

Beyond Datafied Labor: The Algorithmic Dilemmas and Resistance of Delivery Riders

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This paper investigates how algorithmic systems shape the labor experiences of food delivery riders in China's platform economy, and how riders develop counter-strategies to reclaim autonomy. Drawing on mixed methods—surveys (n=83), ethnographic fieldwork, and a technical analysis of the Vehicle Routing Problem (VRP)—the study examines the forms of algorithmic control imposed by dispatch systems, including order allocation, route optimization, and gamified performance metrics. While these systems enhance delivery efficiency, they also generate labor precarity, safety risks, and psychological stress. In response, riders engage in grassroots tactics such as counter-mapping and peer knowledge-sharing to navigate algorithmic constraints. Building on these insights, the paper proposes an experience-informed model of algorithmic planning that integrates rider feedback into system design. It concludes by discussing policy implications and advocating for more participatory and transparent algorithmic governance, arguing that a just platform economy must center worker agency and lived knowledge.

Keywords: Operations Research, Delivery Riders, China, Datafied Labor, Vehicle Routing Problem, counter-mapping, Algorithm

Introduction

In China's booming platform economy, millions of food delivery riders navigate urban streets daily under algorithmic dispatch systems. Platforms like Meituan and Ele.me have rapidly transformed both urban service delivery and labor organization. Unlike traditional courier work, platform-based delivery is governed by apps and GPS tracking, which automate order allocation, route optimization, and performance evaluation in real time. This system has created a new class of datafied workers, valued not for their local expertise but for quantifiable productivity metrics^{1,2}. Riders often feel reduced to "cogs" in an algorithmic machine, with their every movement monitored and penalized by platform software^{3,4}.

This algorithmic governance of labor raises urgent social questions. On one hand, these systems drastically improve delivery efficiency, exemplifying platform capitalism, where platforms extract value from dispersed workforces through data and algorithmic control⁵. Dispatch algorithms solve complex logistics in seconds, matching riders to orders and generating near-optimal routes⁶. On the other hand, such efficiency comes at the cost of labor precarity: riders face strict time limits, wage deductions, and even account deactivation if they fall behind schedule^{7,8}. Gamified metrics—such as rankings and badges—blur the line between play and work, promoting constant connectivity and fostering anxiety and competition among workers⁹. China's platform cities provide a distinctive context. Dense urban forms, rapid digitization, and platform dominance allow platforms to produce space by defining service zones, creating logistical

hotspots, and directing urban movement via real-time data¹⁰. Yet riders' embodied experiences often conflict with this abstract algorithmic space—as they encounter blocked alleys, market congestion, or security checkpoints not recognized by routing software^{11,12}. These frictions highlight the limits of top-down optimization and the necessity of incorporating lived spatial knowledge into platform design.

This paper examines how algorithms govern food delivery labor and explores riders' efforts to regain autonomy through counter-algorithmic strategies. Specifically, I investigate how digital platforms reshape the labor processes and spatial dynamics of food delivery, the resulting consequences for riders' working conditions and agency, the methods riders employ to resist algorithmic control, and how platforms could be redesigned to incorporate rider knowledge. Our research integrates survey data from 83 participants and ethnographic fieldwork with a technical analysis of the Vehicle Routing Problem (VRP), a core mathematical concept underlying many platform algorithms. I focus on identifying forms of algorithmic control that riders experience, analyzing the operations research logic behind routing systems, examining grassroots tactics such as counter-mapping and peer-based knowledge sharing, and proposing an experience-informed optimization model that incorporates rider preferences and practical constraints into algorithmic planning. The structure of the paper is as follows: first, I review existing literature on algorithmic labor governance, platform urbanism, and VRP-based logistics. I then present our methodology and empirical findings. The discussion proposes an extended VRP model and considers the policy implications for fairer platform

governance. I conclude by reflecting on how rebalancing efficiency and human agency may lead to more sustainable platform urbanism in China and beyond.

