

What Drivers Want vs. What Drivers Take: A Worker-Centered View of Fairness in Ridehail Platforms

Samantha Dalal¹, Varun Nagaraj Rao¹, Christine Ao¹, Andrés Monroy-Hernández¹

¹Princeton University

sd3765@princeton.edu, varunrao@princeton.edu, ca4655@princeton.edu, andresmh@princeton.edu

Abstract

Digital labor platforms increasingly mediate work and disrupt traditional employment norms. Since many workers are now classified as independent contractors, established workplace fairness rules, like the Fair Labor Standards Act in the U.S., do not cleanly apply. Frameworks for what constitutes fair work in these contexts remain underdeveloped. Over the past decade, machine learning research has offered mathematical formalizations for defining and operationalizing fairness in multistakeholder platforms, including digital labor platforms. In this paper, we respond to calls to explore what fair work looks like on digital labor platforms and contextualize mathematical formalizations of fairness in ridehail platforms by examining, from the workers’ perspective, how they define fair work and fair compensation. We interview nine ridehail drivers using simulated task offer screens to elicit how drivers define fair work and operationalize these definitions in practice when deciding whether to accept or reject offers. We find that drivers define fairness in task offers based on six features: location, duration, distance, take rate, anticipated passenger behavior, and vehicle operating costs. Rather than reducing fairness to a single metric, drivers construct context- and task-dependent judgements about the work, cost, risk and opportunity each ride requires. We further identify a gap between what drivers consider fair and what they accept, driven by both algorithmic pressure to maintain acceptance rates and the economic reality of market scarcity. Our work contributes a worker-centered operationalization of fairness in digitally mediated work platforms that connects multisided platform fairness with the judgments workers construct in practice.

1 Introduction

Work is increasingly performed through digital labor platforms—intermediaries that facilitate short-term arrangements between workers and consumers through online marketplaces (Pew Research Center 2021). Unlike traditional employment, platform work is allocated and evaluated not by managers but by opaque algorithmic systems that make it difficult for workers to identify who is responsible for the decisions that shape their work (Dalal 2025). The workforce on these platforms is also largely classified as independent contractors (Collier, Dubal, and Carter 2018), which means

the legal protections that operationalize fairness in traditional employment, such as minimum wage requirements and anti-discrimination laws, do not apply. The organization of platform work is therefore structured in ways that existing fair work and compensation norms were not designed to address (Dubal 2023). In traditional employment, fairness is often evaluated through wages, hours, or discrimination across workers. In ridehail, however, drivers must also judge whether a particular ride offer is worth accepting, making fairness not only a question of total pay but of whether a specific ride is worth doing.

In this paper, we examine fairness at the level of the ride offer by studying how drivers in the ridehail industry—one of the largest sectors of work performed through digital labor platforms—assess the fairness of trip offers and fares. Our approach of centering workers’ perception of fairness respond to calls by Qadri and D’Ignazio (2022) to examine platforms from the drivers’ perspective and Cameron (2024) to ground understandings of drivers’ rationales for participating in ridehail platforms in their day-to-day decision making. We seek to understand how drivers assess whether the work required to complete a trip is fairly compensated by the fare they are being offered by asking the following research questions:

RQ1: What factors about a trip do drivers consider when they evaluate the fairness of a ride offer?

RQ2: How do drivers turn those fairness factors into practical decision rules that help them select the kinds of trips they will accept?

RQ3: When and why do drivers accept rides they judge to be unfair?

Using semi-structured interviews with nine ridehail drivers, we find that drivers define fair compensation by evaluating six ride-level features: location, duration, distance, take rate, anticipated passenger behavior, and vehicle operating costs. Drivers translate these criteria into practical decision rules, including distance thresholds, avoidance strategies, and experience-based reinterpretation of platform estimates, and regularly accept rides they judge to be unfair due to algorithmic pressure on acceptance rates and economic scarcity.

Our work makes three contributions. First, we enumerate factors workers consider when weighing the fairness of

a trip offer, illustrating what elements of work ridehail platforms must consider when developing frameworks for fair compensation. Second, we identify how drivers use these fairness factors to make decisions about what kinds of work they will accept. Finally, we demonstrate a systematic gap between what drivers consider fair and what they accept, demonstrating that acceptance of work is not equivalent to satisfaction with work.

2 Background and Related Work

To ground our study, we first provide an overview of how digital labor platforms complicate existing frameworks for fair work and compensation in the workplace and background. We then turn to the fairness in multistakeholder platform literature to identify dominant approaches to modelling fair outcomes in these systems. Our paper contributes to calls in the fairness literature to unpack the abstractions underlying mathematical approaches to fairness by identifying how drivers define, systematize, and operationalize fairness judgments in practice.

2.1 Digital Labor Platforms Disrupt Fair Work and Compensation Norms

Most employees in the United States are given minimum guarantees for fair compensation and treatment in the workplace under the Fair Labor Standards Act (FLSA). For example, employees are protected against discriminatory practices that adjust pay on the basis of protected classes like sex or race and retaliatory behavior by employers if the employee files a complaint. In addition, employees are guaranteed to earn at least the federal minimum wage (U.S. Department of Labor, Wage and Hour Division 2009). The FLSA marked a pivotal moment in labor standards history by creating a baseline definition for the minimum requirements for fair work (Griffith 2018). Importantly, the FLSA only applies to certain classifications of workers. Employees are protected by the FLSA, but independent contractors are exempt, making this classification of workers an attractive option for companies seeking to limit the overhead costs and responsibilities of being an employer (Hyman 2019).

