

Training, Experience and Algorithmic Governance: Food-Delivery Workers' Earnings

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Abstract. The rapid expansion of food-delivery platforms has created employment opportunities for millions of workers, yet it has also brought about unstable earnings, inadequate labour protections and intensifying algorithmic control. Existing studies have largely explored workers' earnings from either an individual-level perspective, focusing on training and work experience, or a platform-level perspective, centring on algorithmic management. This review integrates these two perspectives to investigate how learning and algorithmic management shape food-delivery workers' earnings, as well as how workers respond to such working conditions. A literature-review approach was adopted, drawing mainly on three core studies on food-delivery and platform work together with their key cited references. This paper compares scholarship on human capital, learning-by-doing, algorithmic management, worker agency and platform-imposed control. The findings suggest that learning-by-doing and accumulated work experience are generally positively correlated with workers' income, whereas formal platform training may yield limited or even adverse income outcomes when it is decoupled from real-world job demands. Meanwhile, algorithmic management affects earnings via task allocation, performance evaluation, incentive schemes, customer ratings and information asymmetry. Workers acquire practical knowledge and coping strategies to adapt to these systems, yet stronger adaptation does not necessarily translate into greater worker autonomy. This review concludes that food-delivery workers' earnings stem from the interplay between individual learning and platform algorithmic governance. Instead of relying heavily on a one-size-fits-all minimum wage, future interventions ought to prioritise greater algorithmic transparency and accountability. Further research should explore how workers' accumulated experience is recognised and rewarded across different platform systems.

Keywords: Gig economy, algorithmic management, food-delivery riders, human capital

1. Introduction

Food-delivery industry has witnessed the rapid expansion in the past few decades, as one of the largest and fastest-growing sectors of the gig economy. In China, food-delivery riders, formally classified as "online delivery workers" since 2020, have exceeded 10 million [1]. In Southeast Asia, Grab has become a leading platform in Vietnam's ride-hailing market, holding over 70% of the market share [2]. Despite their large numbers, food-delivery workers occupy a legal gray area—

classified as "independent contractors" rather than employees, which largely excludes them from minimum wage protections and the right to collective bargaining [1, 3]. The economic downturn following the pandemic has further intensified competition, and an oversupply of labor has forced food-delivery riders to accept harsher working conditions [4]. Against this context, income instability should be understood not only as a result of labour oversupply, but also as an outcome of how workers acquire skills and how platforms allocate and evaluate work through algorithms. This review therefore focuses on two closely related influences on earnings—learning and algorithmic management—and then considers how workers respond to these conditions and what forms of collective and institutional protection may be needed.

A growing body of literature has sought to explain what determines platform workers' income. One strand, grounded in human capital theory, examines how individual-level investments—such as training and work experience—translate into earnings [5, 6]. Zheng et al. find that Chinese delivery riders' on-the-job experience significantly raises their income, while platform-provided formal training is negatively associated with earnings [1]. Another strand, drawing on labor process theory and algorithmic management literature, shifts attention to the platform's technological infrastructure [7-10]. Griesbach et al. demonstrate that platforms exert systematic algorithmic control over workers' time and activities, with some approaching "algorithmic despotism" [3]. Nguyen-Thu and Munn extend this inquiry to Southeast Asia, demonstrating how GrabBike workers "tame the algorithm", such as improvising, scrambling, and enduring, to render exploitation more predictable [4].

However, the research approaches mentioned above are largely isolated from one another. The human capital approach has shown that experience influences earnings, but has not explained how experience translates into earnings in an environment where algorithms mediate nearly every aspect of work [1]. Conversely, while the algorithmic control literature has illustrated how platforms constrain workers, it has not yet systematically examined how these control mechanisms interact with individual characteristics such as experience or training to influence income outcomes [3, 4]. Based on the previous review, this paper first examines learning and algorithmic management as two interconnected determinants of food delivery workers' earnings, and then evaluates the limits of individual adaptation before considering collective and institutional responses to income instability and weak labour protection.

