Co-Designing Worker Tools with Gig Workers through Data Probes

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As the use of artificial intelligence in workplaces grows, so too does the amount of data collected about workers. This increased "datafication" combined with the push for companies such as gig worker platforms to allow individuals to request their own data expands the potential for this data to advance design opportunities. In that vein, we present data probes—interactive data visualizations—created using gig workers' own work data as well as city-level data as one avenue of data as a material for co-designing worker tools. In this position paper, we describe the data probes we created for a co-design study with 12 rideshare drivers—the design of data probes and how drivers interacted with them to surface AI design considerations. This is a position paper based on our ACM CHI 2023 paper titled "Stakeholder-Centered AI Design: Co-Designing Worker Tools with Gig Workers through Data Probes".

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

Additional Key Words and Phrases: Data Probes, AI Design, Gig Work

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1 INTRODUCTION

Artificial intelligence (AI) is increasingly used in the workplace to automate repetitive manual tasks to improve worker productivity and efficiency. In digital work (e.g., gig work), AI is especially prevalent in the form of algorithmic management—(often overbearing) algorithms that take on managerial functions to oversee, assign tasks, and evaluate workers—contributing to the intense "datafication" of workers, i.e., troves of data being collected about workers [6, 8, 13].

Though vast amounts of data are collected through these applications on behalf of companies without consideration of the users, exploring one's own data can be incredibly informative and empowering. Personal informatics (PI) research around how individuals desire to track, reflect on, and draw insights from their own data has shown how this can assist people in understanding their patterns [12] and even initiate behavior change [15]. PI researchers often use design probes in order to engage users in exploring open-ended questions—these may be physical or digital artifacts to engage users in exploring open-ended questions, even incorporating data to encourage user inquiry [3, 14]. For example, Subramonyam et al. [14] demonstrated how design probes using data, referred to as "data probes", can help solidify AI system boundaries: they showed how designers and engineers could surface concrete use cases and limitations when considering user data while designing AI. These examples show promise for the use of data in not only supporting individuals understanding their own data but also as a material for advancing AI design, something that has been a persisting challenge due to AI's dynamic nature [2, 5, 16, 17].

Inspired by this and motivated by advances in data transparency whereby users can request their own platform data, we propose the use of **data probes—interactive data visualizations**—created using individual's platform data as a

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method by which data can advance stakeholder-centered AI design. In this position paper, we demonstrate how data probes support worker-centered AI design based on our co-design study with 12 Chicago Uber drivers [18] which will be presented at ACM CHI 2023. We describe 1) the five types of data probes we created for the co-design sessions, and 2) how participants used data probes created using their personal Uber work data and Chicago city-level data to surface AI design suggestions.

2 DESIGNING DATA PROBES

We created five types of data probes that workers explored in co-design sessions. Here, we describe the design principles we adhered to when creating them and the data sources we used. The data probes we created are summarized in Table 1. Figure 3 illustrates the co-design session flow, including at which stage participants engaged with each data probe. The full details can be found in our paper [18].

No.	Data Probe Name	Data Type	Description
1	Driving Animation *(Animation)*	Personal	Visceral animated gif showing a specific day of a worker's movement patterns on a map of their city
2	Neighborhood Map *(Map)*	Personal & City-level	Interactive map showing the neighborhoods of where pick-ups have occurred. Drivers can hover or click on neighborhoods to see statistics such as when and how many trips occurred, average fare, and miles per trip.
3	Calendar	Personal & City-level	Intuitive monthly and weekly calendars that display earning trends and breakdown of trips for a specific day or day of the week.
4	Hourly	Personal & City-level	Interactive bar charts that use personal or city-level data to display trends around earnings and trips depending on hour of the day.
5	Work Planner *(Planner)*	City-level	Interactive prototype that allows a user to input work parameters (e.g., hours, days, and neighborhoods worked) and uses city-level data to provide an estimation of base earnings, tips, and mileage for the driver in a week

Table 1. Summary of the 5 Data Probes.