Digital labor platforms—intermediaries that facilitate short-term work arrangements via online marketplaces—primarily rely on a workforce of independent contractors to provide services to consumers seeking them out via the platform. Legal scholars critique the practice of classifying workers on these platforms as independent contractors rather than employees as a form of regulatory arbitrage (Calo and Rosenblat 2017; Dubal 2017) that belies the control platforms exert over the workforce through a series of algorithmic management systems (Dubal 2023; Teachout 2023). By relying on a workforce of independent contractors which is exempt from the FLSA, digital labor platforms disrupt the norms and protections that guarantee a baseline level of fairness in terms of compensation, opportunity, and freedom to disagree with managers without fear of retaliation. In this paper, we respond to the call by Dubal (2023) to think about what fair work, specifically fair pay, in digitally mediated platforms looks like, when established fairness

frameworks do not apply. We focus our inquiry on ridehail platforms—digital labor platforms that match drivers and riders. While the social sciences literature has extensively documented the problems endemic to ridehail work such as gamification (Woodcock and Johnson 2018), financial precarity (Qadri 2021), and pervasive surveillance (Van Doorn and Badger 2021), few papers bridge these findings with discussions of fairness in digital labor platforms. We contribute to this space by providing a worker-centered perspective on fairness in ridehail platforms.

2.2 Fairness, Equal Work, and Fair Pay in Algorithmic Labor Markets

Mathematical formalizations of fairness in algorithmic systems are often framed comparatively: whether groups face disparate outcomes, called *group fairness* or whether similar individuals are treated similarly, called *individual fairness* (Barocas, Hardt, and Narayanan 2023; Dwork et al. 2012; Hardt, Price, and Srebro 2016). But, prior scholarship has cautioned that fairness in these systems should not be construed as only a mathematical formalization or metric defining problem. This is because fairness definitions encode contested political values (Binns 2018; Narayanan 2018), depend on construct-validity and measurement choices (Jacobs and Wallach 2021), and need to be understood within the broader context of institutions, power, and the political economy (Selbst et al. 2019; Narayanan 2026; Vertesi et al. 2026). Even individual fairness, which seemingly focuses on only the similarity between individuals, also depends on prior moral judgments about which similarities should matter (Fleisher 2021). For labor markets, this means fairness cannot be simply reduced to compensating seemingly similar work similarly; it requires asking what counts as comparable work, and whose understanding of work defines that comparison.

This problem is especially acute in two-sided algorithmic markets, because platforms must balance fairness considerations across consumers, providers, and the platform itself (Mehrotra et al. 2018; Patro et al. 2020; Basu et al. 2020; Smith et al. 2024).

Ridehail platforms, an example of a two-sided marketplace, jointly mediate rider prices, driver pay and access to future work. Prior work has documented disparate impacts in ridehail pricing (Pandey and Caliskan 2021), disparities in driver earnings and work patterns (Dang et al. 2025; Liu et al. 2024), consumer fairness perceptions in platform-mediated services such as tipping (Chong, Yoo, and Cheshire 2024), customer ratings as vehicles for workplace discrimination (Rosenblat et al. 2017), and changing pay, allocation, and take rates under dynamic pricing (Binns et al. 2025). We build on these works by asking how drivers themselves judge whether a specific trip offer fairly compensates the work, cost, risk, and opportunity it requires.

3 Methods

To investigate how ridehail drivers conceptualize fairness in platform-based work, we used a multi-step qualitative research design consisting of an exploratory online discourse

analysis followed by semi-structured interviews.

3.1 Study Preparation

Prior to interviews, we collected data from three large Reddit communities dedicated to gig drivers: r/uberdrivers, r/lyft-drivers, and r/ubereatsdrivers—among the most active online forums for ridehail and delivery driver. We focused on posts from the past three years, prioritizing those with high engagement (multiple upvotes or comments) and those with a screenshot of ride offers. Posts were included if they involved drivers discussing pay, tips, rates, quitting decisions, or fairness. We followed an iterative keyword-based sampling process. Initial searches were conducted using the term “fair pay” and filtered by the most recently posted. From the results, we prioritized posts with higher engagement and recorded them in a spreadsheet. As recurring phrases and evaluation criteria emerged, these terms, such as “airport,” “minimum,” and “dollar per mile,” were used to guide subsequent searches. This iterative expansion allowed the analysis to capture a broader range of discussions and perspectives. The process continued until thematic saturation was reached, meaning that additional searches yielded no substantially new concepts. We used an inductive coding approach to identify the factors drivers consider regarding fairness, focusing on explicit definitions of unfair pay, decision-making criteria for accepting or rejecting offers, and references to costs, risks, and tradeoffs. These findings directly informed our interview protocol.

3.2 Study Overview

We conducted semi-structured interviews that lasted approximately 45 minutes. The interview consisted of three main components: (1) Experience-Based Questions, establishing a baseline understanding of task acceptance and rejection decisions; (2) Ride Offer Card Simulation, in which participants evaluated five simulated offer screens drawn from real Uber ride data, and (3) Reflection and Wrap Up, prompting a reflection on broader fairness perceptions.

3.3 Recruitment and Participant Background

We recruited 9 ridehail drivers for interviews. Participants were recruited through a combination of paid advertisements posted on Reddit and Craigslist, outreach to existing driver group chats, and reaching out to drivers who had participated in a prior related study. This strategy produced a geographically diverse sample that included both part and full time Uber and Lyft drivers with experience working in 11 different regions across the US. We summarize participant demographics and background information in Table 1.

All interviews were conducted using a semi-structured format to ensure consistency across participants while allowing flexibility for drivers to elaborate on their experiences. We audio- and video-recorded the interviews with participant consent and transcribed them for analysis. This study received approval from our Institutional Review Board (Protocol # 18904). All participants were informed of their rights, such as voluntary participation, confidentiality, and the ability to withdraw at any time and still be compensated.

3.4 Data Analysis

Auto-generated transcripts were cleaned to remove identifying information and corrected alongside the audio files for accuracy. We then applied a deductive coding strategy guided by our three research questions. In the first pass through each transcript, we highlighted relevant quotes to the factors drivers consider when evaluating fairness (RQ1), the mechanisms through which they translate those factors into accept/reject decisions (RQ2), and the rationale they applied when deciding to accept rides that they deemed to be unfair. After independent coding passes and analytic memo writing, all authors compiled participant quotes into a shared FigJam board organized by research question. The research team then had two rounds of synchronous discussions to group and consolidate participant quotes into subthemes. Our analysis yielded six themes that capture the dimensions through which drivers think about and operationalize fairness in ridehail work and a key tension around agency and ability to act on fairness judgments in practice.

