GigFitter: Tailored Scheduling Recommendations for Ridesharing Workers

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Abstract

Recent years have seen a rise in the prevalence of freelance work, facilitated by large corporate platforms who mediate contractor-consumer interactions. The distributed nature and scale of this so-called "gig economy" makes it difficult for gig economy workers to mobilize, negotiate, or adequately plan their livelihoods. The GigFitter Team has designed an application to enable gig economy workers to lead more predictable work schedules while maximizing pay and better fitting their work schedules to their preferences.

1 Introduction

1.1 Motivation

The workforce in the gig economy has been steadily growing in recent years. According to the National Association of Counties (NACo), the share of gig economy workers in the U.S. labor market has skyrocketed from 10.1 percent in 2005 to nearly 16 percent in 2015 (Harris, 2017) to nearly 36 percent in 2018 (McCue, 2018). Companies like Uber and Lyft hold a major presence in the market, fulfilling a market demand for ridesharing both across the country and around the world, at least in the case of Uber. The National Association of Counties delineates two primary forms of gig economy work. The first is labor providers ("contractors"), which includes drivers, handymen, and deliverymen, among others. These workers tend to be low-income, less-educated workers who rely on gig economy work for the majority of their livelihood. The other form of gig economy work involves good providers ("freelancers"), including artists, craftsmen, and bespoke clothing retailers. These workers tend to be higher-income, educated workers who rely on gig work as a subset of their earnings (Harris, 2017). For the purposes of this paper, we will largely be focused on the former category for our user base. We chose to focus on contractors because a larger proportion of their daily lives are centered around working in the gig economy.

These workers typically do not enjoy the same rights and benefits that salaried employees enjoy, including minimum wage, overtime pay, paid sick leave, and other benefits (Asmelash, 2019). The result is that a growing proportion of the U.S. labor force is working in a space that is, by virtue of its distributed nature, flexible work style, and lack of regulation, highly volatile and unpredictable. Asmelash (2019) states that approximately 1 in 10 workers depend on low-paying gig work as their primary source of income, leading to criticism of the industry as exploitative of its workforce.

This view of the gig economy has pressed legislative bodies to intervene, as exemplified by California's 2020 law requiring the state's gig work force to be treated with the same rights as those of conventional employees. Several gig economy technology platforms have skirted the issue by defining their business as a marketplace between people who demand services and those who provide them (Irwin, 2019).

Also unique to this space is the ability of workers to switch seamlessly, at essentially no cost, between multiple platforms (known as multi-homing), a practice extremely common amongst drivers in the ridesharing space and in related gig economy spaces like food delivery (Gad Allon, Maxime Cohen, and Wichingpong Sinchaisri, 2018). According to (Campbell, 2017), ridesharing contractors for Uber and Lyft represent nearly 70 percent of the on-call driving work force, and 25 percent of these drivers drive for more than those apps exclusively.

1.2 Business Implications

The gig economy space is now a significant part of the global economy, with total spending estimated at 4.5 trillion USD worldwide and 1.3 tril-

lion USD in the U.S. alone in 2018 (Arcuni, 2019). The global ridesharing market alone was valued at 51.3 billion USD in 2017 and is projected to grow steadily at over 20 percent per year until 2025, at which point it will reach a value of approximately 220.5 billion USD (Costello, 2019). This massive growth has come hand in hand with a large upsurge in the value of platforms which operate within this space. In particular, Uber is valued at an estimated 120 billion USD, and Lyft is valued at an estimated 23 billion USD (Delventhal, 2019). These tech success stories have come at the heels of an increasingly dissatisfied work force which has seen itself excluded and alienated from the success these companies now celebrate. According to McCue (2018), only 34 percent of contingent workers and regular workers said the hours that they work were "good for them," and gig economy workers are less likely to report being paid as timely and accurately as their more traditionally-employed counterparts. This points to the growing concerns among gig economy workers that the space is no longer playing to their benefit, and that the flexibility that was once appealing to them is now leading to high levels of uncertainty.
Exacerbating this issue is the fact that several key players in this space are not yet profitable. In its second quarterly earnings as a public company, Uber reported losses totaling up to 5.2 billion USD. Lyft's earnings report was arguably better, but still negative, at a loss of 644 million USD (Hawkins, 2019). Given the low profitability in this space, Uber, Lyft, and other companies are in a constant struggle against the bottom line, meaning they have little incentive to share earnings with the drivers who facilitate the ridesharing process. In the future, we anticipate that this tension is likely to persist, as it is unlikely that ridesharing companies will be profitable for a long time without a major paradigm shift in technology (like self-driving cars) or regulation (like subsidies and partnerships). Our goal is to cater to the workers in this space in spite of this overarching uncertainty and flux.

