strategies evolve as they gain experience. We also explore how these strategies influence their long-term learning and performance, particularly in terms of task bundling and selection. Our findings provide valuable insights into the diverse ways workers adapt their behaviors in response to platform guidance, contributing to the broader understanding of how gig workers navigate and optimize their interactions with algorithmic management.

2.2 Worker Learning and Performance Improvement

Worker learning is a topic extensively studied in traditional corporate environments. Comprehensive reviews of this research can be found in the works of [4, 10]. Given the depth and breadth of studies in this area, we provide only a brief review here. Worker learning has been studied across various workplace settings. For instance, [18] explored learning in software development, [35] investigated learning in assembly lines, [21] examined manual item-picking processes, and [6] focused on emergency service workers. Researchers have found that workers learn through a variety of mechanisms, with experience-based learning being the most common, see [20, 23]. The learning curve is one of the most widely used methods to measure this process [3]. In addition, [8] studied how workers learn from customers, while [1] explored learning from other team members. Notably, [7] proposed a reinforcement learning model, experience-weighted attraction, to study learning under strategic decision-making and how workers learn from the rewards they receive from past interactions.

As the gig economy continues to evolve, research has also focused on various dimensions of gig worker, including workers' performance, learning, and decision-making. For example, [2] identified that gig workers are motivated not only by pay rates but also by internal motivators such as income and time targets. [22] emphasized the importance of day-to-day experiences in improving both service quality and productivity. [9] proposed a model of exploration-exploitation behavior among gig workers, arguing that during the early stages of experience, workers explore new regions, leading to decreased productivity and lower quality outcomes. As workers gain more experience, they tend to batch more orders and achieve better performance. Additionally, [24] examined how gig workers use self-tracking to manage personal accountability. [19] studied the heuristics used by gig workers to accept and reject the batched orders and proposed a new order batching solution that takes courier needs into account. [32] found that perceived behavioral control influences job satisfaction, with emotional labor serving as a mediator in this relationship.

Our research extends beyond these existing studies by focusing specifically on the learning processes and strategic decision-making of gig workers as they interact with platforms. In particular, we investigate how heterogeneous strategies among gig workers lead to diverse learning outcomes. Leveraging the advantages of our dataset, we are able to employ a multinomial logit (MNL) model to systematically study the choices gig workers make, particularly in response to platform recommendations.

3 Data: Retail Delivery Platform in The U.S.

We collaborate with an on-demand retail delivery company (hereafter referred to as "the company" or "the platform") to analyze a comprehensive dataset consisting of online retail orders complated in New York City over a 364-day period, spanning from November 2022 to October 2023. This dataset captures a wide range of information, including completed orders by workers, order characteristics, and productivity metrics such as time spent shopping, checkout time, and driving time. Additionally, the dataset provides detailed evaluations of each completed order, such as whether the delivery was on time.

One of the key advantages of this dataset is its granularity, which allows us to observe: (1) the orders recommended to each gig worker by the platform's algorithm, and (2) detailed information about orders that were bundled together by the platform for simultaneous delivery.

In the following sections, we provide an overview of the platform's operations, describe the interface through which workers interact with the system, and present descriptive statistics related to the workers and the recommended orders they received. We also outline the supplementary datasets incorporated into our analysis.

3.1 Platform Overview

The company operates as an online retail delivery platform, offering on-demand retail and essential goods delivery services across multiple cities in the United States. Customers place orders through the platform's mobile application or website, with the option to schedule deliveries at flexible times. The platform facilitates prompt delivery by matching customers with gig workers who are responsible for driving to the store, hand-picking the ordered items, and providing real-time communication via chat services for updates on the shopping process. Gig workers then deliver the items directly to the customers' addresses.

Gig workers are compensated on a per-order basis, with payment varying depending on factors such as the size and complexity of the order. In addition to their base earnings, gig workers can receive tips directly from customers, which provide an additional source of income. Furthermore, the platform offers bonuses to gig workers for meeting specific performance criteria, such as fulfilling deliveries during high-demand periods.

3.2 Worker Process

To participate on the platform, workers must first undergo a screening process, which includes verifying that they meet certain eligibility criteria such as being over 18 years of age, possessing a valid driver's license, and owning a vehicle. Upon successfully completing this process, workers are officially designated as gig workers. These gig workers can select their preferred working regions and define their working hours daily, typically within the operational timeframe of 7:00 AM to 12:00 AM. The platform utilizes this information, along with historical information of customer experiences with the gig worker such as on-time delivery rate and customer ratings-to generate order recommendations.

A key distinction between this platform and ride-hailing services (e.g., Uber and Lyft) is the ability of gig workers to exercise discretion in selecting orders. Unlike ride-hailing drivers, who are automatically assigned rides and lack the ability to browse available tasks, gig workers on the focal platform are presented with a list of recommended orders generated by an algorithm. Gig workers can browse through these recommendations and make informed decisions based on details such as payment amount, delivery time windows, store and customer locations, and the items included in the order. Additionally, they have the flexibility to bundle multiple orders and fulfill them concurrently, thus optimizing their work efficiency.

Beyond receiving algorithmically recommended orders based on their selected hours and regions, gig workers also have access to a separate section of the platform where they can view non-algorithmically recommended orders. Gig workers are free to select from this pool of available orders, providing them with additional opportunities to maximize their work during their active hours.

3.3 Descriptive Statistics

The dataset consists of approximately 5,000 gig workers who collectively fulfilled around 1.2 million orders across 800 stores. The number of orders completed by each gig worker within a year varies significantly, ranging from individuals who completed only one order before leaving the platform, to highly active gig workers who processed over 6,000 orders in a single year. On average, gig workers completed 230 orders annually, with the 25th, 50th, and 75th percentiles at 5, 28, and 136 orders, respectively.

Similarly, the volume of orders processed by each store shows considerable variation, from as few as one order per year to over 100,000. On average, stores processed 1,600 orders annually, with the 25th, 50th, and 75th percentiles at 5, 13, and 39 orders, respectively.

A significant portion of orders on the platform–approximately 60%–are bundled. The platform employs algorithms to identify similarities between orders based on features such as store, item selection, and delivery destination. Each bundled order consists of two similar orders.

3.4 Supplementary Data: TLC Trip Records and Weather Records

To account for the potential influence of traffic and weather conditions on workers' behaviors, we incorporate two additional datasets into our analysis.

The first dataset is the New York City Taxi and Limousine Commission (TLC) dataset, which provides detailed trip-level records for taxi and ride-hailing services in New York City (NYC). This dataset includes information such as pickup and drop-off locations, timestamps, trip distances, fares, and payment methods, encompassing millions of rides over multiple years. From the TLC dataset, we derive two key traffic-related proxies: the traffic volume for each hour and the average hourly speed of taxis, both serving as indicators of overall traffic conditions in NYC.

The second dataset is sourced from the OpenWeather platform, which offers global meteorological data across a broad range of parameters, including temperature, humidity, wind speed, and precipitation, as well as specialized metrics like air pollution and UV index. We initially extracted over 50 weather variables from this platform. After performing variance inflation factor (VIF) testing to address multicollinearity, we selected three weather parameters—apparent temperature, rainfall, and wind speed—for inclusion in our subsequent regression analyses.