3.5 Limitations

Our sample of nine drivers is small and also predominantly male, which limits generalization. Despite our small sample size, we reached thematic saturation (Caine 2016), finding that drivers began repeating the same broad criteria for assessing the fairness of ride offers as interviews progressed. The fare card simulation does not fully replicate real-time decision pressure because we did not time the drivers’ responses, and the reflective setting likely made fairness criteria more explicit than they would be in the seconds drivers normally have. Our geographic diversity was a strength, but also complicates comparison as some drivers were in TLC-regulated markets with hidden destinations and others were in upfront pricing markets.

4 Findings

We examine how drivers evaluate whether a ride offer is fair. Our analysis is organized around three research questions (RQ1, RQ2, RQ3) as listed in Section 1.

We find that drivers judge whether a fare compensates them for the entirety of the work required to complete a ride: location, time, distance, fare split, passenger behavior, and vehicle costs. They operationalize these factors through thresholds, heuristics, and avoidance rules. Yet these rules do not always determine behavior: platform penalties, weak demand, and uncertainty can pressure drivers to accept rides they see as unfair.

4.1 Location: Fairness Depends on Where a Ride Leaves the Driver (RQ1, RQ2)

Drivers assessed the fairness of a ride offer by evaluating whether they would likely receive a subsequent ride offer at the passenger’s drop-off location. A fare could feel unfair if the destination left them in a low-opportunity area or took the driver outside their desired working location.

“if I’m driving towards Lower Manhattan... and then it gives me a hit in the Bronx... I’ll probably not accept

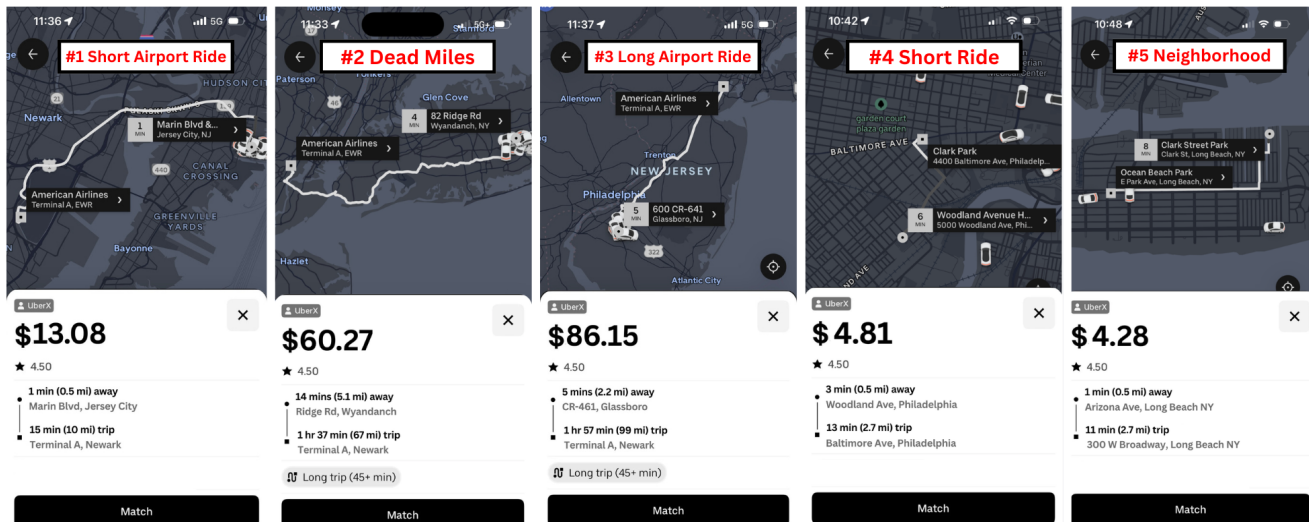


Figure 1: Ride offer cards used to elicit drivers’ fairness evaluations. The five offers vary in fare, pickup distance, trip duration, destination type, and likely return-trip potential, capturing ride scenarios that are important to drivers’ acceptance decisions.

P	Gender	Platforms	# of Rides	Location	Tenure	Full Time	Driving now?
1	Male	Uber	—	Washington/Vancouver	—	Yes	Yes
2	Female	Lyft, Uber	—	Portland, OR	8 years	Yes	Yes
3	Male	Lyft, Uber	—	Virginia/Portland, OR	10 years	Yes	No
4	Male	Uber	2,409 (Uber)	NYC, NY	9.5 years	No	Yes
5	Male	Uber	—	Nebraska/Iowa	8 years	No	Yes
6	Male	Lyft, Uber	2,565 (Uber)	Miami, FL	5.5 years	Yes	Yes
7	Male	Lyft	3,000+ (Lyft)	Colorado	2 years	Yes	No
8	Female	Lyft, Uber	—	Denver/Chicago	9 years	Yes	Yes
9	Male	Uber	—	Philadelphia, PA	2 years	Yes	Yes

Table 1: Participant Demographics

it, because that’s not the direction that I’m going.”
(P4)

Drivers treat destination as part of compensation because it shapes future earning opportunities. Drivers evaluated the destination because the drop-off location affected their opportunities for future work. Airport rides often felt more acceptable for this reason. One driver explained that they might take an airport ride because “*there might be a chance of me catching another ride coming back from the airport*” (P7). The destination made the ride fairer because it reduced the expected unpaid time waiting for a ride after drop-off.

Destinations could make rides unfair by pulling drivers away from profitable areas. One driver described rejecting a ride to Corvallis because it took them away from Portland, where, in their experience, ride offers tended to be more frequent and higher paying. Another driver described the cost of a low-opportunity destination more directly: “*I had to drive back empty, so that kind of, you know, negates the purpose of the whole thing*” (P2). For P2, the destination disrupted the driver’s earning plan and created a likely unpaid return burden.

Drivers also valued rides that aligned with personal route preferences. One driver said they would accept a relatively low-paying ride because “*it was taking me near my house*” (P8). In this case, the ride’s location made the fare more acceptable because the drop-off destination was aligned with their route preference. These examples show that drivers judged location relationally: the same fare could feel fair or unfair depending on where the ride left them.