Literature Review

Algorithmic Governance and Digital Labor

A central concept for understanding food delivery labor is algorithmic management^{4,7}. This term refers to the way that managerial functions—such as assigning tasks, monitoring performance, and disciplining workers—are automated through software. Instead of a human supervisor, the rider interacts with an app that tracks every order accepted, route taken, and minute spent on delivery. The consequences of this are deeply felt in riders' daily routines. Missing a deadline can lead to wage deductions or fewer future orders, and repeated delays may even result in account suspension. As one rider explained: "Nowadays delivery platform deprived riders for too much. It came up with many unnecessary rules to deduct the money I got." This illustrates what Zuboff has described as a form of surveillance capitalism²: riders' bodies and movements are constantly converted into data points that feed predictive models, reinforcing tighter schedules and stricter benchmarks. In practice, this means that a rider's value to the platform is defined less by local knowledge or personal judgment and more by abstract metrics such as delivery time or customer rating. The human effort behind each delivery is made invisible, while the algorithm becomes the *de facto* manager¹³. By focusing on algorithmic management, this paper highlights how a single framework can clarify the everyday dilemmas faced by delivery riders: pressure to move faster, loss of autonomy, and the constant fear of algorithmic penalties. Rather than surveying a wide range of abstract theories, I use this concept because it directly connects the broader debates on digital labor with the lived experiences of riders in China.

A direct consequence of algorithmic management is the datafication and objectification of labor. Workers come to be represented by abstract metrics like acceptance rates, on-time delivery scores, and customer ratings, obscuring the human effort and context behind those numbers¹¹. This aligns with a broader critique of digital labor under platform capitalism: platforms treat labor as an on-demand service commodity, often denying standard employment relationships and protections⁵. In China, food delivery riders typically operate as independent contractors or through third-party agencies, which allows platforms to evade formal employer responsibilities¹¹. The algorithm becomes the *de facto* supervisor, subtly shifting the locus of accountability. For instance, when delays or errors occur, platforms deflect blame onto riders or customers, positioning themselves as neutral intermediaries¹¹. It is observed that platform companies downplay their employer role and transfer conflicts to riders

and consumers: if a delivery is late or incorrect, the customer complains through the app about the rider, and the rider in turn can only appeal via the platform's system – with the platform casting itself as an "arbiter" rather than the party that set the harsh conditions in the first place. This dynamic illustrates how digital control regimes obscure power relations and exacerbates workers' vulnerability.

Another mechanism that extends algorithmic management is gamification. Platforms commonly implement game-like elements—leaderboards, badge rewards, performance levels—to incentivize riders to work harder and longer^{1,9}. While presented as fun or optional, these game mechanics often intensify competition and self-exploitation. A comparative study found that both Chinese and American food delivery apps use datafied gamification to nudge couriers into continually chasing the next order or bonus, effectively "stacking the odds" against workers who might otherwise log off⁹. Workers become locked in an "endless game" of completing missions or streaks to maintain their income, which can heighten stress and anxiety. Survey research in the United States similarly indicates that gig workers feel compelled to adapt their behaviors to the algorithm's opaque rules and incentive structures, undermining the supposed flexibility of gig work⁴. In China, these pressures are compounded by intense market competition among a large labor pool of rural migrants and laid-off workers seeking quick earnings^{14,15}. Temporal arbitrage practices have emerged, where couriers strategically choose when to work to exploit peak pricing or bonuses, highlighting how workers actively navigate platform-imposed temporal rhythms⁶. Nonetheless, the power imbalance remains: the platform can unilaterally change algorithms or policies, leaving workers scrambling to adapt.

Recent ethnographic research in China demonstrates that algorithmic management in food-delivery platforms relies on two interrelated mechanisms—the virtual organization of labor and algorithm-driven process control—highlighting how delivery work is coordinated and disciplined in digital form within the Chinese platform economy. This insight underscores the structural basis of algorithmic labor governance in local contexts¹⁶.

Operations Research and Delivery Algorithms

At the core of food delivery platforms' efficiency is a suite of optimization algorithms grounded in operations research (OR), particularly the family of problems known as the Vehicle Routing Problem (VRP). The VRP is a classic optimization model that generalizes the travelling salesman problem to multiple vehicles and routes. In its basic form, VRP seeks the set of routes for a fleet of drivers (or a single driver with multiple trips) that minimizes total distance or time while serving a given set of orders (locations), subject to constraints. Typical constraints include vehicle capacity, delivery time windows, and each order being served exactly once by one driver. A simplified

formulation of the VRP's objective is:

$$\min \sum_{i,j} c_{ij} x_{ij}$$

subject to assignment constraints $\sum_j x_{ij} = 1$ and $\sum_i x_{ij} = 1$ (ensuring each location i is visited exactly once by some j), with $x_{ij} \in \{0, 1\}$ indicating whether route segment from i to j is chosen. Here, c_{ij} represents the cost (time or distance) between location i and j .

