Social Challenges of Uber's Driver Rating System

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Social Rating Systems and Uber

From the moment individuals enter grade school, they are inundated with a wide range of metrics used to report their performance in a wide variety of personal skills and abilities, from mathematical prowess to financial responsibility. Much of the time, however, these metrics are consolidated into a single metric, intended to summarize all performance metrics into a score or discernable number. From Grade Point Averages (GPA) measuring a student's performance in school, to Fair Isaac Corporation (FICO) scores reporting trust in an adult's financial responsibilities, social rating systems have proven useful for decision makers when they must take action towards individuals, whether it be for college admissions or offering a loan. However, such systems are often agnostic towards the context surrounding individuals being rated, leaving room for disparity to grow between the ratings of different social group.

Enter Uber, a rideshare brokering service which connects drivers to individuals in need of transportation. In order to establish continual trust in its drivers, Uber implements a star rating system, allowing riders to rate drivers on the quality of the ride out of five stars. If a driver falls below 4.6 stars, they become at *risk of deactivation* from use of the service (Cook, 2015). However, this rating system primarily relies on said user ratings to measure driver performance, resulting in different segments of Uber's driver market to experience varying levels of pressure from ratings and systematic biases (Rogers, 2015). Given its varying impacts on the different social groups which utilize the application, Uber's star system provides the case study used throughout the rest of this thesis to explore the social factors which cause social rating systems to create disparity between social groups. Understanding these social factors is important for rating system designers in order to avoid disenfranchising certain social segments of their user base. The Social Construction of Technology (SCOT) framework is used throughout this paper to determine said social factors and their subsequent effects on how individuals use rating technology (Klein & Kleinman, 2002), ultimately answering the following research question; How have various social factors influenced the use of Uber's driver rating system and its subsequent effects on drivers?

Methods of Analysis

Two methods are used to explore the question posed above: wicked problem framing and network analysis. The former characterizes societal issues depending on how deeply engrained they are in culture, resulting in a highly difficult solution space due to the complexity of the issue. This difficulty often leads to the symptoms of a wicked problem being addressed as opposed to the root of the problem. The Wicked Problem framing is used to outline underlying issues that social groups face even outside the context of Uber, particularly social biases (Hua & Ray, 2018) and corporate responsibility in regards to user safety (How Uber Star Ratings Work For Driver-Partners, n.d.).

After the social groups and their environment are characterized through Wicked Problem, they are synthesized through Network Analysis to explore the connections they have with Uber and its rating system. Analyzing the Uber network is mainly facilitated by the use of simulation of a simple model between Uber drivers, riders, and ratings. The simulation tool Simio is used to perform said simulation. Results are tabulated and analyzed in both the short and long run as well as cross-referenced with existing knowledge of network dynamics. Such simulation is helpful for explaining the relationships between actors within the Uber network, each linked together through hierarchies, social group membership, and/or monetary ties. Yamagishi, Gilmore, and Cook's 1998 paper on network structures as well as Antionio Chiesi's 2015 paper on network dynamics in relation to social behavior serve as center points for this analysis.

Firmino, Cardoso, & Evangelista's research on "Uber and Surveillance Capitalism by the Global South" (2019) is also used to outline how Uber's network which restricts the mobility of social groups within given sub-networks. By extracting the relevant social factors through wicked problems and applying them in a network analysis, this paper discusses how Uber's driver rating system can be used by social groups to inadvertently and systematically disenfranchise Uber drivers.

Trends in Uber and Rating System Phenomena

Social rating systems are systems which report the performance of an individual within a specific task area. From financial credit ratings like Fair Isaac Corporation (FICO) scores to student grading systems in public schools, social ratings systems are not unfamiliar to the general public. However, as these systems become more crucial for workplace environments, a discussion has emerged on how certain social groups are disenfranchised more than others from such systems. The advent of China's social credit system provides an extreme example of this, where an individual can receive social benefits or sanctions depending on their everyday behavior (Philipp, 2018). But while that system is still in its prototype phase, there is a much more established rating system present in the western world with very clear social ramifications contingent on a user's performance: Uber.

