Understanding Driver-Passenger Interactions in Vehicular Crowdsensing

DHRUV AGARWAL, Microsoft Research, India
SRISHTI AGARWAL, Ashoka University, India
VIDUR SINGH, Ashoka University, India
ROHITA KOCHUPILLAI, Three Wheels United, India
ROSEMARY PIERCE-MESSICK*, Basis Social, United Kingdom
SRINIVASAN IYENGAR, Microsoft Research, India
MOHIT JAIN, Microsoft Research, India

Smart city projects collect data on urban environments to identify problems, inform policymaking, and boost citizen engagement. Typically, this data is collected by static sensors placed around the city, which is not ideal for spatiotemporal needs of certain sensing applications such as air quality monitoring. Vehicular crowdsensing is an upcoming approach that addresses this problem by utilizing vehicles' mobility to collect fine-grained city-scale data. Prior work has mainly focused on designing vehicular crowdsensing systems and related components, including incentive schemes, vehicle selection, and application-specific sensing, without understanding the motivations and challenges faced by drivers and passengers, the two key stakeholders of any vehicular crowdsensing solution. Our work aims to fill this gap. To understand drivers' and passengers' perspectives, we developed *Turn2Earn*, a generic vehicular crowdsensing system that incentivizes drivers to take specific routes for data collection. Turn2Earn system was deployed with 13 auto-rickshaw drivers for two weeks in Bangalore, India. Our drivers took 709 trips using Turn2Earn covering 79.2% of the city's grid cells. Interviews with 13 drivers and 15 passengers revealed innovative information-based strategies adopted by the drivers to convince passengers in taking alternative routes, and passengers' altruism in supporting the drivers. We uncovered novel insights, including viability of offered routes due to road closure, issues with electric vehicles, and selection bias among the drivers. We conclude with design recommendations to inform the future of vehicular crowdsensing, including engaging and incentivizing passengers, and criticality-based reward structure.

CCS Concepts: • **Human-centered computing** → **Empirical studies in HCI**.

Additional Key Words and Phrases: vehicular crowdsourcing; auto-rickshaw drivers; reward; passenger; interview; deployment; smart city; data collection; route selection

*Work done while the author was at Three Wheels United.

Authors' addresses: Dhruv Agarwal, Microsoft Research, Bangalore, India, t-dhaga@microsoft.com; Srishti Agarwal, Ashoka University, Sonepat, India, srishti.agarwal@alumni.ashoka.edu.in; Vidur Singh, Ashoka University, Sonepat, India, vidur.singh@alumni.ashoka.edu.in; Rohita Kochupillai, Three Wheels United, India, rohita@threewheelsunited.com; Rosemary Pierce-Messick, Basis Social, London, United Kingdom, messick@basisresearch.co.uk; Srinivasan Iyengar, Microsoft Research, Bangalore, India, t-sriyen@microsoft.com; Mohit Jain, Microsoft Research, Bangalore, India, mohja@microsoft.com.

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1 INTRODUCTION

Over 55% of the global population lives in cities, with another 2.5 billion people expected to move into urban areas by 2050 [44]. This influx raises significant challenges as it puts considerable stress on natural resources (air, water) and public infrastructures (roads). Thus, making cities more sustainable while guaranteeing proper living conditions for all its inhabitants has been identified as one of the UN Sustainable Development Goals [14]. To achieve this goal, several smart city projects [26] intend to monitor urban environments by collecting massive amounts of data. This city-scale data can help to identify problems, gauge the effectiveness of policy decisions, and engage citizens [10, 20]. *E.g.*, one such smart city application entails the use of air quality sensors for monitoring pollution levels [57] to suggest minimal pollution paths for pedestrians and cyclists [4].

Typically, such city-scale sensing infrastructures entail *en masse* deployment of in situ low-cost sensor nodes offering localized sensing. However, dense static sensor networks usually involve high setup, maintenance, and other administrative costs, which may not be feasible for budget-constrained developing regions. As a solution, researchers proposed *vehicular crowdsensing* [41], where vehicles are mounted with a supplemental sensing infrastructure to build a network of mobile sensors. It reduces the overall data acquisition cost as just a few sensors mounted on vehicles can traverse a wide area for improved spatial coverage. Past work has examined the potential of vehicle mobility to enable several urban sensing applications, *e.g.,* air quality monitoring [15, 21], potholes detection [13], traffic congestion measurement [42], and available parking spot detection [22, 41, 46].

Apart from investigating the feasibility of such applications, several works proposed solutions to different application-agnostic vehicular crowdsensing problems, such as selecting the right set of vehicles to maximize spatiotemporal coverage [1, 7, 50], addressing security and privacy concerns [5, 31, 32], incentive schemes for the driver [59], *etc.* These works evaluate the performance of their proposed approach using simulation datasets. Even work involving real-world data collection for specific applications [13, 22, 46] consider drivers as “data mules”, who ply their vehicles on city roads to collect data. However, we believe that for successful deployment of vehicular crowdsensing systems, drivers and passengers are key stakeholders, and their *buy-in* is essential in achieving sensing goals. Prior work has not studied the driver-passenger interactions, their strategies, motivations and challenges, in a vehicular crowdsensing setup. Our work aims to fill that gap.

Research in HCI and CSCW have conducted ethnography studies of drivers, and in particular, investigated the impact on drivers with the emergence of ride-sharing services (like Uber) that algorithmically manage their drivers for increased efficiency in hailing cabs. These studies uncovered increased emotional labour requirements from the drivers [16, 40, 45], driver safety concerns [3, 9], and driver-passenger social and cultural interaction [33]. However, none of these studies have explored vehicular crowdsensing systems, which arguably *further* increases the computer-coordinated component of drivers’ work, as the drivers have to follow computed routes to sense data. Even passengers have to invest their time and agree to participate, with minimal/no monetary returns. It is crucial to understand both of their practices, motivations, and challenges faced while participating in such vehicular crowdsensing systems, which is the focus of our work.

To understand drivers’ and passengers’ points-of-view while participating in a vehicular crowdsensing system, we developed *Turn2Earn*, a prototype system in which the driver is asked to drive along a certain path to earn a computed reward. Similar to typical vehicular crowdsensing systems [36, 60], wherein drivers are asked to drive to a specific location to collect data through that route, Turn2Earn *idle mode* does not involve passengers, and hence can be pursued by the drivers only when they are idle. However, for certain vehicular sensing applications, *e.g.*, finding available parking spots [41, 46], air quality monitoring [15, 21], *etc.*, real-time spatial data is needed, and running a vehicle without passenger for such data collection may not be monetarily feasible. Thus, recent systems propose data collection with the passenger in the vehicle [58, 62]. To emulate that, we added a *passenger mode* in Turn2Earn, wherein drivers can enter passenger's destination in the app to receive alternative routes to the destination, with each route having a different reward for data collection. In that, passengers' buy-in is required, and driver-passenger interactions become crucial to understand for the success of such systems.

In this work, we aim to understand the driver-passenger dynamics while interacting with the Turn2Earn system. The Turn2Earn system was deployed with 13 auto-rickshaw drivers in collaboration with an NGO partner, for two weeks in Bangalore, India. They used it for 907 trips, achieving a 79.2% spatial coverage of the city. (Note: Due to strict Ola/Uber policies, we were not able to recruit Ola/Uber cab drivers, and instead recruited auto-rickshaw drivers, who can be part of any vehicular crowdsensing system (similar to [19, 49])). We conducted semi-structured interviews with 13 drivers and 15 passengers, to understand the driver-system and driver-passenger interactions. We found several insights, including usability issues related to limited driving range of electric vehicles, viability of offered routes due to bad/closed roads, and driver-passenger dynamics in negotiating a detour. The drivers came up with innovative information- and discount-based strategies to convince passengers to take alternative routes, while passengers had altruistic and future sustainability reasoning for supporting the drivers. We conclude the paper by proposing design recommendations for future vehicular crowdsensing solutions.