In the context of food delivery, such algorithms rapidly compute optimal or near-optimal assignments of orders to riders and sequencing of stops (restaurant then customer) based on real-time data⁸. Modern delivery platforms extend this model with additional constraints and real-time updates, effectively solving a dynamic VRP with time windows: orders arrive continuously, each order has a pickup and drop-off location and an expected delivery deadline, and the system must keep re-optimizing as new information comes in a paper from the journal *Network*¹⁷. Such algorithms consider numerous factors: rider locations and capacity (who is free or can take another order), restaurant food preparation times, traffic conditions, and even weather or predicted demand surges. All these feed into cost estimates for possible assignments³. Machine learning models may also predict how long a given rider will take for a specific route at a specific time, improving the cost estimation. The platform's aim is to minimize overall delivery time (or maximize orders fulfilled per hour) while meeting customer time expectations. This has clear benefits: it maximizes efficiency and utilization of labor, allowing one courier to handle multiple orders in an optimized sequence where feasible, thus lowering per-order costs and wait times.

Data and Methodology

This study employs a mixed-method research design combining surveys, participant observation, and archival analysis. The research was conducted in 2024 in Shenzhen, a major Chinese metropolis known for its high concentration of food delivery activity. Our survey targeted frontline food delivery riders to capture quantitative data on their demographics, working conditions, and perceptions of algorithmic management. Using a structured questionnaire, I collected 83 valid responses through both in-person distribution at popular rider gathering spots (e.g. outside busy restaurants) and online via rider social media groups. The majority of participants worked for Meituan, a dominant delivery platform in China. While the sample was not strictly random, the recruitment strategy ensured diversity of participants and captured a wide range of experiences among Shenzhen's rider community. The survey gathered data on riders' age, gender, employment status (whether directly contracted or through agencies), daily working hours, delivery load, experiences with accidents, and attitudes towards platform policies. Open-ended

questions invited riders to describe challenges they face and any messages they wish to convey to the platform or customers.

The sample, while modest, provides insight into the profile of Chinese delivery riders. An overwhelming 97.6% of respondents were male (81 men, 2 women), reflecting the male-dominated nature of this job in China (consistent with national figures). The majority (69%) were young adults between 25 and 44 years old. Education levels were not directly surveyed, but conversations indicated many were rural-to-urban migrants with high school or vocational education. Work schedules reported were intense: 80% of riders work over 10 hours per day, far above the standard 8-hour workday defined by China's Labor Law, and often 6 or 7 days a week. This corroborates other studies noting extremely long hours for Chinese gig delivery work³. Such prolonged workdays are partly driven by the need to earn enough through piece-rate pay, as well as platform incentive schemes that reward high order counts. Work-related injuries were another salient issue: about 32% of riders reported having been in a traffic accident on the job, ranging from minor scrapes (experienced by 74% of those with injuries) to more serious injuries requiring medical attention (22% reported moderate injuries).

Additionally, an archival analysis of documents and media reports was performed to situate our findings in a broader context. I reviewed policy papers (including recent government guidelines on platform labor in China), platform corporate reports, and relevant news articles (for instance, investigative reports on delivery algorithms that stirred public debate in China in 2021). I also engaged with academic and NGO reports on platform labor both in China and internationally. This helped us compare the Chinese situation with other countries and to trace any emerging regulatory responses. Notably, China's government agencies have issued directives urging platforms to improve riders' conditions (e.g. guidelines to ensure riders have reasonable delivery times and access to insurance), though enforcement remains uncertain. Meanwhile, the European Union's draft AI Act was found to include provisions requiring companies to explain algorithmic decisions to affected workers (as of 2023), reflecting a trend toward demanding algorithmic accountability. Such documents enriched our discussion on policy and governance.

The combination of quantitative and qualitative methods enables us to triangulate the impacts of algorithmic management and the subtle forms of resistance by workers. To analyze the open-ended survey responses and ethnographic notes, I employed a thematic analysis approach. Responses were read iteratively and grouped into recurring categories such as stress from time pressure, experiences of algorithmic control, and strategies of resistance. These themes emerged inductively rather than being pre-defined, and they guided the organization of the results presented in the next section.

Empirical Results

Algorithmic Control, Efficiency, and Labor Precarity

Our findings reveal a dual reality of algorithmic management in food delivery: on the one hand, it generates remarkable logistical efficiency; on the other, it imposes precarious and stressful conditions on riders. On the efficiency side, dispatch systems clearly optimized workflows. Riders received a continuous stream of orders that were usually clustered geographically, and platforms often batched multiple orders to a single courier—for example, two pickups from nearby restaurants to be delivered in the same apartment complex. These patterns demonstrate how algorithmic sequencing embodies the logic of the Vehicle Routing Problem, making possible the scale of tens of millions of deliveries across Chinese cities each day.