4 Learning to Improve: *How Do Gig workers Learn to Improve Performance?*

In this section, we analyze how gig workers learn to improve their performance over time as they accumulate experiences, focusing on two key performance metrics: (1) the on-time percentage (OTP), which represents the proportion of orders delivered no later than the time specified by the platform and serves as the platform's indicator of service quality; and (2) the number of items picked per hour, which reflects the gig worker's productivity. These metrics provide a comprehensive view of both the service reliability and operational efficiency of gig workers. We begin by presenting model-free evidence to identify general trends in performance improvement. This is followed by the introduction of our empirical approach, which employs a two-way fixed effects regression analysis to control for time-invariant characteristics of gig workers and stores. Finally, we present the results and insights derived from the analysis. These insights will serve as a basis for the subsequent section, where we investigate how gig workers learn to adapt strategically to the platform's recommendation algorithms.

4.1 Model-free Evidence of Performance Improvement

We first consider 1,131 gig workers who joined the platform within the duration of the dataset (e.g., after November 1, 2022) and investigate how their performance may improve over time. Figure 1 illustrates the relationship between the number of orders a gig worker has completed (binned into intervals) and their corresponding average on-time delivery rate. The x-axis represents the binned number of orders worked observed in the data, ranging from 0 to 500, divided into intervals of approximately 10 orders. The y-axis denotes the average on-time rate, varying from 0.75 to 0.925. Error bars indicate the confidence intervals for the average on-time rate within each bin.

The trend reveals an initial dip in the on-time performance measure within the lower order bins (0–10 orders), which can be attributed to the platform introducing bundled orders to gig workers after they have completed few deliveries. Following this dip, there is a consistent improvement in the average on-time rate as the number of orders increases. Once gig workers exceed 100 orders, the on-time rate stabilizes with fluctuations around the 0.85–0.9 range. This pattern suggests that, while accumulated experience has a positive impact on a gig worker's performance, such benefit has diminishing returns as experience continues to grow.

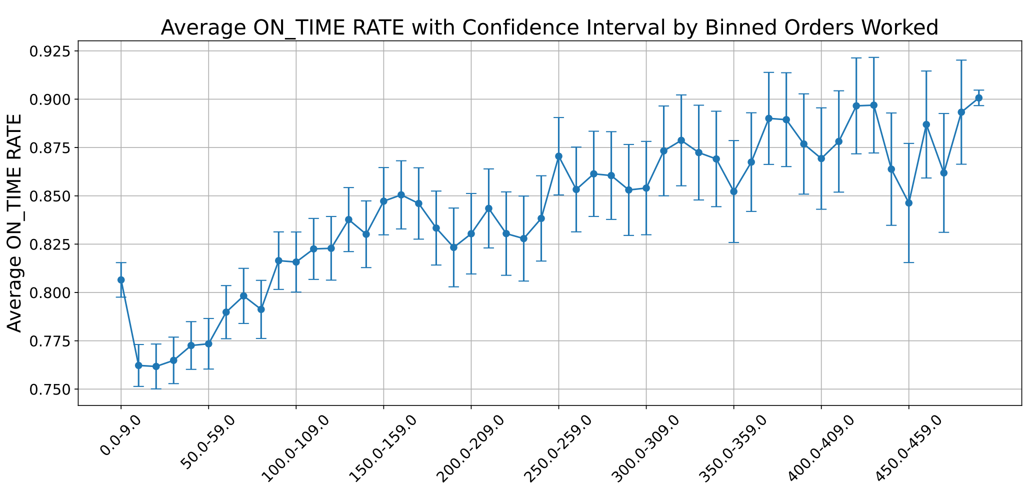

Fig. 1. Average rate of on-time delivery by orders worked

4.2 Two-way Fixed-Effects Regression Analysis of Worker Performance

To establish a causal relationship between gig worker experience and performance, we perform a two-way fixed effects regression analysis for each of the two performance metrics: on-time delivery rate ($OnTime$) and the number of items picked per hour ($ItemsPerHour$) [38].

$$\begin{aligned} PerformanceMetric_{ist} = \beta_0 + \beta_1 OTS_{ist} + \beta_2 OTS_{ist}^2 \\ + \beta_3 OOS_{ist} + \beta_4 OOS_{ist}^2 \\ + \mathbf{X}'_{ist}\beta + \mu_{is} + \gamma_t + \epsilon_{ist} \end{aligned} \tag{1}$$

where

- $PerformanceMetric_{ist}$ is either the delivery performance of or the number of items picked by gig worker i when shopping at store s at time t.
- OTS_{ist} and OOS_{ist} captures the number of orders that gig worker i has completed at store s and other stores by time t, respectively.
- OTS_{ist}^2 and OOS_{ist}^2 are the squared terms.
- $\mathbf{X}_{ist}$ is a vector of control variables, including external factors such as weather conditions (e.g., temperature, rain, wind speed), order-specific variables (e.g., total payment, bonuses, requested item quantities, delivery distance), and urban traffic metrics (e.g., taxi volume, average traffic speed).
- μ_{is} represents gig worker-store fixed effects, controlling for unobserved heterogeneity at the gig worker-store level that is constant over time.
- γ_t denotes time fixed effects, capturing any temporal patterns such as day-of-week or seasonal variations that might influence performance.
- ϵ_{ist} is the idiosyncratic error term, assumed to be independently and identically distributed across i, s, and t.

4.2.1 Description of Key Variables.

Dependent variables. $OnTime$ is a binary variable capturing the rate of on-time delivery, which equals to 1 if the delivery was completed on time, or 0 if the delivery was delayed. This measure of service quality is chosen to be the key performance indicator by the platform. Another performance metric considered is $ItemsPerHour$, which is the number of items the gig worker successfully picked per hour. $ItemsPerHour$ therefore serves as a proxy for the gig worker's productivity.

Independent variables. To examine the relationship between a gig worker's accumulated experience with specific stores and their delivery performance, we introduce two key independent variables: OTS ($OrdersThisStore$) and OOS ($OrdersOtherStore$). OTS represents the number of deliveries completed by a gig worker for a particular store. This variable functions as a proxy for the gig worker's familiarity with that store's unique operational environment, such as store layout, inventory management, and staff interactions. We hypothesize that as a gig worker visits a given store more often, their delivery efficiency will improve due to their familiarity with the store. For example, they might spend less time searching for items in the store and make fewer errors. Additionally, familiarity with the store may allow for more effective route optimization, both within the store during item retrieval and externally during the delivery process. To explore potential nonlinear effects of experience, we also include a squared term, OTS^2, which enables us to test whether performance improvements exhibit diminishing returns after a certain threshold of experience, or whether continued experience yields progressively better outcomes.

In contrast, OOS captures the number of deliveries a gig worker has completed for stores other than the focal one. This variable allows us to explore whether broader experience across different store environments translates to enhanced performance in a specific store. Similarly, we also incorporate a squared term, OOS^2 to account for potential nonlinear effects.

