How Time Flies for Gig Workers

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ABSTRACT

Platforms like DoorDash and UberEats provide tremendous opportunities for gig workers. However, the gig workers are under "algorithmic management" and have to face the black-boxed algorithms with very limited understanding of how the system operates. Their income are greatly influenced by their delivery time. The gig workers often find themselves spending more time waiting than delivering, which in turn decrease their ratings and threats their chances of getting orders. We dived into the problem by algorithm auditing, conducting survey and having 1 on 1 interviews with users. To address this problem we came up with 3 new interface designs and tested with Dashers using storyboard speed dating to get their feedback.

KEYWORDS

gig economy, information technology, algorithmic management, food delivery, user experience

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1 INTRODUCTION

Platforms, such as DoorDash, Uber, and Instacart have produced tremendous opportunities for workers with more flexible schedules and loosen bonds with employers [5]. These gig workers are able to obtain more freedom to arrange their time to work for multiple employers at a time and decide the schedule and amount of work for themselves. On the other side, scholars have worried that these platforms were more complicated than allocating workers to consumers or matching consumers with merchants; rather, they intended to monitor and intervene the behaviors of workers through “algorithmic management”[7]. Instead of being an independent contractor, workers have to face the opaque and black-boxed data-driven system and have very limited understanding of how the system operates [10].

In order to manage the performance of workers, platforms would keep track of workers stats, such as their deliveries, ratings, acceptance rates [10]. For DoorDash workers, their performance is greatly evaluated upon the customer ratings of their previous delivery. Platforms have made policies to deactivate food couriers who failed to obtain a score higher than 4.2 out of 5 stars [5]. Therefore, all Dashers would count on the ratings of customers to maintain their job and get more orders in future. However, Dashers have little information about how companies evaluate the multiple aspects of their performance and allocate orders to them [13].

1.1 Problem Definition

To meet the increasing need during peak time, food delivery platforms such as DoorDash and UberEats usually offer economic incentives to Dashers[13]. When the merchants get busy during the busy hours, the wait time at the restaurant could be longer than expected. Some restaurants are notorious for longer waiting time and Dashers get frustrated when waiting for the merchants to prepare and pack [2]. Though delays related to merchant wait time will not lead to deactivation, Dashers are not compensated for excessive wait times at the restaurant and it might also influence their completion rating which further impacts future orders [1]. During the pandemic, there were even cases when drivers found the restaurant to be closed after they received the order [1]. The delay is also blamed by customers and thus influences their ratings.

2 RELATED WORK

Previous work focused on mainly two aspects of the problem: algorithmic management and delivery time prediction. Griesbach [5] studied “Algorithmic Despotism” exerted by Instacart, the largest grocery delivery platform, to regulate the time and activities of their workers more stringently than other platform delivery companies. UberEats used a dispatch system with a greedy matching algorithm. An estimated time-of-delivery prediction model was designed to be flexible enough to handle various scenarios due to its uniqueness of newly surfaced information in different stages of an order. [14] Eleme, one of the world’s largest On Demand Food Delivery platforms that delivers over 10 million meals in more than 200 Chinese cities every day, also proposed a time estimation model based on a deep neural network (DNN), which further incorporates representations of couriers, restaurants and delivery destinations to enhance prediction efficacy. [15]

Others also studied the motivation and expectations of the receiver of delivery services and assesed the influence of food quality and e-service quality on customer loyalty. Fancello [3] did an analysis of the characteristics of food deliveries in urban areas aimed at understanding the needs and expectations of receivers of last mile deliveries of fresh products by diving into results of a survey carried out in Cagliari (Italy). Ray [9] studied the motivation behing using on-demand food delivery apps(FDA) by using open-ended essays and survey questionnaires and identified eight main gratifications behind the use of FDA, namely, convenience, societal pressure, customer experience, delivery experience, search of restaurants, quality control, listing, and ease-of-use. A case study by Suhartanto

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assessed the direct influence of food quality and e-service quality on customer loyalty toward online food delivery (OFD) service and its indirect influence through the mediation of customer satisfaction and perceived value. [12]

3 RESEARCH METHODS AND RESULTS

Research methods include getting qualitative data through interviews, analysis of archival data from Dashers' online forums, and auditing the algorithms.