2. Influencing factors of earnings of food delivery workers

Research on the income of food-delivery workers shows that both individual human capital and platform-level algorithmic management affect their income. Recently, in addition to the reasons mentioned above, some studies have also found that the skills, experience and strategies of workers are shaped by the technological system of continuous monitoring and assessment of their performance. Therefore, the determinants of income for platform workers can be broadly divided into two categories: learning and algorithmic control.

2.1. Training and experience

Human capital theory provides a foundation for research on how worker attributes affect earnings. Becker views education and training as investments in expanding workers' productive capacity, while Mincer's human capital framework links earnings differences to education and accumulated work experience [5, 6]. From this perspective, workers learn economically useful skills through both formal training and practical experience. Zheng et al. have extended this idea to the gig economy by

distinguishing between formal platform training and learning by doing. Their study of 9,133 Chinese food delivery riders finds that work experience is positively associated with platform income, suggesting that repeated participation allows workers to accumulate practical knowledge and occupational capacity [1]. This finding is consistent with previous study that job experience can improve work performance [11].

However, the relationship between formal training and earnings is more complicated. Classical human capital theory generally believes that employer-provided training would increase the productivity of workers and thus their earnings [5]. Zheng et al. have found that the pattern is reversed for Chinese delivery riders: regular platform training is negatively correlated with platform income. Qualitative evidence helps explain this unexpected result. Training mainly focuses on traffic safety, service rules, and standardised procedures rather than practical techniques for improving delivery efficiency. Therefore, training is relatively time-consuming and has limited immediate value for income generation. The finding indicates that the economic value of training depends not simply on whether training is provided, but on what is taught, how it is conducted, and whether it can be linked to workers' actual production process [1].

Learning by doing is likely to be more effective for platform workers because their work environments are highly variable. Over time, riders learn about traffic conditions, customer demand, restaurant waiting times, profitable locations, and the platform's task allocation system. Nguyen-Thu and Munn's ethnographic research on GrabBike workers provides a clear example. Experienced workers develop their own practical theories of how the platform works through repeated trial and error. Their knowledge helps them anticipate when and where orders are likely to appear and adjust their routes accordingly [4]. In this way, experience can enhance workers' technical competence and help them learn how to operate within the platform's algorithmic system.

This suggests a further development in the human capital literature. Work experience has traditionally been viewed as the accumulation of occupational skills. In platform work, however, experience also involves learning how to interpret algorithmic systems. Jarrahi and Sutherland argue that platform workers develop forms of sensemaking to interpret algorithmic variables, rewards, and procedures [12]. Similarly, Curchod et al. show that workers can use accumulated knowledge to understand and strategically respond to algorithmic control [13]. Therefore, experience may increase income not only because workers become faster or more efficient, but also because they become better at interpreting and responding to the platform itself.

Human capital alone cannot fully explain the income of platform workers. Zheng et al. argue that classical human capital theory is only partially applicable to the gig economy [1]. Platform work is not a typical form of employment; it generally involves short-term participation, weak employment relationships, and algorithmic task allocation. Workers may accumulate valuable experience, but the economic return on that experience depends on whether the platform recognises and rewards it. Therefore, explaining income requires moving beyond an individual-centred perspective toward a broader consideration of algorithmic management.

2.2. Algorithmic management

The second major factor influencing platform workers' outcomes is algorithmic management. Most traditional employment has direct supervision by managers; however, platform work increasingly uses digital systems to allocate tasks, evaluate performance, set rewards and punishments, and regulate the pace of work [9, 10]. Therefore, the algorithm for food delivery workers is not merely a technical tool to match supply and demand. It also specifies when workers receive orders, what kind of orders they receive, and how much effort needs to be exerted to keep their jobs.

A central issue in this literature is the tension between flexibility and control. Workers can choose when to work and which order to accept from a general standpoint. However, these choices occur in a system of incentives and constraints. Griesbach et al. show that food delivery platforms use acceptance rates, customer ratings, scheduling requirements, and bonus schemes to influence workers' decisions, even when workers formally remain free to reject individual orders [3]. Similar evidence from Australia shows that algorithmic systems can reproduce traditional forms of labour process control through digital technology by altering the distribution and assessment of work [14]. Therefore, algorithmic management does not necessarily mean a loss of managerial control; rather, it changes the form of that control.