Control variables. $StoreId$: A categorical variable controlling for store-specific fixed effects, such as differences in store location, management efficiency, or operational processes, that may influence delivery performance. $WorkerId$: A categorical variable controlling for individual gig worker-specific effects, accounting for heterogeneity in personal efficiency, delivery habits, or experience levels.

Time fixed effects: The delivery timestamp is decomposed into months and weekdays to control for temporal dynamics that may affect delivery performance, such as seasonal demand fluctuations or weekday traffic patterns. *Order characteristics*: We include variables that describe the features of each order, such as financial incentives, items, distances from store to customer to account, delivery time window for the complexity of each order, which are hypothesized to impact the timeliness of deliveries. *Traffic*: Variables like hourly taxi volume and hourly average speed of taxi at NYC are incorporated to control for urban traffic conditions that could delay deliveries. *Weather*: Environmental factors, such as apparent temperature, rain, and wind speed, are included to account for weather conditions that may significantly affect delivery times.

4.3 Results: *Diminishing Positive Return on Experience*

Table 1 illustrates the impact of gig worker experience on two key performance metrics: $OnTime$ (the rate of on-time delivery) and $ItemsPerHour$ (the number of items picked per hour).

Table 1. The impact of experience on performance among new gig workers

	$OnTime$	$ItemsPerHour$
OTS	6.0552e-05***	9.4281e-03***
	(0.003)	((0.008))
OTS^2	-8.9995e-09***	-5.4681e-06**
	(0.000)	(0.003)
OOS	5.9109e-05***	6.3414e-03*
	(0.000)	(0.022))
OOS^2	-8.8744e-09***	-7.6253e-07
	(0.015)	(0.235)
Fixed Effects controls	✓	✓
Weather controls	✓	✓
Traffic controls	✓	✓
R^2	0.029	0.013
Observations	105543	105543

Our results offer strong evidence that both store-specific and general delivery experience significantly influence on-time delivery performance and overall productivity. First, we observe that store experiences, as measured by OTS_{ist}, plays a critical role in driving improvements in these metrics. The inclusion of the squared term, OTS_{ist}^2, highlights a pattern of diminishing returns: although early interactions with a store lead to notable gains in performance, these improvements plateau after approximately 100 to 150 orders. This suggests that gig workers quickly internalize the store's processes, with additional experience providing only marginal benefits.

Second, experience accumulated from working at other stores also enhances performance, indicating the presence of transferable skills. Gig workers appear to draw on general knowledge—such as navigating various store layouts, managing diverse customer requests, and optimizing in-store operations—which contributes to timely deliveries even in less familiar environments.

Third, while experience from other stores improves both service quality and productivity, we observe that its impact on service quality is more significant, suggesting that cross-store experience helps gig workers adapt to different customer expectations and service standards.

In summary, our findings show that delivery performance improves rapidly with initial store-specific experience but reaches a plateau after a certain point.

5 Responding to Recommendations: *Orders to Bundle*

Our preliminary findings suggest that gig workers exhibit significant heterogeneity, particularly in terms of how they learn over time. In this section, we first highlight the variation among gig workers, illustrating how different groups of gig workers exhibit distinct characteristics. We then explore how different gig workers strategically respond to platform bundling recommendations differently and how it influences workers' performance. Recall that in the previous section, we demonstrated that the majority of learning occurs within the first 100 orders. Therefore, in this section, we primarily focus on analyzing workers' strategic behaviors during their initial 100 orders.

5.1 Model-free Evidence: Worker Heterogeneity

Figure 2 illustrates the on-time delivery performance of gig workers, segmented into five groups based on the total number of orders they have completed. The x-axis represents the number of orders worked (0 to 100), and the y-axis shows the average on-time rate. The figure clearly demonstrates that gig workers who remain active on the platform and complete the most orders tend to perform better, even from the beginning of their tenure. This suggests that more experienced gig workers, even early on, may have an inherent advantage, whether due to their familiarity with similar platforms, faster learning curves, or better initial strategies.

Additionally, we conducted ANOVA tests to confirm that the performance differences between these groups are statistically significant. The results support the hypothesis of meaningful variation across the groups. For instance, when comparing the on-time performance for the first 10 orders, the ANOVA F-statistic is 3.166, with a corresponding p-value of 0.013.

5.2 Model-free Evidence: Learning to Bundle

One of the key features of the platform is that approximately 60% of the orders are bundled by the platform and recommended to the workers. The platform officially introduces the option to bundle orders to gig workers after they have completed the first few orders. While bundling may initially appear advantageous due to its potential for increasing efficiency, the data reveals a more complex reality. As shown in both Figures 1 and 2, after the first few orders–when bundling becomes available–workers' service quality tends to decline temporarily. This dip suggests that while bundling offers efficiency gains, it introduces challenges that workers must learn to manage effectively. Understanding how gig workers respond to the platform's bundling recommendations and how they progressively learn to optimize their bundling strategies is essential for interpreting this learning phase and the subsequent recovery in performance.

Fortunately, our dataset allows us to not only identify all platform-recommended bundled orders but also estimate instances where gig workers engage in *self-bundling*. Self-bundling is defined as cases where the start shopping time and checkout time of different orders overlap, indicating that the gig worker has independently decided to bundle deliveries without explicit platform recommendations. In the following sections, we will present our findings on both platform-recommended and self-initiated bundling behaviors, providing insights into how these strategies impact performance and how gig workers learn to optimize their use of bundling over time.

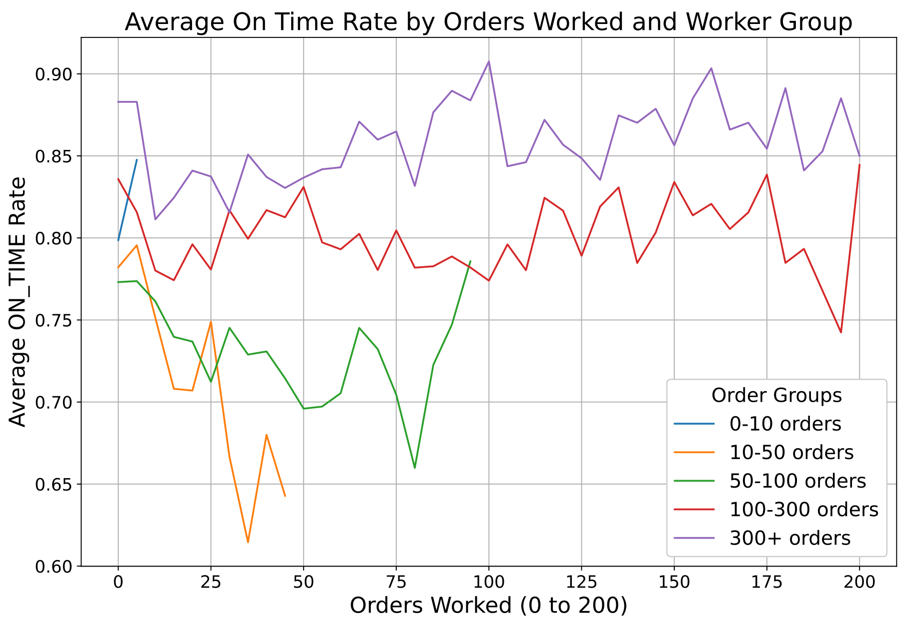

Fig. 2. Average rate of on-time delivery of different groups of workers

5.2.1 Overall Bundle Behaviors. Figure 3 illustrates the average number of bundled orders taken by different gig worker groups across their first 100 orders. The x-axis represents the number of orders worked, while the y-axis shows the average number of bundled orders. Gig workers are categorized into five groups based on their total number of orders: *0-10 orders*, *10-50 orders*, *50-100 orders*, *100-300 orders*, and *300+ orders*.