Drivers operationalize location through route-fit rules, return-ride logic, and destination avoidance. Drivers turned location-based fairness judgments into practical acceptance rules. As the opening quote shows, drivers used route fit to decide whether a ride was worth taking: a ride became less acceptable when it moved them away from their intended direction. Drivers also used return-ride logic. One driver described declining rides outside their usual area because “*I was looking for the return ride. They are not giving me any return ride, but they were taking me towards more south, which was, like, 30 minutes away from there. So it was completely a lost project*” (P3). This rule helped drivers avoid rides that might require unpaid travel after drop-off.

Some location rules became hard exclusions. One driver

Fairness factor	Components	How it shapes fairness	How drivers operationalize it
Location	Pickup/drop-off location; route fit; return-trip likelihood; proximity preferred area	Drivers ask where the ride will leave them. A fare feels less fair if the trip pulls them away from demand, home, or their preferred driving area.	Drivers look for return rides, avoid low-demand destinations, and reject trips that move them away from their intended route.
Time and duration	Pickup time; passenger waiting; airport queues; traffic; total trip duration	Drivers judge the total time required, not only the paid trip time. Unpaid time and inaccurate estimates lower the ride's effective hourly value.	Drivers use hourly earnings targets, pickup-time cutoffs, waiting limits, and airport queue limits.
Distance and trip structure	Miles driven; pickup-to-trip distance; long-trip uncertainty; deadheading	Drivers ask whether the fare is worth the miles driven. Long rides can create added costs and uncertainty.	Drivers use per-mile floors, minimum-fare rules, filters for trip length, checks for fuel, traffic, and deadhead risk.
Platform take rate/fare split	Actual rider payment; driver pay; platform share; surge presence	Drivers compare their pay with what the rider pays. A ride can feel unfair if the platform appears to keep too much of the fare.	Drivers compare rider-reported fares with their own pay and use rough fair-share benchmarks. This often happens after rider payment becomes visible.
Passenger characteristics	Passenger rating; expected behavior; trip type; tipping likelihood	Drivers use passenger information to estimate likely effort, risk, and tips. Ratings and trip type shape whether the fare seems worth the ride.	Drivers use rider-rating cutoffs, trip-type heuristics, and tipping expectations.
Vehicle operating costs	Fuel and charging; rental costs; insurance; maintenance; vehicle wear; accident risk	Drivers judge net pay, not gross fare. Vehicle costs can turn a seemingly profitable ride into an unprofitable one.	Drivers check fuel or charging needs, subtract costs from fares, and use cost-adjusted thresholds before accepting rides.

Table 2: How drivers evaluate and operationalize fairness in ride offers.

described blacklisting a destination after a negative experience: *“regardless of how far I have to drive to pick the person up or any of that stuff, I will not drive people [there] anymore”* (P2). These operational rules show that drivers converted location into concrete filters that protected future earning opportunities and helped them avoid rides whose destination made the fare feel unfair.

4.2 Time and Duration: Fairness Depends on Whether Pay Covers the Full Period of Work (RQ1, RQ2)

Time and duration shaped fairness because drivers evaluated the full time needed to earn the fare, including driving time to the pickup location, waiting for passengers at pick-up, waiting in queues at the airport for ride offers, and navigating traffic.

“If I have to drive 6 minutes to pick them up, but their drop-off location is only 2 minutes away, I look at the total ride time that’s expected. I also factor in that with Lyft, you have a 5-minute wait time before you can mark it as a no-show.” (P8)

Drivers account for unpaid and inaccurately estimated time that the offer screen obscures. Drivers repeatedly described the app’s time representation as incomplete. Pickup time was the clearest example. One driver explained: *“You’re not getting paid for the time that you are en route to the passenger”* (P4). This unpaid time made the offer screen overstate the ride’s value. A fare that looked fair for the passenger trip could become unfair once the driver added the

time required to reach the passenger.

Drivers also consider the time they need to wait for a passenger at pickup. The block quote above shows that drivers evaluated the total expected commitment, which includes time waiting for passengers¹. For short rides, this waiting time could dominate the paid portion of the trip, making the fare feel unfair.

Airport queues created another form of unpaid labor. While airport rides may seem enticing, because the drop-off destination is likely to trigger a subsequent ride offer, drivers cannot immediately pick up new passengers after dropping off their current rider at the airport. One driver explained: *“at the airport, there’s a different system. There’s basically a virtual queue, and you sit in the virtual queue until it’s your time to go, and then after that time, you can get hits. So you could wait there hours”* (P4). P5 explains that the airport queue could be unpredictable: *“...not knowing how busy the queue could be, how many flights are coming in, how many other drivers are sitting there,”* which makes it difficult for drivers to estimate how long they may need to wait for their next ride. Drivers judge airport rides not only by the fare, but also by the unpaid queue time needed to receive them.

Traffic and time of day further changed the fairness of a fare. One driver explained that airport traffic required additional compensation: *“there’s always traffic at an airport. So, I need to be compensated for that time”* (P9). Inaccu-

¹Most platforms will compensate a driver if they have to wait longer than 5 minutes for the passenger to arrive at the pickup location, but any amount of waiting time within the 5 minutes is not compensated.

rate time estimates could also make rides impossible to complete, as shown. One driver explained that *“the 30 minutes that they gave me would not have been enough time to get there. So they would have canceled it on me anyway”* (P1). These accounts show that drivers judged whether the fare covered the actual duration of the work.

Drivers operationalize time and duration through hourly targets, waiting limits, pickup limits, and shift timing. Drivers converted time-based fairness into thresholds. One driver described an hourly earnings target: *“it depends on the area you live in. In Denver, I would target for \$20 to about \$25 an hour. So, if that shoots well below that range, then usually I don’t take it”* (P7). This rule allowed the driver to translate a ride’s total required time, including passenger pick-up, waiting, and trip time, into a minimum fair-pay benchmark.

Drivers also set limits on unpaid waiting. One driver described an airport queue cutoff: *“usually I will not sit in the queue for more than one hour. If it’s more than an hour, then it’s not worth my time”* (P8). This threshold made fairness actionable. Once the unpaid waiting time exceeded the limit, the driver judged the opportunity not worth pursuing.