3.1 Algorithm Auditing

3.1.1 Method Overview. With the deployment of algorithms in more and more platforms, it is of increasing importance to study algorithms themselves. However, the result of the computerizing process in an algorithm is often to reduce our ability to study it.[4]. So we will try to understand the algorithms with certain questions in mind and not try to understand everything about it.

We have several questions in mind about the algorithms, including How does the algorithm decide the pickup time? What will happen after Dashers decline an order? How the estimated prep time that a merchant sets make a difference in the pickup time that Dashers receive?

To answer these questions, we used two types of auditing methods: Code Audit and Sock Puppet Audit, proposed by Sandvig, C, and his fellow researchers. [11].

Code Audit

If researchers worried about algorithmic misbehavior could simply obtain a copy of the relevant algorithm. Unfortunately, today Internet platforms consider their algorithms to be valuable intellectual property and also aim to conceal them using trade secret protection [8]. We were not able to get a copy of the algorithms used by DoorDash. However, we were able to get a copy of the patent they published [6] to the US Patent Application Publication.

We were able to know that the system generates a plurality of ETA time predictions for one or more of the delivery events with trained predictive models that use weighted factors including

- Historical restaurant data
- Historical courier performance
- Time
- Date
- Weather
- Number of dishes in an order
- Sub-total of an order
- Size of markets

And the timeline of all events that happen in the process.

The method they used for a dynamic estimated time of arrival predictions. Initially, when we have the first timestamp, the system automatically generates a first ETA prediction based on trained weighted factors. Then when the following events happen, the system dynamically incorporates the actual timestamp and adjusts the first ETA estimation to form a second updated ETA prediction.

Sock Puppet Audit

The researchers use computer programs to impersonate users, likely by creating false user accounts or programmatically-constructed traffic. However, DoorDash won't give APIs for such action. So instead we acted as the Sock Puppets and did the following:

(1) Requesting for Estimated Delivery Time every 30 minutes for 2 restaurants.
(2) Ordering food from the two restaurants and record time.

We studied two restaurants of different kinds, one is a fast-food chain restaurant Burger King and the other is a Chinese food restaurant China Family. Those two restaurants are of similar distance to the researcher. We requested an estimation of delivery time every 30 minutes from 11:00 to 13:30 and from 16:30 to 20:00 both on Weekday and Weekends. We summarized the data and drew two graphs of estimated time as shown below.

We ordered food using the DoorDash App and recorded the time of events including Order Time, Notify Driver Time, Dasher at Merchant Time, Dasher leaving Merchant Time, and Drop-off Time. We calculated the Geometric Mean of time duration and drew the graph of time distribution.

Figure 1: Results from Algorithm Auditing

3.1.2 Results. From algorithm auditing we were able to know the distribution of time spent on an order by a Dasher as shown in figure 1. On average(6 orders) the Dasher spent 1/3 of the time waiting for an order from a restaurant that is within 5 miles of the customer. We also learned the rush hour and how the estimated wait time fluctuates in a day. It was clear that the peak was reached at noon and 6:30 pm. The pattern for weekdays and weekends didn't show obvious differences.

The algorithm auditing process gave us the necessary knowledge of the algorithm and the ETA system in general. We were also inspired by the graphs from auditing and incorporated similar graphs into future DoorDash UI design.

3.2 Archival Data Analysis

3.2.1 Method Overview. We did archival data analysis using online forums and company websites. We analyzed posts in two subreddits—DoorDash Community and DoorDash Drivers—where many active Dashers share their working experiences. We also visited DoorDash official websites, in order to see what information is publicly shared with Dashers by the platform to help Dashers understand the underlying mechanisms of the platform's algorithmic management.