2 RELATED WORK

2.1 Vehicular Crowdsensing

A vehicular crowdsensing solution aims to increase coverage. Coverage is usually measured in two dimensions—spatial and temporal coverage, or a hybrid spatiotemporal coverage. A majority of recent work focuses on vehicle selection as an optimization problem, such that maximal coverage can be obtained by minimal number of vehicles [1, 39, 50, 63]. As these works focus on enhancing coverage through an initial *offline* process of vehicle selection, they are inadequate in filling spatiotemporal holes that inevitably arise in real-time. More recently, several *online* vehicle scheduling approaches have proposed ways to dynamically manage a fleet of vehicles to improve real-time coverage [13, 15, 58, 59, 64]. Another set of research work is exploring ways to improve vehicular crowdsensing systems by focusing on specific components, such as incentive schemes to convince drivers [59], sensing systems to collect data optimally [58, 64], and addressing security and privacy concerns [5, 31, 32]. Most of these works evaluate their systems using trace- and simulation-based data, ignoring real-world issues—*e.g.*, unavailability of driver due to emergency/accident—that arise during actual deployment. Moreover, a typical vehicular crowdsensing system considers drivers and passengers, key stakeholders, as mere 'data mules', and ignores their needs and concerns, their motivations and barriers, and assumes their commitment to the sensing cause. On the contrary, our study investigates the driver-system and driver-passenger interactions using a real-world deployment, for a successful vehicular crowdsensing system.

2.2 User Studies with Cab Drivers and Passengers

There is a rich body of literature in the HCI and CSCW community that studies the impact of ride-sharing services like Uber and Lyft on their stakeholders (mainly drivers, passengers and corporations). Work focused on drivers has investigated their changing work practices due to technological intervention in the workplace. Early work by Lee *et al.* [37] explored algorithmic management, *i.e.*, how Uber and Lyft drivers in US reacted to being managed by data-driven algorithms instead of humans. Ahmed *et al.* [2] extended this work to the context of auto-rickshaw drivers in India. They found that the information-asymmetry characterized by the opaqueness of these algorithms contributes to drivers losing control over their work practices. Being part of these ride-sharing services has resulted in the drivers' change in work practices and labor requirements, which has been explored from multiple perspectives, including safety hazard incurred by the drivers [3] and emotional labour. Raval and Dourish [45] highlight the added emotional labour undertaken by drivers in 'serving with a smile' to get better ratings, even though neither drivers nor passengers completely understand these ratings [16, 37, 40]. These additional demands from drivers and their socioeconomic vulnerabilities, puts them at the bottom of the driver-passenger-corporation power hierarchy [47], despite their sizeable stake in such systems [40].

There has also been work studying the implications of real-time ride-sharing services on passengers, including accessibility for visually impaired passengers [6, 34] and access for low-resource populations [12]. While these groups of passengers have generally benefited from ride-sharing services, these works also highlight the digital divide created by such systems among passengers due to their race, income, and/or disability. Passenger safety concerns have also been raised as drivers are independent contractors and hence not directly accountable to the corporations [9]. On the other hand, researchers have examined the bright side of the driver-passenger relationships, like their collaboration for navigation [17]. Kameswaran *et al.* [33] framed ride-sharing cabs in US as spaces for rich conversations and the exchange of social and cultural capital.

All these works are limited to studying drivers and passengers in the context of taxi-dispatch systems like Lyft, Uber, Ola, Singapore's CabLink [23], etc. With the advent of a new class of computer-coordinated workplace technology for drivers in the form of vehicular crowdsensing systems, the driver-system and driver-passenger interaction may further change. These systems would *increase* the degree of algorithmic management [37] by also requiring routes that the driver must follow. Due to these differences, existing results from the ride-sharing studies cannot be generalized to the vehicular crowdsensing settings. In this work, we conducted a qualitative analysis of a vehicular crowdsensing system, to uncover on-ground issues faced by auto-rickshaw drivers and passengers, using data collected from a real-world deployment. (Note: Due to logistic constraints, we were not able to deploy and study our Turn2Earn system with cab drivers).

2.3 Work Related to Auto-rickshaw Drivers

Auto-rickshaws, colloquially called 'autos', are commercial three-wheeler vehicles ubiquitous in India. They are an inexpensive alternative to taxis and offer convenient transport within a city. Auto-rickshaw drivers get passengers by roaming around crowded areas like malls, offices, *etc.*, or by using their local knowledge of where they would find passengers [61]. Either drivers slow down near passengers to ask them if they need transport, or passengers wave or call drivers and ask for their services [61]. These drivers are usually male, typically earn Rs. 600–800/day (~$10), and hence are financially vulnerable [43]. Drivers in Bangalore, India, have been found to use a few different models for charging passengers [2]. The most common of these is metered pricing. Each auto-rickshaw is fitted with a small device, a *meter*. The driver 'starts' the meter at the beginning of the journey. The meter displays the fare according to government regulations. A majority of drivers were found to charge a *premium* on the meter fare, usually a function of the meter fare (*e.g.*, 'meter plus 20 rupees' or 1.5 times the meter fare) during high-demand, rain, night time, or for heavy luggage. Although a punishable offence, drivers may deny using the meter, and instead negotiate a fixed-fare before on-boarding the passenger. Due to their popularity, ride-sharing services (Uber, Ola) have also added auto-rickshaws to their fleet [2]. Auto-rickshaws requested through ride-sharing services charge the amount displayed by the app, with no scope for negotiation [2].

Apart from ethnographic studies of auto-rickshaw drivers in India, prior research tried utilizing auto-drivers for crowdsourcing. mClerk [19] offered local language translation micro-tasks to auto-rickshaw drivers in India for extra income when they are idling between rides. However, they offered general purpose tasks, which has a learning curve and does not take advantage of the driving skills of their profession. Samdaria *et al.* [49] propose a crowdsourcing model wherein micro-tasks were forwarded to the passenger in auto-ride via the driver, to earn discounts for completing the micro-tasks. While this work takes advantage of drivers' ability to serve a broad population, drivers here are only intermediaries, not the workers and hence not the primary beneficiaries. In a vehicular crowdsensing system, drivers do not have to learn any new skill. In our system, Turn2Earn, the drivers are further rewarded for convincing a passenger to take an alternative route, and following that route. It takes advantage of characteristics unique to the occupation of auto-rickshaw driving in India — their time on the road, their on-ground knowledge of the city, and their expertise of dealing with passengers; and rewards them for it.

3 TURN2EARN SYSTEM DESIGN

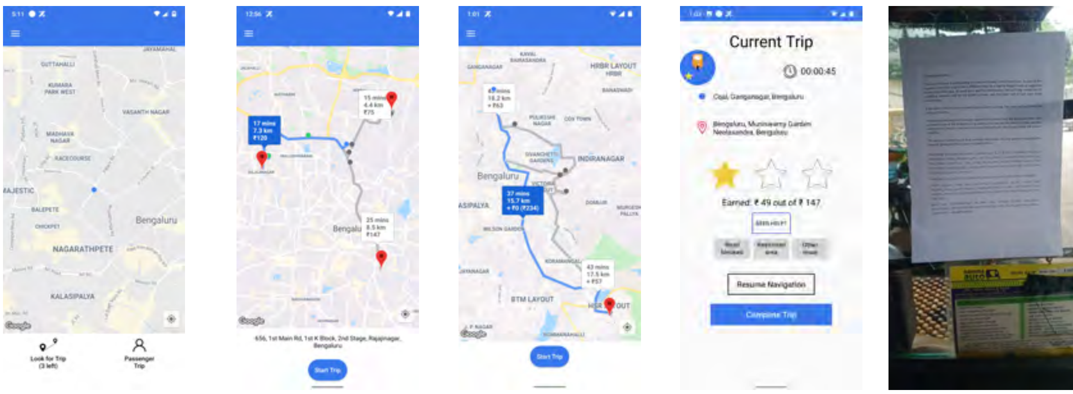
The Turn2Earn phone app offers two modes to drivers: *idle* mode and *passenger* mode. Below, we discuss them, followed by providing an overview of the Turn2Earn system, and describing its major components: user interface of the phone app, routing algorithm to suggest alternative routes, and reward scheme.

3.1 Offered Modes

Idle mode (similar to [36, 60]) was added to Turn2Earn, where the vehicles are dispatched to specific locations for data collection. The mode is meant for drivers when they are free, *i.e.*, waiting for a passenger. Drivers are given multiple routes to choose from, each with a different destination (Figure 1b). As the driver is driving without a passenger solely to collect data for filling critical data holes, the Turn2Earn system pays them the government-defined full fare for the trip and an additional incentive. Since idle mode is expensive for data collection, we limited the number of idle trips to three trips daily for each driver. During our pilot study with five drivers, two drivers travelled far from their starting location while completing idle trips. They later complained that they had to incur losses while driving back to the starting position (or home) without a passenger. To solve this, we modified the last (third) idle trip to *custom idle trip*, wherein the driver needs to enter a destination, instead of the app suggesting them different destination options.