1.3 Goal

We believe that there is a strong need in the gig economy for stability and predictability. On one hand, the flexibility associated with the gig economy and ridesharing in particular makes it an appealing proposition for many workers (Gad Allon, Maxime Cohen, and Wichingpong Sinchaisri, 2018). However, this flexibility also introduces a great deal of uncertainty, which we hope to mitigate. Our first iteration of the app focuses on a subsection of the gig economy: ridesharing, with the hope that in the future we may expand to other domains. We chose this space because of its wealth of data and accessibility of contractors for demand testing.
We have identified three primary areas of greatest need in the gig economy which currently are not available to the workforce:

- *Past projection*. Workers in the industry have no centralized place to share or record information about past trips taken.
- *Predictive recommendation*. While workers are engaged in instantaneous price-comparison, there is currently no mechanism for them to project future earnings days or weeks in advance.
- *Financial recommendations*. We would like to provide high-level information and tips to gig economy workers who rely on sustained long-term contract work in this space.

In this paper, we introduce the methods, key components, evaluation, and business implications [1] of our technology.

2 Business Model

2.1 Stakeholder Analysis

We have identified several key stakeholders relating to our product.
The first stakeholders are our end-users: workers in the gig economy and drivers for ridesharing apps. As described in the introduction section, these users largely suffer from the unpredictable nature of the gig economy, as evidenced by irregular pay and overall worker dissatisfaction (McCue, 2018). Many workers fail to account for depreciation and opportunity costs which make their real wages far below minimum wage. Our product is a solution to this problem because it gives workers in this space the ability to forecast and better understand how they should segment their time between apps. Our goal as an app is to provide resources that tackle the 3 areas of need identified in the goals section. By providing a scheduling app,

[1] For the business analysis of our work, refer to the following sections: Business Implications, Business Model, Demand Scoping

we allow users to record their rides and the revenue they received from them. By providing predictive recommendations through our app, we can increase certainty in scheduling work plans, allowing workers to stabilize their schedules. Our app will also provide resources and financial recommendations to end users through job referrals and aggregated company information to allow users to make informed decisions about their work life.

The companies in the gig economy will also be major stakeholders. Companies such as Uber and Lyft may see our app as an attempt to drive down their revenues, but we are not directly at odds with gig economy companies. In fact, Uber and Lyft may want to better understand driving habits, for which we can provide information regarding driver satisfaction and behavior, as well as multi-homing information. Other companies in this space may want to advertise their services on our platform–we will touch on this more later in our discussion of the GigFitter revenue model. It is also possible that our app can also act as a platform connecting gig economy workers with alternative revenue options, which is an attractive proposition both for the workers who are seeking opportunities as well as the companies seeking more workers.

Another stakeholder segment is the end-consumer for gig economy workers. For example, in ridesharing it would be the riders who benefit from the service and pay for the service itself. While we don't anticipate significant changes to this user base, we acknowledge the possibility that large-scale deployment of our service may lead to higher prices to the end user as both workers and companies optimize for higher earnings. We believe that on our current scale, the impact will be negligible, and any price disparities resulting from our app will be mitigated by price competition.

The final major stakeholder segment we identified was that of governments, particularly municipal and state-level legislature. As mentioned in the introduction, the growth of the gig economy has prompted increased regulation in favor of worker protection and benefits, as exemplified by the new California legislation described by Irwin (2019). We believe that while increased legislation for workers will increase stability, our service provides predictability in other ways that will continue to be a value add even after the introduction of worker-friendly legislation.

2.2 Market Opportunity and Research

Total spending in the gig economy approached 4.5 trillion USD in 2018 (Arcuni, 2019). The global ridesharing market alone was valued at 51.3 billion USD in 2017 and is projected to grow at over 20% per year until 2025 (Costello 2019). Within the ridesharing space, two companies, Uber and Lyft, have dominated the US market and competition has largely consolidated. Despite the success of these companies (and in part because of it), contractors in this space have increasingly voiced dissatisfaction with their treatment and the inability to have predictable work lives. These issues include, but are not limited to, those of scheduling, pay, and worker's benefits. According to McCue (2018), only 34% of contract workers said they enjoyed their work schedules. This is contrary to the very objective of working in the gig economy relative to a more traditional employment space.