We sorted data into themes and mapped them into the full delivery workflow which involves multiple stakeholders (Dashers, merchants and customers), in order to thoroughly explore the causes behind excessive wait time and its effects on multiple stakeholders.

3.2.2 Results. Through the archival data analysis, we found that:

(1) There exists mistrust between Dashers and merchants, as well as their mistrust towards DoorDash's time prediction model.
   - Dashers are supposed to arrive at the restaurant no later than the estimated pickup time as required by the platform. However, they complain that some restaurants don't start the order "deliberately" until they show up. A restaurant employee admitted that his manager asked him to do so since food like coffee got cold quickly.
   - "Busy Kitchen" feature allows restaurants to extend the food preparation time when accepting an order, which will be used by the time prediction model to update the estimated pickup time. However, merchants think the time prediction model doesn't work, since no matter what time they select they are always having a Dasher arrive as soon as they accept the order. They also complain that it is Dashers that arrive too early regardless of the estimated pickup time.
   - Dashers and restaurants discussed the problem of excessive wait time in DoorDash's communities on Reddit and ended with attributing it to DoorDash's unreliable time prediction model.

(2) Experienced Dashers have already developed their own strategies to avoid or minimize the loss caused by excessive wait time. However, several factors, like task allocation, hidden tips, rating systems and batched orders, which are parts of DoorDash's algorithmic management system, add difficulty to Dashers' individual confrontation against excessive wait time.
   - Dashers strategically decline orders that are likely to take longer wait time. Though there is no minimum required acceptance rate, Dashers who frequently decline orders find it harder to receive orders in the future, which is not revealed by the platform but personally perceived by Dashers.
   - Dashers set themselves a rule about wait time. They might wait longer either passively (due to sunk cost) or actively (due to potential lager hidden tip). Some restaurants are dishonest with the time needed to prevent Dashers from un-assigning the order as food gets cold when waiting for the second Dashers, which makes it harder for Dashers to decide whether to keep waiting. Non-transparency of DoorDash's pricing models also makes it difficult for Dashers to predict if there is a hidden tip and to decide if it is worth the wait.
   - Dashers are supposed to inform customers of potential delays. However, even though Dashers have already communicated with their customers, late delivery caused by restaurants is always being misattributed to Dashers, because of the bad design of DoorDash's customer rating system. To make matters worse, Dashers are only able to view their average ratings without specific feedback.
   - Dashers are stressful with batched orders when restaurants are late. When one of batched orders with earlier pickup time is not ready on time, experienced Dashers choose to pick up the other order first. However, they need to check with the second restaurant whether the order is ready by themselves.

(3) DoorDash somewhat provides an opportunity for Dashers to report the problem of excessive wait time. However, Dashers don't think it makes any difference.

3.3 Survey

3.3.1 Method Overview. Our survey design intended to investigate the following aspects of Dashers' experience: work experience, order pick-up experience at the restaurant, customer review, etc. The questions are mainly centered on their delivery behaviors, attitudes towards wait time, and their understanding of their own performances. The survey was distributed on two subreddits: DoorDash Community and DoorDash Drivers and remained open for more than one week. Participants were also asked to fill in their contact information if they were willing to join future user testing. At the end of the survey collection, we have collected 47 survey responses in total on Qualtrics and it includes 41 valid and complete responses for analysis.

3.3.2 Results. From the survey responses, we have gained many descriptive data and insights into their behaviors and attitudes towards their delivery experience. The overall distribution of participants was quite even with 54% (n = 22) participants working as Dashers to earn their primary income and 46% (n = 19) not. One third (n = 13) of these 41 participants have worked as Dashers for 3-6 months, while 12 percent (n = 5) are newbies and 19% percent (n = 8) have worked for more than a year. More than 70% of participants (n = 29) worked 10-30 hours on average per week. With regards to their working preferences, these participants prefer to work on weekends than weekdays and prefer to work on 5pm-9pm (dinner hours) than 11am to 2pm (lunch hours). This can predominantly be attributed to the volume and value of orders during the specific range of time.

