Data Probes as Boundary Objects for Technology Policy Design: Demystifying Technology for Policymakers and Aligning Stakeholder Objectives in Rideshare Gig Work

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ABSTRACT

Despite the evidence of harm that technology can inflict, commensurate policymaking to hold tech platforms accountable still lags. This is pertinent to app-based gig workers, where unregulated algorithms continue to dictate their work, often with little human recourse. While past HCI literature has investigated workers' experiences under algorithmic management and how to design interventions, rarely are the perspectives of stakeholders who inform or craft policy sought. To bridge this, we propose using data probes—interactive visualizations of workers' data that show the impact of technology practices on people—exploring them in 12 semi-structured interviews with policy informers, (driver-)organizers, litigators, and a lawmaker in the rideshare space. We show how data probes act as boundary objects to assist stakeholder interactions, demystify technology for policymakers, and support worker collective action. We discuss the potential for data probes as training tools for policymakers, and considerations around data access and worker risks when using data probes.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**.

KEYWORDS

Gig Work, Policymaking, Data Probes, Algorithmic Management

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1 INTRODUCTION

Increasingly, calls are being made demanding regulation and policy to address the accountability of technology use and the platforms developing them, given evidence of how unregulated technology can and has impacted people negatively. Companies' collection and sharing of personal data has enabled predatory online marketing [57], hiring algorithms have been found to reinforce racial and gender biases [33], and recent generative AI is already intensifying security risks such as realistic AI-enabled voice scams [99].

The need for comprehensive tech regulation and policy is of particular importance for upholding labor rights: as technology-mediated work continues to proliferate and evolve, policies specifying requirements around algorithm disclosure, data transparency, and privacy continue to lag. The algorithmic management practices of app-based platforms expose workers to opaque practices such as undisclosed A/B testing [27] that can reduce a worker's earnings [85]; unclear work assignment or termination appeal methods that can lead to lost wages while workers' cases are researched without their input [66, 86]; variable platform commissions decreasing worker wages [62, 86]; and confusing contract language masking workers' requirements to cede rights to arbitration [70]. Platforms obfuscate their intent through lobbying and tactics, preventing government agencies and policymakers from understanding the implications of poor algorithmic labor infrastructure. These practices decelerate legislation and regulation intended to keep platforms in check.

Additionally, the atomization of app-based workers often prevents drivers from collectively organizing to address these policy gaps [24, 104, 126], and even when they do, platform lobbyists wielding political clout often muddy organizers' demands [110] by countering worker experiences [52, 117] and threatening consumer price hikes to intimidate policymakers and regulators [25, 112]. Furthermore, the data required for analyzing these tactics has been difficult to obtain due to companies claiming trade secrets [40, 80]. This leads to confusion for policymakers about how platform practices adversely impact workers and how to craft policy to hold platforms accountable.

To bridge the challenges of worker organizing and limited policymaker knowledge of platform inner workings, we offer the use of data probes—interactive data visualizations that show the impact of technology behaviors on workers—to advance technology policymaking. While concerted efforts have been made to surface these impacts by describing workers' lived experiences [8, 21, 66, 130], policymakers consistently value data over anecdotes [71, 72, 109]. We explore data probes with 12 stakeholders—lawmakers, policy informers, litigators, and organizers—who craft or inform policy around app-based gig work to determine how data probes may assist the policymaking process in the United States. Our findings illuminate how data probes may aid the design of tech policy as boundary objects that can 1) **assist different stakeholder interactions** throughout the lawmaking process, 2) **demystify platform practices** and worker experiences for non-gig workers, and 3) **enable worker collective action**. We expand on our findings by discussing the potential for data probes as training tools for policymakers and regulators, the importance of designing data probes and tools centered on workers' lived experiences, data access considerations when creating data probes, and risks to keep in mind when using them. Our study is confined to the U.S. context, thus there may be limitations in generalization given the role of unique political-legal structures that influence policymaking.

2 RELATED WORK

Our research aims to support technology policy creation advancing the well-being and rights of app-based gig workers. To study the contribution of data probes towards this objective, we focus on the data and stakeholders of rideshare platforms, or "Transportation Network Companies" (TNCs), a sector in the U.S. To frame the complexity of policymaking in this space, we describe how platforms employ algorithmic management to oversee workers and attempts of worker-centered TNC policy to highlight existing policy directions and debates. Then, to situate the role HCI research can play in tech policymaking, we detail efforts supporting worker collective action, often through data-driven tools.

2.1 Rideshare Drivers and the Need for Policy

2.1.1 Rideshare Drivers' Experiences with Algorithmic Management. Platforms often frame rideshare driving as an attractive option for workers due to low barrier of entry, the opportunity to "be your own boss", and the allure of flexibility to "work when you want". A closer look reveals algorithmic management supersedes autonomy—in the absence of human managers, platform algorithms will assign work, calculate wages, and determine performance and termination [66], as well as influence temporal and spatial movement [105]. Early social science and HCI research surfaced that platforms exert power and information asymmetries (e.g., concealing how variable pricing is determined, withholding trip information when assigning it) [38, 66, 98, 124] at the expense of drivers' physical and financial well-being [38, 48, 124, 130].

In response, drivers employ strategies of varying defiance—from resistance [81] or deviance [20] such as liberally rejecting or cancelling underpaying or unsafe trips; gaming [81] or engagement [20], where drivers may collectively make sense of the system to manipulate it; switching [81] or working multiple apps simultaneously to maximize up-time; and compliance [20] or allowing platform features to shape their decision-making. Dubal [31] characterizes these drivers' behaviors akin to a gambling mindset. This is troubling when it results in drivers trying to "win" at a system designed to favor platforms as evidenced by the ever-changing nature of platforms [59, 82, 91], often to drivers' financial detriment [31, 107]. Though complementary work explores how to design interventions or alternative systems to improve the well-being and experiences of workers [26, 50, 114, 130], the need for policy holding platforms accountable, when platforms otherwise lack incentive to, cannot be overlooked.

2.1.2 Rideshare Drivers: Earnings and Racial Disparities. Driver-focused organizing and policy attempts emerged in the second half of the 2010s, centering around two issues: minimum wage standards and worker classification. In 2018, New York City's Taxi and Limousine Commission (TLC), tasked with regulating medallion cabs and for-hire vehicles including Uber and Lyft, was concerned that TNC drivers were earning less than minimum wage and commissioned researchers to investigate the need for and potential implications of proposed minimum wage standards [89]. Using administrative data provided to NYC by 4 major app-based companies, Parrott and Reich [89]'s findings showed drivers earning below minimum wage and hinted at how vulnerable the NYC rideshare driver population was—mostly full-time, immigrant drivers (60%) dependent on the income for essential needs rather than part-time drivers working out of convenience for supplemental income as TNCs often state [113]. The TLC report importantly established 1) the standard wage metric as earnings *post-expenses* and 2) that working time includes not just time spent transporting passengers, but the entirety of their work, e.g., commuting, driving to passengers, circling blocks while anticipating a work assignment [89]. These are important distinctions as the underlying assumptions about earnings, expenses, and time directly frame whether worker wages are livable.

Additional cities and states have proposed minimum wage policies or worker classification determinations, and similar economic analyses have been conducted to calculate drivers' earnings under such policies and the impact on customers and the regional economy [46, 54, 56, 73, 95, 97, 103, 108, 132, 133]. These reports found that on average, drivers earn sub-minimum wages in the absence of policy. For example, Reich and Parrott [97] commissioned by the City of Seattle to inform a minimum wage ordinance, surveyed 30k workers and found drivers on average earn $9.73/hr after expenses, with most rides completed by full-time drivers for whom the work is their primary source of income. The Mayor's Office conducted its own extensive driver outreach through townhalls, interviews, focus groups, and surveys of over 10k drivers, finding the majority of respondents were non-white, two-thirds drive for a TNC as their only job, and drivers face extreme pressures due to rising expenses, limited flexibility, and uncertainty inherent to platform work [1]. Platform-based policies to classify workers as independent contractors have also been scrutinized such as the Economic

Policy Institute (EPI) comparing independent contractors with in-house employee counterparts, revealing the independent contractor classification of gig workers risks underpayment [103, 108, 132].

Unsurprisingly, platforms have pushed back on policy and regulation attempts [52, 117]. On the same day Reich and Parrott [97]'s City of Seattle report was published, an Uber-Lyft sponsored study [52] was released, claiming median driver earnings at $23.25/hr. Researchers have countered these [55, 79, 96], such as Reich and Parrott [96] breaking down the assumptions used by Hyman et al. [52] that inflate driver earnings, such as 1) including tips in their calculations and disregarding time drivers spend waiting to receive an assignment, and 2) underestimating driver expenses by assuming most are casual, part-time drivers when [1] and [97] both found contradictory patterns in Seattle. Though surveys have shown that nationwide most gig workers[1] work part-time [10, 35], [10] found that gig work income remains essential or important to meeting basic needs for most workers, and separately, [132] found 29% of respondents made below their state's minimum wage.

While comprehensive regulation remains lacking, recent work suggests legal paths forward. Dubal [31] explains that platforms' data extraction of workers' labor allows them to create opaque, algorithmically determined and personalized pay and incentives, engendering **algorithmic wage discrimination**, a troubling practice that violates worker autonomy, reduces wages, and risks reinscribing social and racial equity issues. She frames this as violating fair employment models and argues for a ban on these practices. Recently, workers in Rideshare Drivers United have been pursuing a class action suit against Uber and Lyft for violating antitrust laws by fixing passenger prices, overriding the control that drivers are entitled to as independent contractors [102]. Government organizations have also indicated an interest in scrutinizing platform wages more closely. The Federal Trade Commission (FTC) has stated an intention to investigate deceptive and anti-competitive wage pay practices of gig companies [3]. The Department of Labor has proposed a revised rule to determine who is an employee for purposes of the minimum wage under federal law [4]. And at the state level, the Colorado legislature introduced legislation to make gig worker pay transparent [5].

2.2 Worker Advocacy and Collective Action: Understanding and Supporting Drivers' Collective Action

2.2.1 Drivers and Collective Action Efforts. Although app-based drivers currently classified as independent contractors do not have the right to unionize under federal law, several organizations have formed to spur worker rights. Rideshare Drivers United is one of the largest with over twenty thousand driver members, and has been the driving force for California legislation. This includes the passage of AB5, which declared gig workers to be employees entitled to benefits, as well as the on-going fight over Proposition 22, a platform-led ballot initiative which seeks to reverse AB5 [15, 30].