Initially, all groups exhibit a sharp rise in the number of bundled orders after 10 orders (when the platform officially introduce bundling). Notably, the group of gig workers with more than 300 orders in a year (represented by the purple line) consistently shows the highest average number of bundled orders throughout, peaking at around 3 bundled orders per 100 orders. This suggests that top-performing gig workers engage in bundling more frequently as they continue using the platform, possibly as a way to increase efficiency and maximize earnings.

In contrast, early dropouts (0-10 orders, shown by the blue line) engage minimally with bundled orders before leaving the platform. The *10-50 order* group (orange line) shows an initial increase but stabilizes at a lower level compared to more experienced groups. Similarly, the *50-100* and *100-300* order groups (green and red lines) exhibit increases in bundling behavior but maintain averages lower than the most experienced gig workers (300+ orders).

Overall, the results suggest that frequent bundling is positively correlated with higher retention and performance on the platform. Gig workers who eventually have a longer tenure with the platform are the most likely to engage in bundling, whereas early dropouts tend to bundle less, which may contribute to their early departure from the platform.

5.2.2 Platform-bundled vs. Self-bundled. Figure 4 shows the percentage of platform bundled orders of different groups of gig workers, while Figure 5 shows the percentage of self-bundled orders.

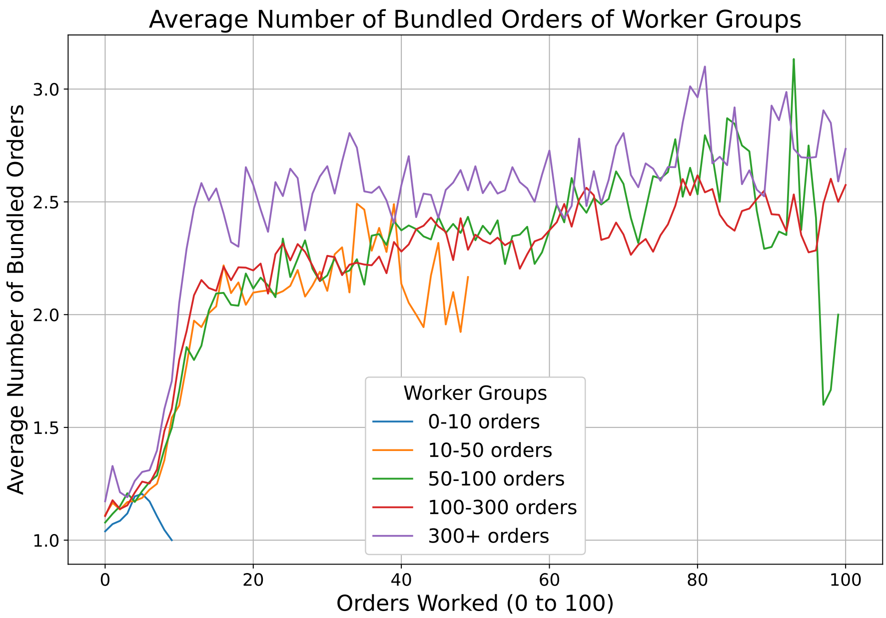

Fig. 3. Average number of bundled orders, across worker groups and over time

Taken together, these results suggest that high-performing users (e.g., completing more than 300 orders) achieve success by leveraging platform recommendations effectively and engaging less in self-bundling, which may save time and effort. On the other hand, mid-tier users tend to explore self-bundling strategies as they progress through their orders, experimenting with different methods to optimize their shopping experience. Overall, the data highlights the importance of developing a balanced bundling strategy—whether self-created or platform-guided—as users become more familiar with the platform to enhance efficiency and retention.

6 Responding to Recommendations: *Orders to Select*

While gig workers can freely choose to work on any order available on the platform, the platform typically recommends a number of orders to them based on the demand level and past performance. We denote the orders that are recommended by the platform as *algorithmically recommended orders* and the remaining orders as *non-algorithmically recommended orders* .

In this section, we break down the first 200 orders into 5 periods and apply a multinomial logit (MNL) model [33] to estimate the choice a gig worker makes in each of these periods. This analysis allows us to investigate how gig workers' decision-making processes evolve over time as they gain more experience and become more familiar with the platform's recommendations. Understanding these dynamics provides insight into the strategic choices gig workers make as they navigate the platform.

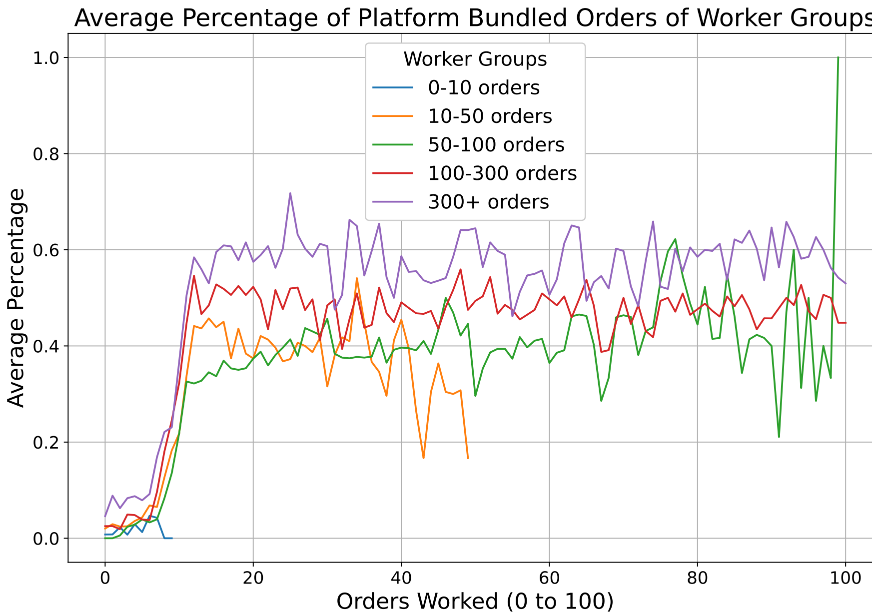

Fig. 4. Average percentage of platform bundled orders, across worker groups and over time

6.1 Multinomial Logit Model of Workers' Selected Orders

6.1.1 Description of Key Variables. We describe the variables used in the multinomial logit model to analyze gig worker behavior across different choice sets. The dependent variable is the choice outcome, and the explanatory variables represent the characteristics of the alternatives and the gig workers.

Dependent variable. The dependent variable *CHOSEN* in the model is a binary indicator representing whether a specific alternative was chosen that takes the value 1 if the alternative was chosen by the gig worker, and 0 otherwise.