In terms of their pick-up behaviors at the restaurant, these Dashers would prefer to arrive earlier than the pickup time than being late and the majority would go directly into the restaurant and wait inside. Sixty-three (n = 26) percent of participants are willing to wait 10 minutes at the restaurant and 26% (n = 11) would accept 10-20 minutes. On the other hand, their wait time for the recent two weeks was not as satisfying as expected, with 38% (n = 16) participants having waited for more than 10 minutes. Around 45% of participants would choose to leave if it passed their acceptable range. However, 46% (n = 19) of participants would keep waiting and the top reasons include sunk cost (time) and potential large hidden tips.

Forty percent of Dashers do not really know how their rating was determined. Dashers are only able to see the average but cannot see specific comments (especially for poor ratings). Factors that are out of Dashers' control but might lead to problems: restaurant being late (especially stacked order) or missing item, confusing locations, no reasons. Dashers tended to rate their own experience if it's extremely good or bad. However, they know it is unlikely to make any difference (for restaurants and customers). On the other hand, they prefer to think restaurant ratings would affect them. Excessive wait time is a common phenomenon.

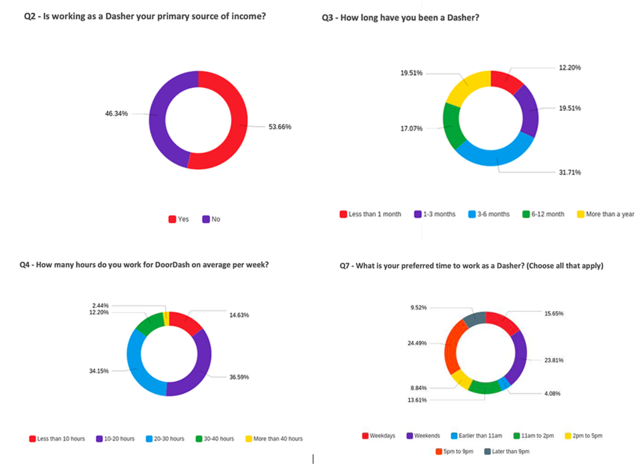

Figure 2: Results from Survey part 1

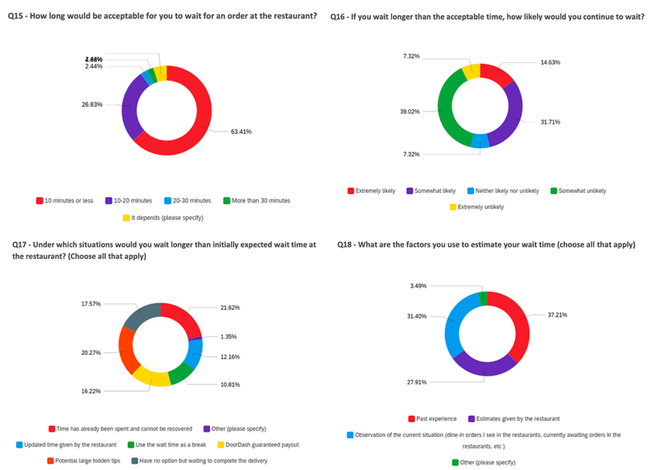

Figure 3: Results from Survey part 2

3.4 Interview

3.4.1 Method Overview. Through archival data analysis, we found that empathy from customers to Dashers also has an influence on work experience of the latter. Therefore, we conducted one-on-one interviews with three customers, in order to learn how estimated delivery time provided by the platform shapes their experience and to gain an insight into their tipping and rating behaviors.