For reducing costs in vehicular crowdsensing applications, the data collection can happen with passengers onboard [58, 62]. Following that approach, we developed the *passenger mode*, wherein the driver needs to enter the passenger's destination. Rather than passively collecting data, the app shows multiple alternative routes to the destination, along with the rewards offered for following each of the routes (Figure 1c). These deviations help in improving the spatiotemporal data coverage of the city. Each alternative route consists of *way-points*—specific locations on the routes that the driver needs to pass through in order to earn the offered reward. In this mode, as the passenger is paying the fare, our system only pays the driver for the *extra* distance travelled due to the suggested deviations (plus an additional incentive to choose an alternative route in the first place).

For the study, in idle mode, the app shows three routes to three different destinations, while in passenger mode (and custom idle trip), the app shows three routes to the entered destination. One of the routes in passenger mode is always the Google Maps route with no way-points and zero reward, which we call the *optimal* route. This is done so that drivers can still use our app



(a) Search screen (b) Idle mode (c) Passenger mode (d) Trip detail (e) Info. Sticker

Fig. 1. Turn2Earn app UI screenshots (a-d) and information sticker pasted in auto-rickshaw (e).

for navigation even if the passenger disagrees to take an alternative route. In passenger mode, each alternative route has three way-points, while in idle mode, there are two way-points and the destination acts as the third way-point.

3.2 User Interface

We developed an Android application, called Turn2Earn (Figure 1a-d), to suggest alternative routes to auto-rickshaw drivers. We chose Android as >95% of smartphones in India run on Android [27]. Most drivers in our target population are familiar with Google Maps as they drive for Uber/Ola, which use Google Maps for navigation [2]. To minimize learning curve, the design of our app is similar to Google Maps. We conducted two pilot studies to iterate over and finalize the design of the app. In the first pilot study, two male drivers (30-40 years old) used the app in idle mode for a day, with two researchers sitting in the passenger seat answering questions and observing their interactions with the app. In the second pilot study, five male drivers (30-40 years old) used the app independently for two days in both the modes. Log data, questions, concerns, and suggestions made by the drivers were taken into account to iterate over the app design. Note: Different set of drivers were used for each of the two pilot studies and the final deployment study. Our app has three primary screens: search screen, route selection screen, and current trip detail screen.

Search Screen: The search screen (Figure 1a) acts as the landing screen where the driver can choose between an idle or a passenger mode. On tapping the idle trip button, the app sends the current GPS location to the backend server, and receives three different route options each to a different destination. On tapping the passenger trip button, the app shows a search bar for the driver to enter the passenger's destination. The app sends the destination and the current GPS location to the backend server, and receives three route options.

Route Selection Screen: One of the three route options is randomly auto-selected. Following the design pattern of Google Maps, the selected route gets highlighted in blue color, and the other two routes are shown in grey. The driver's current location is shown as a blue dot, and the destination(s) is/are shown as red marker(s) (Figure 1b, 1c). Each route has an associated information window, showing the duration (in mins), distance (in kms), and reward (in rupees) for crossing the way-points by following that route. The driver can pan and zoom the map to further understand the routes, and can tap on the route or the information window to select that route. The way-points on each route are marked as grey dots, which turn green on route selection. After finalizing the route, the driver needs to tap on the 'Start Trip' button to view Google Maps based navigation from their current location to the destination via the way-points.

During the pilot study-2, drivers raised concerns that a few passengers disagreed to follow an alternative route to their destination as it might incur extra fare. Thus, we decided to show the expected meter fare for the non-deviated trip in the information window of the optimal route (in which the reward is Rs. 0; Figure 1c). We asked the driver to inform the passengers that in a Turn2Earn alternative route ride, they need to pay minimum of the meter fare and the expected meter fare shown in the information window. The same information was provided in the sticker (Figure 1e) that was pasted next to the passenger's seat. The sticker also provided a brief overview of the research study.

As the driver does not input a destination in idle mode, the destination address for each route is shown above the 'Start Trip' button (Figure 1b). This was added after pilot study-1, as the drivers wanted to explicitly know the destination *address* (not just a point on the map) to help them in choosing a route.

Trip Detail Screen: During an ongoing trip, a floating button is persistently shown (Figure 1d top left portion showing the button with an auto-rickshaw icon and a single yellow-colored star). This button is movable around the screen and persists even over the Google Maps navigation screen. Tapping on that button takes the user to the current trip detail screen (Figure 1d), showing details of the ongoing trip including trip duration, start and destination addresses, number of way-points crossed (as yellow stars), total offered reward, and the total reward earned so far. To ensure that drivers get rewarded for partially following the route, we added the concept of way-points, which was gamified using stars. Each star corresponds to one-third of the total offered reward. On earning a star, for instant gratification, the driver gets notified by a bell sound along with highlighting the star in the floating button.

During our pilot study-2, from the GPS log data we found drivers trying multiple ways to reach two particular way-points for collecting stars, before giving up. Later we discovered that those way-points were not reachable due to restricted road access or COVID-19 related road blockages. To deal with this, we added the 'Help' button (Figure 1d). Clicking on the Help button shows three options—'Road blocked', 'Restricted area', 'Other issue'. Selecting any of the options adds the next star and the reward associated with that way-point, and instructs the driver to move on to the next way-point/destination. The other buttons on this screen are 'Resume Navigation' to go back and continue with the Google Maps based navigation, and 'End Trip' to end the trip. The app has other screens, such as driver's trip history and app information, which are self-explanatory. The app logs all user interactions and the driver's GPS location every second during an ongoing trip. All the data gets stored locally on the phone and periodically uploaded to cloud storage.

3.3 Routing Algorithm

The routing algorithm takes as input the source and destination, and the maximal amount of deviation allowed from the optimal route's duration (as a percentage of the optimal route's duration). Based on our pilot studies and discussion with the NGO partner, we kept max deviation to be at 30%. The algorithm outputs way-points for each alternative route suggested to the drivers. This algorithm is a simplified version of the route generation approach mentioned in prior work [65]. Next, we will describe the one-time pre-processing setup needed by our routing algorithm. Following this, we will discuss the two steps of the routing algorithm for handling each request.

Pre-processing Setup: We divide ('gridify') the Bangalore city into 4096 grid cells, each of size 500 m x 500 m. The approach for overlaying the city with grids to measure spatiotemporal coverage is similar to multiple prior works [38, 59, 65]. This (large) cell size was chosen to significantly reduce the routing algorithm's runtime, thus making the interaction real-time with minimal lag.

Our system assumes the visitation of any point inside a cell equivalent to visiting the entire cell. Specifically, a cell is a spatiotemporal hole if there is no visitation in the last t minutes—a time interval governed by the sensing application requirements. For our deployment study, we kept $t = 120$ minutes. Note that a grid cell is an abstract concept; each cell may have multiple (or zero) roads, buildings, *etc.* Hence, the routing algorithm computes the way-points for each route in two steps: (1) select the grid cells to cover, and (2) identify the exact way-point (latitude-longitude) inside each of the selected cells.

Step 1—Selecting Grid Cells: For this step, the algorithm needs to select cells that maximize the data collection (*i.e.*, minimize spatiotemporal holes) while staying within a time budget (130% of the optimal route's duration). To model this problem, we represent the gridified city as a complete directed graph $G = (V, E)$. Each vertex represents a cell, hence $|V| = 4096$. The weight of each edge $w(u, v)$ represents the travel duration from cell u to cell v which is pre-obtained from Google Maps Distance Matrix API. Further, each cell $v \in V$ has a score $s(v)$ which represents the urgency of visiting cell v. For our purpose, $s(v)$ is the number of seconds elapsed since v's previous visitation, which the algorithm computes from the drivers' GPS logs.

Now, with the driver's source vertex S, destination vertex D, and the optimal travel duration $t_{opt} = w(S, D)$, the algorithm needs to find a path $P \subset V$ from S to D with cost t_P that maximizes the score accrued, $\sum_{v \in P} s(v)$, while staying within the allowed deviation, *i.e.*, $t_P \leq t_{opt} + 0.3 \times t_{opt}$. This problem is similar to the Orienteering Problem (OP) [8], a $\mathcal{NP}$-hard routing problem to determine a subset of nodes (cells) to visit, and in which order, so that the total collected score is maximized and a given time budget is not exceeded [18]. Thus, we approximate a solution using a heuristic approach proposed by Chao *et al.* [8]. Briefly, the heuristic solution works as follows: (i) in the initialization step, it tries to fit in as many cells into a route as possible without exceeding the time limit, (ii) it then iteratively runs a series of optimizations on the initialized route to add, remove, or reorder the cells to maximize the total score accrued by the route. The two steps are performed multiple times independently, and the best route is chosen. We implemented this approach using parallelization and memoization to ensure interactive response time on the app.