At the same time, the survey and fieldwork data point to the substantial human costs of this system. More than half of respondents (56%) acknowledged violating traffic rules such as speeding or running red lights to avoid late deliveries, and nearly 27% of participants had experienced a traffic accident while working, with some requiring medical care. Riders also described skipping rest breaks, and in participant observation I observed individuals managing multiple phones or accounts to keep up with demand. As one rider explained, “I have to climb so many stairs when there are no elevators. They should pay us extra money for that.” These findings suggest that algorithmic time pressure translates directly into bodily risk. They illustrate what Chang and Behrendt describe as a “vicious cycle of speed”: once riders deliver faster—often by taking risks—those behaviors are recorded as data, which then become the new benchmark for the algorithm¹². This feedback loop locks workers into ever tighter schedules, forcing them to ride faster simply to meet escalating expectations.

Our data also highlight how gamification intensified stress. Riders referred to leaderboards, achievement badges (e.g., 100 deliveries in a week), and bonuses as continual pressures rather than playful incentives. While these features motivated a minority of participants, a much larger share—roughly two-thirds (about 50 out of 83 riders)—described them as a source of mental pressure. Riders repeatedly emphasized that the leaderboard and bonus schemes pushed them to extend their shifts or take on additional orders despite exhaustion. Several even used multiple phones or accounts to increase order flow, underscoring the sense of constant competition. These findings indicate that gamification operates less as a motivational tool than as a mechanism of labor intensification. By framing overwork as competition, the system compels riders to self-exploit to maintain their income, undermining the supposed flexibility of gig work and embedding anxiety into daily routines⁹.

The career and livelihood implications of this algorithm-driven work model are troubling. Food delivery in the platform



Fig. 1 Algorithmic Labor in Urban China: Left. A delivery rider with an overloaded scooter, reflecting physical and safety pressures. Right: A dispatch board showing real-time orders and algorithmic scheduling.

era offers limited upward mobility—there are no promotions or new skills gained from making more deliveries faster. Riders recognize this; many see the job as a stopgap for quick money rather than a sustainable career. In our survey, half of the respondents had been in delivery for under a year, and only a small minority (17%) had worked for more than three years. This high turnover aligns with the idea that gig work is a last-resort or transitional job for many. The lack of formal labor protections (no guaranteed minimum wage, no paid leave, often no insurance) means riders’ income can be highly variable and precarious. The algorithm’s role here is twofold: it creates hyper-efficiency that lowers per-delivery costs (and thus pay) and simultaneously individualizes performance, making collective bargaining or solidarity more difficult as each worker is rated and rewarded separately.

Riders’ Counter-Mapping and Algorithmic Resistance

Despite the top-down power of platform algorithms, delivery riders are not merely passive victims of digital control. Our research uncovered a range of bottom-up strategies that riders employ to assert their agency and cope with, or even subvert, the algorithm’s constraints. The most common was knowledge-sharing through WeChat groups or face-to-face exchanges. Through an interview with a rider, I understand how the counter-mapping strategy is spread between riders: When a new rider has difficulty to find the customer’s address, experienced riders will accompany him/her through the delivery process and share the detailed map of the community. This helps new riders to familiarize with more complicated district and understand some traffic rules that doesn’t show in GPS, for example, some routes don’t allow for motorbike. This process suggest that resistance was widespread and continue through riders with different ages in the field.

Central among these is the practice I term counter-mapping:

the collective creation of alternative maps, as illustrated in Figure 2, and spatial knowledge that better serve the riders' needs than the official app maps. I encountered a striking example during fieldwork: a crumpled, hand-drawn map passed around among riders in a district I call "Guangqian Village". Drawn with a simple ballpoint pen on paper, the map lacked any scale or professional cartographic polish, but it was dense with information relevant to couriers. It marked building numbers from 1 to 97, corresponding to addresses in the area, but unlike a standard map, the numbering was subtly altered based on rider experiences. Notably, between buildings #86 and #88, the map listed not #87 (which would be expected sequentially) but the character "墓" (Chinese for "tomb"). In the real geography of Guangqian Village, there is a small old cemetery between those buildings – a feature that would appear as just empty space or a generic label on Google Maps or Baidu Maps. For the riders, however, this "tomb" is a critical landmark used to navigate the maze of alleys. By labeling it on their hand-drawn map, they transformed a piece of local knowledge (an informal landmark) into a shared navigational reference. As one rider explained: "This hand-drawn map is more useful than the app, because it marks the places that actually matter for us. In some place, I only rely on the hand-drawn map instead of the GPS." Another rider noted: "Everyone in our group has a copy on their phone. I send it around when new people join, so they won't get lost." This is illustrative of how rider-generated maps depart from official spatial representations. They incorporate what I might call functional landmarks – elements of the environment that have meaning for delivery work (a tomb, a prominent tree, a neon sign, a security gate) – rather than the formal street names or addresses that might be incomplete or confusing. Moreover, the riders' map showed numerous addresses with sub-numbers like "92-2" and "92-3" that do not officially exist in postal records. Riders explained that these were their own designations to distinguish multiple drop-off points within the same building or complex (for instance, a large apartment building might have several entrances or delivery drop zones; if the official address 92 covers them all, riders subdivide it in their internal lingo as 92-2, 92-3, etc., to be more precise). In essence, they created a folk numbering system to deal with ambiguities in addresses that often confuse the platform's routing algorithm. As one participant commented: "The app sends me to one entrance, but the customer is waiting at another. Only our version of the address shows the difference."

These counter-mapping efforts amount to more than just handy sketches – they represent a form of tactical spatial knowledge that riders continuously produce and update. Experienced riders often snap a photo of their hand-drawn maps and send it to group chats of local couriers or even make quick diagrammatic maps on their phones. Over time, this becomes a crowd-sourced knowledge base for the hardest-to-navigate neighborhoods. I observed that in areas with complex layouts (e.g., old residential

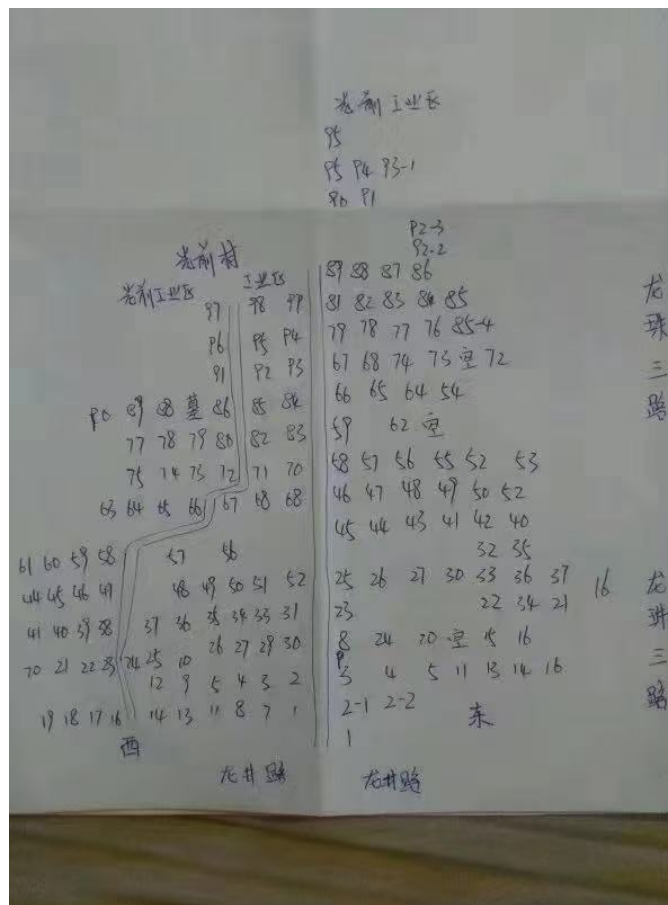


Fig. 2 Counter-mapping of Guangqian Village from a random delivery rider

compounds, university campuses, or urban villages), riders rely on such shared knowledge to avoid the delays that the platform's navigation might cause. In other words, counter-mapping directly addresses the algorithm's blind spots by injecting local spatial intelligence into the delivery process.

The existence of these maps also has an important social dimension: it fosters a sense of community and solidarity among riders. Collaboratively maintaining a map or exchanging tips builds trust and mutual support. In an occupation often described as isolating – riders zooming around the city largely alone, communicating mainly with an app – these practices create a collective space outside the platform's control. It is a peer-to-peer support system that operates in parallel to the algorithm. Sociologically, this can be seen as riders reclaiming their role as knowledgeable agents rather than just algorithmic subjects. By creating and sharing a counter-map, they assert that their knowledge of the city matters and can outperform the official algorithm under certain conditions. This is a subtle form of resistance: it doesn't confront the platform directly, but it circumscribes the platform's authority by demonstrating

that the riders' experiential knowledge can trump algorithmic prescriptions.