3.4.2 Results. Before placing the order, interviewees mentioned that they would usually check the estimated delivery time and only place the order if it is within their acceptable range (less than 40-50 minutes). However, they noticed that the estimated time would change after placing the order and the time could be ahead of schedule but sometimes would be delayed; however, customers mentioned that they would not be informed of how long the Dashers have been waiting at the restaurant. Therefore, it would be hard for them to figure out the cause behind the delay. On the other hand, customers normally blame the restaurant for running late but felt frustrated when their orders were late among batch orders; therefore, Dashers would still undergo potential blames or lower ratings from the customers even though they did not make any mistake. In terms of tipping, customers would typically tip Dashers from 15% to 30% of the total order price and also take factors such as distance or weather into consideration. However, they did not have the option to add tips on DoorDash as an appreciation of their service. Moreover, customers did not feel obligated to complete reviews of the merchants or Dashers and would possibly rate when the food and experience is extremely good or bad. Since they were only provided with the options to give thumb-up and thumb-down to food of the merchants without preparing services, they would possibly give lower ratings of Dashers for mistakes such as delays or missing items which were originally caused by the restaurant

3.5 Summary

Through the above research methods, we have gained profounding insights into DoorDash's algorithm, Dashers' delivery experience, and customers' attitudes towards Dashers' service. These insights enabled us to come up with design concepts to inform our design.

(1) There exists mistrust between Dashers and merchants and mistrust towards DoorDash's time prediction model. Based on the analysis of archived data, we noticed Dashers complained frequently on Reddit about the excessive wait time and were dissatisfied with restaurants' dishonesty, while merchants did not think the prediction model was accurate and complained Dashers of arriving too early. The survey identified 20% of Dashers who don't believe they can get the food on time and they would prefer to trust their own experience and observations instead of the estimates provided by the restaurant.

(2) There exists mistrust between Dashers and customers in terms of late delivery and uncontrollable factors. Customers were not able to keep track of Dashers' wait time at the restaurant and to figure out the cause of the delay, thus blaming Dashers for running late. Dashers, as mentioned in the survey, tended to be rated poorly for factors that were not within their control, including missing items, late delivery, and traffic. Especially in cases like batch orders, Dashers were not able to change the situation when one of the orders was already late, while customers were not even aware that Dashers were delivering multiple orders at the same time. We found a few comments from Dashers mentioning that the delay from the restaurant led to low scores even though they communicated with the customers throughout. These comments made us to be more aware of the importance of building empathy in the design process.

(3) DoorDash gave Dashers opportunities to rate their experience but most Dashers did not believe it would have any effect on merchants or customers. Less than 30% of Dasher rated their experience while nearly a half of participants would choose to rate based on the circumstances. We noticed that they tended to write reviews when the experience

was extremely bad; however, they still did not think it would have any actual effect on merchants or customers.

4 SOLUTION AND FEEDBACK

4.1 Storyboard Speed Dating

Based on the findings and insights that we generated from the research, we decided to use storyboards to illustrate our design concepts and integrate our prototypes.

4.1.1 Method Overview. The first storyboard depicted a typical scenario when customers order food from DoorDash but encounter delivery delays due to the overwhelming amount of orders at the restaurant. We have introduced new features including visualization of waiting time, real-time status, the customer's evaluation system, the customer's adding tip function, and the detailed customer feedback visualization to Dashers. We mainly aim to build customers' empathy and understanding towards Dashers and late delivery by providing more details of the process so that customers can better evaluate their experience and fairly review Dashers.