The problem becomes more serious if the rules of the platform are not fully disclosed to the workers. Previous studies have pointed out the importance of information asymmetry in platform labour [15]. Workers can generally see the results of an algorithm's decision, such as whether they have been assigned work or how much they will be paid, but they cannot know the reasons for this decision. Burrell refers to this as algorithmic opacity, and Rosenblat and Stark have shown that limited access to information can increase the platform's power over workers [15, 16]. In the work of food delivery, it means that the workers are aware that ratings, acceptance rates, speed, etc., are important, but they do not know how exactly these factors affect future orders and income. As a result, the workers are motivated to try different behaviours and learn from the results.

Ratings, rankings and incentive systems also extend algorithmic control to the workers' daily lives. The platform will directly use the consumer's rating of the employee's work to offer rewards or restrict employment opportunities [3]. Gamification further encourages employees to compete for bonuses and higher performance ratings, making the acquisition of income a continuous process of self-monitoring and performance enhancement [17, 18]. Although the above mechanisms may increase the efficiency of the platform, they can also make workers more dependent on the platform's performance indicators.

Overall, the studies have shown that algorithmic management has changed the form but not the function of managerial control. Platforms combine flexibility and incentives, performance monitoring, information asymmetry, and control over access to work [3, 9, 10]. Not all of these platforms use the same control. Griesbach et al. have shown that the intensity of algorithmic control differs greatly, and some platforms have set relatively strict limits on the time and content of work for employees [3]. Therefore, the effect of algorithmic management on the income of delivery workers will vary depending on the existence of an algorithm and how the platform designs and applies its system of control.

3. Challenges

The literature reviewed above shows that food-delivery workers face a common set of challenges: opaque algorithms, unstable income, weak employment protection, and an oversupply of labour.

3.1. Individual responses: taming the algorithm

Nguyen-Thu and Munn's ethnography of GrabBike workers provides the clearest account of how riders respond to algorithmic control on their own. Faced with an algorithm they cannot see or fully understand, experienced riders develop a set of practical strategies that the authors term "taming the algorithm", consisting of three moves: improvising, scrambling, and enduring [4]. Improvising means learning, through trial and error, how the app "thinks", knowing where to wait for orders, which services yield more rewards, and how to make one's movements visible to the algorithm.

Scrambling describes the frenetic, performance-oriented labour of meeting exacting time targets while juggling traffic, weather, and customer demands. Enduring involves sustaining these efforts over long periods, often 12 to 14 hours a day for months, until the worker's productivity is registered by the system as a stable pattern [4].

These strategies do improve workers' immediate situation. Successfully tamed, the algorithm becomes more predictable, and workers can count on a steadier flow of orders and a baseline income. Yet the authors are careful to stress that taming does not overturn the platform's power. Rather, it makes exploitation more consistent and predictable. Workers adopt what they call "platform realism", a bleak but pragmatic agency in which the goal is not to hack or disrupt the system but to live with it, tolerating a chronic state of precarity in exchange for enough work to survive [4].

3.2. The limits of individual adaptation

These findings suggest that individual adaptation, while necessary, has clear limits. First, the burden of adaptation falls entirely on the worker: the physical, emotional, and cognitive costs of improvising, scrambling, and enduring are borne silently by riders, while the platform only "sees" an optimal performer [4]. Second, the benefits of adaptation are fragile. Platform memory is short, a few weeks away from work can undo months of accumulated "training", forcing delivery workers to start over [4]. Third, individual strategies do not address the structural rules that govern task allocation, pay, and penalties. As Griesbach et al. show, even where riders formally remain free to accept or reject orders, acceptance rates, ratings, and scheduling requirements continue to shape their choices [3]. In other words, riders may perform better within the platform without changing the conditions under which work is distributed.