Independent variables. We document the important independent variables included in the MNL model here. We defer the complete list of variables to Appendix A. These variables represent characteristics of the alternatives and other relevant attributes influencing the decision. Each of these variables contributes to the deterministic component of the utility function, V_{ij}, for each alternative j faced by gig worker i.

- *LIST*: Indicates whether the order is in the recommendation list by the platform's algorithm (1) or it is not (0).
- *REINFORCEMENT*: The total earnings from the gig worker's previous 100 orders at a given store. This variable reflects how exploratory gig workers are, measuring whether they prefer familiar stores or explore new ones. It mimics a reinforcement learning model, as described by [7], where it is assumed that people learn from the rewards they receive from past interactions.

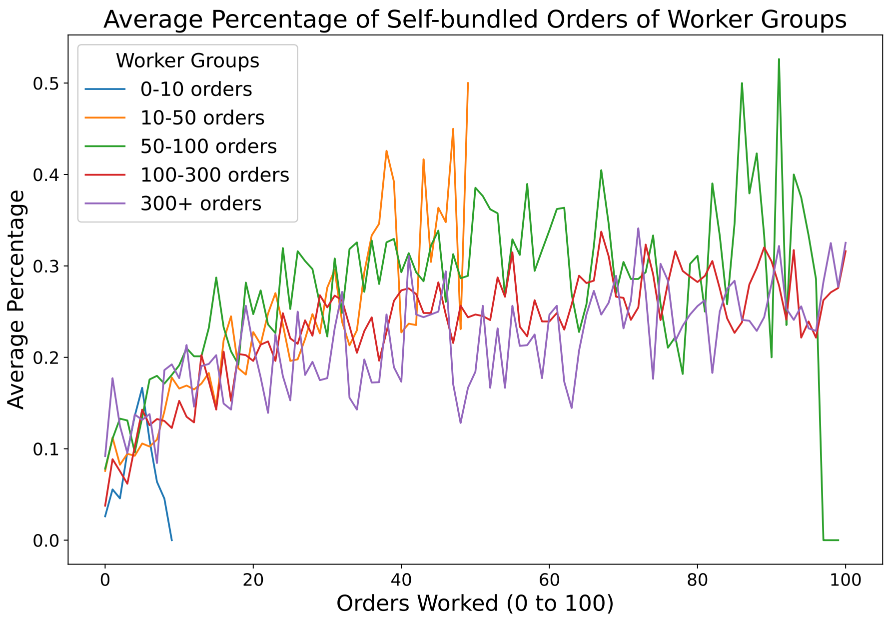

Fig. 5. Average percentage of self bundled orders, across worker groups and over time

Independent variables. We again classify gig workers into 5 groups based on the total number of orders they have completed. We then introduce group-specific effects in the MNL model by converting the group category, into dummy variables using one-hot encoding. The group `300+` was designated as the reference group, and dummy variables were created for the remaining groups. Interaction terms were then generated between these group dummies and key independent variables (e.g., *LIST*), allowing us to capture how the effect of these predictors varied across gig worker groups. Only interaction terms with non-redundant information were included, ensuring efficient model specification. This approach allows us to interpret coefficients in relation to the reference group, revealing group-specific differences in decision-making behavior.

6.1.2 *Model specification.*

Utility function. The utility function U_{ij} for alternative j and gig worker i is composed of a deterministic component V_{ij} and a stochastic component ϵ_{ij}:

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{2}$$

The deterministic component V_{ij} is modeled as a linear function of the explanatory variables:

$$V_{ij} = \beta_0 + \beta_1 \cdot \text{Bundled}_{ij} + \beta_2 \cdot \text{List}_{ij} + \dots \tag{3}$$

Here, β_k represents the coefficient associated with each explanatory variable, and ϵ_{ij} is the error term, assumed to follow a Gumbel distribution.

Choice probabilities. The probability that gig worker i chooses alternative j is given by the following multinomial logit probability function:

$$P_{ij} = \frac{\exp(V_{ij})}{\sum_{l=1}^{J} \exp(V_{il})} \tag{4}$$

where J is the number of available alternatives in the choice set.

6.1.3 Estimation method. The parameters β are estimated using Maximum Likelihood Estimation (MLE) by maximizing the log-likelihood function:

$$\ln L(\beta) = \sum_{i=1}^{N} \left(V_{iy_i} - \ln \left(\sum_{l=1}^{J} \exp(V_{il}) \right) \right) \tag{5}$$

where y_i denotes the alternative chosen by gig worker i. The MLE process yields estimates of the coefficients β, which quantify the effect of each independent variable on the choice probability.

6.2 Results: *Workers Follow Recommendations Less with More Experience*

We estimate the Multinomial Logit (MNL) choice model across five distinct groups of gig workers categorized by their total completed orders: those with fewer than 10 orders, between 10 and 50 orders, between 50 and 100 orders, between 100 and 300 orders, and those with over 300 orders. This analysis is conducted over five time periods, representing different stages in their shopping history: the first 10 orders, between 10 and 20 orders, between 20 and 50 orders, between 50 and 100 orders, and between 100 and 200 orders.

Figures 6 and 7 present the estimated coefficients and their corresponding confidence intervals for the two primary independent variables *REINFORCEMENT* and *LIST*. The x-axis represents the order period for which the choice model is estimated (e.g., 0-10 indicates the estimated coefficients for a worker's first 0-10 orders). The y-axis displays the coefficient values. The different colored columns correspond to the five distinct groups being analyzed.

To facilitate interpretation, we generated dummy variables in 6.1.1, using the group with yearly orders $\geq$ 300 as the reference category. Consequently, in the two figures presented, only the rightmost bar (in purple) depicts the actual coefficient for this reference group. All other bars represent the differential coefficients relative to the reference group, illustrating the deviation in effect sizes for each corresponding category.

Figure 6 illustrates the extent to which different groups of gig workers exhibit exploratory behavior. The variable measures the total dollar amount a gig worker has earned at the same store over their last 100 orders. Higher coefficient values suggest that gig workers are placing more weight on stores they have previously visited when making choices. This behavior indicates a tendency toward exploitation rather than exploration. The figure demonstrates that, for gig workers with fewer than 10 orders, only the group that exits the platform early within 10 orders–represented by the blue bar–shows a negative coefficient relative to the reference group. Notably, the absolute value of this negative coefficient exceeds that of the reference group's (purple bar). This finding suggests that early dropouts are the only group that exhibits negative weighting for this variable, implying that they rarely return to previously visited stores and may engage in excessive exploration during the initial stages of platform use.