Other groups and efforts include NYC's Los Deliveristas Unidos securing app delivery drivers a set of bills addressing minimum pay, transparent wages, and several well-being measures (e.g., the repurposing of NYC infrastructure as rest/recharge stations) [64]; NYC's New York Taxi Workers Alliance securing the first time-based wage floor for gig workers [41]; Teamsters 117 pushing Seattle's 2021 ordinances that provided minimum pay and deactivation recourse[2] [131]; Colorado Independent Drivers United advocating for state legislation that platforms provide fare transparency to drivers and passengers [23]; and the Chicago Gig Alliance organizing for safety standards, deactivation recourse, and driver wage policies [6]. Additionally, advocacy and driver-led organizations have released their own reports, similar to [89, 96] in Section 2.1.2, to provide more context into local conditions and worker experiences [34, 67, 76, 77, 115, 120]. This includes McCullough et al. [77]'s driver-led initiative to collect and analyze driver data finding median driver wages to be $6.20/hr under Prop 22 and Leverage and Dalal [67]'s findings of similar sub-minimal wages in Denver and understanding about the driver population being primarily full-time and people of color.

Yet, groups have had varying levels of success in moving policy and regulation. Challenges include lingering atomization [121, 126] wherein many drivers are not part of an organization or involved in organizing efforts (perhaps due to fear of retaliation or lack of knowledge [49]), and differences in workers' desires and understandings about being classified as independent contractors or employees [93]. The latter is an issue capitalized upon, and arguably caused, by platforms through tactics such as the formation of platform-funded driver groups [2] and lobbying of state legislatures for state preemption laws around platform regulation [106]. Groups also face obstacles such as platform retaliation, e.g., Uber and Lyft threatened price hikes and service cut-offs contributing to Minnesota's governor's decision to veto a worker-backed pay raise bill [58].

2.2.2 HCI and Collective Action for Workers. While HCI researchers have studied how to support collective action through general activism [9, 44, 68, 101, 119, 125] or community-based organizations [12, 14, 63, 65, 92, 116], work specific to *digital worker* collective action initially focused on crowdworkers and content moderators—from creating tools and platforms for crowdworkers to share information about employers [53] and mobilize worker campaigns [100], to understanding factors contributing to participation in collective action against online platforms [75].

Recently, research on app-based workers has explored how to design worker-centered interventions and platform alternatives [26, 50, 114, 127, 129, 130]. A common motif surfaced has been around using worker data to strengthen collective action, such as drivers' desires to use collective data to investigate safety- and discrimination-related concerns [114] or audit platform gamification practices [114, 130]. In fact, Calacci and Pentland [18] collaborated with app workers of a non-profit worker collective to conduct worker-driven auditing of the Shipt algorithm. More calls are being made to explore how to aid worker-led data collection to empower collective action [17, 19], hearkening back to Khovanskaya et al. [60] who proposed historical US union tactics for app worker advocates to secure data access to conduct wage contestation.

[1]In these surveys, gig workers include responses from app-based workers and others who are independent contractors as opposed to in-house employees.

[2]These measures have since been replaced by Washington's statewide TNC regulatory requirements.

Worker data also holds strong potential for bridging collective action goals and policymaker efforts. Past studies have investigated the persuasive power of data visualizations around public issues [74, 88, 118], including techniques to appeal emotionally to observers [22, 28]. This suggests the promise of using worker collective data with policymakers—such as illustrating worker conditions caused by algorithmic management—to take official action on worker issues. However, though HCI work has emphasized the need to formalize collective action goals through policy [50, 69, 119, 129], few have engaged directly with policymakers or others who impact gig worker policy. Hsieh et al. [50] is one exception exploring issues gig workers face with regulators/advocates, finding they view platforms responsible for creating safe working conditions but do not detail how regulation should compel platforms to do so. Here, we observe an opportunity to align the worker collective action efforts detailed in Section 2.2.1 with the lesser-explored perspectives of policy-informing and policy-enacting stakeholders through worker data.

3 BRIEF OVERVIEW ON RIDESHARE EXPANSION & REGULATION

Founded in 2009 as *UberCab*, Uber was initially purported as an impressive solution for using big data to bring together riders and drivers through its powerful matching algorithm [83]. Uber grew rapidly, and within 4 years of its public launch, had expanded to

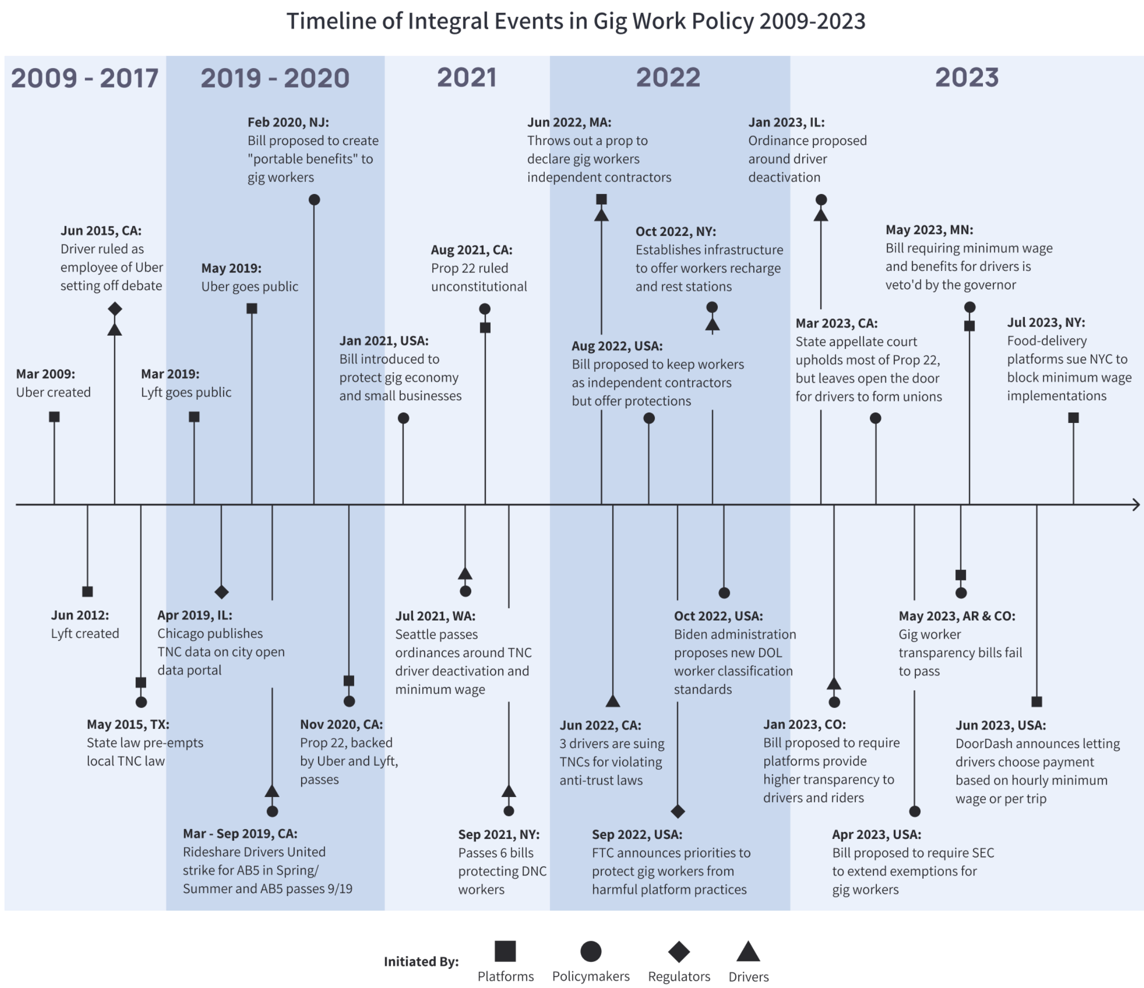


Figure 1: An abbreviated overview of events in the United States related to app-based gig work policy and regulation evolution. Noticeably, there is a large gap between 2009-2017 of meaningful attempts, with more efforts occurring in 2022-2023. The endpoint(s) of each line denotes who the event was initiated by and/or benefited. For example, the passage of Prop 22 is denoted with a square (platform) and circle (policy) as it was a platform-backed policy that passed. In some cases, a policy does not have a corresponding square (platform) or triangle (worker groups) because it resulted in mixed outcomes for both groups. Please see our supplemental material for a more extensive list of gig worker policymaking related events in the United States.

60 countries and 300 cities. Ridesharing remained a largely unregulated industry in the United States, despite its surface similarity to the highly regulated taxicab industry [32]. The lack of regulation, paired with the piecemeal and localized nature of the rare legislation, resulted in driver experiences characterized by precarity, uncertainty, and manipulation [66, 130]. In 2013, California became the first state to regulate ridesharing, by mandating universal background checks and a corporate insurance policy, among other changes, which began a long journey of inconsistent and reactive regulation [37]. Other local governments attempted to follow suit, with early legislation mainly taking the form of background checks, fingerprinting, and minimum wage laws. Platforms retaliated by threatening to leave markets—e.g., Seattle (2017), California (2020) [45], and Minneapolis (2023) [47]—to lobby against pro-driver regulations. In rare instances, platforms completely abandoned regions—e.g., Alaska (2014) [128], San Antonio (2015) [39], Houston (2015) [78], Austin (2016) [43]—until such regulations were lifted.

Across the U.S., platforms began lobbying states over two main objectives: 1) pushing states to establish state-preemptive policies overriding local, city-initiated regulations restricting rideshare companies and protecting drivers, and 2) pushing states to declare drivers as independent contractors thereby concretizing their status as workers without benefits [106]. These, along with changes in platform work algorithms, led to drivers seeing drops in their fares. In response, drivers launched grassroots organizing efforts to push back against platforms (detailed in Section 2.2.1). Since then, driver collective action has been the primary impetus advancing pro-driver legislation, with unions and driver cooperatives rivaling platforms' lobbying efforts, often seeing mixed successes [84, 94].

This volley between drivers and platforms lobbying policymakers to support the respective party's interests has created confusing legislative agendas that belie the tilt towards policy enforcing the status quo. For example, in California, drivers and organizers rallied to pass AB5 in 2019, a legislation that reclassified drivers as employees in order to promote drivers' wages and benefits. Uber and Lyft responded in kind with a ballot initiative, Proposition 22, to withhold AB5's driver protections and permanently classify drivers as contractors. Passed in 2020, Prop 22 remains unresolved in California courts with drivers and platforms in contention over its legality [15].