4.1.2 Storyboards. The storyboard for the first story is shown in Figure 1.

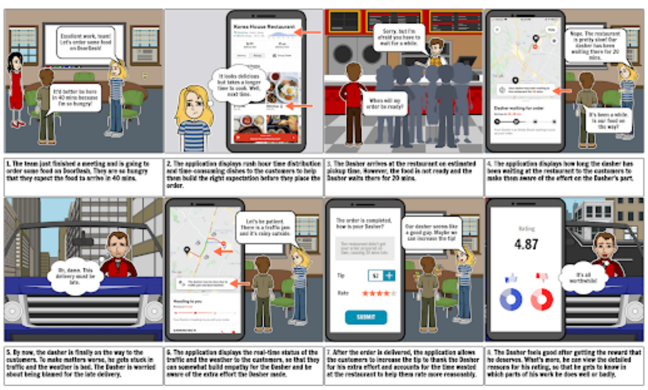

Figure 4: Storyboard 1: Delayed Delivery

The second story intended to encourage more responsible restaurants and to provide more timely feedback to the time estimation system. Informed by the carrot and stick approach, we proposed two designs: a crowd-sourcing website for Dashers and promotion of more punctual restaurants. On the crowd-sourcing website, Dashers can report their waiting time and rate restaurants based on their experience. The website would generate a list of merchants which are notorious for being late and Dashers, especially novices, can have a better picture of which restaurants they might want to avoid in future. Therefore, the website mainly works as a community where Dashers can search and share information and strategies. In order to encourage punctual and responsible restaurants, on the other hand, the algorithm would recommend restaurants that are on time so customers can order more frequently with these restaurants.

The second storyboard is shown in Figure 5 and Figure 6.

The last story is centered upon time management of batch orders, as Dashers frequently come across delays when delivering for

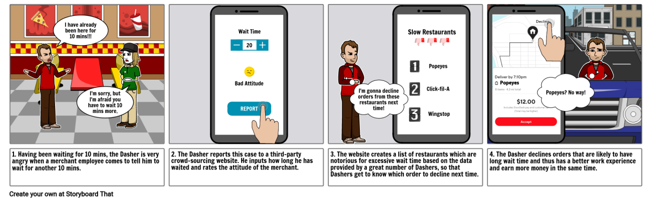

Figure 5: Storyboard 2: Report

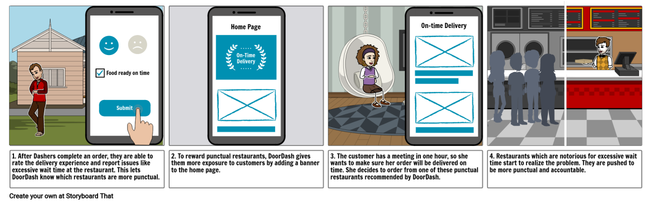

Figure 6: Storyboard 2: Reward

multiple orders. We aim to optimize the routes and save time for Dashers by providing them with re-routing features in cases such as delays. The re-planning intends to recommend possible pick-up at other merchants first so Dashers won't waste time waiting for one specific order.

Figure 7: Storyboard 3: Batch Orders

4.1.3 Feedback. We conduct storyboard speed dating [16] with 2 Dashers to get feedback on our proposed solutions. Two participants both gave positive feedback to all three of the concepts and were looking forward to the implementation. This suggested we were on the right track and successfully identified the needs of Dashers that were worth addressing. Our participants also raised concerns about the influences of Concept 1 and 2 from the perspectives of restaurants and customers, which motivated us to conduct more testing sessions with other stakeholders in the next phase. Interestingly, our participants were more engaged with Concept 3 and expressed more opinions on Concept 3, probably because Concept 3 is more integrated into Dashers' daily workflow, compared to Concept 1 and 2.

Here are detailed feedback from our participants.

Concept 1

- "It could definitely help with currently less communicated parts of our work", such as late delivery caused by the slow restaurant or a traffic jam.
- How the design will shape customers' experience and affect their behavior needs to be further verified.

  - Will customers notice the small changes on the screen when waiting for the order?
  - Will labeling some food as "long time to cook" make customers not order it?

Concept 2

- "It's good for Dashers, especially newbies, to know which restaurants they should avoid."
- In addition to on-time rate, participants would like to give more detailed feedback. They voiced for the effective use of their feedback.
  - "You should allow Dashers to add more detailed notes and then you could use the information to provide tailored or specific feedback for restaurants and customers", like suggesting a restaurant to arrange more employees at a certain period of time or asking a customer to specify his/her address for the convenience of later Dashers.