Drivers set thresholds for how long they would drive to pick up a passenger. One driver stated: *“So 7 to 10 minutes [to passenger pickup] is kind of my cutoff”* (P2). This rule converted unpaid pickup travel into a practical decision threshold. Drivers also structured their shifts around times when the same fare was more likely to produce fair hourly earnings, such as lower-traffic periods. One driver operationalized this by limiting their work to low-traffic hours: *“I also only drive between 2 a.m. and between 6 a.m and 7 a.m.... Because there’s no traffic, you can get to your locations faster”* (P1).

4.3 Distance and Trip Structure: Fairness Depends on Whether Mileage and Ride Type Justify the Fare (RQ1, RQ2)

Distance impacts drivers’ perception of ride fairness. When considering how fair a ride offer was, drivers considered whether the fare was proportional to the miles required. They examined whether a ride met a per-mile standard, whether a short trip justified the effort of accepting it, and whether a long trip created too many downstream costs.

“I’d like to be a dollar or above per mile. More realistic, if I’m at 80 cents or above per mile, I feel like it’s worthwhile.” (P5)

Drivers use distance to judge whether the fare matches the work and uncertainty of the trip. Drivers consider distance when assessing the fairness of a trip. Trips with longer distances tended to have more uncertainties, which shaped how the driver assessed the adequacy of a fare. Long trips tended to offer higher gross pay, but they also increased exposure to traffic, fuel constraints, return-ride uncertainty, and vehicle wear. One driver explained: *“I don’t do long trips like that... there’s just a lot of unknowns, like more in terms of traffic, is my vehicle fully gassed...”* (P5). P9 explained that a longer ride: *“increases my risk of getting in an*

accident or not picking up another ride”. In these cases, distance mattered because longer rides created costs and risks that the fare might not cover.

Drivers also used their local knowledge of driving conditions when assessing the estimated distance of a trip. One driver questioned a short urban trip because the platform’s estimate did not match their experience of city driving: *“the price is too low... 2.7 miles within the city take a lot longer than 11 minutes... it would probably be much more time than that”* (P4). Drivers contextualized the estimated mileage in the ride offer using their knowledge of local conditions to assess whether the fare would adequately compensate them for their labor.

Drivers operationalize distance through per-mile floors, minimum fares, and long-trip filters. Drivers made distance actionable through simple rules. The opening quote shows one of the clearest operationalizations: a per-mile floor. By setting a target of 80 cents per mile, the driver translated fairness into a rule for comparing ride offers.

Long trips required drivers to consider whether the distance would incur additional costs or reduce their ability to continue earning afterward. Fuel level became part of this rule: *“if it’s a further trip, I always look more [at how full my tank is]”* (P7). Another driver described rejecting trips where the pickup distance dwarfed the paid trip: *“drive 20 minutes and pick this person up and take them, you know, on a one-mile trip. And it’s like, no, I’m not going to do that for \$3”* (P2). Here, P2 demonstrates how they assess both the time to passenger pick-up and the distance of the passenger’s trip to their destination in conjunction to decide whether to accept the trip offer.

Drivers operationalized distance as a metric for fairness by combining mileage with fare amount, trip length, fuel readiness, and actual driving conditions.

4.4 Take Rate: Fairness Depends on Whether Drivers Receive a Reasonable Share of the Rider Fare (RQ1, RQ2)

Drivers judged fairness relationally by comparing their pay with what riders paid. A ride could feel unfair if the platform appeared to keep too much of the riders fare.

“I feel like we’ve been paid more money in the past, and over the years, you’re getting paid less and less... the passenger feels, in my opinion, that the driver is making so much money, and that’s not the reality. A lot of times, it’s less than half of what the passenger is paying” (P4)

Drivers treat large gaps between rider payment and driver pay as evidence of unfair compensation. Drivers interpreted fare split as a fairness issue because it revealed that earnings from higher fares were not proportionally shared between platforms and drivers. As P4 points out in the block quote above, unfair fare splits affect both riders and drivers: riders pay more while drivers still receive too little. P2 reiterated this point, explaining that in surge-pricing situations the unequal distribution of higher rider fares between the platform and driver becomes clear: *“So, particu-*

larly if it's surge pricing, I've had people pay up to like \$160 for a trip that I made \$18 on". In these cases, the unfairness came not only from low driver pay but from the perceived mismatch between rider payment and driver compensation. This made fare splits a distinct fairness factor: drivers judged whether the platform's share was fair, not only whether the ride met a minimum amount that they wanted to earn.

Drivers operationalize fare splits as a measurement of fairness by setting concrete thresholds for what constitutes a fair split. Drivers cannot see how much passengers are paying for a ride on the ride offer screen, yet they still set thresholds for what they consider a fair fare split. P1 explains what they would consider to be fair, saying: "To us, we would like to see it go back to the 80% take where the driver would get 80% of the fare". Drivers retroactively seek out information about passenger fares during rides to calculate fare splits: "if I were driving for Uber, I would ask the passengers...how much they paid for that trip and share with them how much I made on it. Because it's only fair that they know... when I ask them what they think we make, 80% is [what they think we make]. And a long time ago, that is what we made. It was a fair amount" (P2).

However, operationalizing a threshold for fair fare splits to decide which ride offers to accept is not feasible for drivers because they are not shown rider fares at the time of ride offers. Instead, drivers learned about rider fares and fare splits retroactively, either through conversations with passengers during the ride or, in some cases, by looking up rider fare information in their trip history. P2 explains that locating rider fare information in their trip history is difficult: "[Ridehail platforms] have to, by law, let us know how much [riders] paid, but they don't, by law, have to make it easy, apparently". One driver stopped asking because it created frustration rather than control: "I really stopped asking this [rider's pay]. I felt like it will create my frustration rather than solution" (P3). While drivers do operationalize fare splits into judgments about ride fairness, due to the lack of rider fare information at the time of ride offers, they cannot operationalize these judgments into decision criteria for ride acceptance/rejection.