> "Going forward, you'll see us more loudly advocate for new laws like Prop 22. [Uber hopes to] work with governments across the U.S. and the world to make this a reality." - Uber CEO Dara Khosrowshahi [123]

The journey towards ensuring rideshare driver rights is not a linear one due to struck-down legislation, sidestepped issues, and highly active platform lobbying efforts. Gradually, however, more local and state governments are attempting to pass ordinances, laws, and regulations to improve drivers' well-being (See Figure 1), due to the ongoing—and still evolving—collective fight to ensure driver rights, as we discussed in Section 2.2.1.

4 DATA PROBES AS AN APPROACH FOR ALIGNING TECHNOLOGY AND POLICY THAT SUPPORTS WORKERS

We first describe how to develop data probes for use as a research approach by explaining design considerations and data collection requirements. We then present the data probes used in this study developed for the purpose of rideshare gig work.

4.1 Data Probe Development

Researchers have created various methods to engage users in exploring design spaces and generating creative ideas. This includes cultural/design probes [36]—(physical) objects given to users to elicit feedback and imaginative ideas for design; and technology probes [51]—lightweight technologies to surface user needs and ideas, and enable field-testing and collection of probe usage data. Data probes similarly support the exploration of users' ideas and feedback for design. However, uniquely, they take the form of interactive data visualizations and tools, created using real worker data, in order to show the impacts of technology behavior on workers.

Additionally, design probes and data probes have been observed to act as "boundary objects"—entities that can "adapt to local needs and constraints of the several parties employing them, yet robust enough to maintain a common identity across sites" [111]—such as supporting collaboration amongst diverse experts [42] and for workers to explain their work and contexts to researchers for designing AI [129]. This property suggests the potential for data probes to be used as boundary objects between researchers, workers, and policymakers in the creation of worker-centered tech policy.

Design Principles for Data Probes. The data probes used in this study are built on two design principles. First, data probes must support policymakers and other relevant stakeholders in reflection and action—reflection over working conditions induced by platforms, and action around policy that protects workers or holds platforms accountable. Data probes must be intuitive and visceral to support a spectrum of data analysis skills and persuade policymakers about the need for worker protection policies [22, 28]. Second, data probes must center the impacted stakeholders' context—here, the worker. This is important so policymakers understand what kinds of policy are most needed. Thus, the topic of a data probe should target a specific worker concern or platform feature and accurately represent workers' experiences.

Data Sources and Data Collection for Data Probes. Data used for data probes should illustrate working conditions and impacts on workers. This may be platform-generated data such as earnings and work locations. This can also include work data not provided by platforms—e.g., total working time for rideshare or delivery drivers, the time freelancers spend scoping out potential contracts—and manually collected data about worker contexts and well-being—e.g., daily questionnaire responses about mood, sleep quality, and stress levels.

Data sources can include the outputs of worker data requests to platforms; publicly available data from governments; responses from worker surveys; and online forum posts or polls. The feasibility of the former two data sources will depend on the region's data access policies and/or purview over gig work platforms. Survey or poll responses can be combined with platform-generated data to strengthen the connection made by data probes between platform work conditions and worker-reported well-being. The latter data source of online forum posts might be challenging for creating data probes due to its unstructured nature, but can supplement data probes by contextualizing individual working conditions.

4.2 Rideshare Data Probes

The data probes used in this study are based on prior work where we created five data probes, originally designed to support workers in reflecting on their work data, well-being preferences (i.e., financial, physical, psychological), and personal contexts (e.g., whether they are a caretaker). In this study, we include these same data probes as in [129]—although the Work Planner was modified to incorporate driver-participants' suggestions—and one new data probe, the Questimator, based on driver-participant feedback about forms of platform manipulation they experience. We describe the data sources and data probes below.

4.2.1 Data Sources. The Work Planner and the Questimator are created using publicly available data from the city governments of Chicago[3] and New York City.[4,5]

The remaining four data probes are created using a worker's own Uber data. For this study, we showed participants the individual data probes of an anonymized past participant.

4.2.2 Work Planner. The Work Planner is an AI work planning prototype, intended to simulate inputs (e.g., labor, expenses) and outputs (e.g., gross and net earnings) that drivers face in the real world. Users select inputs such as working hours, pickup locations, and car type, and receive prediction data such as predicted fares, tips, and expenses.

We updated the original Work Planner based on past participants' suggestions as well as feedback from policy informers[6] in order to reflect worker experiences more accurately. For example, originally, workers could only select one set of hours to apply to all the days they selected as working. After workers explained their shifts are more granular, we changed the input type to a timetable so they can select the specific hours for each day of the week. Additionally, we updated the inputs workers can include/exclude to be more comprehensive of the expenses they face, e.g., their car ownership situation to account for expenses such as car rentals if applicable. See Table 2 for a full input and output variables list and Figure 2 for a depiction of the Work Planner used in this study.

4.2.3 Questimator. The Questimator was created to predict how long it may take a driver to complete a "Quest"—Uber's short-term rewards promotion. Quests task individual drivers to complete a certain number of rides in a specific time period, typically between a few days and a week[7]. Lyft's equivalent is called "Challenges" and operates similarly. This probe was created as a means to aid drivers in predicting the estimated time commitment and financial implications of completing different Quests, information that is not currently provided by platforms. For inputs, the user can enter the number of rides the Quest requires drivers to complete, as well as the specific days and hours they wish to work as it corresponds with the time period the Quest allows. The Questimator will output a statement of whether the user has reached their Quest goal and summarize the number of trips, hours, miles, and total fare they are estimated to accumulate from the hours of work selected. If the selection of working time does not meet the Quest goal trips, the Questimator will tell the user how many more hours they must work.

4.2.4 Individual Worker Data Probes. Participants viewed four individual worker data probes, created using data from an anonymized driver. Two of these represent spatial information—the *Animation* is an animated gif displaying a driver's movement patterns across a map of their city during a specific shift, and the *Map* is an interactive map that allows the user to hover over or click on neighborhoods the driver has worked in to view personal work statistics (e.g., number of pick-ups made in the selected neighborhood). The *Calendar* displays driver data on a monthly calendar: the user can hover or click on days to view personal work statistics, and days are shaded as a heat map to visually cue low to high earning days. The *Hourly* data probe is a bar chart that displays the driver's earning trends for each hour of the day.

5 METHOD

5.1 Participants

Technology policymaking encompasses multiple stakeholder types—the impacted communities who raise issues, advocates or researchers who inform the need for policy and directions to pursue, officials with the power to initiate and oversee policy or regulation around technology, and practitioners who can enforce policy on behalf of the public or individuals. We recruited participants with prior experience around gig worker issues across these different roles, reaching out through email or website contact forms, and speaking to those who returned our inquiries. We spoke to 12 participants: five policy informers, four organizers, two litigators, and one lawmaker (see Table 1). We did not seek to specifically recruit drivers as our prior work, which this complements, explored data probes with drivers [129]—however, four participants were or are active app-based rideshare or delivery drivers. Next, we provide an overview for each stakeholder type we spoke to, to situate how they are integral to technology policymaking (also illustrated in Figure 5).

Policy Informers: Policy informers influence policy by conducting research to shape what goes into legislation, creating reports that analyze the impact of proposed or enacted policies, or advising policymakers about directions to focus on. We spoke to two policy informers from academic institutions, one policy analyst from a state non-profit organization, one director from a national non-profit think tank, and one designer who was a city employee and conducted driver research to inform the parameters of two rideshare driver ordinances that were later passed.

Community Organizers: Community organizers are directly impacted individuals forming coalitions to promote policy changes at local, state, and federal levels, serving as the interface between

[3]https://data.cityofchicago.org/Transportation/Transportation-Network-Providers-Trips-2023-/n26f-ihde
[4]https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page.
[5]These datasets are both available as a result of city government legislation mandating their collection and public distribution.
[6]These individuals are different from those included in our study.
[7]https://www.ridesharingdriver.com/uber-eats-promotions