Step 2—Identifying Exact Way-points: We need only 3 waypoints (or 2 in idle mode), but for long distances, $|P| >> 3$. Hence we pick the 3 (or 2) highest score cells, and this step-2 finds the exact way-points (latitude-longitude) the driver must cross inside these cells. For this, we use another graph representation of the city generated from Open Street Maps (OSM) data. This graph represents the city (not the grid cells): edges represent roads, and vertices represent junctions/dead-ends. Each grid cell may contain any number of junctions/dead-ends. In this graph, Dijkstra's algorithm is used to find the shortest path from the driver's current location (nearest junction/dead-end) to the destination, while ensuring that this path goes through each of the 3 (or 2) cells selected from P in step-1.

3.4 Reward Scheme

The reward scheme has two components: trip fare and incentive. Presenting drivers with a range of rewards for completing a trip is inspired from previous work [59]. In our case, the minimum reward amount is decided as per the Bangalore government-defined rules—a flat fare of Rs. 25 for the first 1.9 km and Rs. 13/km thereafter [53]. Trip fare also adds night-time multiplier (1.5× for rides between 10 pm to 5 am) and traffic-time multiplier (1.05× for ≤10 mins delay and 1.1× for >10 mins delay). Thus, $TripFare = DistanceFare(distance, isIdle) \times NightMultiplier \times TrafficMultiplier$, and $DistanceFare(distance, isIdle) = ((25 + [\max(0, distance - 1.9) \times 13]) \times isIdle) + (extraDistance \times 13 \times (isIdle - 1))$, where $isIdle \in \{0, 1\}$, $distance$ is the total trip distance in idle mode, and $extraDistance$ is the extra distance travelled (= distance in alternative route − distance in optimal route) in passenger mode.

Apart from the required trip fare, we incentivized the drivers to collect stars. Based on our pilot studies and discussion with our NGO partners, we decided to pay the extra money based on the total distance traveled in the idle mode (Rs. 5/star, 10/star, and 15/star for distances <5 km, between 5 km to 10 km, and >10 km, respectively), and based on the total extra time traveled in the passenger mode (Rs. 5/star, 10/star, and 15/star for duration <10%, between 10% to 20%, and >20% of optimal route duration, respectively). In idle mode, we incentivized the driver to take the longest distance-wise route. In passenger mode, we found that the alternative routes were only a few kilometres more than the optimum route but were through less-traveled, traffic-prone, and/or broken roads, leading to an increase in trip time. Hence we incentivized the extra *duration* traveled in passenger mode.

4 STUDY DESIGN

We conducted a deployment study in Bangalore (Karnataka, India) during August 2020, to understand the usability and effectiveness of the Turn2Earn system. The study was approved by our internal IRB. It was conducted in collaboration with a local NGO working for the betterment of auto-rickshaw drivers.

4.1 Participants

Thirteen male auto-rickshaw drivers ($D_1 - D_{13}$) with average age of 40.1 ± 6.1 years and driving experience of 15.9 ± 6.3 years participated in the study. All drivers were fluent in one or more of these languages: English, Hindi, Kannada and Tamil. Only one driver did not attend school, 2 finished primary school, and 10 finished secondary school. All drivers owned a touch-screen smartphone, and were typical smartphone users, using the phone for browsing Internet, watching videos, and extensive WhatsApp usage. All of them have been or are current drivers for Uber/Ola, hence they were very familiar with Google Maps and navigation. Participation was voluntary, with financial compensation based on the total number of stars earned during idle and passenger mode trips. All the drivers were part of an association which refrains them from charging negotiated fare, hence they claimed to charge meter fare or meter fare with premium. Eleven drivers drove gas (LPG) operated vehicles, while two drove electric vehicles (battery) having a range of ∼100 kms.

Fifteen passengers ($P_1 - P_{15}$; 4 female) with average age of 32.1 ± 9.1 years were interviewed for the study. Six passengers had a bachelor's degree, 1 attended high school, 7 attended secondary school, and 1 attended primary school. Four of them were small business owners, two software engineers, two electricians, two heavy-vehicle drivers, and one each of bank executive, security guard, government employee, auto-rickshaw driver, and unemployed. Each passenger's participation was limited to an interview detailing their experience of riding in a Turn2Earn auto-rickshaw.

4.2 Procedure (and COVID-19 Challenges)

The study was conducted during the COVID-19 period in Bangalore. This added the constraint that the study needs to be conducted online with minimal physical contact between the researchers and the participating drivers. Our study required signing the consent form, training the drivers to use the Turn2Earn app, and conducting semi-structured interviews. We actively collaborated with a local NGO for this study; neither the NGO nor its staff received any funds from us. Based on the inputs from a Senior Manager at the NGO, Relationship Managers (RM) working at the NGO acted as a bridge between the auto-rickshaw drivers and the researchers. RMs, as part of their job, manage 20-50 drivers and engage with them regularly (even during the COVID-19 period). Endorsement of the RMs helped us build initial trust between the drivers and the system [12].

We trained the RMs, who in turn trained the auto-rickshaw drivers. For the training, three researchers, the senior manager at the NGO and three RMs, joined a two-hour video conference call.

All the NGO staff members—one Senior Manager and three RMs—were female, in the age group of 30-45 years, and were fluent in English, Hindi and Kannada. The training session was divided into four parts. To begin with, we provided an overview of the Turn2Earn approach, including motivation, reward scheme, and study details. As a concrete use case, we explained to them how city-wide air pollution data can be collected using this approach. Note: In this deployment study, we did not collect any sensing data, and were just trying to understand the feasibility of our proposed solution. Second, using a PowerPoint presentation consisting of Turn2Earn app screenshots, we provided a tutorial on the app usage. The slide deck was later emailed to the RMs for future reference. Moreover, we taught them when (*i.e.*, at what point in the driver-passenger interaction) and how to mention the Turn2Earn program to the passenger. We gave them the following script to convince passengers:

> I am participating in a research project, wherein this app will tell me the route to take. If I follow that route, I will earn some extra money, which will help me during this tough COVID time. [Case 1: Negotiated fare] — Whatever fare we decided upon won't change. [Case 2: Meter fare] — If the app tells me to take a different route, you should pay the minimum of the two: meter fare or the fare shown in the app.

We also gave them a live demo of the Turn2Earn app using an Android mirroring software. Third, we gave the RMs a link to download the app APK file, and instructed them to register. Finally, we asked them to perform several tasks: searching and starting a trip in idle and passenger mode, stopping an ongoing trip, checking number of stars earned, and using the Help button to earn a star without reaching the starred location. The RMs asked many questions both to understand the app, and also questions which they thought the drivers might ask them during training. We created a WhatsApp group with the researchers, RMs, and the Senior Manager, for future queries and updates.

For the study, the NGO Senior Manager recruited 13 drivers, 4-5 drivers under each RM. These drivers were then trained by their respective RMs, in a 1:1 session. According to the RMs, during the training, they explained the Turn2Earn approach to the drivers and got their signature (or thumb impression) on the consent form. After that, the RMs installed the app on their phones, trained them how to use the app, how to convince passengers, and answered all their queries. During these training sessions, the RMs called the researchers to obtain answers to any tricky questions raised by the drivers. As all the participating drivers already had an existing relationship with their RM, the driver training went smoothly. We also asked the RMs to paste a sticker (Figure 1e) on the auto-rickshaw to make the passengers aware that the driver is participating in a research study and may follow the route suggested by the Turn2Earn app (only if the passenger agrees to it). As suggested by the NGO Senior Manager, the sticker had text in both English and Kannada.

The idle mode was enabled for the driver by default, as it had no passenger interaction and can help with the learning process. After taking five successful idle mode trips, the passenger mode got enabled automatically. The drivers were paid the total amount they earned daily using the Turn2Earn app as a PayTM gift card, within the next 3 days (similar to [25]). PayTM is a popular digital payment platform in India, and the gift cards can be used by the drivers to buy groceries, pay utility bills, refuel their vehicles, *etc.* A researcher conducted two telephonic interviews with each driver: (1) a mid-study interview after two days of using the Turn2Earn app, to obtain their demographic details, driving history, and challenges faced while using idle mode trips, and (2) a post-study interview at the end of the study, to understand challenges faced and their strategies for passenger mode trips. Each interview lasted for ~30 minutes.

The pasted sticker, along with providing Turn2Earn research related information, also requested passengers to give us a missed call to voluntarily sign up for a 15-minute feedback interview for a PayTM gift card of Rs. 250. Of the received 24 missed calls, fifteen agreed to participate in our return calls and were interviewed. Both driver and passenger interviews were conducted in one of the local languages (Hindi, Kannada, Tamil or Telugu), were audio-recorded with their permission, and were later transcribed and translated to English.