Another important observation is that early dropouts, including those who leave within 10 orders (blue bar) and within 50 orders (yellow bar), exhibit high variance in their coefficients compared to other groups. This suggests that early dropout behavior is linked to inconsistent exploratory store

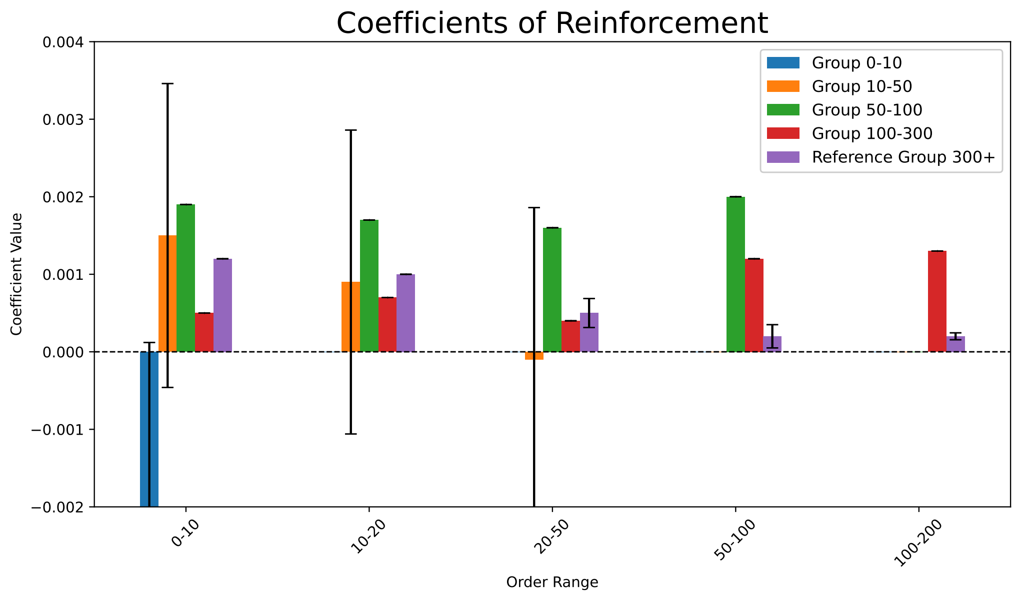

Fig. 6. Estimated coefficients of REINFORCEMENT, defined by total earnings in the chosen store in the last 100 orders, across worker groups and levels of experiences

choices. In other words, users who do not settle into a consistent store selection pattern — through repeated visits to familiar stores —are more likely to abandon the platform.

In addition, we observe that the best performers—gig workers who have completed more than 300 orders per year and exhibit the highest performance metrics, as demonstrated in previous sections—while placing positive weights on the variable, actually have the lowest coefficient value among all groups except for early dropouts (noting that the other groups' coefficients in the figure represent differences relative to the reference group). This suggests that a moderate level of exploration may be beneficial. As discussed in Section 4, gaining experience in other stores can also contribute to improved performance, implying that balancing exploration and exploitation is key to long-term success on the platform.

Figure 7 illustrates how different groups respond to the platform's recommendation algorithm over time. A higher coefficient value indicates that the group is more likely to choose recommended orders compared to other orders. We can observe that: (1) the best performers tend to follow the platform's recommendations at the beginning but gradually shift towards ignoring them or even placing negative weights on choosing recommended orders. (2) Other groups, while initially following fewer recommendations than the top-performing group, also tend to decrease their reliance on the platform's recommendations over time. This trend suggests that although gig workers initially tend to follow recommendations, over time, they become more selective or independent in their order selection, likely as they gain more experience and confidence in making their own choices, reducing their reliance on algorithmic suggestions.

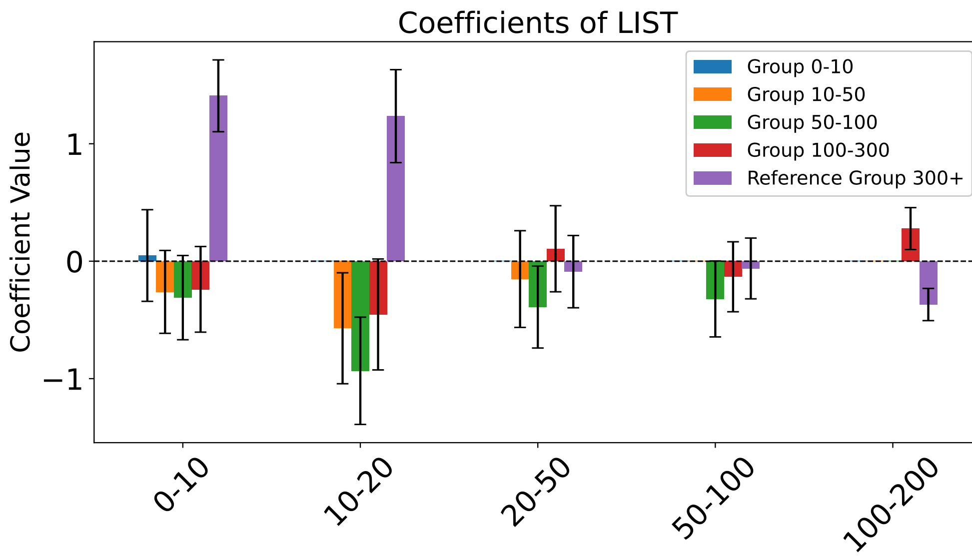

Fig. 7. Estimated coefficients of LIST, defined by whether recommended by the platform's algorithms, across worker groups and levels of experiences

6.3 Implications for the Design of Recommendation Algorithms

Our findings reveal key insights into gig worker behaviors, suggesting multiple ways to enhance recommendation algorithms on gig economy platforms to better support workers and improve overall performance.

Early dropouts: inconsistent behaviors and excessive exploration. The group of gig workers who exited the platform within their first 10 to 50 orders demonstrated a distinctively inconsistent decision-making pattern. Our results indicate a lack of store loyalty or a tendency to avoid returning to previously visited stores of these early dropouts. Additionally, they exhibited high variance in their store choices. Such inconsistency suggests that the lack of store exploitation and stable shopping routines early on is strongly correlated with dropping out early from the platform.

To mitigate early dropout rates caused by these factors among new workers, platforms should recommend tasks from stores where they have previously visited can help induce familiarity and reduce indecisiveness in the early stage. By supporting a healthy level of exploitation early on, platforms can improve worker welfare, consequently promoting worker retention and better integration into the cooperative work environment.

Optimal exploration among high performers. In contrast, gig workers who achieved the highest performance and remained active on the platform for the longest time were those who engaged in the moderate level of exploration. Among the remaining groups besides early dropouts, the high performers still explored more. This underscores the importance of finding an optimal balance in exploration behaviors, where excessive exploration may hinder performance, while a strategic level of exploration enhances success.

Recognizing that high-performing workers engage in optimal levels of exploration, recommendation algorithms should balance familiar and new task suggestions. Platforms can design systems that encourage strategic exploration without overwhelming workers, tailoring recommendations based on individual performance histories and preferences. This approach supports workers in developing effective strategies and enhances their learning processes over time.

Declining selection of platform-recommended orders. Furthermore, the data indicates that, over time, gig workers tend to select fewer platform-recommended orders. This shift away from algorithmic recommendations indicates that these gig workers might perceive platform suggestions as less beneficial or aligned with their evolved needs, pointing to the need for adaptive recommendation algorithm. As workers become more proficient, platforms should adjust their algorithms to provide greater flexibility, allowing experienced workers to align task selections with their personal strategies. By incorporating worker feedback mechanisms, platforms can further personalize recommendations, ensuring they remain relevant and beneficial as workers' needs evolve over time.