2.1 Design Principles

2.1.1 Supporting Reflection and Action. Our primary principle for data probes is to support drivers' ease and comfort when using data to reflect on and identify subsequent actions to take. Recognizing how data analysis can be daunting to participants without analysis experience [10], it was important for us to create data probes that reflect data in formats that are familiar to them, ideally, that remind them of everyday representations. For example, the *calendar data probe* displays driver data on a calendar. This format was inspired by how drivers in our previous study discussed reviewing earnings at the end of the day or week [19]. Additionally, given the ubiquity of calendars, we hoped such a format could support drivers in reflecting on their personal calendar of activities to discuss how life events or contexts influence their driving.

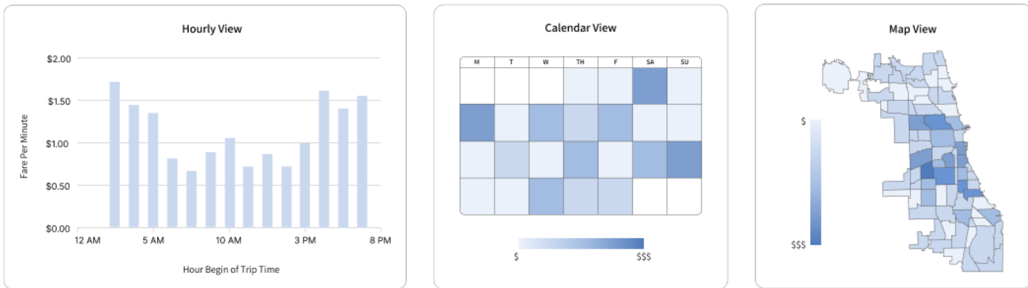


Fig. 1. Individual Data Probes

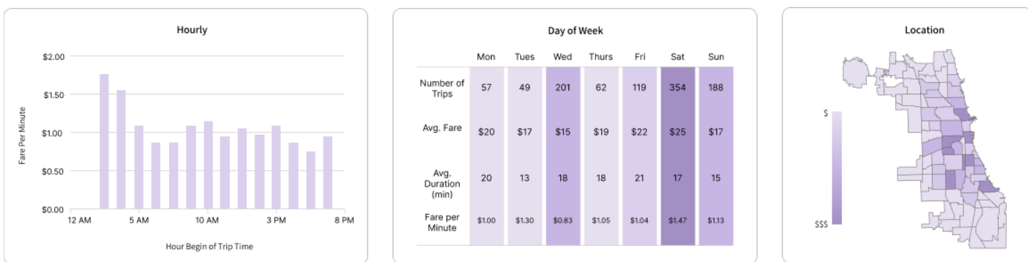


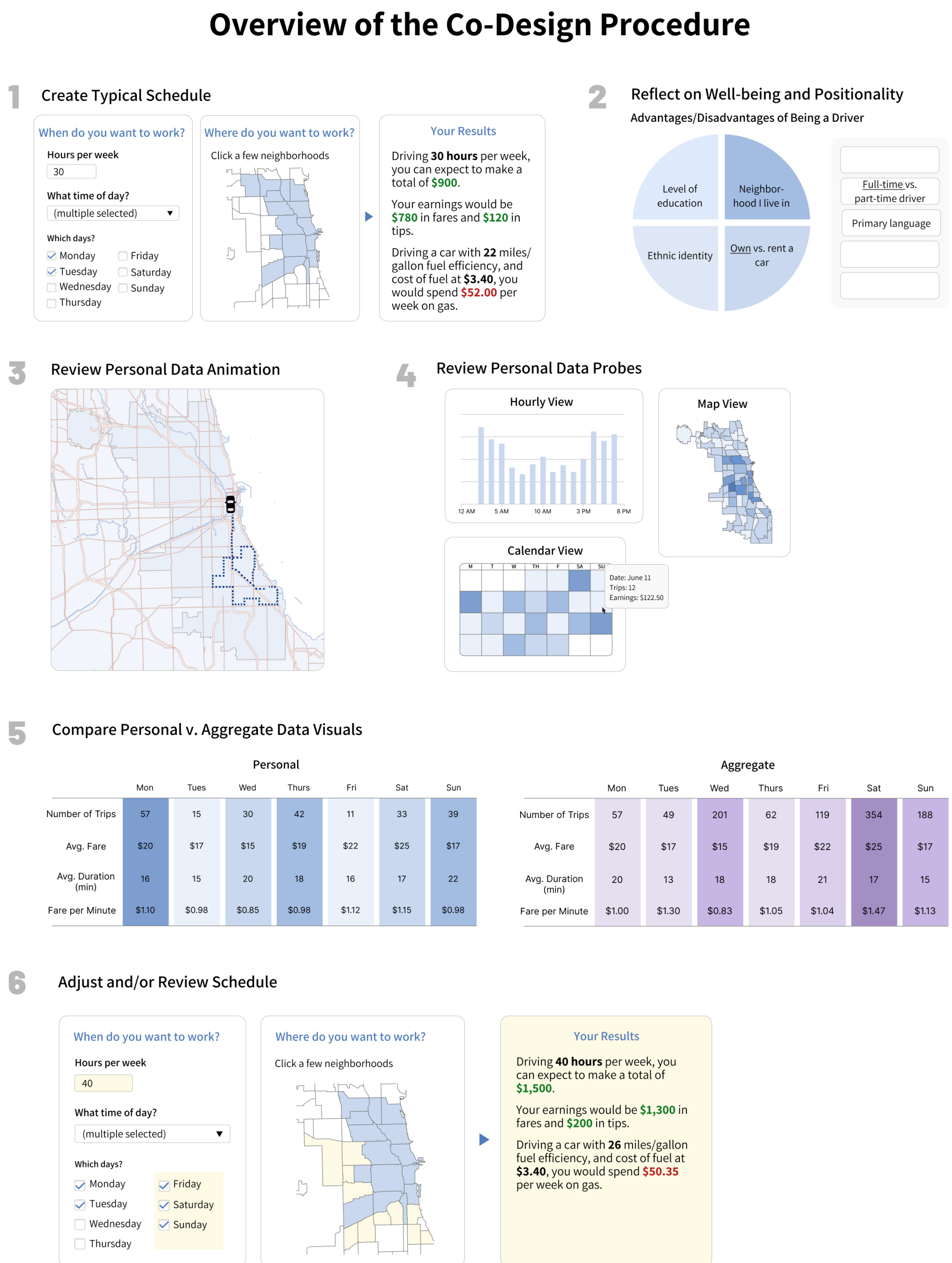
Fig. 2. City-level Data Probes

2.1.2 Centering Context. Our second principle, largely informed by suggestions from D'ignazio and Klein [1], centers on individual contexts that drivers hold which influence their work preferences, patterns, and limitations. Having drivers discuss their strategies and patterns within the contexts that bind their work may make AI capabilities more certain and outputs more attuned to what drivers need. We combined data probes with probing questions around well-being and positionality to encourage drivers to consider the personal contexts influencing their work. We focused on three types of well-being: physical, psychological, and financial, building