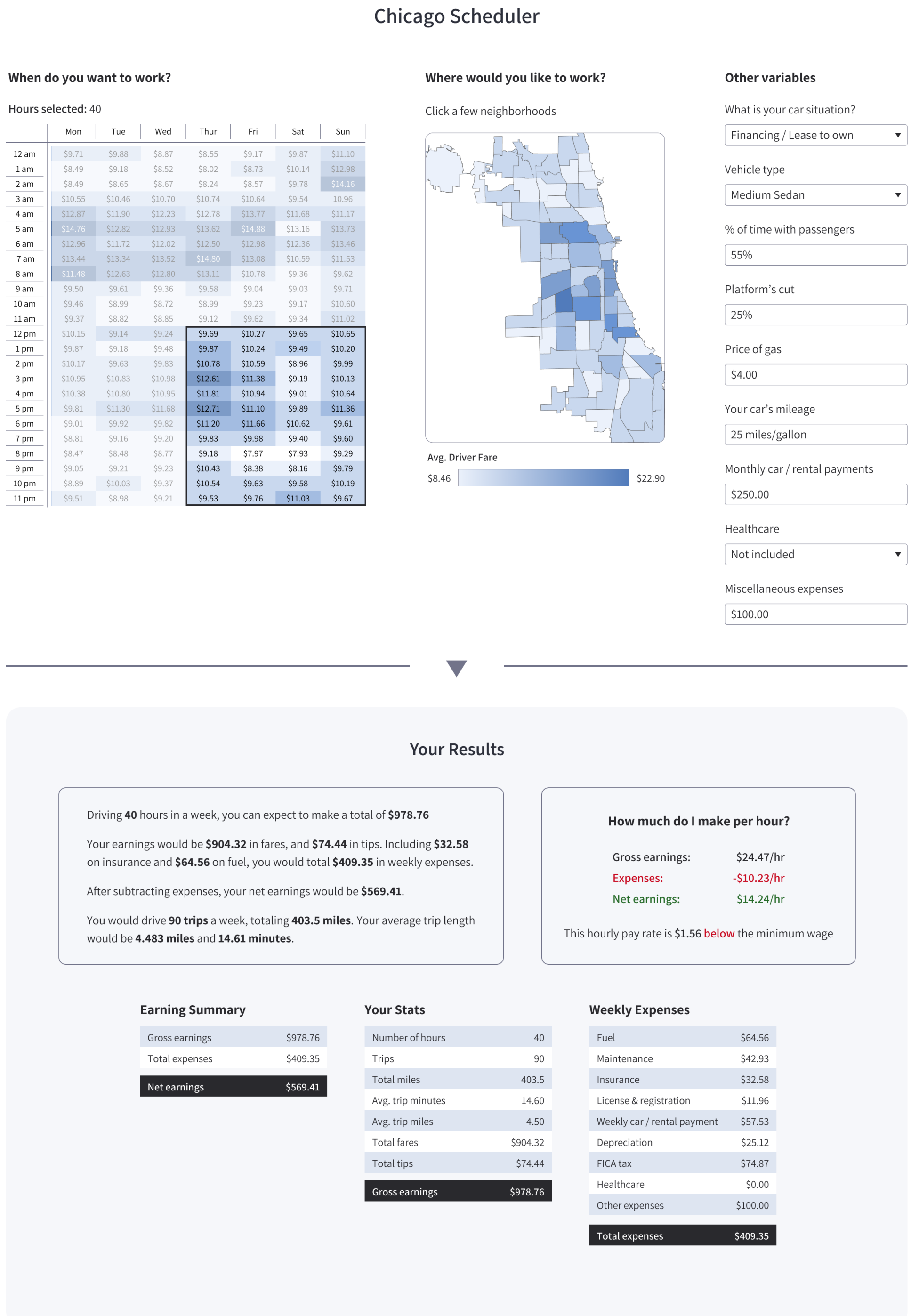


Figure 2: Work Planner. This is an interactive work planning prototype built using Tableau. Users can select specific work hours using the top left figure as well as neighborhoods to work in using the map selector. Average earnings shown for each hour in the top left figure are static and displayed before a user selects their working hours. Users can also input information to calculate weekly expenses they incur such as whether they are renting a car and if so, what the weekly car payments are. The Work Planner will output net wages calculated by subtracting weekly expenses from the summed hourly wages.

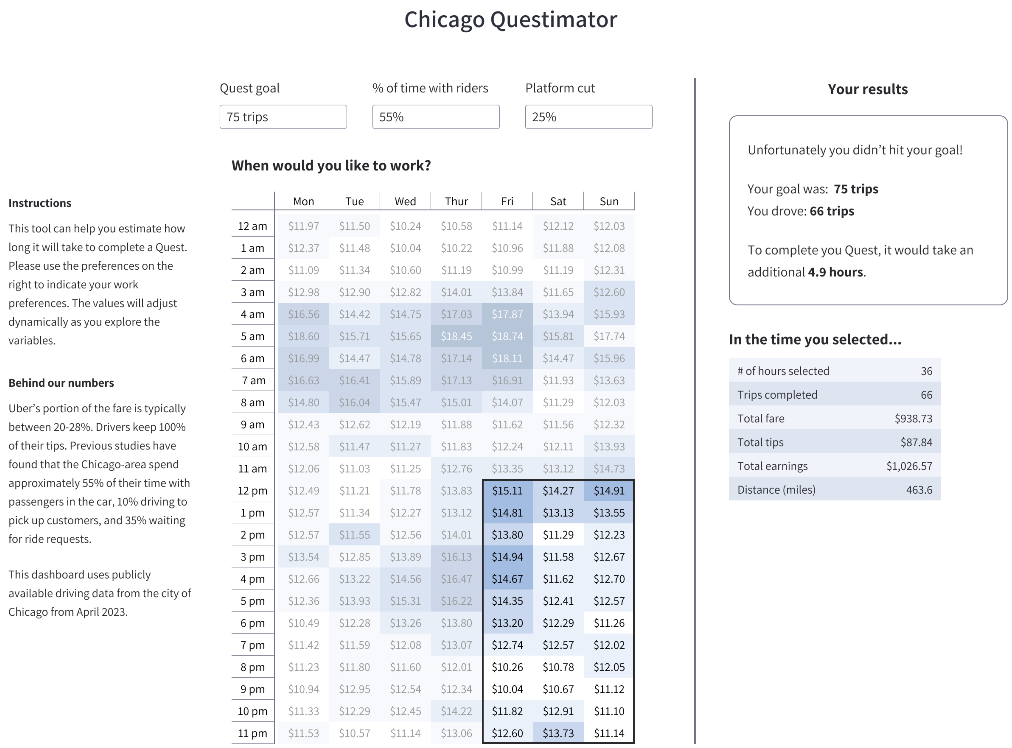
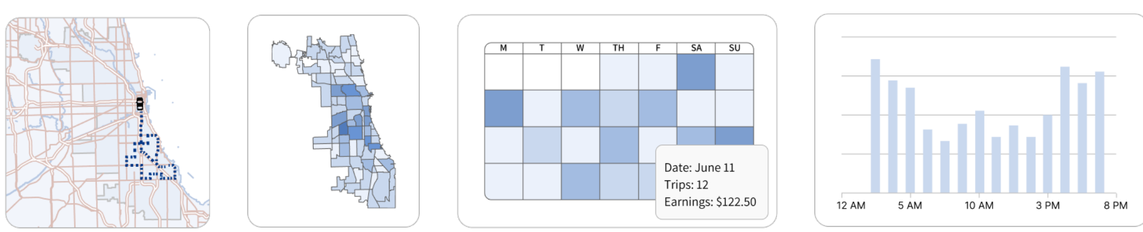


Figure 3: Questimator. The Questimator probe allows users to input the Quest's goal trips to achieve the compensation bonus, with users designating the hours they'd like to work, the percentage of time with riders, and the percentage profit that platforms take. The Results section on the right then projects an estimation of earnings and rides completed. If the number of hours selected do not result in the Quest goal trips achieved, the Results text will display the number of rides remaining and hours estimated to reach it.



(a) (b) (c) (d)

Figure 4: Individual Worker Data Probes. (a) Animation: A screenshot of the Animation probe illustrating a grid of Chicago following the route of one driver for a shift. (b) Map: A density map of Chicago with darker sections indicating regions the driver earned higher fares. (c) Calendar: Driver's data depicted on a calendar, where days are hoverable to review the driving statistics such as total fare earned that day and number of trips completed, (d) Hourly: A bar chart depicting a driver's average earnings for each hour of the day.

citizens and elected officials. Historically, gig worker organizing has taken three forms: political organizing to lobby lawmakers for worker protections policy; union organizing to educate workers on labor rights; and grassroots organizing to protest against driver exploitation by manipulative business practices. We spoke to four organizers—one with experience supporting app worker campaigns (O5), and three of whom are active drivers, including O9, who is a driver and elected board-member of Rideshare Drivers United, one of the biggest driver-organizing groups that played a key role in AB5. While O5 is not a driver-organizer, at the time of their interview, they were working directly with local driver organizations to advocate for worker-centered policy, and have extensive experience in worker organizing.

Litigators: Litigators are "trial lawyers," representing their clients in civil suits at court. In rideshare driver cases, litigators often represent class-action cases where the driver-plaintiffs represent the

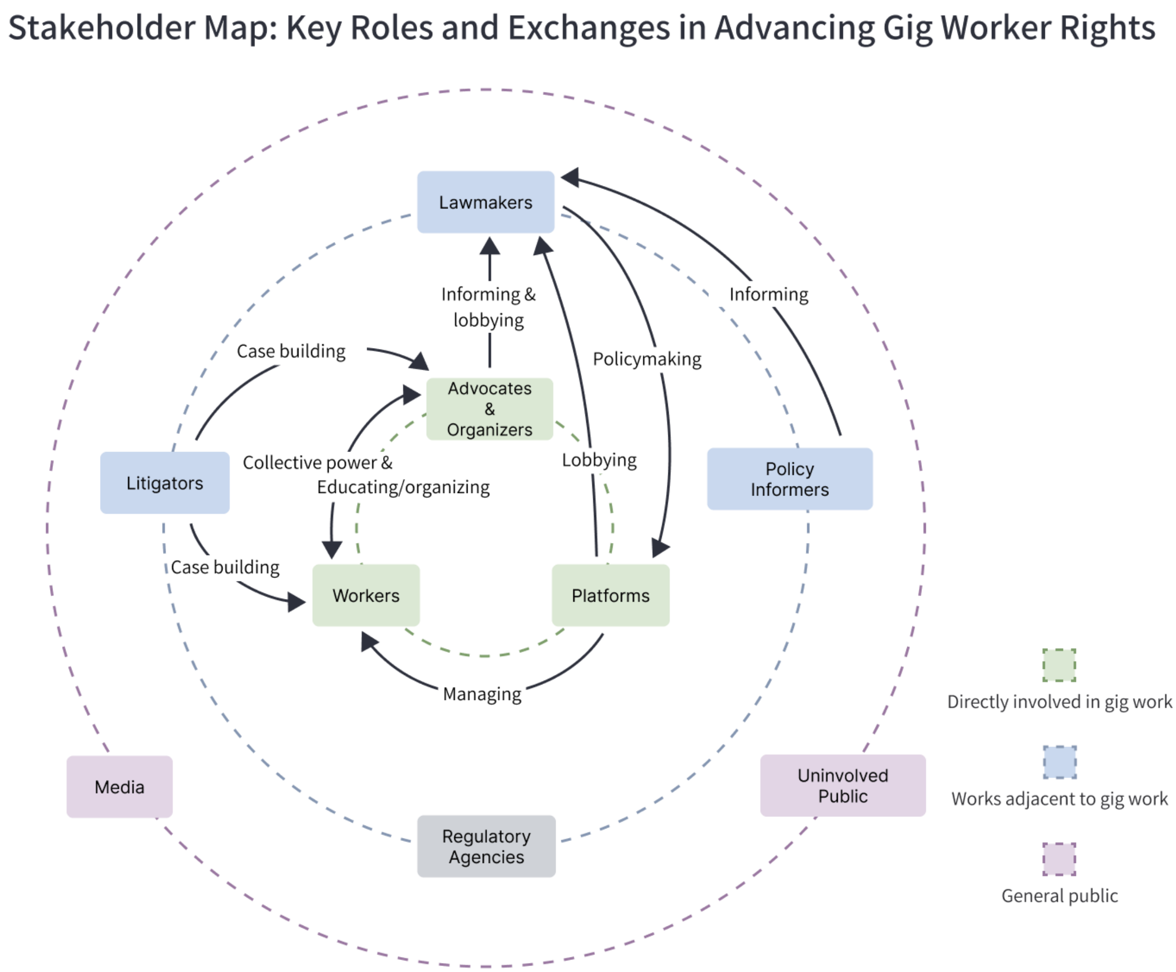


Figure 5: This **Stakeholder Map** illustrates the key groups involved in advancing driver labor rights, depicted in three concentric rings. The inner circle comprises workers, platforms, and advocates (green), influencing lawmaking. The middle ring includes lawmakers, litigators, and policy experts (blue), along with regulatory agencies (grey), who shape legislation and enforce worker rights. The outer circle represents the media and the public (pink), amplifying labor rights messages. Arrows show connections: platforms manage workers, who collaborate with organizers; policy experts, platforms, workers, and organizers advocate for laws; litigators and regulators work with organizers and workers to protect labor rights. While in our interviews, we did not speak to media, regulatory agencies, or the uninvolved public, we recognize the crucial role they play and include them in the figure.

grievances of drivers at large. This requires listening to driver experiences and gathering evidence supporting the specific driver claims that will be argued at court. They may also help with crafting language in bills. We spoke to two individuals with litigation experience about drivers—one who works for Towards Justice, an organization currently representing drivers in an anti-trust lawsuit with Uber/Lyft, and one who works for a driver organizing group.