These variations also help explain why some strategies became more common than others. Knowledge-sharing and counter-mapping were low-cost, collective practices that required little technical skill and carried minimal risk of punishment from the platform. Riders could exchange information informally in WeChat groups or during breaks, building on existing social ties and mutual trust. By contrast, practices such as turning off GPS or spoofing location data were riskier, as they could lead to penalties or account suspension if detected. In this sense, the prevalence of everyday practices like peer exchange and mapping reflects both practical considerations and the social fabric of rider communities. As Chen and Sun note in their study of temporal arbitrage, riders often adopt strategies that balance efficiency with risk, choosing forms of resistance that are sustainable under precarious working conditions⁵.

Our data also suggest differences in resistance strategies across rider groups. More experienced riders, who had spent several years navigating urban districts, were more likely to rely on counter-mapping and local spatial knowledge. They emphasized practical shortcuts and landmarks that only long-term familiarity could provide. By contrast, younger riders, often in their twenties, showed a greater tendency to experiment with digital tactics such as using multiple accounts or, in a few cases, spoofing GPS signals. Older riders, meanwhile, tended to depend more heavily on peer networks and knowledge-sharing, drawing on community support rather than technological manipulation. These contrasts highlight how resistance is shaped not only by platform design but also by the age, experience, and digital literacy of the riders themselves.

Gender and age patterns in our sample also shaped riders' experiences. The overwhelming majority of respondents were men (81 out of 83), which reflects the male-dominated nature of delivery work in China. Although the small number of female participants makes it difficult to draw broad conclusions, their responses suggested heightened concerns about personal safety and greater reliance on peer support networks. Age differences were more visible: most riders fell between 25 and 44 years old, and younger riders in their twenties were more open to experimenting with digital tools such as multiple accounts, while older riders tended to avoid high-risk tactics and leaned more heavily on community-based knowledge sharing. These patterns underscore how both demographic and experiential factors mediate the ways in which riders navigate algorithmic management.

Discussion

Integrating Local Knowledge

One of the key insights from our findings is that riders' local knowledge and experience are invaluable assets that could

be harnessed to improve platform algorithms. Currently, the platform's routing and dispatch algorithms, grounded in OR (Operations Research) models like VRP, tend to be one-way: the system directs riders based on its calculations, with little formal mechanism for incorporating feedback from those riders on the ground. If platforms were to systematically integrate the ground truth data that riders accumulate (such as which shortcuts really save time, or which delivery sequences work better in practice than in theory), the algorithms could become more realistic, efficient, and worker friendly. Our findings show that riders possess valuable local knowledge that is currently excluded from algorithmic planning. I propose an experience-informed optimization model that would adjust routes dynamically using rider feedback. This approach aligns with what I call an "experience-driven OR" paradigm, where human expertise refines computational optimization.

While platforms do not officially acknowledge counter-mapping or similar rider strategies, there is evidence that they are aware of these practices. Riders reported occasional adjustments in routing software that appeared to respond to common detours or reported delays, suggesting that platforms indirectly monitor such behaviors. However, none of the riders I interviewed described explicit efforts by companies to ban or penalize the sharing of alternative maps. This indicates that counter-mapping currently occupies a gray zone: tolerated as long as it does not openly challenge the platform, yet not formally integrated into system design.

In a traditional cost model for routing, I have a cost c_{ij} representing the estimated time or effort to go from point i to j . Let us introduce a dynamic adjustment term $\delta_{ij}(t)$ which represents the improvement or correction to that cost based on rider experience at time t . If riders consistently find a faster way between i and j than the algorithm expects, $\delta_{ij}(t)$ would be positive (indicating the algorithm's base time could be reduced by that amount). Conversely, if there's a hidden delay (say, building is hard to access) the rider feedback might indicate a negative improvement (effectively a penalty). The algorithm could update its cost estimate as:

$$c_{ij}^* = c_{ij} - \delta_{ij}(t)$$

where c_{ij}^* is the adjusted cost that incorporates the collective experience $\delta_{ij}(t)$. The value of $\delta_{ij}(t)$ could be derived from multiple sources: historical GPS traces of riders (if riders often take a particular detour from i to j that is faster, the data would show consistently lower travel times than the official route); direct rider input (through an app feature allowing riders to report a better route or a delay cause); or aggregated community knowledge (for instance, if many riders agree that "route X is better than route Y" between two points, that consensus informs δ_{ij}). Over time, machine learning could be used to learn $\delta_{ij}(t)$ for various conditions t (time of day, weather, etc.), continuously

refining the routing model. Essentially, the platform’s algorithm would “learn” from the riders, not just from abstract map data.