4.5 Passenger Characteristics: Fairness Depends on Expected Passenger Behavior and Tips (RQ1, RQ2)

Passenger characteristics shaped fairness because drivers used ratings, trip type, and tipping expectations to estimate the likely burden and total value of a ride.

"Because [their rating] is a 4.5. 99% of the time, they're not tippers. Or they're rude or they've vomited in somebody's car. But to have a rating that low, you're doing something wrong as a passenger." (P1)

Drivers treat passenger ratings and trip type as proxies for burden, tips, and ride quality. Drivers used passenger ratings as shorthand for the likely burdens they might encounter due to passenger behavior. In the block quote above, P1 explains that a rating of 4.5 likely indicates that the rider may be more trouble than the fare is worth, as a rider would

have had to behave badly to lower their rating to that level. Several other drivers reacted similarly, saying that a passenger rating of 4.5 was simply too low for them to accept, as they correlated low ratings with poor passenger behavior (P3, P4, P5). In these cases, ratings shaped whether the driver believed the fare compensated for the expected work of potentially dealing with a poorly behaved passenger. A low-rated passenger could make the fare seem unfair because the driver expected the ride to require more effort or create greater uncertainty.

Drivers also used trip type to estimate likely compensation, which impacted how fair they perceived a trip offer to be. One driver explained that airport rides often carried better tipping expectations: "typically, when you take [passengers] to the airport... they tip you" (P9). Another made a similar point about long rides: "some of the people would end up tipping more" (P7). But ultimately, drivers felt these passenger characteristic rules are heuristics, not reliable formulas: "tips are not based on the neighborhood.... It depends on the person's personality and the mood during that time" (P3). Trips that were more likely to result in tips, based on ride characteristics such as destination, were thought by some drivers to be fairer because they offered opportunities to earn additional money on top of the base fare. However, as nearly every driver we interviewed pointed out, trip-type heuristics could be unreliable.

Drivers operationalize passenger characteristics through rating cutoffs and trip-type heuristics through cautious assumptions about tips. Drivers made passenger-related fairness actionable by establishing an acceptable cutoff for passenger ratings. For example, P1 sets a passenger rating threshold of 4.8 to screen out potentially troublesome passenger behavior. Rating thresholds allowed drivers to refuse rides they expected to involve higher service burdens. Trip-type heuristics helped drivers identify rides that might produce better total compensation, such as airport or long-distance trips. At the same time, drivers treated these passenger and trip-type heuristics as uncertain. P9 explains, saying: "You can't predict tips, but you hope that wealthier people tip better."

Across our interviewees, drivers expressed divergent opinions about which passenger and trip heuristics they could rely on to predict the likelihood of receiving a tip—there was no single passenger or trip archetype that all drivers agreed signaled the likelihood of receiving a tip. Drivers associated passenger ratings with trip fairness, as ratings could signal how much additional work a driver may have to take on to manage a potentially unruly or rude passenger. Drivers associated trip types with fairness, believing that certain trips were more likely to generate tips, making a trip appear fairer when the base fare would otherwise be insufficient.

4.6 Vehicle Operating Costs: Fairness Depends on Whether Gross Fares Produce Net Earnings (RQ1, RQ2)

Drivers evaluated fairness in net terms. They subtracted fuel, charging, insurance, rental fees, depreciation, maintenance,

and wear from the displayed fare.

"I mean, you can write off 70 cents a mile on your taxes because that's what the government figures it costs you to run your car. So if you take that away from any one of those, you're netting nothing." (P2)

Drivers subtract fuel, charging, rent, insurance, and wear because fair pay must cover the cost of making the ride possible. The block quote above makes the cost problem concrete. The fare is not fair if the costs incurred from operating the vehicle are greater than or equal to the driver's earnings from the ride. Another driver similarly described the share of earnings absorbed by vehicle-related expenses: "20% or 30%, we are paying our vehicle rents, we are paying our insurance, we are paying our electric vehicle charging cost, or fuel cost." (P3). For this driver, fairness required recognizing that drivers paid the costs of completing the ride.

Electric vehicle charging adds both time and energy costs. One driver explained that charging expanded the workday: "if you're charging your car, it's really more like 15 [hours]. So I was doing, like, 15-hour days" (P6). Charging time, therefore, lowered the effective hourly value of the work. It made the displayed fare an incomplete representation of compensation.

Vehicle rentals also raised the minimum amount drivers needed to earn. One driver explained: "when I do Uber, I don't use my own car... [renting is] about \$500 a week, which sounds insane" (P6). Fixed costs like rentals changed the fairness threshold for each ride because drivers first had to cover the cost of participating by renting a vehicle before they could earn income.

Drivers operationalize operating costs through net-pay calculations. Drivers used net-pay calculations to decide whether a fare was fair. They subtracted fuel, charging, and mileage costs from the displayed fare: "At \$30 an hour, that sounds a whole lot better than it is until you start taking off, you know, fuel costs and all of that stuff. Then that brings it down pretty fast" (P2). Another driver described the costs of insurance: "Uber charges me 10% of whatever the passenger pays... And then we are forced to have a \$2,500 deductible through Uber if we're in an accident" (P1). Drivers internalize these operating costs into their assessments of whether a ride offer is actually fair. As P2 explained, although the gross hourly earnings appeared high, net earnings fell substantially after accounting for the vehicle's operating costs. Through experience working, drivers develop mental models of their costs, which they then apply to incoming ride offers to screen out unfair offers that wouldn't result in net earnings.

4.7 Platform Constraints Create a Gap Between Fairness Judgments and Accepted Rides (RQ3)

The preceding sections show how drivers evaluate and operationalize fairness. However, drivers' acceptance decisions did not always reflect those judgments. Drivers sometimes accepted rides they considered unfair because plat-

form penalties, weak demand, and uncertainty constrained their ability to refuse: "Right now, I don't have any option, right?" (P3). The gap between fairness judgment and accepted ride was therefore not a contradiction. It reflected drivers' constrained agency to act on their definition of fairness.