2.3 Customer Segments

We conducted several live interviews with on the order of 50 Uber and Lyft drivers throughout the semester. We identified broader trends within the driver base and used them to inform our high-level decisions in the design of our applications.

We segmented the driver base into three primary driver types:

- *Optimizer Drivers*. These consist of highly committed drivers who actively engage in multi-homing. These drivers typically take an active approach to optimize pay, and work up to 40 hours per week.
- *Scheduled Drivers*. These consist of drivers who largely adhere to a set schedule, or who set a daily quota or window for when to drive.
- *Spontaneous Drivers*. This driver segment consists largely of students or retirees who tend not to follow a particular schedule. Most of these drivers tend to drive part-time and leverage this job as additional income and spending money rather than core earnings.

Note that of these three groups, optimizing drivers tended to have the highest pay per hour by virtue of when and how they drive. Next, we set out to identify common strategies within the optimizer segment to inform our recommendations to other users. We identified the following common strategies among the optimizer segment which led to increased pay per hour in ridesharing:

- *Multi-homing.* Optimizers were overwhelmingly more likely to be multi-homers. They described how they used both Uber and Lyft simultaneously and concurrently waited for requests from both. Upon receiving a request, they would silence the other app until the trip was finished. This allowed workers in this space to maximize the utilization of their car and minimize waiting time between rides.

- *Strategic Time Allocation.* Optimizers were also more likely to have more flexible time allocations, choosing to drive during peak demand times such as rush hour or during peak event times, such as Friday evenings or after sporting events.

- *Strategic Geographic Positioning.* Finally, we found that optimizers were likely to position themselves strategically in locations that would allow them to have the highest demand with shorter trips, such as downtown Philadelphia. They would also position themselves in locations with high anticipated demand, such as sports stadiums and airports.

Among the scheduling drivers and spontaneous drivers, few incorporated multi-homing or strategic time allocation or geographic positioning in their decisions behind when and where they drove. Notably, even optimizers tended not to consider long-term demand planning for the future.

2.4 Related Work and Existing Services

We have identified two primary services that also operate in the gig economy space. *Gigworker* [2] is a centralized website that shows various openings for gig economy jobs and their expected hourly payout, and although it does a good job of enumerating a multitude of available opportunities, it does not give recommendations or forecast profit at a granular level (e.g. expected profit hourly). Its dataset is limited and the product is built on top of Wordpress with limited engineering and data scalability.

Ridester [3] is a mobile application specific to Uber and Lyft that switches between the two depending on which service will provide a higher payout by leveraging a screen reader on users' devices. It also takes into account other user preferences, such as automatically rejecting rides when the destination is out of range of the user's preferred area of operation. However like Gigworker, Ridester does not provide any predictive forecasting, and instead only recommends the highest paying option at the time of use, not the future.

Neither of these services combine a high-level analysis of the gig economy and provide future recommendations around scheduling work for extended periods of time. We believe that these aspects are crucial in allowing ridesharing (and more generally, gig economy work) to approach the level of stability afforded to individuals in regularly employed work.

Our service differs from these existing services by covering all three of the needs that we described earlier. Our app is a scalable, data-driven recommendation system that provides recommendations for the future, not just instantaneous price comparisons. Our application also provides services which allow users to track previous and future rides. Finally, our app integrates company information and aggregated news to allow gig economy workers to make financial decisions relating to their work.

2.5 Value Proposition

We view ourselves as a provider and aggregator of information and opportunity for gig economy workers. Our goal is to address the needs for (1) past projection, (2) predictive recommendation and (3) financial stability among gig economy workers. Each of our components is tailored to address one or several of the needs outlined here, which we believe are central to the overall predictability of working in the gig economy space.

2.6 Revenue and Cost Model

We considered several revenue models for our service, including subscription and ad-based revenue models. We concluded that subscription models were not aligned with our value proposition as a service provider for the workers in the gig economy (it did not make sense to charge them for a scheduling app), and that generic ad-based revenue models would be innocuous and counterproductive, decreasing overall user satisfaction with our application.