Uber provides an interesting case study due to its relative youth and its driver rating system detailing very clear consequences for drivers with low ratings; that is, *risk of deactivation* if a driver's rating falls below 4.6 stars (Cook, 2015). With different segments of Uber's driver market carrying various amounts of autonomy in relation to Uber, different social groups receive varying levels of pressure from the driver rating system, particularly as it pertains to opposing bias from riders (Rogers, 2015). Part-time drivers, who usually consist of well-off non-immigrant drivers, tend to enjoy much more flexibility in their work and less stress from ratings (Bowman, 2019) and less bias to work against for their ratings. Full-time drivers on the other hand are typically immigrants or minorities (Hua & Ray, 2018) and feel they must work harder to dissipate preconceived notions of themselves from riders to obtain higher ratings. Actions include consistent upkeep of their car's interior or providing free items such as water for their passengers (Rogers, 2015).

In his 2007 paper on rating systems in E-Commerce, Dr. Eric K. Clemons, a professor at the University of Pennsylvania, describes how rating systems can cause an information deficit for buyers due to rating information being more visible on a seller's side. This in turn causes room for doubt from the buyer in the quality of a good provided by a seller. Thus, it's been found that information asymmetry is a key factor that can explain how raters may cast initial doubt on ratees and question the quality of a good or service due to the absence of sufficient information (Clemons, 2007). This concept is adapted to the scope of Uber's rating system in a later section of this paper.

In the journal of *Surveillance and Society*, Firmino, Cardoso, & Evangelista's 2019 research on hyperconnectivity describes how hyperconnected societies can actually close off particular social groups from entry into the network. This translates to hyperconnected networks shaping themselves in a way that discriminates against the weakest social groups. In particular, it describes Uber as a brokerage service that outsources its labor. And without direct control over its work force or consumer base, Uber's usage is more directly shaped by actions and movements in society, facilitated to an extent through its rating system.

Social Construction of Technology

This research serves as an exploration of the relationship between social groups (in particular, driver workforce segments in Uber) and a driver rating system technology. As such, a Science, Technology, and Society theory is used to explain the driver behind their relationship. In particular, Social Construction of Technology (SCOT) is used to explain the relationship Uber's driver workforce holds with its rating system.

By analyzing the customs and norms within a social group, SCOT practitioners seek to understand the underlying reasons behind a technology's varying usages due to cultural differences between social groups (Klein & Kleinman, 2002). In the context of Uber, this comparing how different raters use the rating system and how their backgrounds influence the ratings different drivers get. In his paper titled "Technological Momentum," Thomas Hughes, a history professor at the University of Pennsylvania, describes how technologies in their early phase are more shaped by the surrounding society while more mature technologies tend to shape society. Founded in 2009, Uber, one can argue, is a young company and as such hasn't had the time for its rating technology to yet be the larger determiner of societal motion, particularly that of biases between social groups.

In his 1993 paper, "Upon Opening the Black Box and Finding It Empty: Social Constructivism and the Philosophy of Technology," Social Scientist Langdon Winner, from Rensselaer Polytechnic Institute, criticizes SCOT, describing how the framework often fails to take into account the views of people weren't involved in the creation process of a technology, but must use it regardless. In Uber's case, this can refer to how the demographics of a particular segment of their labor market aren't represented in the composition of the design team. As such, rather than looking at how the social background of the designers' factor into the development of the application, this research explores how the background of the designers allows the rating system to cater towards particular labor segments but not others.

In this paper, SCOT is used to explore how the circumstances of drivers in different market segments change their view of the driver rating system, and thus have shaped the system itself. Such information on change is supplemented by Uber's own documentation of their rating system updates in 2017 (Improved Rating System and Feedback Protection for Drivers, n.d.). Subsequently, various rider segments within the network are included in the analysis to see how their varying norms or preconceptions of driver segments affect the ratings they give.