from Hickok et al. [4]'s definitions of the terms [9]. For positionality—"the personal values, views, and location in time and space that influence how one engages with and understands the world" [7]—we had participants consider what advantages and disadvantages them as a driver, deriving factors from existing positionality wheels (e.g., "Level of Education, Age, Race & Ethnicity") [11] and including others specific to gig work ("Own vs. Rent My Car", "Single vs. Multi-Platform Worker").

2.2 Data Sources and Calculations

2.2.1 Data Sources. For individual data probes, we used the driver's own Uber data[1]. The data for city-level data probes came directly from the City of Chicago[2]. Available back to 2018, we limited our dataset to the most recently available month (June 2022) because of size and processing power limitations. To prepare the dataset for analysis, we used Pandas—a Python-based data manipulation tool—to classify all the pick-up and drop-off coordinates into Chicago's official neighborhoods, as defined by the City of Chicago[3]. Next, we used Pandas to add time-appropriate weather data

[1]Uber's methodology can be found here: https://help.uber.com/driving-and-delivering/article/request-your-personal-uber-data?nodeId=fbf08e68-65ba-456b-9bc6-1369eb9d2c44
[2]https://data.cityofchicago.org/Transportation/Transportation-Network-Providers-Trips/m6dm-c72p
[3]https://data.cityofchicago.org/Facilities-Geographic-Boundaries/Boundaries-Neighborhoods/bbvz-uum9



Personal

	Mon	Tues	Wed	Thurs	Fri	Sat	Sun
Number of Trips	57	15	30	42	11	33	39
Avg. Fare	$20	$17	$15	$19	$22	$25	$17
Avg. Duration (min)	16	15	20	18	16	17	22
Fare per Minute	$1.10	$0.98	$0.85	$0.98	$1.12	$1.15	$0.98