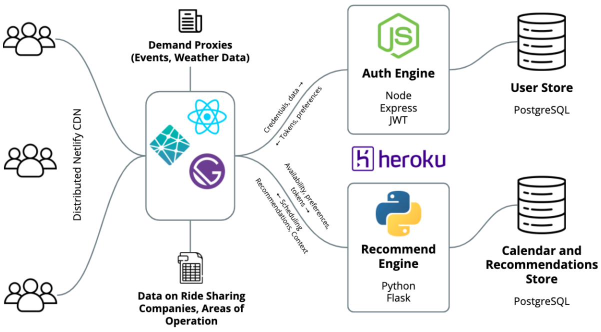
Our revenue model centers around our identity as an aggregator of information and opportunity. Our app will generate revenue by referring registered users to job sites. When users sign up through our platform we will set up affiliate accounts with each of these companies, and we will do the same for

[2] https://gigworker.com/
[3] https://www.ridester.com/

financial and educational service providers in this space. Being a work-life planning platform enables us to partner with a variety of financial planning services and offer more tailored, monetizable services as workers continue to use the platform.

Our costs are relatively lean. We plan to acquire customers through paid advertising campaigns and word of mouth. Web based storage and computing costs are low recurring costs. Upfront development costs and costs to adapt the product to new geographies and verticals are our highest costs.

3 Technical Components



3.1 Data Collection

Our data collection consisted of two main components: (1) data collection for broader frontend recommendations and (2) data collection for our predictive revenue model.

The data we collected for our model came from a variety of sources. One dataset originated from the Uber TLC-FOIL response released by FiveThirtyEight on Github [4]. The most significant dataset which we used to train our preliminary models came from a set of Boston ridesharing data released on Kaggle consisting of Uber and Lyft rides within the city [5]. This data consisted of information such as price, distance between destinations, cab type, source and destination information, ride type (e.g. UberXL, Uber Black), surge multipliers, and timestamps.

3.2 Model

The initial model we chose used the Boston Dataset to train a decision tree regression model of depth eight. The surge multiplier was dropped in order to ensure that our model interacted with as little price information as possible. The output variable was the price of the ride. Our initial choice of a decision tree architecture was informed by the prevalence of categorical information. The decision tree was trained on an ID3 algorithm using scikit-learn. The code for the model and the output of the decision tree in a graphical format is available in our model GitHub repository [6].

Over the course of development we realized this model did not give the functionality we needed given that, when a user is planning their week, we do not have control over features like location once they actually start driving. Thus, we migrate to a rules-based model for segmenting users based on their preferences (like willingness to drive in traffic, number of hours, desire for a consistent schedule, etc.) and providing noisy recommendations to cater to their preferences. A discussion of the model efficacy is included in the following section.

3.3 App

Our final deliverable is an application that is accessible to gig economy workers via the Internet both on mobile phones and desktop computers. The app provides recommendations to ridesharing and other freelance contractors on available opportunities and ways to optimize their work. The application consists of several components. These components are aligned with the primary areas of greatest need in the gig economy as well as the strategies we derived from our demand scoping work as outlined earlier in this paper:

- *Learn.* Centralized news curation relating to gig economy work. This page will allow gig economy workers to stay up-to-date on the latest trends and changes in legislation regarding gig economy work.

- *Companies.* A compilation of companies that are active in the freelance / gig economy space, as well as information about pay, wage, required skills, and required assets.

- *Scheduling.* Scheduling functionality for ridesharing drivers using a combination of predictive analytics and information gathered through demand scoping. Drivers can submit their availability for any week and can receive recommendations within their availability windows for when to work.

[4] https://github.com/fivethirtyeight/uber-tlc-foil-response

[5] https://www.kaggle.com/ravi72munde/uber-lyft-cab-prices

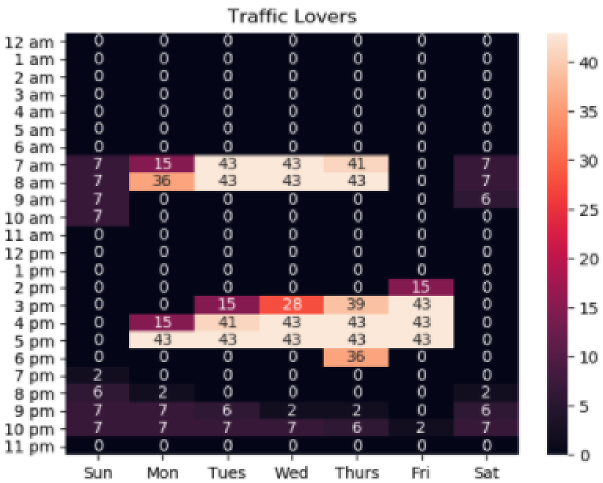
[6] https://github.com/jordanlei/gig-economy