4.3 Data Analysis

We conducted a mixed-methods analysis [30, 56] to systematically analyze the collected data. The logs generated by Turn2Earn app interactions were quantitatively analyzed. We subjected our interview data from both drivers and passengers to open coding, and rigorously categorized our codes to understand drivers' usage pattern of and passengers' response to Turn2Earn. Two authors participated in the coding process and iterated upon the codes until consensus was reached. Over the course of analysis, they discussed coding plans, developed a preliminary codebook, reviewed the codebook and refined/edited codes, and finally condensed codes into high-level themes.

4.4 Ethical Considerations

In passenger mode, the driver can choose routes with detours that might increase the travel time for the passengers onboard the auto-rickshaw. While designing the system, we considered providing incentives to passengers to participate in the study. However, the RMs strongly discouraged us from taking this course. Their rationale was the information overload to the drivers and their inability to properly communicate with the passengers [1]. Thus, we asked the drivers to get prior consent from the passenger by asking them to go over the sticker discussing the study. Due to this, passengers could feel that they were not compensated for participating in the study. We explore this in more detail during our interviews with the drivers and passengers.

Another concern raised by RMs was with the use of idle mode. As Turn2Earn maximizes spatiotemporal coverage, the idle mode trips could take the drivers to the city's outskirts. Taking rides to the outskirts entails an opportunity cost, *i.e.*, a loss in earnings due to a lower chance of getting rides from these locations. To address this concern, we provided three route options to the drivers. Thus, drivers can use their insight to select a destination where they most expect to find rides. In case they are still unable to find rides, they can use the custom idle trip option to reach a location of their liking without incurring a loss. Similarly, in passenger mode, the passenger can refuse to participate in the study, in which case the driver can choose the Google provided route (zero incentive) from our app.

Finally, as we will see, drivers were very happy with their monetary gains due to Turn2Earn. So, to avoid a financial shock to them upon the end of the study, we asked the RMs to inform the drivers beforehand that this was a short pilot study. Further, we informed drivers 3 days in advance that the study was going to end soon.

5 DEPLOYMENT RESULTS

Overall, 13 auto-rickshaw drivers used the Turn2Earn app for for an average 15.3 ± 5.2 days (total 199 days, maximum 23 days by D_1 and D_{10}, and minimum 7 days by D_{11}). Overall, they completed 907 trips (548 in idle mode and 359 in passenger mode), collecting 68.8% of the stars in idle mode and 70.3% stars in passenger mode. Drivers chose the default selected route in 51.2% of idle mode trips and in 67.1% passenger mode trips. They chose the optimal route (zero way-points and zero reward) in 33.1% of passenger mode trips. In idle mode, drivers chose the farthest destination in 49.8% trips and the shortest destination in only 13.3% of the idle trips. The average distance of a

[1]With a large migrant population, Bangalore attracts people from various parts of India with little to no understanding of the local language spoken in the city.

trip taken was 12.9 ± 6.5 km in idle mode and 7.7 ± 5.5 km in passenger mode. Note, the average distance of the custom idle trips was highest, at 18.7 ± 8.2 km.

All the drivers expressed happiness in using the Turn2Earn app and adopted it quickly, mainly because it acted as an extra source of income. On average, the drivers earned Rs. 108.4 ± 121.9 per trip using our app, with Rs. 166.5 ± 125.3 from every idle mode trip and Rs. 19.6 ± 23.9 from every passenger mode trip. Moreover, all of them found the app easy to use, maybe because they had previous experience with Ola/Uber and Google Maps based navigation: *"I can use the app easily as only very few things to know, like start location, end location, stars, how much you earn."* – D_4.

Next, we present qualitative results on strategies used to convince passengers, motivation to adopt the system, comparison of Turn2Earn with ride-sharing apps, and drivers' and passengers' behaviourial characteristics. Following this, we will discuss quantitative results on the spatiotemporal coverage obtained by our study.

5.1 Strategies to Convince Passengers

During training, we provided a script to help drivers in convincing passengers to take an alternative route. None of the drivers used the script as-is. They formed their own strategies to convince passengers. These strategies stem from drivers' knowledge about the research and their experiences with handling passengers. We classified these strategies as: information-heavy, discount-based, and no/mis-information. Most drivers used a combination of these strategies.

5.1.1 Information-heavy. Prior work found that drivers are more likely to cooperate with a work assignment when they know the reason behind it [37]. In our work, we found this behaviour manifesting as knowledge of the underlying research and its purpose. Eight drivers used varying degrees of their knowledge about the research to convince passengers in taking an alternative, sometimes longer-than-usual, route to their destination. The most common explanation was that it would help to collect air pollution data: *"Taking this route would help both of us... by helping research about pollution."* – D_1. Though for this deployment study we did not collect any sensing data, it seems that the RMs used air pollution monitoring use case to explain Turn2Earn to the drivers, which led to such driver-passenger conversations.

When passengers asked questions about the research, such as *"What is the pollution in this area?"* – asked to D_5, drivers admitted their lack of knowledge: *"I told him* [the passenger] *that I don't know the full working of the research, I am just doing my duty."* – D_3. As a quick response, they directed passengers to read the sticker providing more information. However this was not very helpful, as passengers informed that they were uneducated, tired, and/or simply not interested in reading the sticker. In such scenarios, the drivers showed them the Turn2Earn app.

> "*Passengers ask me questions like, 'You told me you will get pollution data here. How are you measuring it?' ... and 'Can you tell me how much pollution is there at this moment?' I don't know what to tell them, sir. ... So, I show them the stars on the app... I tell them that our operators are getting the pollution data.*" – D_4.

Many drivers (7) mentioned using the app as a tangible tool to gain the passenger's trust. The drivers believed that convincing only verbally might come across as "*hearsay*". They showed their passengers the routes displayed on the app, and explained the routes in varying detail. For instance, *"This route takes you straight to your destination, this route will take you through internal roads, and the third one will take you from around the city."* – D_3. A few drivers explained to their passengers the exact deviations they would take: *"I will take a left from here and go to this point. When I reach the point, the app will show me that I have collected one star. Then I will come back and continue on the same road."* – D_4

In spite of the drivers' claim of providing information about Turn2Earn app and its air pollution use case, most of the interviewed passengers had knowledge about the research limited to three route options and similarity of the app with Ola/Uber. This may be due to selection-bias, as passengers who did not have enough information about the research called us to learn more and to participate. Moreover, most passengers were disinterested in talking to their driver due to traffic noise, mental fatigue, phone calls, etc. *"Maybe he explained that, I couldn't hear over traffic."* – P_4, *"I was on a call when the driver was saying all this."* – P_{14}. This shows that auto-rickshaws in India, unlike ride-sharing cabs in the US, are not conducive spaces for the exchange of information between drivers and passengers [33]. Innovative solutions are needed to bridge this information gap for successful vehicular crowdsensing deployments.

Two drivers strongly collaborated with their passengers. To take an alternative route, they asked the passengers which of the three routes offered on the Turn2Earn app they should follow. As per the drivers, adding passengers in the decision-making of the route-selection process helped them in convincing more passengers.

5.1.2 Discount-based. Four drivers offered discounts to convince their passengers in taking an alternate route. Interestingly, this strategy evolved despite the app showing the expected meter fare for the optimal route, *i.e.*, the *fair* price the driver could charge the passenger based on the meter without any detours. Auto-rickshaw drivers and passengers usually negotiate the fare (instead of following the meter), and passengers find it attractive to get instant discounts on their rides [49]. A few passengers indeed desired monetary compensation in return for their time: *"Why should I waste my time if I am not getting any profit?... maybe discounts on my fare."* – P_{11}. Nine passengers said that they would allow drivers to take a longer route if time permits, however only three of them did not expect a discount in return. This hints that drivers were correct in their belief that discounts will help in convincing passengers.

We found two main reasons quoted by drivers to offer discounts: compensating passengers for their time, and offering incentive as a negotiation tactic. A few drivers were worried that taking passengers via a longer route is unethical. D_2 complained, *"How can we charge them fairly... they will be wasting their valuable time."* They were respectful of their passengers' time, and thought that the passengers were not gaining anything by agreeing to travel via an alternative route. Consequently, they offered discounts as compensation, and informed the passengers upfront. D_7 told his passengers, *"I will take a slightly longer route, which will take 5-7 mins extra... You can pay 20 rupees less."*

Another set of drivers used discounts as an incentive-cum-bribe to lure passengers. They first tried to convince passengers without offering any discounts, but in case the passengers disagreed, they offered discounts as a negotiation tactic. E.g., *"Telling them* [passengers] *that they have to pay 10-20 rupees less makes them compromise."* – D_4.

