Understanding How Customers Attribute Accountability in Food Delivery Breakdowns

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Abstract

In on-demand workplaces, the worker's ability to work is highly dependent on a number of factors that they have limited control over. As such, food delivery platforms are prone to unfair treatment of workers involving incident accountability in transaction breakdowns. A breakdown in delivery transactions may result in averse perception from customers towards the worker, restaurant or the platform company, however the accuracy and fairness of these perceptions are unclear. To address the potential effects of such crumple zones in food delivery, we will study how customers make judgements when the responsible party is unclear and whether or not customers can identify a worker's responsibility in a given incident. Through an online experiment centering contentious scenarios in food delivery, we will explore how customers may attribute accountability differently depending on the mode of explanation and transparency of who the accountable party is. Overall, in hopes of further empowering workers, we aim to understand the imbalanced perspectives in food delivery that can exacerbate unfair outcomes.

Keywords

Algorithmic accountability, automation, gig work, food delivery

1. Introduction

On-demand workplaces support a large amount of temporary gigs that are scheduled, managed, delivered and paid through online APIs [1]. As a prominent sector of the on-demand economy, food delivery has gained massive growth since the beginning of the COVID-19 pandemic [2, 3]. Like many other on-demand platforms, food delivery platforms promise flexible work [4, 5], despite the fact that workers are managed through platform functionalities that strictly dictates the what, when and where they work [6]. More importantly, the worker's ability to work is highly dependent on a number of factors that they have limited control over. As such, food delivery platforms are prone to unfair treatment of workers involving incident accountability in transaction breakdowns. Through this study, we hope to further understand how and why food delivery customers may form unfair and inaccurate perceptions of accountability in such breakdowns.

In discussion of socio-technical systems, research is increasingly recognizing the importance of accurately attributing the responsibility of actions [7]. However, these responsibilities cannot always be easily discerned in varied social and cultural contexts. Similarly, food delivery platforms—which involve multiple stakeholders (i.e., platform company, worker, customer and restaurant)—are prone to fall into a crumple zone where there might not be a single clear responsible party. To address the potential effects of such crumple zones in food de-

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livery, we will study how customers make judgements when the responsible party is unclear and whether or not customers can identify a worker's responsibility in a given incident. Furthermore, we will examine how customers perceive particular modes of explanation and the extent to which this perception affects the level of blame. We aim to answer the following questions through our research:

1) How do customers distribute accountability in unsatisfactory experiences, especially when the cause of the incident is not immediately transparent?

2) Do differing modes of explanations affect customers' perceptions in unsatisfactory experiences with multiple factors at fault?

Through an online experiment centering contentious scenarios in food delivery, we will explore how customers may attribute accountability differently depending on the mode of explanation and overall transparency of the accountable party. We use the phrase "mode of explanation" to refer to the context in which the customer receives an explanation of the transaction breakdown: in food delivery, this entails app design, communication with the driver or communication with customer service. Meanwhile, "transparency of accountability" refers to the clarity of the perpetrator. For instance, as we are determining whether or not customers unfairly attribute accountability, this entails scenarios in which the perpetrator clearly is or is not the driver, and scenarios in which the actor at fault is unclear. In all, we aim to understand the many ways in which misattribution manifests in food delivery platforms, as well as the ways in which customers' perception of particular contexts may reduce the potential of misattribution in transaction breakdowns.

2. Related Work

2.1. Algorithmic management and consumer surveillance

Research has previously focused on the issues of algorithmically managed labor, especially in the context of fairness, accountability, transparency, and ethics (FATE) [8, 9, 10, 11]. Existing work in gig platforms has discussed the ways in which on-demand workplaces take advantage of customer feedback as an element algorithmic management; some perspectives on rating argue that companies' valuation of customer feedback, in tandem with features such as route surveillance, act as a new form of "middle management" that can be described as consumer surveillance [12]. Many on-demand workplaces require certain approval ratings for workers to continue working: for example, Doordash requires drivers to have an average of 4.2 stars and UberEats requires a user satisfaction rating around 75-80% depending on the location [13, 14]. This requirement further imbalances the dynamic between workers and customers, who can easily give a poor rating—and influence the deactivation of a worker's account—if dissatisfied [15, 16]. In addition to its intrinsic pressure, customer feedback can become another workplace control mechanism for companies, allowing them to encourage workers to act in a particular manner [17]. For example, Uber sends messages to drivers suggesting that passengers give low or high ratings based on expected behaviours, using feedback to nudge drivers toward delivering a standardized service [10].

Dependence on ratings can be especially damaging in the context of on-demand workplaces, as these companies do not seek out other metrics or perspectives of worker attitude and behaviour, and customer feedback can be inaccurate as it is typically based on subjective interpretation [17]. A common complaint from Uber drivers is that "passengers do not understand how ratings work," therefore making ratings "not reflective of performance and services" [16, 8]. In fact, in a study regarding the potential polarity of ratings and reviews across a variety of platforms, sharing economy platform reviews were found to skew positively overall, with a tendency to be highly polarized [18]. To further complicate the issue of subjectivity, Uber drivers "noticed that passengers misattributed system faults and negative experiences that drivers could not control to drivers themselves" such as surge pricing, traffic jams, and GPS errors, or even the customers' mood and context during the ride [8, 16]. Similarly, food delivery drivers in forums often describe situations in which incidents are caused by issues with restaurants or app, commonly reporting that they lose tips or receive low ratings in these encounters, despite their lack of control of such factors.