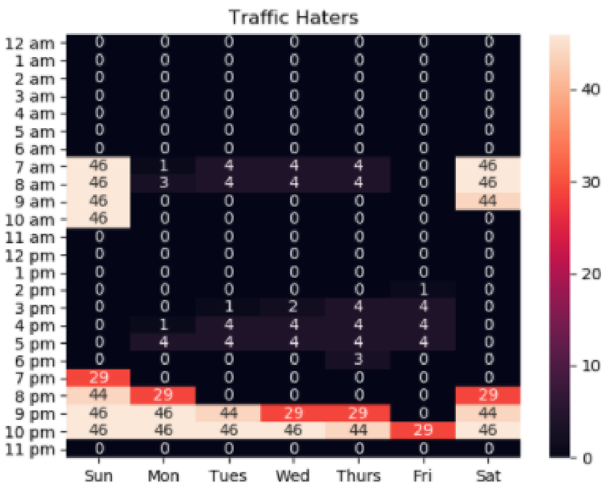
4 Evaluation

4.1 Preference-based Recommendation Differentiation

In this section, we evaluate the fact that different user profiles would result in distinct recommended schedules. In the absence of a user-study, we've generated a set of 100 users, split into two user-profile groups consistent with possible ranges we observed in preferences for traffic. Users were generated with availability from 7 AM to 11 PM with a weekly driving time normally distributed $hours_{week} \sim N(20, 3)$. 50 users were selected to emulate traffic-loving drivers on a 5-point Likert Scale $w_{traffic} \sim N(4, 1)$ and 50 were assigned to be traffic-hating drivers $w_{traffic} \sim N(1, 1)$.

4.1.1 Results





4.1.2 Discussion

Based on our aggregate results, it is clear that our algorithm generates divergent recommendations for users with different traffic preferences. Based on this proof of concept, we can extend this work to other preferences including weather and events to allow for more holistic user representations and user segments in the future.

4.2 Simulation

In the absence of a user study and due to social distancing limitations, we have proceeded to conduct a large-scale user simulation based on possible rides from the Boston Kaggle Dataset. More specifically, this simulation is designed to evaluate our hypothesis that for profit-maximizing users, the realized wages from our recommended driving times would be higher than a baseline (defined by spontaneous scheduling decisions). In the following subsection, we describe the parameters of the simulation, the results, and a brief discussion.

4.2.1 Simulation Design

The simulation was designed with the following strong limitation in mind: drivers can choose where they start driving but cannot choose where the ridesharing app takes them. The design of the simulation is specifically tailored to address this parameter; drivers are assigned the next available ride based on where they currently are (the source) and taken to some secondary location (the destination), which will then become the source for their next drive. This is consistent with how drivers are assigned rides in the real world.

Note that in addition to simulating realistic driving assignment scenarios, our simulation also realistically represents drives taken. Each simulated drive is taken from the Boston Kaggle Dataset, representing a real drive taken by an Uber or Lyft driver in the past. This data also includes the true distance, source, destination, and price of the ride, so these values are true-to-life.

For a given weekly schedule, a driver may be assigned to several different shifts, with each shift having a start and end time. By simulating their earnings on each shift, we can aggregate their earnings to estimate a set of possible weekly earnings.

As mentioned earlier, ride simulations make use of the Boston Kaggle Dataset, consisting of 693,071 unique rides conducted over several months in Boston. The dataset consists of a few important fields, including but not limited to: Start Time, End Time, Price, Start Location, End Location [7]

[7] Locations are listed within the city of Boston, consisting of the following: 'Back Bay', 'Beacon Hill', 'Boston University', 'Fenway', 'Financial District', 'Haymarket Square', 'North End', 'North Station', 'Northeastern University',

There are a few primary inputs to the simulation–a start time, start location, and an end time [8]. We construct a simulated ride in a framework described by Algorithm 1.

In simple terms, the algorithm describing a ride

Algorithm 1 Ride Shift Simulation

Require: startTime, startLoc, endTime, rideList;
Ensure: rideList is sorted by start time
ridesTaken = {}
runningPrice = 0
possibleRoutes = $\{x$ *in rideList s.t.* $x.start > startTime, x.end < endTime, x.source = startLoc\}$
while len(possibleRoutes) > 0 **do**
  wait = genWait()
  takenRoute = drives[0]
  ridesTaken = ridesTaken $\cup$ {takenRoute}

  runningPrice += takenRoute.price
  duration = takenRoute.duration
  startLoc = takenRoute.dest
  startTime += duration + wait