Concept 3

- "It could be pretty helpful, because now I can jump to another task but I don't know whether the second order is ready."
- Participants asked for detailed information, like the distance to the second restaurant and the specific time needed for the first order to get ready, to help them make the decision.
  - "What if the second restaurant is far away?"
  - "The problem is restaurant managers never say specific 10 minutes but 'it's on the way'. If they can specify the time needed to get food ready, I feel more comfortable to leave and head for the second restaurant."
- They thought it was important to guarantee timely responses from both restaurants.
  - "How will you guarantee the responsiveness from the second restaurant?"
  - "For batch orders, you should tell both restaurants they're in batch orders and notify the Dasher when the order is done."
- They wanted to avoid messing up orders after changing the order of picking up.
  - "After re-planning the order of picking up, you should also re-plan the order of dropping off, because I'm always messing it up."

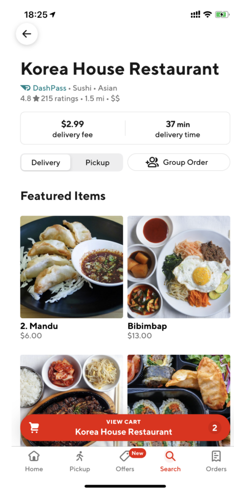

Figure 8: Interface 1

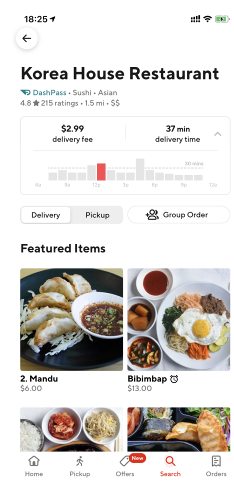

Figure 9: Interface 2

4.2 Interface Design

4.2.1 Method Overview. We designed the interfaces for several key features when building the storyboards, in order to better demonstrate our ideas. We also expected to modify them based on the feedback we gathered from speed dating sessions for the purpose of conducting more testing sessions with other stakeholders in the next phase. We chose speed dating as a method for our design phrase, as it not only allows us to explore possible concepts with future users with more breadth but also helps to identify the overlap between observed needs and perceived needs and to re-frame our topic [16].

4.2.2 Interface Design. Here are some features we designed.

Feature 1: Rush hour distribution and time-consuming dish labeling. Figure 8 is the current design of what a customer can see when he/she clicks into a restaurant on DoorDash. Figure 9 is the redesigned interface which includes a chart showing rush hour distribution and labels time-consuming dishes with an "alarm clock" icon.

Feature 2: Visibility of the time that Dasher spend waiting at the restaurant and uncontrollable factors that cause late delivery. Fig 10 is how the screen currently looks like on DoorDash when a Dasher is waiting for order and Fig 11 is how the screen currently looks like on DoorDash when a Dasher is heading to a customer. The banner added on both Fig 12 and Fig 13 is to communicate how long a Dasher has been waiting at the restaurant and uncontrollable factors that might cause late delivery.

Feature 3: Third-party crowd-sourcing website Fig 14 shows a list of restaurants that are notorious for excessive wait time in a certain city selected by the user. The rank is generated based on the data provided by a large number of Dashers who have ever received the order from the same restaurant. Factors, like the attitude of the