2.2. Misattribution in social psychology

In social psychology, misattribution of negative events is often attributed to the "fundamental attribution error," which describes how, when evaluating the behaviour of others, observers tend to overestimate intrinsic factors while underestimating extrinsic factors [19]. In the context of customer service, this means that customers "are likely to attribute a negative outcome to an employee's effort and abilities, even when they know that something else, such as a computer system error, bad weather, or just bad luck, was responsible for it" [20]. Misattribution can have a tangible effect on customer feedback, according to "correspondence bias": people "often conclude the person who performed the behaviour was predisposed to do so... even when a logical analysis should not" [21]. Correspondence bias is caused by lack of awareness, unrealistic expectations, inflated categorizations, and lack of motivation to correct inferences made. Such traits can be found in food delivery experiences: one of our presumptions coming into the study is that customers are not motivated to give much thought to their perception of the worker, the service, and the rating and tipping they provide due the fact that a purchasing (of service) behavior is ephemeral and serves a relatively non-essential portion of one's goals. Furthermore, as described by the "illusory causation" phenomenon, people tend to overestimate the role of a particular person in a situation when the person is the most salient actor in the interaction [22]. Due to the fact that they are the most salient actors for customers in food delivery interactions, compounded with the fact that they are the primary focus in the ratings in these systems, drivers can become the wrongful recipients of blame if an order goes awry.

2.3. Moral crumple zones

In an article titled "Moral Crumple Zones: Cautionary Tales in Human-Robot Interaction," Elish uses the concept of a "moral crumple zone" to explain how responsibility and blame may be misattributed to human actors working within complex systems when these systems breakdown. Particularly, Elish discusses how systems may be designed or set up in a manner that allows the system to take advantage of human actors to "fill in the gaps of accountability that arise in the context of new and complex systems" [7]. Similarly, in the context of algorithmic management, Moradi and Levy argue that "AI-driven managerial practices redistribute the risks and costs of these inefficiencies to workers while serving a firm's bottom line" [23]. Typically, in the context of companies, the larger organization will take accountability for any faults: in "Computing and Accountability," Nissenbaum gives the example of milk producers being liable for spoiled milk, even if they have taken the expected degree of care. The larger organization or management is expected to compensate for the faults even if they did not enact them, risk distributed to “those best able to pay, and those best able to guard against the harm” [24]. However, in the context of algorithmically managed labor, the people who could be considered best able to guard against harm are those who are not best able to pay. Of course, if an order goes wrong in food delivery, the company will refund the customer and apologize to all parties for the inconvenience. But unlike the milk producers, in this scenario, the company does not take accountability for the harm caused; the worker may still lose their tips, their ratings may drop, and they are still completely responsible for themselves and whatever else may come their way.

Algorithmic reliance and collection of human stakeholders can cause food delivery systems to fall prey to “the problem of many hands”: by passing pieces of responsibility amongst different, unrelated members of the system, the company can rescind accountability for any issues, leaving the matter of blame hanging in the balance [24]. A breakdown in delivery transactions may result in averse perception from customers towards the worker, restaurant or the platform company, however the accuracy and fairness of these perceptions are unclear.

3. Method

We propose a 3x3 survey centering contentious scenarios in food delivery, varying the transparency of the accountable party and mode of explanation. In Table 1, we present a factorial design table with summaries of sample contentious scenarios based on anecdotes from forums such as /r/doordash and uberpeople.net. The dependent variables for this study will be the percentage of accountability assigned to each stakeholder in the scenario, as well as participants’ estimated ratings and tips for the worker. In the survey, we will first present scenarios through narrated video storyboards. After each scenario, we will ask participants to provide an evaluation on each of the parties in regards to responsibility in the scenario. A preliminary survey sample is provided in Figure 1. The survey-based method has been studied to be effective in allowing participants to accurately consider their behaviours as they would in a real situation [25]. Scenario-based studies are commonly used in research studying perceptions of fairness in algorithmic systems, and the reach and scale of an online experiment can be beneficial in seeking patterns in subjective matters like perception [9, 20].

Allowing participants to rate each stakeholders’ percentage of accountability in each scenario will give us nuanced understanding of the extent to which modes of explanation can affect participants’ perceptions of a scenario, and any qualitative data supplied with these ratings will help us further understand participants’ judgements and decision-making process, particularly in incidents where it is difficult to determine an accountable party. Additionally, by surveying participants’ estimated tips for each encounter, we will gain a stronger understanding of the real consequences of unfair dispersion of blame in transaction breakdowns.