Lawmakers: Lawmakers oversee the lawmaking process, where they introduce, research, draft, and pass laws. To do this, they engage with interests groups, organizers, and lobbyists to understand necessary provisions in the bill and formulate the bill language. The proposed laws go through a rigorous process: introduction, committee evaluation, public hearings for input, full legislative body debate, and voting. If approved by the executive branch, typically the head of state or government, the bill becomes law and is enforced by relevant authorities. We spoke to one state legislator with experience sponsoring a gig worker rights bill who has also worked as an app-based delivery driver.

5.2 Procedure

The goal of interviews was to use data probes to speak with different stakeholders to get new knowledge as well as gather feedback to inform the design of new data probes. Interviews began with the facilitator asking participants for their background and experience

ID	Stakeholder Type	Role	Institution	State
P1	Policy Informer	Labor Specialist	University of CA	CA
La2	Lawmaker	Lawmaker	State Government	CO
Li3	Litigator	Litigator	Towards Justice	CO
P4	Policy Informer	Designer	City Government	WA
O5	Organizer	Deputy Campaign Director	Action Center of Race & The Economy	IL
Li6	Litigator	Staff	Driver Organizer Group	NY
O7	Organizer	Driver-Organizer	Communication Workers of America/ Colorado Independent Drivers United	CO
P8	Policy Informer	Professor	University of Chicago	IL
O9	Organizer	Driver/ Elected Board Member	Rideshare Drivers United	CA
P10	Policy Informer	Director	Non-profit Think Tank	DC
O11	Organizer	Driver-Organizer	Colorado Independent Drivers United	CO
P12	Policy Informer	Policy Analyst	Non-profit Advocacy Group	CO

Table 1: Participant Table Overview: IDs are prefixed by a letter indicating the stakeholder type they represent. In addition to the stakeholder type we classified participants as, we include here their role, institution, and state to provide more context.

related to gig work. Next, we provided an overview of the Work Planner, explaining its input variables and output calculations. We asked if any clarifications were needed, and for initial impressions and concerns, e.g., whether they felt any components were missing from it to provide reasonable estimations of driver weekly net earnings. We asked participants how they might use the data probe in relation to their own work, as well as their ideas for how each of the different stakeholder groups—organizers, litigators, policymakers, and regulators—might use the Work Planner, and whether any modifications would be necessary for the groups to use the data probe effectively. We followed the same line of introduction and questioning for the Questimator. Finally, we presented the individual data probes: for each, we explained how past driver-participants used the individual data probe (showing driver's own Uber data) to explain how personal contexts and platform tactics impact work strategies, and asked participants how this data probe could be used for their work as well as by other stakeholder groups. We ended the session by asking participants for final thoughts and preferences about the data probes that they saw.

5.3 Analysis

Each interview was conducted over Zoom, transcribed using Otter.ai, lasted one hour, and participants were offered a $60 gift card for their time. Two members of the research team reviewed notes and transcriptions from each interview, and analyzed the data following Patton et al. [90]'s qualitative data analysis method: the researchers first reviewed the transcripts according to data probe type and interview questions, and coded the transcripts at the sentence or paragraph level, then clustered the codes to form emerging themes. The research team collectively discussed these themes to determine the final results reported in the paper.

6 RESEARCH TEAM & POSITIONALITY

Our research team comprises academics with backgrounds in HCI, Law, Government, and Communication. One author has expertise in employment and labor law, and frequently provides consulting to lawmakers and policymakers on precarious work such as gig work. Another author has experience organizing for food and education equity. All team members are deeply interested in understanding the technology policy landscape for the modern labor rights movement to ensure that policies are built with dignity, equity, and transparency. We recognize our privilege as academics removed from base-building work. With this reflexivity in mind, we followed-up with participants to inform them of how their interviews shaped our findings, and welcomed any feedback and modifications they suggested.

7 FINDINGS

Our results indicated ways that data probes can assist the creation of technology policy, acting as boundary objects to facilitate different stakeholder interactions throughout the lawmaking process, demystify platform practices and worker experiences for non-gig workers, and enable worker collective action. We first give an overview of the lawmaking process, describing different ways stakeholders interact and the data probes that participants felt could be supportive. We then explain the technology behaviors and worker experiences that data probes can support demystifying, as well as the ways data

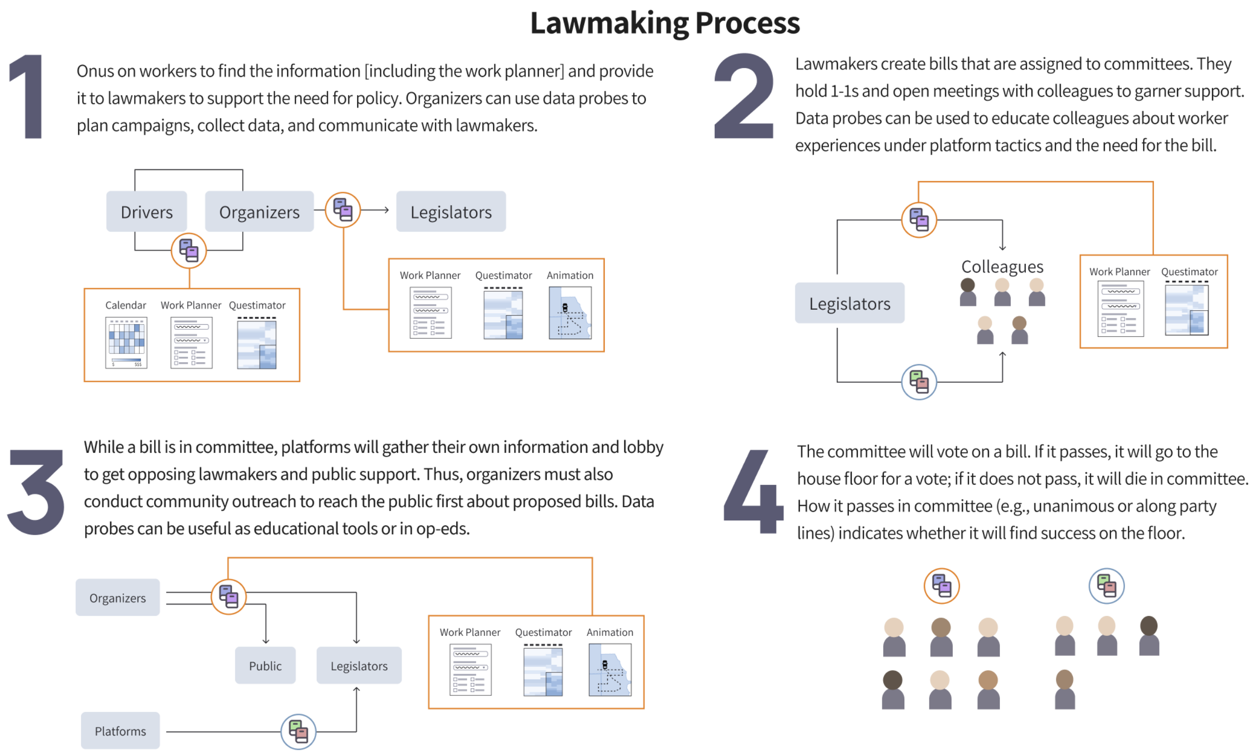


Figure 6: Abridged Lawmaking Process with Stakeholder Interactions and Data Probe Usage. The figure lists four steps for an abridged lawmaking process, and calls out which stakeholders are involved, how they are interacting, and which data probes may be able to support the interactions. Steps are also explained in Section 7.1.

probes can support workers individually and worker-organizations to enable collective action.

7.1 Stakeholder Interactions and Data Probe Usage in the Lawmaking Process

From how participants explained they might use data probes, we constructed an understanding of different stakeholder interactions occurring within the policy creation process. Below and in Figure 6, we demonstrate this through (abridged) steps of a state lawmaking process, highlighting interaction junctures where data probes can assist stakeholder communication. While policymaking may look different at other jurisdiction levels, the general process is the same across U.S. states and is valuable to understand due to the concentration of power states have over cities in overseeing TNCs.

Step 1. Issue Introduction. La2, O5, O7, O9, and P10 all discussed the necessity of drivers themselves advocating for gig worker issues as constituents of their elected official. To that end, they spoke of how "it's really incumbent upon us" (O7) to present both narrative and numerical data as "proof" (O5) of their lived experiences. We provide examples of how participants envisioned organizers and workers using the Work Planner, Questimator, Calendar, and Animation for collecting and presenting data to their legislators in Section 7.3.

Step 2. Bill Construction. Lawmakers with interest in an issue can sponsor—e.g., write—a bill, after which it will be assigned to committee for review. To garner support for the bill, lawmakers hold 1-1s and open meetings with colleagues to explain important policy nuances. They may also provide lawmakers with a 1-pager on the bill—a "skimmable [document] that has some basics on it" (La2). La2 saw value of the Work Planner accompanying such a 1-pager as a digestible visual of the effort workers expend, expenses they incur, and whether they can achieve a livable wage. Emphasizing the significance of garnering bipartisan support for passage of a bill, La2 also suggested that the Work Planner could help present different policy framings depending on the audiences. We expand on examples of data probes to support bill sponsors communicating with committee members in Section 7.2.