Aggregate

	Mon	Tues	Wed	Thurs	Fri	Sat	Sun
Number of Trips	57	49	201	62	119	354	188
Avg. Fare	$20	$17	$15	$19	$22	$25	$17
Avg. Duration (min)	20	13	18	18	21	17	15
Fare per Minute	$1.00	$1.30	$0.83	$1.05	$1.04	$1.47	$1.13

Fig. 3. **Co-Design Procedure:** 1. Participants input their typical work schedule and expense information on the Planner, and review the predicted earnings for whether it aligns with their experiences. 2. They discuss well-being and positionality to reflect on well-being goals they have and the advantages or disadvantages they face as drivers. 3. They view an animation of their past trips on a map of Chicago. 4. They review individual data probes for trends and reflect on what factors impact their work. 5. They compare these probes with ones made from Chicago city-level driver data to reflect on similarities and differences with the city driving population. 6. Participants create another work schedule based on the trends they identified using the probes and compare the results with the schedule from step 1 to review which satisfies their preferences.

acquired from VisualCrossing, a live weather API[4]. Most data probes were created using Tableau. The personalized trip animation data probe was generated using Unfolded.ai[5].

2.2.2 Metrics and Calculations. Four of the data probes are data visualizations that participants can click on or hover over to see metrics calculated from their personal work data or city-level data such as average fare per minute (hourly, calendar, and map data probes) or total number of pick-ups per neighborhood (map data probe).

The fifth data probe is an interactive work planning tool, "Planner", that we created to let drivers test driving strategies and as a use case for drivers to anchor their ideas about AI components such as predictions or constraints to consider. Drivers input driving parameters such as times and places they work, and weekly expenses to obtain weekly predictions (e.g., total earnings, trips, and miles driven in a week) based on city-level driver data. This output is displayed as a table and text summary to support individual preferences for reading and reflecting on data. To generate the output statistics, city-level data is filtered to the subset of trips matching participant inputs and then used for prediction calculations. Figure 4 shows the Planner's full input and output options.

3 INSIGHTS FROM CO-DESIGN SESSIONS USING DATA PROBES

We observed that using data probes with drivers for co-design, combined with well-being and positionality prompts, can be an effective means to produce AI design considerations that center worker contexts. We summarize three main insights for how drivers used data probes and corresponding AI design implications.

Drivers interacted with data probes to review their driving patterns and explain that the probes reflect their well-being and positionality constraints. For example, as drivers reviewed hourly data probes (leftmost frame of Figures 1 and 2), they explained a trend that low-earning but "safer" hours for work are typically 10AM-2PM. However, after exploring his personal hourly and calendar data probes (center frame of Figure 1), one driver shared that these hours overlap with when he stops working to begin caretaker duties for his father. This leads us to the first AI design implication from data probes: tools intended to support worker well-being must elicit such constraints from workers in order to generate predictions that genuinely support them, otherwise they risk outputs that violate immovable constraints drivers operate under. Instead of having work schedules prescribed for them, drivers indicated interest in AI tools that could help them establish and track well-being goals.

Drivers also used data probes to identify new factors that we did not include. They explained that passenger characteristics, the precariousness of gig work, and the perceived success of their driving strategy can influence their well-being in addition to, or more than, the factors we included (e.g., schedule-related variables). Thus, they gave suggestions for other predictions they would like to see the Planner (Figure 4) provide to help overcome some of these factors, such as predicting optimal work start time and location to anchor their day and, in a way, mitigate the precarious and unstructured nature of gig work.

Drivers in past studies have expressed that rideshare platforms often employ unfair algorithmic management such as manipulative incentive systems [19]. Our participants echoed these sentiments as they explored their data probes—e.g., one driver explained that viewing her animation data probe (Step 3 in Figure 3), which showed erratic driving patterns, confirmed the ride assignment algorithm deliberately prevents her from maximizing her earnings. Correspondingly, drivers came up with ideas for how data probes could be used to quantitatively prove their hunches about existing algorithmic unfairness as well as reverse engineer platform algorithms in order to empower drivers.