Social Challenges

Three major issues are identified as wicked problems which propagate via the Uber's rating system to disenfranchise immigrant and part-time drivers. These issues are racial bias against immigrant drivers, asymmetry of expectations between riders and drivers, and Uber's lean application structure contrasting with the motivation of full-time drivers. As wicked problems, these issues are complex and manifest uniquely between different cases, with no clear solutions other than those that serve to help mitigate the symptoms. These factors do no act independent of one another, but rather, confound each other to create greater roadblocks to the success of drivers within immigrant and full-time social groups. These roadblocks serve as the way in which rider social groups influence the use of Uber's rating system away from a way of giving objective quality of service feedback. These influences occur on both a micro scale, where riders will superficially rate their individual drivers, as well as on a macro scale, where the strength of immigrant and full-time drivers within the network is weakened by competition from non-immigrant and part-time drivers.

Racial Bias against Immigrants

In his 2015 article titled “The Social Costs of Uber,” Professor Brishen Rogers describes the phenomenon of “emotional labor,” where minority drivers perform extra tasks in order to appeal to riders and ultimately increase their chance of receiving a high rating. This emotional labor occurs because minority drivers need to overcome racial preconceptions riders have of them, particularly immigrant drivers of Middle-Eastern descent, who have expressed facing abuse from riders after the events of 9/11 (Hua & Ray, 2018). A supplementary task that minority drivers must then perform, Roger describes, is “identity work,” or “a conscious effort to track white, middle-class norms.” Such a task contrasts against social groups in traditional ride-share industries such as the taxi-cab, where drivers feel more comfortable being themselves without feelings of servility. This factor in particular often propagates through many different channels beyond just the rating system, encompassing many conscious and unconscious biases and constructively interferes with the other factors described below the most.

Asymmetry of Expectations

As humans, we typically opt to take the road which requires the least cognitive effort, and often will take many cognitive shortcuts and make assumptions to reach quick initial judgements. This pattern of thought leads to people taking shortcuts in regards to ratings and how to interpret both them and the services people receive. People are used to seeing high ratings, so as a result, they don't critically consider the performance of highly rated items or services beyond simply high expectations of quality (Kim, Moravec, & Dennis, 2019). For Uber drivers with high ratings, this means drivers run the risk of riders not expending enough cognitive resources when evaluating a driver. Often, this presents itself as riders forming expectations based on the high ratings that ultimately go unmet. The result is an information asymmetry, a phenomenon where between two parties, often that of buyer and seller, one has more access to specific information on the good or service provided, creating distrust between the two parties (Clemons, 2019). Asymmetry in Uber is found between rider and driver, where drivers are unaware of the expectations a person holds for their experience, and riders are unaware of the driver's capacity to meet their expectations.

This issue is agnostic of the specific demographics of a driver. For instance, researchers Juliette Hua and Kasturi Ray illustrates the story of a white, middle-aged, mother who drove part-time for Uber. Despite seeming to fit the quintessential Uber demographic (white, part-time), the mother described her experience as maddening, with riders often making her feel “lame,” as she describes, due to failures to meet excessive service expectations such as knowing the area perfectly enough to not use a GPS (Hua & Ray, 2018). Stories such as this demonstrate the effect of misalignment of expectations, which ultimately leads to dissatisfaction and subsequent poor ratings. The demographics of a driver serve to further exacerbate this phenomenon by adding more expectations and preconceived notions between rider and driver.

Lean Application Structure

Uber’s promises to drivers are laid out on their sign-up page as “Earn anytime, anywhere. Set your own schedule. Signing up is easy.” Such promises align with a vision of empowering users who are looking to make supplementary income, or in other words, become part-time drivers (Driver Signup Form, n.d.). Promises of ownership and freedom made available through the application not only draws in potential part-time drivers however. Given its value proposition of easily accessible ride sharing (seeing the car as a shared resource), Uber is designed to be very easy to join, making it attractive for anyone (or any social group) who to wants to explore it as an option to instantly start generating income (Hua & Ray, 2018). Herein enters the large demographic of immigrant, full-time drivers.