Step 3: Anticipating Platform Rebuttals. O7 noted a crucial step while a bill is being worked in committee—O7 warned that platforms will lobby lawmakers to "kill" a bill, e.g., vote it down so it does not advance further, and use platform data to produce and spread counter narratives to community groups. This occurred when platform lobbyists undermined a driver-organizer backed bill by convincing a community leader that drivers' demands for location transparency would lead to discrimination against riders. P12 pointed out the irony of platforms' claims given that 1) drivers hail from the very communities platforms claim they will discriminate against, and 2) a recent report using Chicago rideshare data found platforms themselves engage in discriminatory pricing against low-income neighborhoods [87]. In Section 7.3.3, we explain ideas by La2, Li3, and O7 for how the Animation, Work Planner, and Questimator could assist organizer educational efforts.

Step 4: Committee and Legislative Floor Votes. The bill is put to vote in committee, and if it passes, additional processes such as debates, voting, or amending occur on the legislative floor. La2 explained that how a bill passes in committee is indicative of its future prospects, stating, "Anything that you can get out of committee with say like a unanimous or near unanimous vote is like destined for greatness."

7.2 Demystifying Platform Practices and Worker Experiences For Non-Drivers

Multiple participants stressed that policymakers often lack a true understanding of gig worker experiences because most are not ones themselves and platforms **"mystify everyone with their technology** into thinking that the same rules [existing employment regulations] don't apply to them" (P10). P10 shared policymakers and informers unfortunately often overlook this initial step of understanding, "leaping to the discussion about employment law and regulatory frameworks without a lot of pre-existing knowledge among non-drivers about...what the app interaction is even like." Relatedly, La2 has observed how lawmakers entangle employee classification with basic worker rights, believing erroneously that the latter is contingent on the former, which often stalls worker protection efforts. La2 argued that determining employee classification is separate from whether workers are allowed to have information about their work: "If you get on an algorithmic...tech-driven application where you get your job assignments...there are some things that you should have rights [to] within that system, to know, to see and [to] have available to you."

Promisingly, participants indicated data probes can bridge the "distance" between driver experiences and policymaker understandings by elucidating 1) real worker wages and conditions as a result of platform features, and 2) how platform algorithms and incentive structures can adversely impact workers.

7.2.1 Dispelling Assumptions About Workers and Wages with the Work Planner. Participants universally appreciated the Work Planner for shedding light on worker wages. They emphasized the need for transparency in driver earnings (O5), underscoring that both passengers and policymakers often do not realize the expenses rideshare drivers have and how it impacts net earnings. For example, the default inputs in the Work Planner (e.g., full-time worker who owns a paid off car), showcase earnings of $24.23/hr reduced to $11.19/hr after expenses. Furthermore, participants felt that the Work Planner's categorization of expenses (e.g., license and registration, depreciation, fuel) helps dispel misconceptions that policymakers hold about workers: "Policymakers believe, 'Oh, [gig work] is what kids do when they're out of school...' No, it's not." (P4).

Platforms often tout high earnings for drivers by asserting most work part-time, already own vehicles, and incur minimal expenses. P1 countered that these assumptions are "not true for the set of drivers who do the most miles", overstating earnings for full-time drivers dependent on the job for essential needs. La2 weighed in that rideshare drivers are "almost certainly leasing a car or buying kind of a newer one" due to vehicle safety standards and implications of car conditions on worker ratings and tips. P4 and Li6 also shared how in their cities, most workers are full-time and quite vulnerable: "Most drivers I talk to are working 100 hour weeks...especially migrant drivers" (P4). P8 explained that from his analyses, the rideshare population at the national level mostly works part-time, but he imagined how policymakers can use the Work Planner to model and understand how individual differences can lead to different outcomes across drivers: "What types of drivers or what types of conditions does one need for gig work to be a good deal?" Through its range of inputs, the Work Planner can allow stakeholders to get a visceral representation of these differences and driving conditions that may exist, and the ways they can impact people's wages and instability of earning potential.

Additionally, while several participants described the Work Planner as being assistive in illustrating the need for a minimum wage standard, La2 raised that they explicitly avoid attempts to codify minimum wage policies as these require "having to battle over [adjustments for inflation and cost of living] every single time." Separately, Li6, in a city where minimum wage standards *have* been passed, corroborated this residual effect La2 raised. He explained worker groups have ongoing efforts to re-calibrate minimum wage, commenting that the Work Planner could assist in updating the city's policies in line with the Consumer Price Index.

7.2.2 Revealing Opacity and Variability In Payment and Work Assignment with the Work Planner, Hourly Data Probe, and Animation. One platform practice that concerns participants is the lack of transparency around driver payment calculations and variability of earnings across hours and days. They raised this when reviewing the "Percentage of Platform Cut" variable of the Work Planner. While we explained this value is currently incalculable from Chicago public rideshare data, several participants elaborated how this practice is harming workers and how the data probes can assist. Li3 and O9 explained that this variable—referred to as **"take rate"**—was a constant 25% when platforms were first introduced. However, over time, it has changed and can now vary greatly without any platform explanation. Participants shared their own experiences of the take rate fluctuating widely: "That's a very difficult number, because you know, you might get a ride where you get 20% of the fare. Your, your next one might get 60% of the fare." (O9). Li3 noted a variability of 15-70% from the drivers his organization has assisted.

P12 felt this opacity to drivers and passengers can further harm drivers dependent on tips to make livable wages: passengers, under the impression that most of the fare has gone to the driver, are likely discouraged from tipping. Li3, O9, and others were also concerned that the take rate may be algorithmically individualized to exploit drivers and passengers. They believe the platform uses algorithms that analyze individual driver and rider past histories to determine "the customer's highest price point" and gauge "the driver's lowest pay point" (O9) to maximize the platform's own profit. O9 attributed this algorithmically determined take rate to why Uber was able to post profits in August 2023, echoing a speculation in media about how Uber has been able to grow its revenue and profit impressively [107].

Participants also voiced concerns around platform practices of masking passenger destination information, largely through the Animation data probe's illustration of "**deadheading**". Deadheading in the rideshare context refers to drivers driving without a paying passenger, thereby accumulating miles and expending fuel with no recompense. The Animation shown to participants traced a real driver's trip data on a map of Chicago, driving out of the city to drop off a passenger and deadheading it the reverse direction to his home. O11 hoped that this data probe could be used with policymakers to show them the extent that drivers are having to compensate for time driven yet not characterized by platforms as working hours, an experience that Li3 describes as unfortunately common: "it's not unusual, at the end of the night to get that kind of assignment." P4 noted that while city leadership advocated for fair wages for drivers, they overlooked concerns around deadheading possibly due to limited data to illustrate it as a pressing issue. She described deadheading for workers as "the longest portion and most arduous part" of their job, and voiced frustration over technology platforms' incomplete concept of work time.

7.2.3 Understanding Inherent Manipulation of Incentive Structures and Driver Responses to Algorithmic Management with the Questimator. Because rideshare companies' business models depend on a high volume of online drivers to decrease passenger wait time, they employ methods like incentives—e.g., Quests (see 4.2.3)—to lure drivers to work. While participants were familiar with these tactics, they pointed out that typical policymakers, regulators, and passengers are not. The Questimator resonated strongly as a tool to demystify platform terms and raise awareness about the multifaceted manipulation drivers experience from incentives such as pressures to overwork, lack of flexibility, and sub-minimal base wages.

To show the participants how the Questimator works, we used a real example of a rideshare platform incentive posted in a Uber/Lyft Driver Facebook Group—the offer was a $295 bonus for completing 120 rides between Friday 5AM to Monday 5AM—and selected hours until the 120 rides were met. The Questimator displayed that a worker must work 64 hours total from Friday 5AM to Monday 5AM, with a break of 8 hours in order to meet the bonus.

> "I can think of 17 people I would like...local lawmakers and lawyers to see this...allow them to play with it to understand—*Here's the offer from Uber. And this is what it means, right? Drivers get these kinds of offers, and in order to make a living, you really have to get these bonuses and Quests. So here's what happens when you click a Quest, right? Here, try to figure out when you would drive to accomplish this Quest*—and then have people play with the numbers." (O9)

Using the Questimator, participants raised driver and passenger safety concerns. P12 felt that the data probe's display of hours and days accumulated to complete a Quest might signal overwork and exhaustion: "How long would this take relative to like working hours per day and sleep...It is also a consumer safety thing where it's like, if they're rushing to complete this and they're not sleeping, and it's just not attainable." P4, O5, Li6, and O9 suggested regulators use the Questimator to investigate whether platforms are constructing incentives that are "ever safely possible or possibly in compliance with [rules around maximum shift lengths]" (Li6).

Participants explained that working longer will not even guarantee that a driver can complete the Quest because of dynamic factors surrounding supply and demand (P1, P8) and opacity in when and what kinds of trips drivers will be algorithmically assigned (La2, Li3, O9, P4). The structure of Quests impel drivers to work until they complete the trip requirement and to prioritize short trips (Li6, O7, O11). However, because the platform uses black box algorithms to assign trips or incentive offers and do not provide passenger destination to all drivers before they accept a trip, there is no guarantee when or what type of assignment they will receive—(in fact, it is in a platform's best interest to increase driver idle time and trip length)—and paradoxically drivers can be punished if they try to exert control over trips (e.g., turning down trips may result in longer wait times for the next).

In conjunction with steering driver behaviors, platforms can also assign trips that pay sub-minimally or risk their safety. O9 and O11 explained how workers trying to complete a Quest are more likely to accept trips that individually are "garbage offers" because after a bonus, it can equate to reasonable earnings. But La2 and Li3 reminded us that if a worker does not meet the bonus, the overall payment they receive for the work risks being sub-minimal, describing this phenomenon as a "nonlinear compensation model", and something La2 expressed interest in using the Questimator to investigate further. P12, O5, and others explained additional concerns that because of Quests, workers will be more likely to accept or not end trips that make them feel unsafe due to the pressure of completing enough trips.

Though Li3 felt the Questimator was an important tool that he wanted lawmakers and regulators to use for understanding how workers are treated by platforms, he suggested adding a caveat to drivers who may use it about potential limitations. Specifically, he explained that because platform algorithms can be individualized to drivers, it is still possible that a Quest which seems to be attainable on the Questimator becomes infeasible in practice due to the platform's intentional efforts to prevent them from completing it: "the algorithm knows who you are...[it] will manipulate the routes you take, also manipulate what rides you get based on who you are...that's what we can't overcome...I think it's something drivers understand, but I think it's also just an important thing to flag."