  possibleRoutes = $\{x$ *in rideList s.t.* $x.start > startTime, x.end < endTime, x.source = startLoc\}$
end while
return runningPrice, ridesTaken

simulation takes data points from the Boston Kaggle Dataset which fit the source, start time, and end time descriptions. Then it generates a set of rides where the destination of the prior ride becomes the source or starting point of the next ride. If we view the city of Boston as a graph where the nodes are the districts listed in the dataset and the edges are the time it takes to travel between districts, we may view this simulation alternatively as taking several possible contiguous paths through the graph. The pseudocode description obscures some of the minute details required to model the traffic, ride duration, and wait times, associated with a more accurate simulation. Our model also takes into account the difference between the price earnings and the wage received, which are not described here for simplicity; however, the pseudocode provides a reasonable approximation for what our current simulation does on a large scale.

The following image shows a sample output of a single simulated ride with the following specifications:

```
startLoc = "Boston University",
startTime = 04:40:56 2018-11-26,
endTime = 06:40:56 2018-11-26
```

```
Boston University
2018-11-26 04:40:56
2018-11-26 06:40:56
[Time_Start : 2018-11-26 04:45:58]
        $6.75
        [28.20 (7.06 wait)]
        [Boston University] to [Financial District]
[Time_Start : 2018-11-26 05:21:14]
        $2.1
        [6.18 (4.77 wait)]
        [Financial District] to [North End]
[Time_Start : 2018-11-26 05:32:11]
        $9.0
        [9.18 (5.42 wait)]
        [North End] to [Theatre District]
[Time_Start : 2018-11-26 05:46:47]
        $2.85
        [15.72 (3.90 wait)]
        [Theatre District] to [Boston University]
[Time_Start : 2018-11-26 06:06:24]
        $3.15
        [18.06 (8.67 wait)]
        [Boston University] to [West End]
[Time_Start : 2018-11-26 06:33:08]
        $5.85
        [16.98 (6.36 wait)]
        [West End] to [Boston University]
Earned $29.70
```

In the full simulation, each schedule would consist of several shifts, which would each be represented in a similar way.

4.2.2 Experiment Design

The experiment was conducted as follows. 100,000 simulated users were generated with traffic preferences normally distributed $w_{traffic} \sim N(4, 0.5)$ with availability from 7AM to 11PM and weekly hours normally distributed $hours_{week} \sim N(20, 3)$. Users were either assigned to be in the control group $(n = 5000)$ or in the treatment group $(n = 5000)$. Those in the control group were assigned to drive spontaneously, a random set of driving times within the specified time window that matched the hours they were willing to drive. Those in the treatment group were assigned to follow the recommendations given by our model. We tracked simulated user earnings over the course of one week.

4.2.3 Results

We found that the treatment group, which was assigned to adhere to our model, outperformed the

'South Station', 'Theatre District', 'West End'

[8] Uber/Lyft riders have limited control over where they are routed to–our choice of not defining an end location is consistent with this reality

baseline. On average, the treatment group earned $\$335.37$ (SD = 58.88), compared to the control group $\$318.79$ (SD = 53.06). The average user gained $\$16.58$ compared to the baseline, a 5.20% improvement within a given week.

Because we observed large variances in our data, we conducted a one-sided t-test for independent samples to determine the statistical significance of our effect. Our null hypothesis, H_0, is that $\bar{x}_{control} \geq \bar{x}_{treatment}$, and our alternative hypothesis H_1 is that $\bar{x}_{treatment} > \bar{x}_{control}$. After our t-test, our t-statistic was found to be 14.78, meaning our p-value was well below our threshold of 0.01.

4.2.4 Discussion

Our simulation realistically modeled driving situations that would be faced by a ridesharing worker in real-time scenarios. Our experiments demonstrated a statistically significant ($p < 0.01$) increase in earnings from the treatment group compared to the control, demonstrating that our offering truly adds value to ridesharing workers who are willing or able to optimize for earnings.

5 Societal Impact and Ethical Concerns

GigFitter is designed to bring stability to the lives of ridesharing workers, who often come from marginalized communities and many of whom rely on ridesharing services as their primary source of income.

We believe our offering provides stability on the individual level in several key ways:

- *Economic Stability*. A significant subsection of the ridesharing workforce depends solely on the industry to make a living. Our app provides a way for them to anticipate future earnings and maximize utilization, based on their preferences.

- *Bookkeeping*. Working in this space is associated with high uncertainty that stems from a lack of job security, insufficient tools to record and track earnings, and no ability to unionize or share information. Our app provides a way for them to track past expected earnings and learn relevant information pertaining to industry-wide changes.