4. Suggestions

Policy interventions should explore feasible minimum-wage institutional design for food-delivery riders while improving algorithmic transparency on labour platforms. Statutory minimum wage standards can help mitigate the income risks created by algorithmic scheduling and rating systems, preventing riders from being pushed into overwork to secure sufficient earnings [4]. Meanwhile, platforms should be required to disclose core calculation rules behind order allocation, rating assessment and reward mechanisms, reducing the information asymmetry between workers and algorithmic systems [15]. Rather than relying solely on individual riders' adaptive strategies to "tame the algorithm", institutional safeguards can grant workers more bargaining power and stabilise their income under platform governance.

4.1. Delivery workers' right to simplified algorithmic explanation

The existing literature has documented widespread algorithmic opacity and information asymmetry within platform labour systems [15, 16]. Drawing on these findings, this review proposes that delivery riders should be granted the right to receive simplified explanations for unfavourable algorithm-generated outcomes. Currently, riders are only able to witness the end-products of automated decision-making, which may include fewer assigned orders, unexpected rating declines or automatic financial sanctions. They rarely understand precisely which performance metrics have led to these negative consequences. As a result, many riders invest months of intensive labour

through improvising, scrambling and enduring, merely to infer unwritten platform rules, and this process imposes substantial personal costs [4].

This proposed right would not oblige platforms to release commercially-sensitive source code or intricate mathematical calculation formulas. Rather, relevant legislation could compel platforms to offer straightforward explanations focused on measurable indicators whenever serious algorithm-related disadvantages arise. For example, if a worker receives a fine or experiences a noticeable drop in order volume, platforms ought to clarify whether this situation stems from acceptance-rate thresholds, customer feedback, delivery speed or other quantifiable standards.

This measure can mitigate information gaps and ease the heavy individual burden associated with "taming the algorithm" [4]. Nevertheless, its practical influence remains limited. Clearer explanations help workers comprehend established algorithmic logic, but they cannot reshape fundamental platform incentive structures. Nor can they relieve downward income pressure created by an oversupply of labour in the delivery sector.

4.2. Institutional-level hybrid labour protection

Much of the insecurity experienced by food-delivery riders originates from their ambiguous legal position. When workers are categorised purely as independent contractors, they become ineligible for fundamental safeguards laid out in traditional labour legislation [3]. The enduring legal division between employees and independent contractors is not suitable to reflect the mixed reality of platform delivery work. Although the riders have some freedom in choosing their working hours, they are still under the control of an algorithm.

Therefore, the government should introduce a special legal status for platform-based delivery workers in the future. Under such a system, the riders would not receive the full range of benefits for regular staff. Nevertheless, they should still be entitled to some basic guarantees, such as essential work-related accident insurance, an official channel for collective consultation, and procedural safeguards against unfair algorithmic penalties [3].

The hybrid model is more feasible than a single, uniform minimum-wage rule. It is more suitable for the task-based, piece-rate payment model of food-delivery platforms and will not impose an excessive operating cost on service providers. However, this policy option also has some administrative risks. The regulator should set a clear and specific boundary to prevent the platform from using this intermediate legal status to avoid legal responsibility [3].

5. Conclusion

Food-delivery work is now a typical form of gig economy employment that offers workers flexibility but also suffers from income instability and algorithmic supervision, as shown above. This literature review set out to unpack how work-related learning, practical experience and algorithm-based management collectively influence the income of delivery riders.

Based on the previous studies, this paper has found that on-the-job learning and accumulated experience can increase food-delivery riders' income, but formal platform training often has little actual effect. Although the experienced riders have learned to use the algorithm system, this kind of adaptation does not give them actual control and is still subject to serious physical, psychological and economic risks. The key contribution of this paper is to explore how individual workers' experiences and the algorithmic governance of platforms interact to affect their income, rather than examining them independently.

However, this paper carries clear limitations. Most of the existing evidence is in specific national and platform contexts, so it cannot be generalised. Also, it has not been determined how the various algorithms will affect the long-term value of workers' experience. Scholars can study the above dynamic interactions in different labour market environments in their future studies. Such work would help design a more balanced policy that protects the income of delivery workers while still being attractive to the public.

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