Societally speaking, immigrants have a more difficult time finding a steady source of income, having just immigrated to the country. As a result, immigrants are often drawn to Uber and its promises, utilizing the app to generate full-time income, subsequently shaping its usage away from that of a form of supplementary income and towards a sole source of income. However, Uber’s application is not built upon the premise of steady income drivers, but rather, payment is made on a per-run basis, meaning payment is given out between a driver and a rider, with a cut going to Uber. This flipped payment system (with Uber taking a cut rather than delivering income) means that income is unstable for full time drivers, leading into a precarious line of work with minimal job security. Hua and Ray describe another driver, a full-time immigrant driver Adham Shaheen, who even purchased a vehicle to drive full-time, leaving him with a large debt to pay off through the unstable income Uber provides, ultimately destabilizing his personal life (Hua & Ray, 2018). It should be noted that these experiences are not unique to immigrant full-time drivers. The very nature of full-time driving for Uber is unstable, with full-time drivers working much more than part time drivers (Hua & Ray, 2018).

Network Effects

These factors are not all separate, but rather, confound each other. The lean structure of the application disservices full-time drivers, who are attracted by the prospect of freedom and instant income, only to be met with an unstable revenue stream where ratings from individuals effect their job stability and net income. The struggle of providing ride-sharing services full time opens the door for unmet expectations to create barriers for drivers, who cannot adequately meet the desires of each individual rider. These factors provide outlets for racial biases to come into play, putting increased pressure on the immigrant demographics to subvert preexisting expectations to achieve higher ratings. These ratings can then be represented in the larger network in the form of probabilistic links, increasing or decreasing the probability of a specific driver in a social getting more riders (and hence, more ratings).