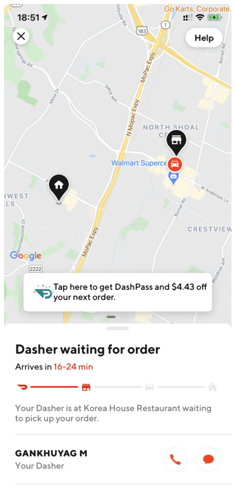

Figure 10: Interface 3

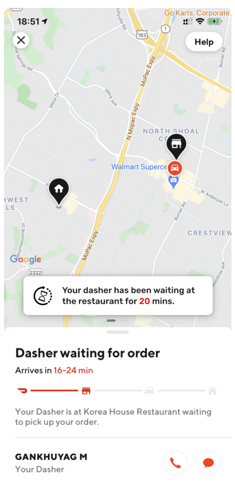

Figure 11: Interface 4

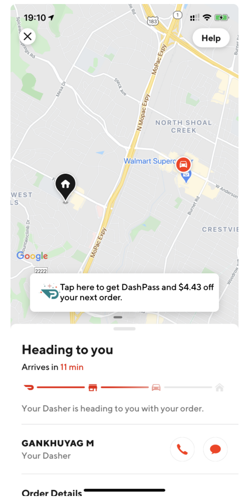

Figure 12: Interface 5

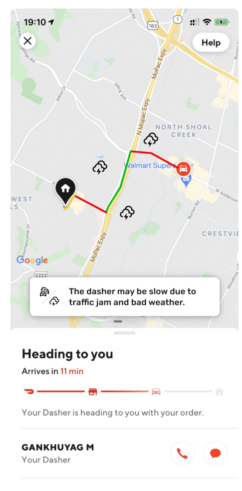

Figure 13: Interface 6

employees of this restaurant and the possibility of receiving large tips from customers who order from this restaurant, are taken into consideration. The grey section in both Fig 14 and Fig 15 displays more details that are related with wait time at a restaurant, like average wait time, on-time rate, average wait time in a certain time period, communicability and generosity. Fig 15 is the detailed page of a restaurant, which includes reviews from Dashers who have ever delivered for this restaurant. A review can serve as a note that helps later Dashers, for example finding a pickup point, or merely a complaint through which a Dasher expresses his or her displeasure.

5 CONCLUSION

In this paper, we unveiled existing problems that limited Dashers information and impacted their delivery efficiency and navigated the problem through multiple stakeholders, including Dashers, merchants, and customers. We investigated if and how their delivery efficiency were impacted by the merchants and how their ratings could impact them.

Our research results show that there exists different layers of mistrust. There is mistrust between Dashers and merchants and Dasher's mistrust towards DoorDash time prediction model. There exists mistrust between Dashers and customers in terms of late delivery and uncontrollable factors. Cases of miscommunication is also presented. Although Dasheres can rate their experience, most Dashers do not believe it would have any effect on merchants or customers.

In the end, we made an effort to address this problem with new DoorDash interface designs and third-party crowd-source website that enables empathy, increases transparency and builds trust among stakeholders. The feedback we received from Dashers were encouraging. Two participants both gave very positive feedback and were excited to the implementation of our solution. However, we

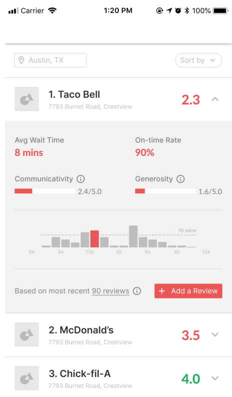

Figure 14: Interface 7

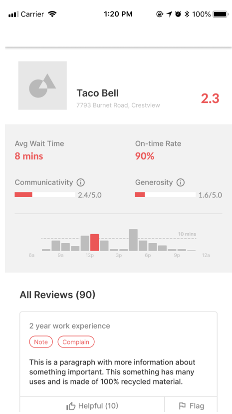

Figure 15: Interface 8

do realize the limitations of our stury. Firstly, we only intervewed 2 Dashers, which could introduce a bias due to the small sample size. Secondly, we weren't able to actually audit the algorithm of Doordash because the API was not made public. So our knowledge of the algorithm is still limited. Thirdly, we weren't able to actually see how it works on merchants end and might have misrepresented their benefit. Finally, The solutions we designed needs further tests as history has shown that a new solution also brings new problems. We do hope further efforts will be made to improve our research and help to create a more transparent and trusted on-demand food delivery platform.

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