Overall, these implications emphasize the importance of human-centric recommendation systems that adapt to workers' learning trajectories and experience levels. By aligning algorithmic recommendations with the evolving strategies and preferences of workers, platforms can enhance collaborative dynamics, improve performance outcomes, and foster long-term engagement within the gig economy.

7 Concluding Remarks

Our study offers important insights into how gig workers in the retail delivery sector learn and adapt to platform recommendations over time, particularly in task bundling, selection strategies, and learning processes. Through a mixed-method approach–incorporating descriptive analysis, two-way fixed-effects regression, and a multinomial logit model–we observe a clear learning curve among workers. As they accumulate experience, workers enhance both their efficiency and on-time delivery rates, improving their contributions to the platform's overall performance.

We explore how workers respond to platform-recommended order bundles. While the introduction of bundling initially caused a temporary decline in service quality, workers quickly became more proficient through repeated interactions with the system. High-performing workers increasingly rely on platform-suggested bundles, leading to greater coordination and time management efficiency. However, mid-tier workers who experiment with self-bundling often experience inconsistent outcomes, underscoring the challenges of balancing personal autonomy with algorithmic recommendations.

Our findings also highlight dynamic worker-platform interactions in task selection. Newer workers tend to depend heavily on platform recommendations, while more experienced workers develop individual strategies that deviate from algorithmic suggestions. This suggests that platforms should adjust recommendation algorithms over time, offering greater flexibility for experienced workers to align tasks with their evolving strategies. Additionally, introducing feedback mechanisms could further personalize recommendations, ensuring that task suggestions remain responsive to workers' changing needs and preferences.

A key takeaway from our research is the importance of balancing exploration and exploitation in task selection. While excessive exploration—such as accepting tasks from new or unfamiliar stores—can reduce performance and increase the risk of early dropout, moderate exploration is essential for long-term success and adaptability. Platforms should tailor recommendations to encourage familiarity in the early stages of worker engagement and then offer a balanced mix of familiar and new tasks as workers build confidence and experience.

In conclusion, our research contributes to the understanding of how gig workers co-adapt with algorithmic systems, with practical implications for platform design. Platforms that align recommendations with workers' learning trajectories and evolving decision-making processes can better support performance improvement, worker retention, and sustainable engagement. Furthermore, our findings emphasize the need for platforms to foster collaborative worker-algorithm interactions by balancing structured guidance with individual autonomy.

Despite these insights, our research has some limitations. First, we focus on the learning behaviors of newer gig workers, whereas the strategies of experienced workers could offer additional perspectives. Second, our dataset is limited to a single city over one year, restricting the generalizability of our results to other geographic locations and time frames with different market dynamics. Third, we observe only successfully delivered orders, meaning we lack data on unclaimed or rejected tasks, which may provide further insights into worker decision-making and platform efficiency. Finally, while our models address individual learning, they do not fully capture the role of social interactions or external influences in shaping worker behavior. Future research could explore these dimensions to develop a more comprehensive understanding of gig worker dynamics in algorithmically managed environments.

References

[1] Zeynep Akşin, Sarang Deo, Jónas Oddur Jónasson, and Kamalini Ramdas. 2021. Learning from many: Partner exposure and team familiarity in fluid teams. *Management Science* 67, 2 (Feb. 2021), 854–874.

[2] Gad Allon, Maxime C Cohen, and Wichinpong Park Sinchaisri. 2023. The impact of behavioral and economic drivers on gig economy workers. *Manufacturing & Service Operations Management* 25, 4 (2023), 1376–1393.

[3] Michel Jose Anzanello and Flavio Sanson Fogliatto. 2011. Learning curve models and applications: Literature review and research directions. *International Journal of Industrial Ergonomics* 41, 5 (2011), 573–583.

[4] Linda Argote. 2012. *Organizational learning: Creating, retaining and transferring knowledge* (2 ed.). Springer, New York, NY.

[5] Hamsa Bastani, Osbert Bastani, and Wichinpong Park Sinchaisri. 2024. Improving Human Sequential Decision-Making with Reinforcement Learning. https://doi.org/10.48550/ARXIV.2108.08454

[6] Hessam Bavafa and Jónas Oddur Jónasson. 2021. The Variance Learning Curve. *Management Science* 67, 5 (May 2021), 3104–3116.

[7] Colin Camerer and Teck Hua Ho. 1999. Experience-weighted attraction learning in normal form games. *Econometrica* 67, 4 (1999), 827–874.

[8] Jonathan R Clark, Robert S Huckman, and Bradley R Staats. 2013. Learning from customers: Individual and organizational effects in outsourced radiological services. *Organization Science* 24, 5 (Oct. 2013), 1539–1557.

[9] Hongyan Dai, Jayashankar M Swaminathan, and Yuqian Xu. 2022. Leveraging the Experience: Exploration and Exploitation in Gig Worker Learning Process. (May 2022).

[10] Ezey M Dar-El. 2013. *HUMAN LEARNING: From learning curves to learning organizations* (2000 ed.). Springer, New York, NY.

[11] Vedant Das Swain, Lan Gao, Abhirup Mondal, Gregory D Abowd, and Munmun De Choudhury. 2024. Sensible and sensitive AI for worker wellbeing: Factors that inform adoption and resistance for information workers. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, Vol. 105. ACM, New York, NY, USA, 1–30.

[12] Vedant Das Swain, Lan Gao, William A Wood, Srikruthi C Matli, Gregory D Abowd, and Munmun De Choudhury. 2023. Algorithmic power or punishment: Information worker perspectives on passive sensing enabled AI phenotyping of performance and wellbeing. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, Vol. 105. ACM, New York, NY, USA, 1–17.

[13] Esra Cemre Su de Groot and Ujwal Gadiraju. 2024. "Are we all in the same boat?" Customizable and Evolving Avatars to Improve Worker Engagement and Foster a Sense of Community in Online Crowd Work. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 640, 26 pages. https://doi.org/10.1145/3613904.3642429

[14] Berkeley J. Dietvorst, Joseph P. Simmons, and Cade Massey. 2015. Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General* 144, 1 (2015), 114–126.

[15] Berkeley J. Dietvorst, Joseph P. Simmons, and Cade Massey. 2018. Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them. *Management Science* 64, 3 (March 2018), 1155–1170. https://doi.org/10.1287/mnsc.2016.2643

[16] Kimberly Do, Maya De Los Santos, Michael Muller, and Saiph Savage. 2024. Designing gig worker sousveillance tools. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, Vol. 1. ACM, New York, NY, USA, 1–19.

[17] Steven Dow, Anand Kulkarni, Scott Klemmer, and Björn Hartmann. 2012. Shepherding the crowd yields better work. In *Proceedings of the ACM 2012 conference on computer supported cooperative work*. 1013–1022.

[18] Wai Fong Boh, Sandra A Slaughter, and J Alberto Espinosa. 2007. Learning from experience in software development: A multilevel analysis. *Management Science* 53, 8 (Aug. 2007), 1315–1331.