7.3 Enabling Collective Action and Worker Empowerment

Data probes were viewed by participants as tools that can empower workers with vital information for truly understanding their work, assist organizers in recruitment to strengthen collective action, and serve as interfacing tools between workers and organizers with other stakeholders to advance efforts for pro-worker policy.

7.3.1 Empowering Workers with Information to Reframe Their Labor Efforts. We often heard participants describe the ability to access information in the Work Planner (i.e., a breakdown of trip statistics, earnings, and expenses) or Questimator (i.e., amount of hours required to complete an incentive) as basic rights drivers should have to make informed decisions about work. O9 suggested regulatory bodies should be the ones providing access to a data probe like the

Work Planner for that express purpose of providing drivers transparency on whether their wages from platforms are fair/livable.

O9, Li3, and P4 noted that the information presented in data probes, particularly expenses, is not always carefully considered by drivers, and is therefore valuable for drivers to assess how much they're making, and "if they are living off of this or if they are *surviving* off of this" (P4). Presented this way, Li3 believed the Work Planner could help drivers reframe and advocate for the recognition of deadheading as part of their working time: "You talk to drivers about this, and they're like 'well, I wasn't really working, there's no one in the car'—you WERE working!" P4 and O5 emphasized drivers using these tools to see it is the system's design, rather than their fault for not earning enough or completing a Quest. P8 and P12 also raised points about additional information that could support worker education—tax incentives or deductions that they may be eligible for (P8) as well as state-run benefits programs like Colorado's new Family and Medical Leave Insurance that gig workers can opt to pay into (P12). Data probes such as the Work Planner could present this information to drivers to increase their knowledge around what programs exist to assist them.

Li3 also explained how drivers often assume a gambling mindset, echoing [31]'s metaphor, and that using the Work Planner to view the extent of expenses on their earnings, they can realize "that they're not actually beating the house". Along those lines, Li6 talked about how the Questimator can be a tool to educate workers about what "algorithmic management" means. Though this language is used by academics to study gig platforms and workers, it is not necessarily a commonly term for workers themselves. However, Li6 felt the Questimator could help validate their gut instincts about platforms intentionally manipulating their behaviors by giving it a name: "They [drivers] know what's happening, sort of on these isolated data points. But to be able to get the whole sense of how the companies might be planning how they might want to spend their days...I think it would just be edifying."

7.3.2 Growing Driver-Organization Membership. Alongside driver education, participants felt data probes could assist organizers in recruiting drivers. O11 felt data probes were effective in helping drivers connect their intuitions about platform treatment with data proving it: "You gotta get them [drivers] in the head and the heart". P12 hoped the Work Planner, with its breakdown of expenses, could convince drivers how paying a couple dollars a week for organizing fees minimally impacts their earnings compared to other expenses but contributes to collective action for change. Li3, O5, and O7 displayed enthusiasm for the Questimator as well for recruitment—they explained that these engaging tools can show drivers platform manipulation that is occurring to incense them to join a collective cause championing driver rights.

P10 also discussed how data probes can support setting directions of organizing campaigns. For example, we explained that the Calendar in its current form only supports displaying Uber data due to platform constraints around workers downloading their own data. P10 felt the gaps in the visual could be specifically repurposed for discussions amongst organizers and drivers about what additional data they may need workers to log to support their goals, the effort it may take, and whether it is feasible in their timeline.

Participants, driver-organizers in particular, had desires to extend data probes for organizing data collection purposes. Tools such as the Work Planner and Questimator are powered by aggregate Chicago data, but participants wished to power these with local worker data to show local legislators their constituents' experiences.[8]

7.3.3 Data Probes for Interfacing with Different Stakeholders. Participants explained ways drivers and organizers could use data probes as interfaces when communicating with different stakeholders—policymakers, regulators, community members, and even other workers.

Lobbying Policymakers. La2 and O5 explained data probes can be used for citizen lobbying: "They can even open their phone [to the Work Planner] and tell their member of the lege[9] 'here's how much I'm working, here's what it costs me to do it, here's what they're paying me, your constituent. Do you see how much of a problem this is for me to earn a living in our state?" (La2). While O9 saw the potential, she emphasized that to provoke action, estimations from the Work Planner or individual data probes would need to be paired with aggregate statistics, such as what percentage of drivers are falling below minimum wage.

Demonstrating Safety and Compliance Infractions to Regulators. Participants specifically envisioned regulators using data probes to demonstrate 1) false marketing exploiting workers and passengers, and 2) unsafe working conditions harming workers and passengers. For example, P4, O7, O9, La2, and P12 explained the Work Planner could illustrate false marketing to regulators by showing estimated net hourly earnings for an average worker, in direct contrast to what platforms state workers can make in recruitment advertisements. Participants also shared that the Questimator could compel regulators to action by demonstrating unsafe working conditions induced by unrealistic platform incentives. Regulators could use the Questimator to test real incentive offers, view how many days and hours are estimated to complete it, and examine whether the incentives violate safe working hours (Li6). P4 mentioned the secondary health impacts the Questimator illustrated—working and sitting for extended periods can lead to physical ailments detrimental to physical and financial well-being for workers who do not have health insurance. Policy informers explained the inextricable link between driver and passenger safety: "It is also a consumer safety thing where it's like, if they're rushing to complete this and they're not sleeping, and it's just not attainable." (P12). O7 and O9 reminded us that regulators will be most compelled into action if tools can communicate clearly the harm to both workers *and* customers by platform tactics. This idea is practical and notable because city regulators may have limited reach where their states preempt them and workers are considered independent contractors, but most should have the power to investigate on behalf of workers and customers as consumers of platforms.

Resolving Driver Differences and Drawing Out Specific Instances of Manipulation. P4 shared that data probes could be used to resolve differences between drivers. She explained that during city townhalls held to get driver feedback to inform TNC

[8]We note that the individual probes can be reproduced using driver data from any location.

[9]Shorthand for "legislature"

ordinances, drivers argued over their earnings and experiences and the need for minimum wage standards, whereas data probes could have illustrated to them exactly what workers were experiencing through the use of data. P4 also offered ideas for how data probes could have aided as tools when she was interviewing driver to surface specific experiences and concerns about platform work. While her research questions had to stay high level "just to get [drivers] to start talking", individual data probes like the Calendar could have offered a way for drivers to describe manipulation more pointedly. For example, rather than stating surge pricing as a frustration they face, a driver could point to a day on their Calendar data probe to say, "this day was surge pricing, and I actually made less than I did on this other day" (P4).

Engaging with and Educating Community Members. As explained in Section 7.1, O7 was concerned about narratives that platform lobbyists may spread to community groups to jeopardize lawmaking efforts that protect workers. O7 wanted to show data probes to community members to get ahead of the narrative and educate them about challenges workers are facing because of platforms. In line with this, La2 suggested the use of the Questimator for op-eds, and P10 and P12 suggested letting the Work Planner and Questimator be online, public standalone tools for anyone to experiment on, with P10 pointing out the necessity of defining all terminology if this is the case.

8 DISCUSSION

Our findings showed that data probes can support tech policy by acting as boundary objects to facilitate stakeholders in lawmaking, demystify technology behavior impacts on workers, and support the efforts of worker collectives. Based on this, we first discuss the implications of data probes to help policymakers and regulators understand platform operations and ask the "right" questions to hold platforms accountable (8.1). We explain one way to introduce data probes to policymakers and stress the importance of these tools being grounded in workers' lived experiences to advance meaningful policy. Finally, we reflect on data access considerations and risks to mitigate for when using data probes (8.2).

8.1 Data Probes as Tools to Support Policymaker and Regulator Awareness for Asking the "Right" Question

P10 pointed out that, "The mystification of the new technology is sort of obscuring the reality that we [U.S.] have very long standing kind of regulatory models for dealing with the ways in which employers have tried to suppress wages or exploit loopholes in employment law." This reminder of existing frameworks policymakers and regulators have available suggests how **training** can support them in understanding how to exercise their power to hold platforms accountable. While a normal citizen is unable to pose questions and get answers from companies, some state or federal attorneys and regulatory agencies—like the Federal Trade Commission and Consumer Finance Protection Bureau—can issue "civil investigative demands"[10] which require companies to "file written reports or answers to questions". Yet because policymakers and regulators lack a clear understanding of how platforms work and impact workers, it is questionable whether they can create policy or regulation to successfully hold companies accountable.

From interviews, it was evident how challenging it has been to support the gap in policymaker knowledge but also that data probes could fill the gap. Participants repeatedly described wanting to use data probes to educate policymakers on how platforms manipulate workers to compel policymakers to take action. This points to the need for training tools like data probes which break down how platforms operate, the terminology they use, the algorithms and features they deploy, and how these affect workers. By employing these tools, bureaucrats can understand platform functions and importantly, formulate the "right" questions to ask or data requests to make to hold platform companies accountable.

8.1.1 *Data Probes as Educational and Training Tools.*

One way to introduce data probes to policymakers is through **training sessions or workshops that specifically teach how gig work platforms function.** These sessions can be conducted by researchers for groups responsible for workers or gig work company oversight, such as Offices of Labor Standards or Public Utilities Commissions. A session can begin with a platform overview—how they work and the specific terms for algorithmic features they create to manage workers. Next, facilitators can instruct policymakers on research and case studies about how algorithmic management has impacted worker well-being and autonomy. Here, the Calendar, Animation, and Location data probes can help policymakers visually link worker stories with how their data reflects it. Finally, policymakers can practice with interactive data probes (e.g., Work Planner, Questimator) to simulate how platform features impact worker well-being. For example, for rideshare apps, they could be shown a historical Quest offer and asked to use the Questimator to determine what days and hours they must work to complete the Quest that respects their personal obligations, incorporates adequate rest, and earns a livable net wage.

Without this training, policymakers or regulators might only think to investigate traditional topics such as worker wages or make data requests that platforms can subvert or obscure to protect their interest in remaining unregulated. However, after training, they may be equipped to pose algorithm-specific questions. For example, after using the Questimator to complete a Quest offer, regulators may become concerned about whether platforms are endangering workers through unrealistic incentive offers and request platforms turn over data on incentives each worker received and hours spent working to achieve them.