[4]https://www.visualcrossing.com/weather-history/chicago/us
[5]https://www.unfolded.ai/ is a geospatial analytics platform

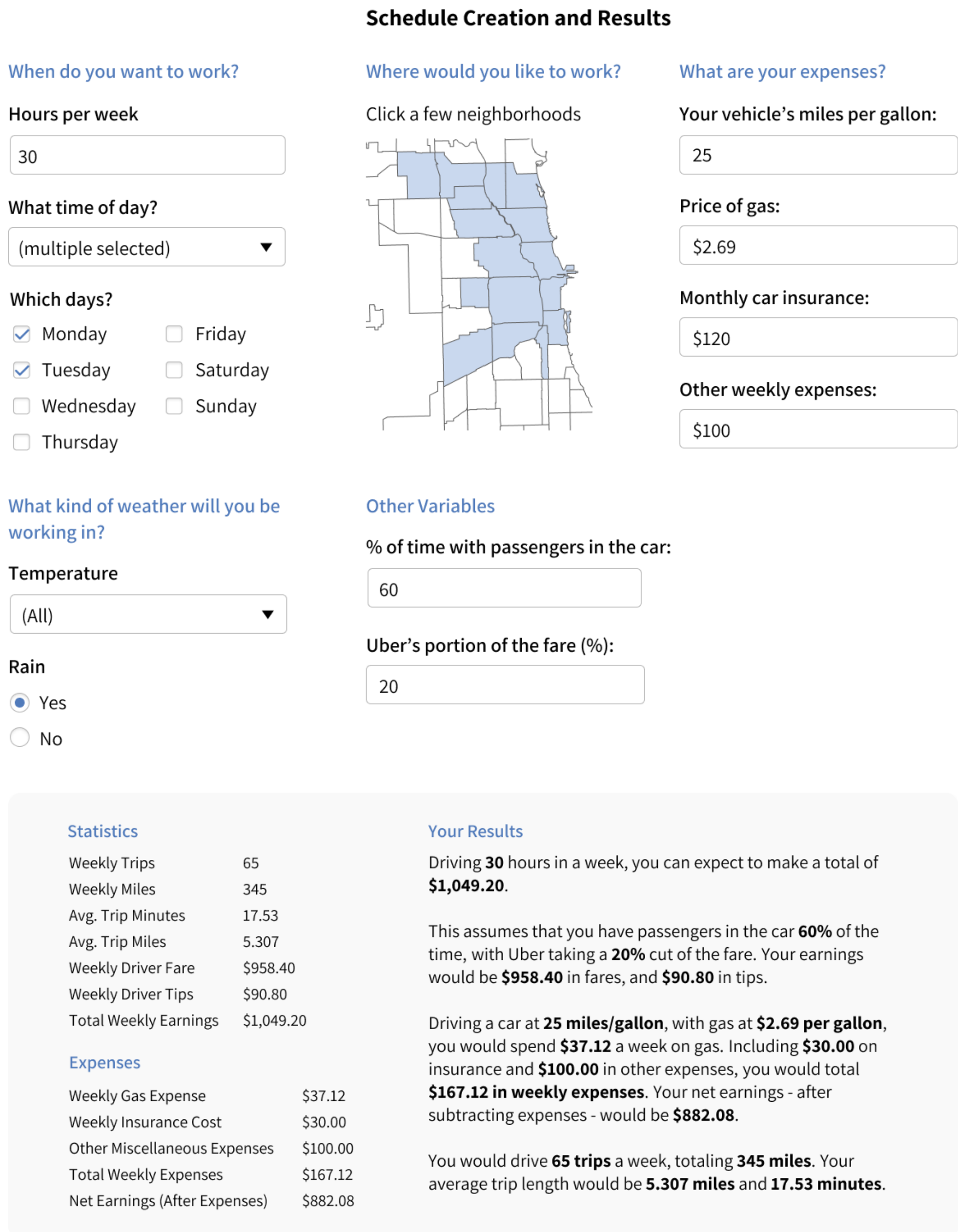


Fig. 4. Work Planner data probe that participants interacted with to view predictions of their schedules and surface design considerations.

Lastly, in addition to how data probes surfaced these types of insights for AI design, we highlight the importance of using multiple data probe types as we did in order to elicit such considerations. We found from our study that not only can different data probes illustrate and draw out different types of insights and ideas from participants, but using multiple data probes was also crucial for allowing participants to gain familiarity with the probes and comfort during the co-design session.

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