- *Scheduling*. Despite being marketed as a liberating option for work, only 34% of contract workers said they enjoyed their work schedules (McCue, 2018). Our app provides a way for them to schedule their work and plan a week or more in advance.

Beyond these metrics, we also believe that our service is essential to the long-term health of the ridesharing service industry:

- *Turnover*. 68% of workers stop driving within 6 months of starting (Brown, 2019). Our app makes it possible to sustain long-term work in this uncertain environment, which would drive down turnover rates.

- *Social obligation*. Companies, users, and contractors who depend on this space have an obligation to ensure the stability of the lives of the drivers. Our app fulfills this obligation by giving drivers the negotiating power to set their own hours and plan ahead.

- *Worker benefits*. Our role as a stabilizing force in the industry actively supplements efforts made in legislation to give contractors more legal rights and representation by spreading information about such initiatives and providing alternative sources of value.

5.1 Data Privacy

All location or route data is and will be provided directly by users. No data is kept without the consent and knowledge of the users, and no data can be used to trace the driving patterns directly back to the user. Users know what data is entering our system. For scaling our recommendations beyond the rules based model, we will take advantage of ride data. This data will be in similar format to our base ride datasets from Kaggle namely in that we remove as much information about drivers and rides as possible, keeping only essential information like a generated driver ID, time, and start and end approximate location of ride.

5.2 Algorithmic Bias

One concern that was brought up was algorithmic bias in favor of certain drivers or geographic locations. In this section we respond to both of these concerns.

With respect to driver bias, we do not prioritize different drivers differently. The drivers are anonymized to the recommendation system, so there is not any bias we insert in terms of recommending when to drive. In the updated algorithm where we reroute certain drivers, it will come at a "first come first serve" basis–after a threshold is reached, we will reroute drivers once we predict dropping prices.

With respect to different geographic locations, the main concern here is that the app will route users away from under-served locations. While we agree that this is a point of concern, we believe it is out of the scope of this course project. We have no control over where drivers are routed or where they choose to drive. Our recommendation system only recommends when they should drive. While we agree that this is a larger issue, we neither recommend nor exacerbate any part of the routing process. This could be a larger conversation about the ethics of the gig economy in general, and we believe we can address other latent needs for low-income individuals in the gig economy space while this debate plays out on a different stage.

5.3 Scaling

One possible concern is that if all drivers use our services, this would hypothetically drive up supply with constant demand, driving down prices and wages for drivers—-the outcome of this scenario is that drivers go back to earning the same wages they did before. Our app has several mitigation strategies to prevent this. First, we segment users based on preferences: different users will be given different recommendations, based on their own unique preference which they set in the GigFitter web app. Thus, different user segments will not compete directly in terms of when they supply their labor based on our recommendations. Right now we have two user segments as a proof of concept. Second, as we scale, we can alter recommendations to make sure that users do not interfere with one another. Once we have aggregate user data it will be possible to make more granular recommendations based off our user base beyond information they currently supply through surveys.

5.4 Future Work

Our recommendation model can also expand beyond its current form by incorporating weather data (e.g. many rideshare users are more likely to request rides in increment weather, though many drivers per our interviews perfer only driving in nice weather or under predictable conditions) and events data (e.g. Valentines, Christmas, festivals, etc.). Our model allows for easy integration with these data sources. While we have generated predictions on short term events data and weather data already, we look forward to implementing more long term and automated sourcing of this data in generating our recommendations. This, in tandem with basing recommendations on data collected from users of our app, will enable us to scale to more geographies and to more granular levels of recommendations.

5.5 Lessons Learned

The gig economy is a rapidly moving space on all fronts: the software and products are forever shifting, consumers demand new things every week, and workers in the space are all caught somewhere in the middle. COVID-19, if anything, has accelerated trends in this space and has highlighted the disproportionate impact it has on different groups of people. To this point, we have truly loved exploring how we can use technology to play to the benefit of workers in the gig economy and to better understand how the space is evolving. There is certainly a lot more work to be done by us, by other companies, and by regulators.

6 Conclusion

The gig economy space is currently seeing a massive upsurge in growth across a variety of different industries, from ridesharing to food delivery to outsourcing. While these jobs confer a high degree of flexibility in work hours, this work also comes with a high degree of uncertainty, both in scheduling and financial security.