"If I decline a bunch of them in a row, [the platform] will then just not send me any requests for a long period of time and so your average rate is going to go down, your hourly rate." (P1)

Platform penalties and incentives make it costly for drivers to enforce their fairness thresholds. Drivers described declining unfair rides as risky because it could reduce access to future work. The block quote above shows how rejection could threaten future hourly earnings. P8 explains how pressure to maintain acceptance rates directly impacted their willingness to reject rides: "I used to never reject rides because Lyft had a requirement that you had to be at a certain acceptance rate. And they removed that. Once they removed it, I felt more comfortable rejecting rides." While P8 explains that Lyft's removal of the explicit requirement to maintain a certain acceptance rate made them feel more comfortable rejecting rides, other drivers we interviewed believed they were still being punished for not maintaining a high acceptance rate. For example, P4 described how the amount and quality of trips drivers get offered depend on their tier status within the app, which in turn depended on their acceptance rate: "if you get a certain amount of points, which is based on how many trips you accept, and your cancellation rate, and a variety of different things, you can move up in tiers." Their experience aligns with Uber and Lyft's public documentation about their tier status programs that say that only high-tier drivers are eligible for certain types of potentially more lucrative rides².

Platform incentive systems encouraged uncritical acceptance of ride offers. One driver explained that reaching a higher tier and accessing the corresponding earnings benefits "means you just have to take every job they give you, no matter how it is" (P6). In this case, the platform tied access to benefits to acceptance behavior. The driver could recognize a ride as unfair but still accept it to preserve future access or status.

Weak demand and uncertainty make below-threshold rides feel necessary. Drivers also accepted rides below their fairness thresholds when few alternatives were available. One driver explained: "there could be a ride for less than that, maybe €75, €80 a mile. But I would accept it because it's slow" (P9). Scarcity changed the practical meaning of fairness thresholds. A driver could know that a ride was underpaid and still accept it because waiting for a better ride would also cost time and income.

This dynamic clarifies why acceptance should not be treated as evidence of perceived fairness. Drivers' thresholds and heuristics show what they consider fair under workable

²See Lyft's driver statuses and corresponding perks here: <https://www.lyft.com/driver/rewards> and Uber's Pro Drivers rewards program here: <https://www.uber.com/us/en/drive/uber-pro/>

conditions. Their actual acceptance behavior shows how platform dependence limits their ability to act on those judgments. As a result, accepted rides can reflect constrained agency rather than consent.

5 Discussion

Our findings, as seen in Figure 2, show that ridehail fairness is multidimensional: drivers evaluate fares through location, time, distance, fare split, passenger characteristics, and vehicle costs rather than any single metric. We discuss what this means for defining “equal work,” interpreting acceptance as fairness, and designing platform or policy interventions that protect drivers without creating new harms for riders.

5.1 Fairness in Ridehail Requires Both Common Baselines and Driver Agency

Our findings complicate the fairness principle of “equal pay for equal work.” In ridehail work, the unit of work appears simple: a ride from one place to another. But drivers evaluated work as a bundle of costs, risks, and opportunities: location, time, distance, fare split, passenger characteristics, and vehicle costs. Two rides that look equivalent to a platform or auditor may not be equivalent to drivers. Equal distance is not equal work if one ride leaves the driver without the possibility of a return trip. Equal duration is not equal work if one ride includes unpaid airport queueing. Equal fares are not equal work if the platform keeps different shares of the rider payment.

This creates a practical challenge for platforms to account for fairness in their decisions. Broadly, platforms could try to realize fairness in two ways: by applying a common baseline to all ride offers, or by personalizing offers around each driver’s circumstances and preferences. This reflects a broader tension in fairness debates between outcome-oriented approaches that prioritize aggregate welfare and agency-oriented approaches that prioritize individual judgment. In ridehail, each approach creates risks. A narrow baseline, such as equal pay for equal time and distance, can miss hidden labor, return-trip risk, passenger burden, fare split, and driver costs. But a fully individualized definition can also create problems. In marketplace models such as TaskRabbit³ or Upwork⁴, workers may set prices or preferences, but this agency can shift new burdens onto them: pricing their own labor, competing against lower-priced workers, absorbing unpaid search or bidding costs, and remaining dependent on platform rankings, reviews, and fees. The question is therefore not whether ride offers should be evaluated uniformly or individually, but which factors should be standardized, which should be disclosed, and which should remain part of drivers’ own judgments.

A more plausible approach then, combines baseline protections with worker agency. Regulation can set floors and require platforms to compensate pickup and waiting time, disclose rider fare and platform take, provide accurate time and destination information, prohibit retaliation for rejecting rides, and audit pay differences across comparable ride-

level factors. Worker-facing tools can then help drivers define thresholds above these floors, such as minimum hourly pay, per-mile floors, maximum pickup time, and return-trip preferences. This approach treats equal work as both a regulatory question about which factors should be standardized across rides and a worker-centered judgment about what makes a ride worth accepting.

5.2 Acceptance Rates Do Not Measure Driver Satisfaction with Compensation

One of our central findings is that a systematic gap exists between what drivers say is fair and what they actually accept. Drivers operationalize fairness through three main mechanisms: explicit thresholds, avoidance strategies, and experience-based reinterpretation. Thresholds include concrete cutoffs for pickup distance limits, minimum fare amounts, dollar-per-mile targets, and hourly goals, which function as fast decision rules for the few seconds they have to accept or decline a ride offer. Avoidance strategies operate at a broader level and shape the types of rides drivers encounter before offers even appear: drivers restrict their work hours to low-traffic periods, avoid accepting rides from passengers with low star ratings, and stay within familiar zones. Experiential reinterpretation occurs when drivers rely on their accumulated knowledge rather than taking the platform’s information at face value to make more informed decisions about the amount of labor required to perform a task.

These mechanisms operate against structural constraints that systematically pressure drivers into accepting rides they have already judged as unfair. First, multiple drivers stated that they tend to accept unfair rides because declining too many rides in a row could mean they receive fewer future requests or lose access to certain platform features. P8 even mentioned that they felt comfortable rejecting rides only after Lyft removed a minimum acceptance rate requirement. Second, drivers sometimes accept rides they consider unfair, simply because no better option is available. As P7 explained, “there’s times where I would take [lower rides], only because that’s the only ride available.” Workers’ ability to translate their perceptions of fare fairness into decisions about what work they actually do is constrained by both the scarcity of work opportunities and platforms’ use of acceptance rates to reward and punish drivers.