Such discount-based strategies were not always successful, as a passenger pointed out on being offered a discount, *"If I had free time, I would have taken a bus instead. It would have costed me lesser as well."* – P_4. Discounts may not work for such passengers who take private transportation like auto-rickshaws only to save time. Moreover, the response to discount varies across days, as passengers usually are not in hurry during weekends compared to weekdays.

5.1.3 No Information or Misinformation. Another strategy used by four drivers involved misleading the passengers. Three drivers decided to simply not inform the passengers about Turn2Earn at all (*no information*), while in other cases, two drivers provided wrong information about the route and/or Turn2Earn when questioned by the passenger (*misinformation*). While this was the least popular strategy according to the drivers, but to our surprise, we found it to be the most common strategy when we interviewed passengers. This may be because of passengers' selection-bias, as passengers who received doubtful information called us to learn more and to participate.

In the case of 'no information', drivers did not inform the passenger about the alternate route. They used the Turn2Earn app as if they are simply using a routing/navigation app, an alternative to Google Maps. They entered the passenger's destination on the app and started the trip with one of the alternative routes. They followed the navigation to collect as many stars as possible, before the passenger noticed and/or instructed them to take another route. Even after receiving this instruction, D_5 neither mentioned Turn2Earn nor tried to convince the passenger, as he thought it would be a "*hassle*". Interestingly, drivers did not perceive this as malpractice.

> "*Instead of telling this long story about the app, route, pricing, etc. etc., it is much easier to start the trip and keep moving... If the passenger notices, he will complain, and I will just take the usual route... If he doesn't, I will simply take the app route and earn some extra money. What's wrong in it?*" – D_5.

This strategy worked well for D_5, as he took the maximum number of successful passenger trips (74 trips) among the 13 drivers. Another driver, D_8, employed this strategy during the first few days of the deployment study, but later shifted to the information-heavy strategy upon being reprimanded by a few passengers. Interestingly, most (8) passengers we interviewed were of the opinion that the drivers took the usual route to their destination. This hints that if the alternate route finding algorithm is effective in identifying minimal detour for maximum coverage gains, in such case, a no information based strategy may work well for both drivers and passengers.

Moving on to misinformation, two drivers admitted lying to their passengers when asked about the specific route being taken. Similar to the no information strategy, these drivers started their trips by selecting an alternative route without informing the passenger about Turn2Earn. However, when the passenger questioned them for not taking the usual route, they cited reasons like "*there is more traffic on the other road*" – D_9, "*that road is blocked due to construction*" – D_{10}. Passenger P_3 reported about this strategy. When she asked the driver to follow a shorter route, she was told that there was traffic on that road. Being a regular traveller, she was aware of the traffic condition and persisted in taking the specific road. Such malpractices by the drivers might result in the passengers distrusting a vehicular crowdsensing system. Thus, drivers need to be better trained in answering the passengers' questions honestly.

5.2 Motivation

The drivers stated a variety of reasons to use the app, most prominent being earning extra income. On the other hand, our interviewed passengers agreed for the alternate route mainly due to philanthropic reasons.

Monetary Gain: All the drivers reported decline in income due to COVID-19 related measures taken by the public and the government, hence they used the Turn2Earn app extensively, mainly to earn extra money. During the interviews, drivers thanked the interviewer researcher multiple times for providing them an extra source of income. A few drivers even expressed unhappiness to their RMs when we ended the study as they wanted to continue using the system for longer.

Passengers were also sensitive to drivers' financial needs. They agreed for taking an alternative route as they felt that the proliferation of Ola/Uber cabs has negatively impacted the business of auto-rickshaws, and/or to help the drivers during the difficult COVID-times. Three drivers mentioned exploiting the altruistic tendencies of their passengers in convincing them. In addition to informing the passengers about the research, these drivers told their passengers that, "*following the route shown on the app would help me earn a little extra money... especially during this COVID.*" – D_3. Drivers also presumed that the broader purpose of the research was to help drivers. For instance, D_6 told his passengers: *"They are doing research... we are getting extra money... they are helping us."*

For a Better Future: Prior work has highlighted ride-sharing drivers' altruistic motivations of driving, in addition to financial ones [37]. In our study, a few drivers enthusiastically supported our system believing that the research is collecting air pollution data. Due to the increasing level of air pollution in urban India, the drivers felt it was their responsibility towards the future generations, showing their emotional involvement in the cause [45]. In idle mode, D_1 mentioned choosing longer routes to collect more data, in order to help with the air pollution research (our logs confirm that D_1 selected the longest route in 71.4% of his idle mode trips). Eight drivers mentioned the feeling of "*guilt*" on not being able to reach the desired location to collect the star. A driver even lectured his passenger who complained about wasting time due to the alternative route, about the relevance of measuring air pollution: *"There is pollution everywhere, I am helping in measuring the pollution in this area... thus have to take this road." –* D_4.

Even the passengers who did not allow the drivers to take an alternative route, during the interviews were willing to allow: "*It's okay to waste a few minutes, if it is for a good cause like air pollution.*" – P_{12}. Similarly, P_{14} was completely against the idea of a longer route, even with a hefty discount, as it requires wasting time on road. However, for future sustainability, he was willing to co-operate. P_{12} was even willing to pay extra money for such auto-rickshaw rides to participate for the betterment of the city. This idea of finding motivation in helping the future generations has been pointed in prior work among urban Indians [28, 54].

5.3 Comparison with Existing Apps

Prior work [23] describes workplace technology adoption as a three stage process — initial, transitional, and post-adoption. In our study, we see evidence that ride-sharing technology has reached a post-adoption stage among drivers; it has now become common sense and deeply embedded into their work routines [23]. In spite of the fact that Turn2Earn did not assign passengers to drivers, which is the primary function of ride-sharing apps, during the interviews, the drivers constantly referred to Ola/Uber and compared Turn2Earn with those apps. One of the main reasons behind such comparisons was that the drivers found the interface of our app to be similar to Ola/Uber's interface. This was intentional in order to reduce their learning curve.

> "*The app is just like Ola... The only difference is that it asks us to visit three of those star locations.*" – D_8.

Second, a few drivers thought the idle mode trip is similar to Ola/Uber trip, but with "*an invisible passenger*" (D_2). Prior work reported Ola drivers facing issues like ride cancellation by the customer, hard to find pick-up location, etc. [2]. Idle trips help relieve such uncertainties, not just in availability of work, but also by removing passengers for three rides/day. Third, drivers used Ola/Uber analogies when communicating with passengers, as that helped in gaining their trust. "*I tell them, that this is a new app... similar to Ola... it will show the route to follow....*" – D_{12}.

Contrasting with ride-sharing apps, two drivers stated positively that Turn2Earn app forced them to explore new roads and/or areas. Usually drivers ply in their known localities, or follow Google Maps which shows them "*common routes*". Further, when driving with Ola/Uber, drivers are penalized if the passenger complains that they did not follow the app shown route (D_8). Indeed, two passengers we interviewed booked their autos through Ola/Uber and therefore expected a higher standard of service. So, the drivers are not able to use their on-ground knowledge of the city to take shortcuts and save time and fuel. Instead, our system *benefits* (in terms of coverage) when drivers take shortcuts that are not recommended by Google Maps. A previous GPS-enabled taxi-dispatch system encouraged drivers to accept rides beyond their usual geographical boundaries in order to gain spatial knowledge of the city [23].

5.4 Miscellaneous Qualitative Findings

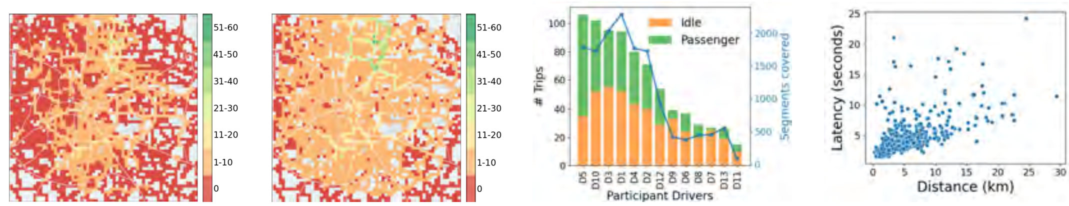
Innovative Turn2Earn Usage: Drivers came up with ingenious ways to utilize/exploit our system. Two drivers mentioned using the passenger mode without a passenger on-board. When the drivers needed to commute for their personal work, they just entered their destination in the passenger mode to earn extra money. "*I use the passenger mode if I have to go somewhere to meet a friend.*" – D_{13}, "*When I go home at night, I choose passenger mode and enter my home address as destination.*" – D_3. We are uncertain how many passenger trips are '*fake*'; however from a data collection perspective, such trips are a win-win for both the drivers and data collectors. This hints that there can be other valid use cases of Turn2Earn, which we need to explore in future. Also, it reaffirms that the drivers were satisfied with the offered rewards, as they were using Turn2Earn even in situations where the relationship managers did not ask them to use it.