We further highlight the importance of data probes for education and training of regulators and policymakers given 1) recent news of Minnesota's governor veto-ing an app worker minimum wage standard and requesting a commission to make alternate recommendations [16], and 2) the recent trend of congressional testimonies with leaders of tech companies [7, 122]. A commission would need to understand how platforms function—from the specialized terminology platforms have created to the ways their features are designed and impact workers—to inform the information or data requests they make of platforms as they construct recommendations for minimum wage. Congressional testimonies also require lawmakers to understand how platforms work so that they are

[10] https://www.ftc.gov/about-ftc/mission/enforcement-authority

asking the "right" questions as mentioned earlier, in order to get clear, accountable answers from platforms.

8.1.2 Importance of Creating Worker-Centered Tools That Foreground Lived Experiences for Policy Oversight. Many past successes in app-worker movements have been worker-centered, including Los Deliveristas pushing for NYC's delivery driver ordinances [64], and Rideshare Drivers United leading pivotal strikes for AB5 [30]. Organizer participants highlighted that workers or organizers are responsible for raising awareness of concerns, tools, and data to stakeholders with regulating or lawmaking power. So though we suggest they can be used to train regulators and policymakers, we caution the creation of new data probes that diverge from worker goals, a possibility when stakeholders with different objectives are involved [61]. Data probes must ultimately center on worker concerns and lived experiences.

We reflect on two data probes several participants suggested function as stand-alone tools—Work Planner and Questimator—and why they were successful. Both were based on worker-led concepts, the Work Planner a prototype devised directly from ideas of a (now former) driver-organizer for a tool to help drivers plan their work week, and the Questimator based on concerns voiced by driver-participants of our past studies [129, 130]. We observe that the Work Planner highlights and elicits responses about the more traditional topics of wage and employee classification, which can also apply to other gig worker types or independent contractors. While the Questimator enables the investigation of one rideshare platform feature—Quests—we note the concept of illustrating a specific feature and its impact on workers can be extended to new data probes for different gig work types—e.g., rideshare, delivery, petsitting. These can teach specialized terms and processes to non-workers so they can recognize violation and manipulation of existing labor governance.

In fact, participants offered ideas about other platform features and worker experiences for investigative data probes like the Questimator that future work can pursue. P12 described investigating whether platforms are using racial redlining tactics to assign customer fares, and nearly all participants wanted to investigate driver deactivation for discriminatory patterns. Li3 and La2 raised the platform practice of confusing and constantly changing contract terms, concerning because workers are shown this when they begin their work day. They cannot proceed without agreeing and may hastily agree to arbitration terms that strip their right to file a court claim against the platform. Oversight for platform-specific features like these has not typically been pursued by labor regulation, however, data probes that spotlight workers' lived experiences can bring them to the attention of regulatory bodies.

8.2 Considerations When Adapting and Using Data Probes In Practice

We reflect on potential challenges when creating data probes and risks when using them, with initial ideas for how to address these in future work.

8.2.1 Data Sources for Creating Data Probes. We were able to use publicly available datasets from the City of Chicago and New York City to create the Work Planner and Questimator. However, in many places, platform data is not as easily accessible to adapt aggregate-level data probes without upfront effort in data collection. We describe two possible approaches for this data access challenge—legal methods and worker-collected data.

Data Collection Via Legal Requests. While the topics participants suggested may not have readily available data to create equivalent data probes, such as driver deactivation data to identify unfair, discriminatory instances, **legal methods such as Freedom of Information Act (FOIA) requests**[11] may be possible paths for receiving data from platforms. Rideshare companies are already collecting and able to share this data, as evidenced by a Chicago media company successfully filing a FOIA to access the city's list of deactivated drivers and corresponding reasons [29]. Information like this has been provided freely to the city in the name of improving safety—Uber's official statement declared, "The public has a right to know and secrecy doesn't make anyone safer". It could be advantageous for HCI researchers to explore supporting legal options like FOIA requests—e.g., assistive tools to help workers streamline FOIA data demands and investigate the resulting data for instances like discriminatory deactivation of drivers. This would be no small feat requiring legal expertise and time for navigating a FOIA request, but we observe that in the UK where data is theoretically more obtainable due to data access laws (i.e., Data Protection Act), organizations such as ADCU[12] and Worker Info Exchange[13] have assisted or acted on behalf of workers in requesting and making sense of their data.

Worker-Led Data Collection. Worker-collected data can also be data sources while platform-provided data is unattainable. Researchers have explored how platform or social media data can be collected and harnessed to rebuff platforms [18, 69, 114, 119], offering frameworks to support users "donating" their data [11, 13], case studies of small scale (worker-led) platform auditing [18], and various collective data infrastructure designs [114]. We find that while past research focused on how data can empower users themselves to compel platform change, data probes can complement this work by transforming the data for communication with other stakeholders—***e.g., policymakers***—to stoke action.

Data probes created from worker-collected data may offer two things to assist worker collective action efforts. First, data probes could help direct initiatives of worker collectives, e.g., defining data requirements for organizing campaigns. For example, the use of data probes with policymakers might surface additional data that can bolster worker-centered policy. Workers can review whether data proposed by policymakers align with their goals, and if so, use them to define new data collection efforts. Second, data probes can encourage policymakers to act on worker-collected data. Before they act on findings of any data they are presented, policymakers must trust the data source, requiring transparency around things such as data collection methodology and metrics calculations. While platforms currently operate with data and algorithm opacity that can reduce trust, in contrast, data probes can be designed to make

[11] https://www.foia.gov/faq.html: FOIA requests are requests that any person can make of a US Government Agency for agency records.
[12] https://www.adcu.org.uk/
[13] https://www.workerinfoexchange.org/

these attributes transparent to policymakers so they are prompted to pursue worker-centered policy.

8.2.2 Addressing Possible Misinterpretation or Misuse of Data Probes.

Building Data Probes with Workers to Prevent Misinterpretation: Data probes can pose a risk to the advancement of worker-centered policy if the assumptions used to create them are incorrect or unclear to users. For example, the Work Planner allows users to input variables to calculate potential weekly earnings and expenses. If crucial expense categories are omitted or any inputs are unclear to workers for what to enter, the Work Planner could incorrectly over- or underestimate workers' net earnings. An overestimation can risk policymakers retracting support of needed worker-centered policies, while an underestimation could push workers to overwork. It was extremely important for us to iterate on the Work Planner design and assumptions under the guidance of policy informers and workers (see 4.2.2) to ensure the calculations reflect workers' realities, and we urge future data probes be created collaboratively with workers to mitigate potential misinterpretation or inaccuracies.

Integrating Transparent Data Practices to Pre-empt Platform Misuse: Recalling O7's comment around platforms spreading misinformation about worker-centered policy, we caution that platforms may call into question the credibility of data probes. As mentioned in 8.2.1, it will be necessary to document data sources, how metrics are calculated, and any reasoning or assumptions made (e.g., variables included as expenses). This will increase transparency and trustworthiness of data probes to policymakers and prevent the efficacy of platform counter tactics. Record-keeping may also allow workers more credence if platforms attempt to change algorithms based on data probes in order to generate data for counter narratives. Li3 hinted at this possibility when he explained workers believe platform algorithms can dynamically change to undermine their efforts. With clear data transparency and documentation, it could be possible to create "versioning" of data probes to support platform algorithm auditing and compare results across date periods for suspicious discrepancies.

Anticipating Policy Effects on a Heterogeneous Worker Population: It is possible that not all workers will benefit from data probes equally. For example, the Questimator might inspire a policy around fair platform incentive structures. This would likely have a bigger impact on full-time workers as incentives typically require the completion of a high volume of work. Part-time workers will probably see less improvement because their limited hours prevent them from pursuing bonuses to begin with. Future work should consider how to expand on the data probe approach to support investigation of how policy would affect workers of various backgrounds. This is especially important in order to not exacerbate existing disparities, something we are reminded of given participants' concerns over how marginalized workers are the most vulnerable to inequities caused by algorithmic management.

9 LIMITATIONS

The findings presented here reflect participants' ideas for how data probes can be used with different stakeholders. However, the next step would be testing these ideas by deploying data probes for the public, media, workers, organizers, policymakers, and/or regulators to use. Additionally, we examined this from a United States context—examining and comparing data probe usage with other regions where different labor policies and regulations exist may lead to different outcomes or uses for data probes.

10 CONCLUSION

We explore how data probes—interactive data visualizations that show the impact of technology practices on people—can support technology policymaking. Through 12 semi-structured interviews with stakeholders who craft or inform policy around app-based work, we find that data probes can assist the design of worker-centered technology policy acting as boundary objects that could 1) facilitate stakeholder interactions in the lawmaking process, 2) demystify platform practices and worker experiences for non-gig workers, and 3) enable worker collective action. We discuss the implications of our findings around the potential for data probes as training tools for policymakers and regulators, and reflect on how to address data access challenges and risks to workers when creating or using data probes.

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11 APPENDIX

#	Variable Type	Variable Name	Calculation
1	Inputs	Hour & Day of Work	Dataset average, given the specified parameters
2		Pickup Neighborhood	
3		Car Ownership Situation	*Categories from AAA's Your Driving Costs study*[15]
4		Vehicle Type	
5		% of Time with Passengers	Default of 55% from [73] as an average value for Chicago-area drivers
6		Price of Gas	User Input.
7		Vehicle Mileage	User Input.
8		Monthly Car/Rental Payments	User Input.
9		Health Care	Inclusion was inspired by P1.
10		Miscellaneous Expenses	User Input.
11	Outputs	Number of Hours Worked	Number of hours selected in variable #1.
12		Weekly Number of Trips	Number of Hours Worked (#11) / Average Trip Duration (in hours, from dataset)
13		Weekly Miles	Average Trip Distance (from dataset) * Variable #12
14		Total Earnings	(Average Trip Fare + Average Trip Tip (both from dataset) * Variable #12
15		Fuel Expense	Price of Gas (#6) * (Weekly Miles (#13) / Vehicle Milage (#7))
16		Weekly Expenses (Maintenance, Insurance, Licensing, Registration, Auto Taxes, Vehicle Depreciation)	*Values from AAA's Your Driving Costs study*[16]
17		FICA Tax	Flat 7.65% of Variable #14
18		Health Care	Value given by Kaiser Family Foundation[17]
19		Total Expenses	Variables 8 + 15 + 16 + 17 + 18
20		Net Earnings	Total Earnings (#14) - Total Expenses (#19)

Table 2: Work Planner Inputs & Outputs