5.3 Design and Policy Implications

Our findings suggest concrete ways that platforms, policy-makers, and worker-facing tools can support driver fairness evaluations. Because drivers evaluate fairness across multiple factors, and because pressure to accept rides can separate acceptance from perceived fairness, interventions should address both the information drivers see and the constraints under which they make decisions.

Display Total Time, Not Just Trip Time Drivers evaluate ride fares against the total time a ride will consume, including unpaid pickup driving, anticipated return trips, and queue waiting. Current offer screens separate time to pickup

³<https://www.taskrabbit.com/>

⁴<https://www.upwork.com/>

How Drivers Judge Fairness and Decide Whether to Accept

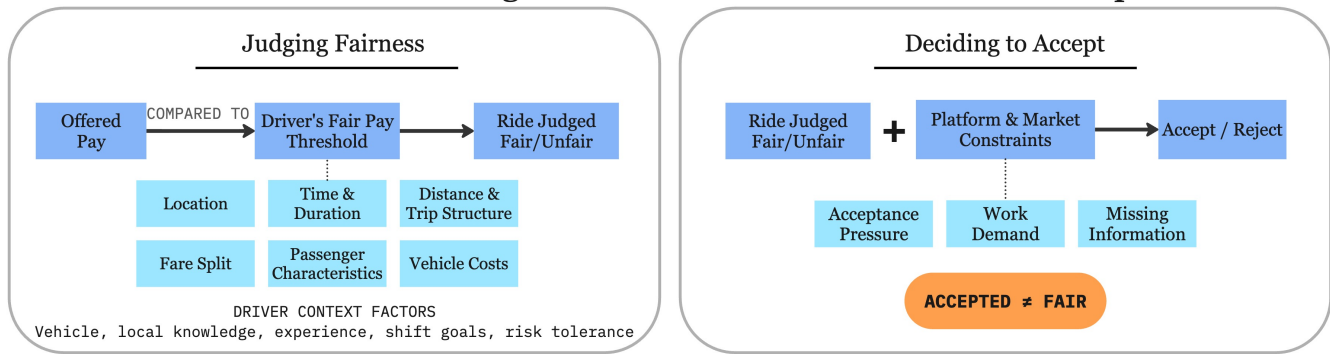


Figure 2: A simplified model of driver-perceived ride fairness. Drivers compare offered pay with a driver-specific fair-pay threshold shaped by ride, passenger, platform, vehicle, and driver-context factors. Acceptance is a separate decision because drivers may accept rides they judge unfair when platform or market constraints limit their ability to refuse.

from time to destination, forcing drivers to calculate total time under time pressure. Platforms should display the total estimated time commitment for each ride and compute per-hour earnings using that total. This would align offer information with the evaluation drivers already perform mentally.

Surface Return Trip Likelihood at the Drop-off Location Return trip potential was central to driver evaluations, yet offer screens provide no information about it. Platforms should display a simple high, medium, or low demand indicator for the drop-off location. This would help drivers evaluate prospective costs instead of relying only on personal familiarity with specific areas, especially for newer drivers.

Make Acceptance-Rate Consequences Transparent or Remove Them Drivers adjusted their behavior based on perceived penalties for declining rides, and P8's account shows that these perceptions shaped acceptance decisions. If platforms use acceptance rates to change ride offers, driver tiers, or eligibility for offers, they should disclose that relationship clearly. If they do not, they should say so. Either way, drivers should not have to make trade-offs under uncertainty.

More broadly, systems that pressure drivers to accept rides they view as unfair undermine the autonomy that platforms use to justify independent contractor classification. Regulators should examine whether acceptance-rate requirements are compatible with the legal and normative frameworks governing independent contractor work.

Move Regulatory Frameworks Beyond Wage Floors Wage floors address one dimension of fairness, but they miss other factors central to drivers' evaluations, including long pickup distances, inaccurate time estimates, poor return trip prospects, and unsafe drop-off locations. Policymakers should consider requiring platforms to compensate pickup time at the same rate as trip time, mandate accurate and accountable time estimates, and provide accessible complaint mechanisms in all states. P1's account of having "*nobody to complain to*" in Oregon shows the structural exposure

drivers face in less regulated markets. National ridehail fairness policy must therefore address regulatory unevenness.

Do Not Treat Acceptance Rates as Fairness or Satisfaction Future research on ridehail pay adequacy should measure driver fairness perceptions directly rather than infer satisfaction from acceptance rates. Our method of simulating ride offers and asking drivers what a ride should pay provides one such approach.

6 Conclusion and Future Work

This study shows that ridehail drivers evaluate fairness through multidimensional, situated judgments rather than through pay alone. Drawing on Reddit analysis and interviews with nine U.S. drivers, we find that drivers weigh six main factors through practical decision rules, including distance thresholds, avoidance strategies, and experience-based reinterpretations of platform estimates. These findings challenge narrower fairness frameworks: wage floors, audits, and take-rate measures capture important dimensions of compensation, but they miss how drivers integrate destination, timing, return-trip likelihood, safety, opportunity cost, and platform pressure in real time. Most importantly, the rides drivers accept are not necessarily the rides they judge to be fair, because acceptance is shaped by algorithmic pressure and market scarcity.

Future work should test whether these fairness criteria hold across larger and more diverse driver populations, including women, non-English-speaking drivers, and drivers in different regulatory contexts. Comparing regulated markets like New York City with less regulated markets could show whether policy interventions change how drivers evaluate fairness or simply raise the compensation floor. Further work should also compare ridehail and delivery work, examine how fairness judgments change with experience, and evaluate whether worker-facing tools like FairFare can improve driver decision-making by surfacing hidden costs such as return-trip likelihood or total time.

Acknowledgments

We are grateful to the Princeton Center for Information Technology Policy and the Princeton School of Engineering and Applied Science Design for Innovation Fund for providing support to the authors. We would also like to recognize and acknowledge the driver-informants whose perspectives on fairness in the ridehail industry made this paper possible.

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