Driver D_4 had negative experiences in convincing passengers in taking alternative routes. Hence during low-demand hours in the afternoon, he converted his auto-rickshaw into a shared auto-rickshaw, similar to a carpool. Shared auto-rickshaws charge less fare from each passenger, as they pick and drop multiple passengers on the way, often by taking short detours from the optimal route. Hence, for 2-4 hours every day, he collected stars as a shared auto-rickshaw because passengers did not complain about detours on these trips. It might be interesting to study the impact of Turn2Earn in tier-2 Indian cities where shared auto-rickshaws are the norm.

Custom Idle Trip: After our initial pilot study, we added the custom idle trip, an idle mode trip (*i.e.*, without passenger) in which drivers need to enter a destination of their choice, instead of being suggested destinations. Nine drivers used the custom idle trip as intended, to go back home or their starting location, at the end of the day or after the two idle trips. This feature helped the drivers in choosing far-off destinations in idle trip, without worrying to return back to their base location at their own cost. Logs revealed the same — the average distance of custom idle trips (~19 km) was much higher than idle (~13 km) and passenger trips (~8 km). Four drivers mentioned exploiting the custom idle trip to travel to areas where they were likely to find passengers, such as office areas, shopping malls, markets, *etc.*. Without the Turn2Earn app, they have to make these trips at their own cost, if the previous passenger was dropped far away from these crowded places. Thus, novel use cases of the custom idle trip emerged during the deployment.

Passenger's Micromanagement: Most interviewed passengers (12) did not opt for the suggested alternative route. Apart from being in hurry, there were other reasons quoted by them. First, many of them were regular riders traveling on the same route daily, *e.g.*, commuting to workplace from home. Such passengers are aware of the shortest route to their destinations [52], and therefore instruct the drivers to follow their *"personalized"* routes. With such passengers, drivers do not even have the freedom to follow routes shown on any app, including Google Maps. Second, a few passengers did not allow the drivers to follow alternative routes because they had not heard of Turn2Earn before and found it "*suspicious*". Even when the passenger agreed initially, they became antagonistic en-route: *"See... now we are stuck in traffic, because of this."* – a passenger told D_8. A passenger paid D_4 less than the deserved meter fare, complaining that the driver wasted his time. These instances show that, unlike in the US [17], auto-rickshaw passengers tend to significantly micromanage navigation with no scope of collaboration with the driver. Hence solutions involving passengers in the decision-making process might work better.

Drivers' Selection Bias: Drivers initially tried to convince all their passengers to take alternative routes. However, five drivers noticed that women passengers were often taken aback at the suggestion of a different route, mostly due to safety concerns. Subsequently, they stopped asking women passengers. A concerned D_4 explained, *"If I asked them* [women] *about using an app to follow unknown route... I might come across as problematic."*. Similarly, two drivers stopped asking



(a) Coverage (passenger) (b) Coverage (all) (c) Trips & Cells / Driver (d) Distance vs Latency

Fig. 2. (a, b) Spatiotemporal coverage attained by Turn2Earn for 4-hour time segments in only passenger mode trips and in all trips (including idle) respectively. (c) Number of trips taken (bars) and spatiotemporal segments covered (blue line) by participating drivers. (d) Scatterplot showing end-to-end latency variation in passenger mode with respect to the distance between source and destination.

passengers who 'looked' aggressive/rude, as they were susceptible to pick up a fight. One driver did not mention the app to a few construction workers travelling in his auto-rickshaw, because he thought that they would not understand the meaning of 'research'. Selection bias by profiling passengers on the basis of age, gender, and appearance, has been previously seen in auto-rickshaw drivers in India [49] and Uber drivers in the US [33, 47].

Electric Vehicles: Drivers with electric vehicles (EVs) had mixed feelings about Turn2Earn.

> "*EVs are different than traditional autos. EVs are white-blue, different from the usual yellow-green autos. Since they are new on the roads, passengers don't board them thinking they are more expensive or are cargo vehicles. Hence I am mostly free.*" – D_7.

Hence, D_7 was happy to use Turn2Earn's idle mode to earn money in his "*abundant*" idle time. On the contrary, three EV drivers declined to participate in our study when the RMs approached them initially. They were uncomfortable driving long distances in idle mode fearing running out of battery "*due to absence of public charging stations*", explained D_{11} who agreed to participate, however did not use Turn2Earn extensively (14 idle trips; least out of all drivers). In passenger mode, both the EV drivers performed poorly with only 2 (D_7) and 5 (D_{11}) successful Turn2Earn passenger trips, which may be because very few passengers board EVs in general.

5.5 Spatiotemporal Coverage

Using the trip logs, we computed the spatiotemporal coverage achieved by Turn2Earn. As discussed in Section 3.3, we gridified the Bangalore city into 4096 grid cells, each of size 500 m × 500 m. Of these, 3195 cells are accessible by road; the rest are inaccessible (lakes, gardens, private property, restricted cantonment area, etc.). There were 138 time segments of 4-hour intervals over the deployment study duration, thus obtaining 440, 910 spatiotemporal segments.

Figure 2a and 2b shows the spatiotemporal coverage achieved by passenger-only and all trips, respectively. The cell colors represent the number of 4-hour time segments in which these cells were visited—from dark red (zero visits) to dark green (most visited), and inaccessible cells are colored grey. Red cells are usually in the city outskirts, while green cells are in the downtown area. With 13 auto-rickshaws running for 15.3 ± 5.2 days, Turn2Earn covered 13,544 (3.1%) spatiotemporal segments. Considering only the passenger mode trips, 40.4% cells were visited at least once, and the idle mode trips visited 76.8% cells at least once. Combining both, we achieved a spatial coverage of 79.2% of the accessible cells at the cost of Rs. 39 (~\$0.54) per cell. Accounting for the 4-hour intervals, passenger and idle mode trips combined covered each accessible spatial cell in 4.2 ± 5.9 segments, and 1.3 ± 2.7 segments considering only passenger trips.

On average, a passenger mode trip costs one-eighth of an idle mode trip (Rs. 19.6 v/s Rs. 165.5). In idle mode, drivers visited cells that they would not usually visit with passengers, especially in the city outskirts (Figure 2b). Hence, even though idle mode costs more than passenger mode, it may be needed as it helps in collecting data from areas not typically frequented by passengers. We found that seven drivers always chose the longest route in idle mode, as it offers the highest fare. This suggests that idle mode can be used to cover crucial spatiotemporal data holes, even if the nearest driver is far away from the holes. Thus, idle mode can be a useful addition to the Turn2Earn approach, to further enhance spatiotemporal coverage in real-world settings.

Figure 2c shows the number of idle and passenger mode trips (orange and green bars, respectively) and the number of spatiotemporal segments covered (blue line) for each driver. It seems that drivers who took more trips covered more segments. There are a few interesting observations: D_1 covered the maximum number of segments with the fourth-highest number of trips; D_2 covered similar number of segments as D_{10}, but with 30% fewer trips. This shows that some drivers are more willing than others to drive beyond confined geographic areas and/or at varied times of the day.

5.6 System Analysis

As discussed in Section 3, every Turn2Earn search request involves three steps: heuristically solving an instance of the Orienteering problem, running Dijkstra's algorithm on a large graph (~484k vertices), and web calls to Google Maps APIs. Drivers are often in high-pressure traffic situations when on-boarding passengers. Further, they use low-speed 3G/4G mobile networks for internet access. Hence, we had to optimize for end-to-end latency, *i.e.,* the time between the driver's request and the server's response, including network delays and computation time.

For our latency analysis, we only consider requests received in passenger mode, as that is time critical. Figure 2d shows how latency varies with the distance between the source and destination. We find distance and latency to be positively correlated with $r = 0.59$. With longer distances, more nodes need to be considered for both the Orienteering Problem and Dijkstra's algorithm, thus increasing the computation time. The median latency is 3.5 sec and the 95th percentile latency is 11.8 sec. Turn2Earn served 92.8% search requests in passenger mode in <10 sec. The highest latency is 72 sec, which might have been caused by unexpected network delays due to occasional dead-spots in mobile networks. (Note: we remove the ten highest latencies in Figure 2d to remove outliers and focus on the trend).