Our app, GigFitter, addresses a social need among gig economy workers to allow for a more stable and predictable work life without sacrificing earnings. Our application combines insights drawn from drivers who optimize earnings as well as predictive analytics tools to make curated recommendations for drivers in the ridesharing space. We also provide a centralized website which compiles news articles and company information to allow users to make informed decisions about their involvement in the industry. Our hope is that our service will allow the gig economy to become a sustainable and stable industry for the growing population of workers who depend on it.

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A Appendix

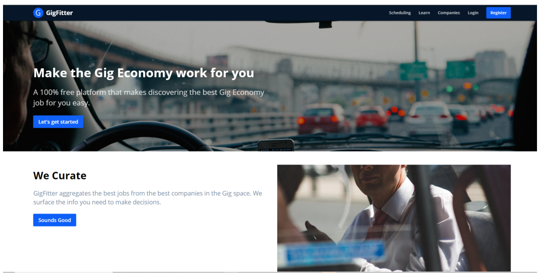

Figure 1: Home Page

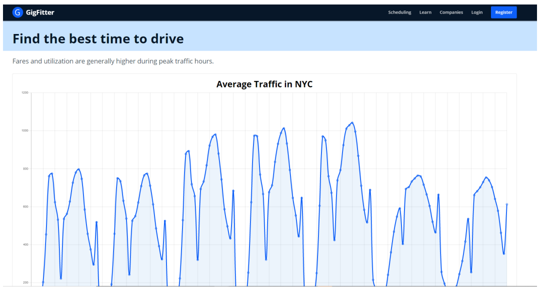

Figure 2: Traffic Page

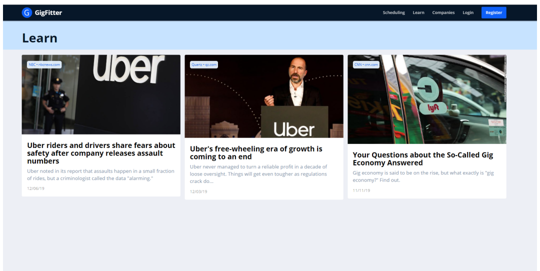

Figure 3: Articles Page

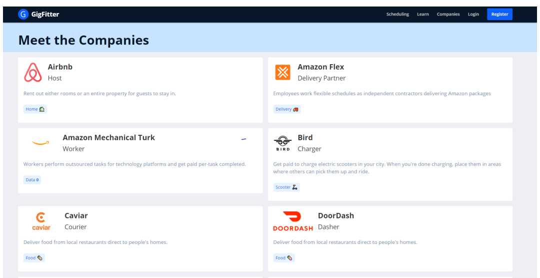

Figure 4: Companies Page

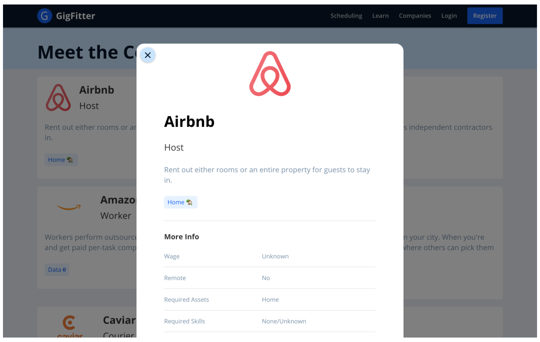

Figure 5: Gig Page

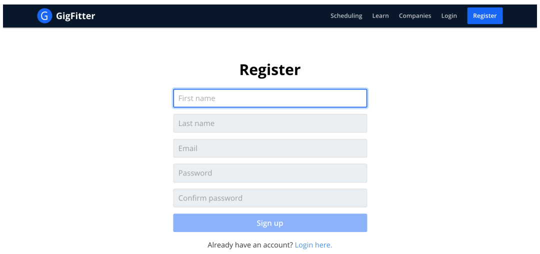

Figure 6: Registration Page

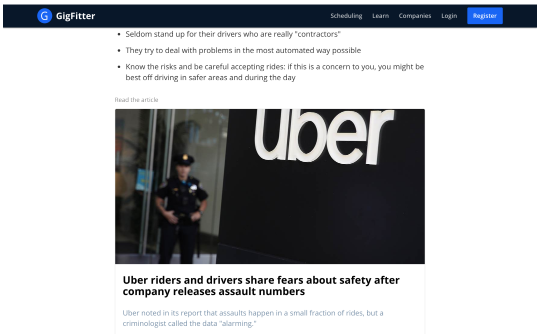

Figure 7: Linked Article Page