Mode of explanation	Transparency of accountability		
	Clearly not driver's fault	Crumple zone	Clearly driver's fault
App design	Tracking map shows that driver is waiting at the restaurant for a long time and then order is cancelled	Tracking map shows the driver drove near the location and says the order has been dropped off, but customer receives nothing	Tracking map shows that the driver drove in the wrong direction completely and order is cancelled
Driver	Driver texts saying the restaurant is closing and refuses to make the order	Driver texts saying they dropped off the order, but the GPS led them to the wrong location	Driver texts saying they could not find the location and gave up on delivering the order
Customer service	Customer service contacts customer saying the restaurant closed and could not make the order	Customer service tells customer the driver accidentally delivered to the wrong location nearby	Customer service tells customer the driver could not find the location and ended up dropping the order

Table 1
Summaries of sample scenarios. Scripted based on transaction breakdown points discussed in driver anecdotes posted on forums such as /r/doordash and uberpeople.net.

4. Expected results and discussion

We envision three potential outcomes for the study, along with potential results for each outcome. These potential outcomes are not mutually exclusive, and all potential results may occur correspondingly.

Customers give differing distributions of accountability depending on the mode of explanation. If responses present particular patterns or skew when considering differing modes of explanation, we will closely consider the qualitative data given with the percentage of accountability rating to understand how design may contribute to or alleviate misattribution in a complex system. Participants' reasoning can tell us how and why their perception may be affected by how they receive the information, especially considering elements like trust and perceived agency. Due to the role of the customers' ratings in food delivery systems, we would closely consider the relation of participants' percentage ratings with their estimated ratings and tips, to consider how such perceptions manifest in real life. We would likely move forward by reaching out to interview participants with thoughtful qualitative responses in hopes of gaining a deeper understanding of their thought process: How or why does a particular mode of explanation evoke stronger feelings of blame toward a specific stakeholder in the food delivery system? If a participant's estimated ratings and tips tend to change with differing percentages of accountability, why? If a participant's

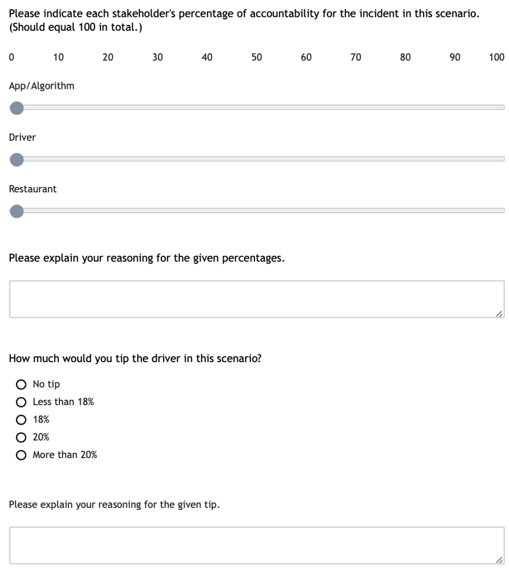

Figure 1: A screenshot of a preliminary survey format. The given questions would be shown to the participant after a narrated video storyboard or a written scenario depicting a transaction breakdown in a food delivery order.

estimated ratings and tips do not change with differing percentages of accountability, why not?

Customers perceive drivers as partially accountable in scenarios even when the negative factor is completely or partially out of the driver's control. If participants commonly give drivers a significant (≥25%) percentage of blame despite the fact that a scenario is intended to fail due to unrelated factors, we will further investigate the reasoning behind the misattribution of accountability. The reasoning behind this misattribution will give us more insight into customers' mental models of food delivery systems; in such a complex system, we can discover who customers see as the primary actor in the system and why. Through the results of the survey, and extra interviews, we can more effectively understand the reasoning behind tendencies to blame the driver: Does the customer believe the driver could have done more to ensure the goal was met? Or, is the system designed such that blame is assigned to the driver, perhaps due to their proximity to the customer or the fact that feedback on the platform is directed towards the driver?

Neither of the above. If we find that neither outcome is true, we can use the data we collect on attribution of accountability as well as estimated tipping and rating behaviour to better understand why and how customers rate as they do. As mentioned above, we would likely conduct further interviews for more context of why participants' responses. Through this study, we could gain a better understanding of the correlation of blame/accountability of an encounter to a given rating or level of tip. Alternatively, we could further extend the study to explore the ways in which the system can be better designed to make the system more transparent to the customer.

5. Conclusion

As algorithmic management and algorithmic reliance becomes increasingly prevalent in the organization of labor, the harms of misattribution of accountability will become increasingly prevalent as well. Crumple zones, stemming from the misattribution of accountability in large, opaque systems with heavy algorithmic reliance, can be used to further take advantage of workers in systems where they may already be inherently disadvantaged. As an industry with systems dependent on a large collection of human and algorithmic actors, food delivery platforms are an appropriate environment to consider the ways harm can be misattributed to particular human actors and the ways platforms can be designed to minimize such harm. By the end of this study, we hope to understand 1) the ways in which customers distribute accountability in negative experiences, especially when the cause of the incident may be hidden by the complexities of the system and 2) the mode of explanation that most transparently expresses context to the customer. Overall, in hopes of further empowering workers, we aim to understand the imbalanced perspectives in food delivery that can exacerbate unfair outcomes.

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