Another area of integration concerns the sequence of deliveries when a rider carries multiple orders. The platform currently decides an order sequence (e.g., deliver A before B) based on distance and promised times. But riders sometimes find that reversing the sequence might be wiser (perhaps customer A is usually late to pick up so dropping B first saves idle time, etc.). I can capture this through a rider’s ordering preference function. For a given pair of orders A and B assigned to the same rider, define $\pi_{AB}^{(k)}(A, B) = 1$ if rider k would prefer to deliver A before B (based on their experience), and 0 if not (or if indifferent). If I gather this preference from many instances (either observed or explicitly polled), I can compute an empirical probability or weight that “A should precede B” across the rider population:

$$P(A < B) = \frac{1}{K} \sum_{k=1}^K \pi^{(k)}(A, B),$$

where K is the number of observations or inputs. If $P(A < B)$ is high (say 0.8) but the platform’s algorithm normally does B then A, this indicates a potential suboptimal ordering according to rider wisdom. The system could then flag a sequence adjustment suggestion to either consider swapping the orders or at least alert the rider that reordering is acceptable.

In an optimization framework, these feedback mechanisms can be embedded by modifying the objective function. Instead of minimizing just $\sum_{i,j} c_{ij}x_{ij}$, the platform could minimize:

$$\min \sum_{i,j} [c_{ij} - \delta_{ij}(t)]x_{ij} + \lambda \sum_{A,B} |P(A < B) - I_{\text{platform}}(A < B)|,$$

where $I_{\text{platform}}(A < B)$ is an indicator (0 or 1) of whether the platform’s current algorithm would schedule A before B, and λ is a tuning parameter that dictates how strongly the algorithm tries to align with rider sequence preferences. The second term effectively penalizes the solution when it deviates from what rider experience suggests as the better order, thus pushing the optimization towards sequences that riders historically prefer (assuming those don’t violate hard constraints like customer promised times). By adjusting λ , the platform can balance pure efficiency with experiential knowledge alignment: a higher λ gives more weight to the collective rider insight.

To make the proposal more concrete, consider the case of a rider who faces two possible routes to deliver an order. On the map, Route A looks shorter, but it goes through a crowded intersection with long traffic lights, where riders often get delayed and sometimes feel unsafe in heavy traffic. By contrast, Route B is slightly longer in distance but usually faster and safer, since it avoids the congestion. If the algorithm only relies on abstract map data, it will almost always select Route A, assuming it to

be more efficient. However, when rider feedback is incorporated—whether through direct reports or by observing repeated detours—the system can learn that Route B is the better option in practice. As one rider explained when he was delivering: “The app tells me to take the main road, but I never follow its instruction. I always use another route, which seems further but faster in fact. It saves time, and I don’t have to rush through dangerous traffic.” This example shows how feedback can be translated into improved cost estimates: the algorithm updates its assumptions, recognizes the hidden delays on Route A, and adapts to recommend Route B. In this way, optimization becomes more realistic, balancing efficiency with rider safety and lived knowledge.

Implementing such an experience-informed model could have multiple benefits. First, it would likely improve performance accuracy – fewer late deliveries or mishaps – because the algorithm would no longer naively assume, for instance, that a certain path is fastest when the community of riders knows it isn’t. Second, it could enhance rider buy-in and trust. If riders see that the system adapts based on their input (e.g., after enough reports, the algorithm stops sending them through a problematic shortcut), they may feel less frustration and more collaboration with the platform. In effect, the algorithm becomes a two-way street – not just a tool of control, but also a tool that responds to workers’ insights. This could mitigate feelings of alienation and objectification, as riders recognize their role as co-creators of the knowledge that drives the system.

I acknowledge challenges in deploying such models: issues of data reliability (not all rider suggestions may be optimal or sincere), potential for gaming the system, and the complexity of updating algorithms in real time. However, conceptually this approach moves toward what some scholars call “participatory algorithm design” – involving stakeholders (here, workers) in the design loop of automated systems (Kellogg et al. 2020). From a technological governance standpoint, it shifts the narrative: algorithms should not be immutable rules imposed on labor, but evolving systems that serve labor and improve with labor’s input.