[19] Shreepriya Gonzalez-Jimenez, Cecile Boulard, Clara Tuco, and Romane Calleau. 2022. Designing Food Delivery Gig-platforms for Courier Needs: the Case of Batched Orders. In *Companion Publication of the 2022 Conference on Computer Supported Cooperative Work and Social Computing* (Virtual Event, Taiwan) *(CSCW'22 Companion)*. Association for Computing Machinery, New York, NY, USA, 163–167. https://doi.org/10.1145/3500868.3559452

[20] Aspen Gorry. 2016. Experience and worker flows. *Quantitative Economics* 7, 1 (March 2016), 225–255.

[21] Eric H Grosse and Christoph H Glock. 2015. The effect of worker learning on manual order picking processes. *Int. J. Prod. Econ.* 170 (Dec. 2015), 882–890.

[22] Reeju Guha and Daniel Corsten. 2023. The Role of Within-Day Learning on Gig Workers' Performance and Task Allocation: Evidence from an On-demand Platform. *Available at SSRN* (2023).

[23] Katharina Hermann, Wim Van Damme, George W Pariyo, Erik Schouten, Yibeltal Assefa, Anna Cirera, and William Massavon. 2009. Community health workers for ART in sub-Saharan Africa: learning from experience–capitalizing on new opportunities. *Human resources for health* 7 (2009), 1–11.

[24] Rie Helene (lindy) Hernandez, Qiurong Song, Yubo Kou, and Xinning Gui. 2024. "At the end of the day, I am accountable": Gig Workers' Self-Tracking for Multi-Dimensional Accountability Management. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, Vol. 54. ACM, New York, NY, USA, 1–20.

[25] Mohammad Hossein Jarrahi, Gemma Newlands, Min Kyung Lee, Christine T Wolf, Eliscia Kinder, and Will Sutherland. 2021. Algorithmic management in a work context. *Big Data & Society* 8, 2 (2021), 20539517211020332.

[26] Mohammad Hossein Jarrahi and Will Sutherland. 2019. Algorithmic management and algorithmic competencies: Understanding and appropriating algorithms in gig work. In *International Conference on Information*. Springer, 578–589.

[27] Sangmi Kim, Elizabeth Marquis, Rasha Alahmad, Casey S. Pierce, and Lionel P. Robert Jr. 2018. The Impacts of Platform Quality on Gig Workers' Autonomy and Job Satisfaction. In *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing* (Jersey City, NJ, USA) *(CSCW '18 Companion)*. Association for Computing Machinery, New York, NY, USA, 181–184. https://doi.org/10.1145/3272973.3274050

[28] Benjamin Knight, Dmitry Mitrofanov, and Serguei Netessine. 2022. The impact of ai technology on the productivity of gig economy workers. *Available at SSRN 4372368* (2022).

[29] Min Kyung Lee. 2018. Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society* 5, 1 (2018), 2053951718756684.

[30] Min Kyung Lee, Daniel Kusbit, Evan Metsky, and Laura Dabbish. 2015. Working with machines: The impact of algorithmic and data-driven management on human workers. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, 1603–1612.

[31] Shuhao Ma. 2024. Advancing HCI and design methods to empower gig workers. In *Designing Interactive Systems Conference*. ACM, New York, NY, USA.

[32] Elizabeth B. Marquis, Sangmi Kim, Rasha Alahmad, Casey S. Pierce, and Lionel P. Robert Jr. 2018. Impacts of Perceived Behavior Control and Emotional Labor on Gig Workers. In *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing* (Jersey City, NJ, USA) *(CSCW '18 Companion)*. Association for Computing Machinery, New York, NY, USA, 241–244. https://doi.org/10.1145/3272973.3274065

[33] Daniel McFadden. 1972. Conditional logit analysis of qualitative choice behavior. (1972).

[34] Saiph Savage. 2024. Unveiling AI-driven collective action for a worker-centric future. In *Proceedings of the 17th ACM International Conference on Web Search and Data Mining*. ACM, New York, NY, USA.

[35] Scott M Shafer, David A Nembhard, and Mustafa V Uzumeri. 2001. The Effects of Worker Learning, Forgetting, and Heterogeneity on Assembly Line Productivity. *Management Science* 47, 12 (Dec. 2001), 1639–1653.

[36] Riyaj Shaikh, Anubha Singh, Barry Brown, and Airi Lampinen. 2024. Not Just A Dot on The Map: Food Delivery Workers as Infrastructure. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 385, 15 pages. https://doi.org/10.1145/3613904.3641918

[37] Clara Tuco, Cécile Boulard, Romane Calleau, and Shreepriya Shreepriya. 2021. Food Delivery Eco-System: When Platforms Get Enterprises and Gig-Workers to Implicitly Cooperate. In *Companion Publication of the 2021 Conference on Computer Supported Cooperative Work and Social Computing* (Virtual Event, USA) *(CSCW '21 Companion)*. Association for Computing Machinery, New York, NY, USA, 183–186. https://doi.org/10.1145/3462204.3481757

[38] Jeffrey M Wooldridge. 2010. *Econometric analysis of cross section and panel data*. MIT press.

[39] Zheng Yao, Silas Weden, Lea Emerlyn, Haiyi Zhu, and Robert E Kraut. 2021. Together but alone: Atomization and peer support among gig workers. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–29.
[40] Angie Zhang, Alexander Boltz, Jonathan Lynn, Chun-Wei Wang, and Min Kyung Lee. 2023. Stakeholder-centered AI design: Co-designing worker tools with gig workers through data probes. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, Vol. 63. ACM, New York, NY, USA, 1–19.
[41] Angie Zhang, Alexander Boltz, Chun Wei Wang, and Min Kyung Lee. 2022. Algorithmic management reimagined for workers and by workers: Centering worker well-being in gig work. In *CHI Conference on Human Factors in Computing Systems*. ACM, New York, NY, USA.

A Full Independent Variables in the MNL Model

- **LIST**: Indicates whether the order is in the recommendation list by the platform's algorithm (1) or it is not (0).
- **BUNDLED**: Indicates whether the order is part of a bundle (1) or not (0).
- **REINFORCEMENT**: The total dollars earned from the gig worker's previous 100 orders in this store. This variable indicates how exploratory gig workers are (whether they always choose stores they have usually visited or explore new stores). This is a variable mimicking reinforcement like [7], where we assume people learn from the rewards they receive from past interactions.
- **ORDER_TYPE_ID**: The type of order associated with the alternative (e.g., delivery or pickup).
- **MAX_CONTRIBUTIONS_CAT_PCT**: The maximum percentage of contributions from a specific item category in the alternative.
- **MILES_DISTANCE_STORE_CUST**: The distance (in miles) between the store and the customer's location.
- **REQUESTED_ITEMS**: The number of items requested in the order.
- **DOLLARS_BONUS**: The dollar amount of any bonuses offered for completing the order.
- **DOLLARS_PAY**: The total payment offered for completing the order, excluding bonuses.
- **LOCAL_DELIVERY_WINDOW**: The delivery time window of the order.
- **PCT_DAILY_NONFOOD_ITEMS**: The percentage of daily non-food items in the alternative.
- **PCT_EXPANDED_FOOD_ITEMS**: The percentage of expanded food items in the alternative.
- **PCT_GENERAL_MERCH_ITEMS**: The percentage of general merchandise items in the alternative.