6 DISCUSSION

Our work presents a quantitative and qualitative evaluation of a proof-of-concept vehicular crowd-sensing system aiming to improve spatiotemporal coverage by incentivizing deviations.

The key idea behind Turn2Earn entails taking an alternative route to collect data and maximize spatiotemporal coverage. When sensing air pollution, this idea may be contradictory to the cause itself — the vehicles may add to the city's pollution by travelling longer distances. However, our data shows that medium-distance (neither optimal, nor longest) routes suggested by Turn2Earn in passenger mode were only 0.59 ± 1.76 km ($9.3\% \pm 17.8\%$) longer than the optimal routes on average. Moreover, although Turn2Earn indeed increases cumulative pollution in a city due to longer trips, it incentivizes drivers to take alternative routes that are farther from the city's main roads. Thus, an outcome of this approach is reduced pollution peaks at such locations [29].

Turn2Earn provides governments an inexpensive way of city-scale monitoring, while providing added income to people who suffer the most from urban issues (traffic, pollution, potholes) due to long driving hours [2]. Although our work focused on independent drivers, ride-sharing services can employ a similar approach to augment their auto-rickshaw and cab drivers' earnings. This has the added benefit that the passengers trust these cab services, and the routes shown in their apps are usually not questioned by passengers, thus helping in easier adoption and integrating Turn2Earn in the broader eco-system. Additionally, India has seen a recent upsurge in app-based hyper-local delivery services like Swiggy, Dunzo, and Zomato [51]. With no passengers on-board, their delivery staff have more flexibility in route selection, and can adopt Turn2Earn with minimal hassle. Further, they usually travel on motorized two-wheelers which can zip through traffic faster compared to auto-rickshaws or cabs, thereby causing lesser increase in travel time. The delivery staff members use mobile phones for accepting requests, which can be utilized for collecting IMU, camera, and other smartphone-based data. Hence, ride-sharing and hyper-local delivery service providers can act as data aggregators to help urban bodies with a ready fleet for granular data collection.

With respect to sensing, Turn2Earn can be used for a variety of purposes, such as GPS and IMU data to monitor traffic congestion [42], camera for road quality[55], microphone for sound pollution [35], *etc.* Moreover, our approach can sense multiple entities with each participating vehicle. For example, an auto-rickshaw can have installed pollution $PM_{2.5}$ monitors, along with recording IMU data from drivers' mobile phones to monitor traffic congestion. In such a scenario, the overall sensing cost can be shared across different use cases. Next, we discuss the design implications and limitations of Turn2Earn.

6.1 Design Implications

Through this deployment, we saw a lack of trust and communication between drivers and passengers. This shows that despite their many proven applications in inexpensive real-time sensing [13, 15, 41, 42], vehicular crowdsensing systems still need design innovations to be feasible among their on-ground stakeholders. Here, we provide design implications for future vehicular crowdsourcing systems such that coverage goals can be met while affording a buy-in from stakeholders.

Engaging Passengers: Only three drivers informed us that a few of their passengers were inquisitive, read the information sticker, and asked questions about Turn2Earn. Most passengers either did not notice the sticker, or noticed it but decided against reading it as they were tired, busy, or uninterested. Hence, the onus of convincing and providing relevant information to the passengers completely lay on the drivers. Unlike cab drivers in the global north [23, 33], this was a difficult task for Indian auto-rickshaw drivers due to their minimal education, language barriers, and gender differences. Drivers need to be better trained using a comprehensive tutorial based on our learning, and multiple rounds of training should be provided to help them with newer challenges and to better engage with passengers. The information gap between the passengers and drivers, and between drivers and relationship managers needs to reduce. Moreover, a system like Turn2Earn should not rely solely on drivers conveying information to passengers. Instead, to establish the system's legitimacy with passengers, they need to be informed more systematically and updated regularly [12], perhaps through a passenger-side app that shows the trip's progress and ETA. Alternate forms of communication, through government announcements, ad campaigns, *etc.* will also help gain the passengers' trust [12]. Finally, passengers should be involved in the decision-making (route selection process), as a few drivers found that giving ownership to the passengers helped convince them.

Incentivizing Passengers: In our current system, the drivers were getting benefited monetarily, but the passengers were also spending extra time on the road, without any reward (by design). This led to many passengers declining to take an alternative route. Although most passengers were not interested in small discounts, they were willing to incur discomfort for a good cause or to help future sustainability, similar to prior findings [54]. Thus, to incentivize passengers, the system can offer a donation to an NGO of the passenger's choice for every extra minute spent on the road. Another way could be to inform the passenger on the impact of the collected data on their city's urban development, making it a citizen engagement project in line with urban HCI practices [11]. Such information- or charity-based solutions have the potential to help convincing passengers.

Personalized Routes: The log analysis showed that three drivers always took the default auto-selected route in idle mode, perhaps to minimize their interaction with the Turn2Earn app as they are on-road [3, 9]. Moreover, in passenger mode, six drivers consistently chose the medium-reward route (neither the optimal route with no reward nor the longest route with maximal reward) to the destination, maybe to balance their monetary gains and the passengers' discomfort. The system should sensitize its route suggestions by learning such driver preferences over time [2], and show the most critical spatiotemporal data hole as part of the default route or medium-reward route. Moreover, instead of three route options, showing one or two options based on the driver's learnt preference might work better. This will reduce app usage complexity and allow them to view Turn2Earn as a navigation application they are familiar with (similar to Google Maps), with the added benefit of earning extra money by collecting stars.

Criticality-based Reward: Our current reward scheme encourages drivers to take longer trips in idle mode or longer detours in passenger mode, in order to maximize their monetary gains. However, the longest trip may not guarantee the highest *score*, thereby resulting in spending more money on less valuable data and vice-versa. The system can offer higher rewards to routes with higher scores (*i.e.*, criticality), not necessarily routes with higher distance/duration. Cab services like Ola/Uber dynamically price their rides based on passenger demand [2, 12, 37]. Similarly, a criticality-based reward scheme for Turn2Earn would effectively create a supply-demand model between the drivers and *data*: a data hole is equivalent to high-demand, causing a surge in rewards for nearby drivers. While this may seem advantageous for drivers, previous work found that cab drivers tend to disregard dynamic pricing as it is complex to understand [37, 40]. Therefore, to implement such complex reward schemes, the driver needs to be well informed about the reward strategy to make informed decisions.

6.2 Limitations

We acknowledge several limitations of this work. First, the timing of our deployment study in August 2020. India was in a state of complete lockdown during the early part of the COVID-19 pandemic (mid-March to mid-May). Although by August, the restriction on people movement was gradually eased, the drivers noted a significant reduction in their earnings. As auto-rickshaw drivers are economically disadvantaged with limited savings [43], a system such as Turn2Earn may have found an easier adoption due to their desperation for additional income. A recent study showed that people's movement behaviors may not return to earlier levels post the pandemic and economic revival [48]. Hence, there is value in understanding Turn2Earn's usage during our study period. Second, the short duration of our study. Due to monetary constraints, we could run the study for $\sim$ 2 weeks per driver. We found that drivers understood the app, and their incomes stabilized within 1-3 days, hinting that the app was part of their daily driving behaviour. As the user's sensemaking through interaction with technology evolves with time [24], it would be interesting to understand longitudinal effects and usage patterns of Turn2Earn in the future. Finally, the small sample size limited our analyses. A larger number of participants is required to identify broader trends.

7 CONCLUSION

In this work, we developed and deployed Turn2Earn, a vehicular crowdsensing system, to understand drivers' and passengers' practices, motivations, and challenges, in adopting such systems as part of their work. In line with recent work in vehicular crowdsensing, we added the passenger mode to understand the driver-passenger interaction. Through qualitative and quantitative data, we studied the drivers' and passengers' usage and perception of Turn2Earn. With 13 drivers, at a low cost of $0.54/cell, Turn2Earn covered 79.2% of the city, at least once in two weeks. The key reason of Turn2Earn's success was that along with augmenting drivers' earnings, our approach made them a part of the solution to challenges faced in their city. We uncovered interesting strategies adopted by the drivers to convince passengers, passengers' reasoning behind accepting/rejecting alternative routes, and our app's perception as an Uber/Ola competitor. Through these findings, we contributed to the rich body of HCI and CSCW work that investigates the impact of technological intervention in cab driving, by studying another such intervention, i.e., vehicular crowdsensing. Based on our findings, we recommended design considerations informing the future of vehicular crowdsensing.

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