Policy Implications and Worker Empowerment

To improve working conditions for food delivery riders, it is important to consider a range of policy-oriented and institutional strategies that encourage more balanced relationships between platforms and workers. While platforms operate under profit-driven logics, supportive public policies can help guide technological design and labor practices toward greater fairness, without undermining operational efficiency. Building on the earlier discussion of algorithmic design and grassroots responses, I suggest that improvements in algorithmic transparency and labor protections can foster a more inclusive and sustainable platform economy.

One area of focus is enhancing transparency in algorithmic systems. Our evidence indicates that current allocation and rating systems are opaque to most riders, creating confusion and mistrust. A sociological study of China's delivery sector similarly identifies a form of "submerged algorithmic management," where platforms mediate and evaluate work covertly while evading formal employer responsibilities, and documents how riders creatively resist through solidarity networks and algorithmic loopholes¹⁸. This aligns with our findings and highlights the importance of making algorithmic governance more transparent. I argue that platforms should make these systems more understandable and accessible, and I suggest that even modest transparency reforms could reduce asymmetries between workers and companies. Such openness may help bridge the asymmetry between platforms and workers and improve trust in the system. In addition, providing riders with some degree of choice in order acceptance could support a sense of agency. Rather than assigning orders unilaterally, platforms might offer a selection of orders during high-demand periods or provide opt-out mechanisms under certain conditions. While a fully decentralized system may not be feasible, limited autonomy in decision-making could acknowledge the realities of riders' daily routines and reduce the mismatch between algorithmic optimization and individual preferences.

Similar considerations apply to delivery routing. Many riders—especially experienced ones—develop strong knowledge of local roads and navigation shortcuts that are not reflected in the delivery apps. Allowing riders to suggest or choose alternate routes when appropriate would validate this situated expertise and potentially improve delivery accuracy. As discussed earlier, riders' counter-mapping practices illustrate how informal spatial knowledge can complement algorithmic design, suggesting potential for hybrid systems that learn from lived experience.

Beyond algorithmic improvements, labor protections also deserve attention. Establishing clear wage floors across platforms and regions may help prevent downward pressure on rider pay due to platform competition. Ensuring access to basic social protections, such as health insurance and accident coverage, would offer more security to workers facing high occupational risks. In particular, procedures for handling work-related injuries should be clarified, with protocols for compensation and medical assistance. While the political context may constrain formal unionization, platforms and policymakers might explore alternative forms of worker representation or dialogue. Even limited mechanisms for collective feedback or consultation could give riders a voice in shaping workplace norms. As noted in earlier sections, riders often build informal peer networks and share knowledge through community practices—supporting these networks through institutional recognition could enhance their resilience and influence.

Public discourse also plays a role in shaping attitudes toward delivery labor. Films, literature, and rider-authored narratives

are helping to draw attention to the lived experiences of gig workers. Educational initiatives, especially at the K–12 level, could introduce students to the structural challenges faced by low-wage workers, encouraging empathy and civic awareness. These broader cultural shifts complement the technical and policy measures discussed here.

Conclusion

This paper began by examining how food delivery platforms increasingly govern labor through data and algorithms, transforming riders into "datafied" subjects whose actions are continuously monitored, evaluated, and optimized. Our findings show that algorithmic efficiency produces clear logistical benefits but also imposes significant costs: most riders face stress, precarious income, and heightened safety risks. Empirically, the evidence demonstrates that riders are caught in cycles of algorithm-induced pressure but also develop grassroots forms of resistance. Counter-mapping and peer-based knowledge sharing illustrate how workers actively navigate and contest algorithmic control in their daily routines. Conceptually, these practices reveal the importance of lived spatial knowledge in understanding platform urbanism. By highlighting invisible geographies—such as shortcuts, blocked gates, or alternative entry points—riders show how human experience can challenge and complement algorithmic representations of the city. In terms of policy and design, I propose that platforms institutionalize rider feedback in route optimization and make allocation systems more transparent, while governments set minimum standards for wages, safety, and algorithmic accountability. Such reforms would not reject algorithms but humanize them, reframing riders not as logistical variables but as knowledgeable participants in a complex urban system. Taken together, these contributions point to a broader lesson: digital infrastructures should support, not displace, human dignity and labor agency. This, I suggest, is the path beyond datafied labor.

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