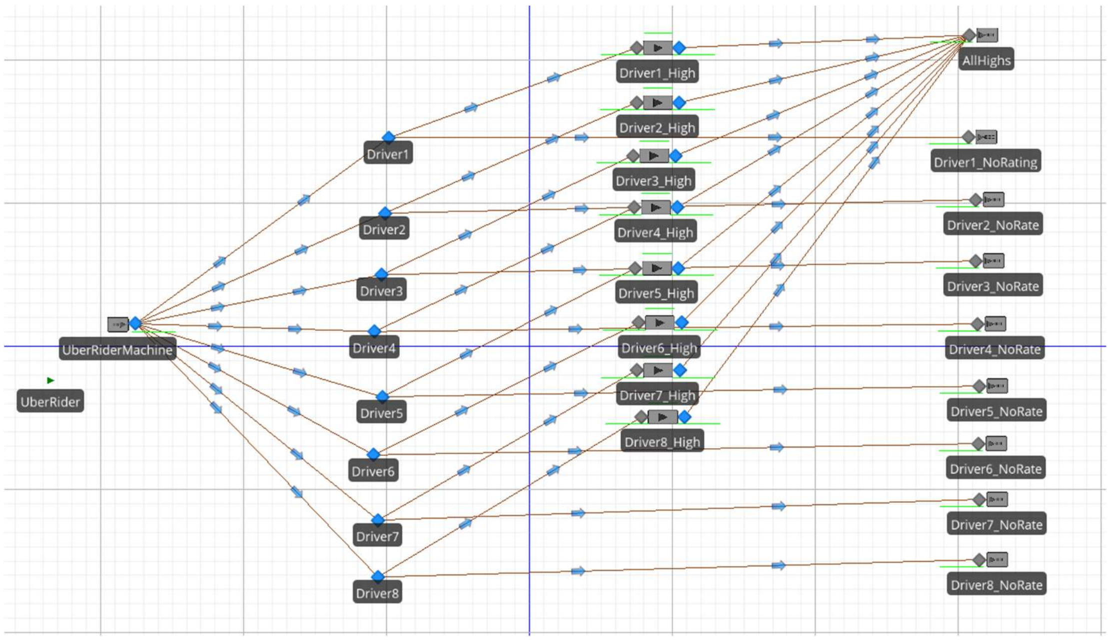

Figure 1. Simple Uber Driver - Rider Network. Created by Ian Tucker in Simio

Figure 1 depicts a simple flow network where Uber riders are randomly generated and connect with a certain Uber driver. Driver nodes are listed on the left, each of whom have a given probability of receiving a rider. Upon completion of a ride, the Uber rider can then give the driver either a high or low rating, represented by the nodes in the middle and right side of the figure. The subsequent ratings a driver receives affects their probability of receiving future riders. The network is modeled as a negative network, meaning drivers must compete with each other for resources, namely for riders (Yamagishi, 1988). One driver obtaining a rider inhibits other drivers from gaining a rider (and thus a subsequent rating). The demographics of each driver are listed below:

	Race	Work Schedule	Initial Ratings
Driver 1	Immigrant	Full-Time	High
Driver 2	Immigrant	Full-Time	Low
Driver 3	Immigrant	Part-Time	High
Driver 4	Immigrant	Part-Time	Low
Driver 5	Non-Immigrant	Full-Time	High
Driver 6	Non-Immigrant	Full-Time	Low
Driver 7	Non-Immigrant	Part-Time	High
Driver 8	Non-Immigrant	Part-Time	Low

Table 1. Driver characteristics within network model

All drivers are assumed to provide high quality ride services that adhere to minimum ride sharing expectations (successful travel to target destination, safe travel, lack of disrespect). The probability a rider is paired with any of these drivers is modeled upon the ratings of each driver relative to the entire network. After being paired with a driver, the rider has the option to either give a high rating (5 stars) or no rating at all. Ratings other than 5 stars are not included in the model in order to both simplify the model and examine how the flow of 5-star ratings alone can influence the flow of riders as a whole. Full-time drivers were treated as though working an 8-hour day while part-time drivers were treated as working a 4-hour day. The model simulates one full work day under two different scenarios; a null model and an equal weight model.

Under the null model, the social factors described previously were not used at all in determining how a rider rates their driver. In that sense, whether the driver received a high rating was treated as totally random. Under the equal weight model, the three social factors were factored into rating decisions, all modeled as roadblocks which decrease the probability of a driver receiving a high rating depending on how much each factor affects their demographic social group. A third and fourth model under the same conditions as the null and equal weight models were also run, but simulating a full week of driving as opposed to just a day.

It should be noted that these are theoretical models with the purpose of understanding how the social factors discussed prior can affect rating system networks at large (even weight model) in comparison to a hypothetical rating system unaffected by said factors (null model). In other words, rather than validating the even weights model, the analysis which follows is only concerned with assessing how drivers are affected by these social factors as opposed to a scenario where these social factors didn't exist. The results are as follows:

Null Model

ID	Full Class	Number of High Ratings	No Ratings	Total Rides	Percent high ratings
Driver 1	immigrant (full time), high ratings	394	525	919	43%
Driver 2	immigrant (full time), low ratings	249	350	599	42%
Driver 3	immigrant (part time), high ratings	197	329	526	37%
Driver 4	immigrant (part time), low ratings	127	239	366	35%
Driver 5	white (full time), high ratings	372	469	841	44%
Driver 6	white (full time), low ratings	235	353	588	40%
Driver 7	white (part time), high ratings	248	350	598	41%
Driver 8	white (part time), low ratings	146	240	386	38%

Table 2. Results from running the null model to simulate a day of working under no social factor conditions

Null Model (Extended)

ID	Full Class	Number of High Ratings	No Ratings	Total Rides	Percent high ratings
Driver 1	immigrant (full time), high ratings	2,226.00	3,184.00	5,410.00	41%
Driver 2	immigrant (full time), low ratings	1,769.00	2,571.00	4,340.00	41%
Driver 3	immigrant (part time), high ratings	1,523.00	2,280.00	3,803.00	40%
Driver 4	immigrant (part time), low ratings	1,187.00	1,879.00	3,066.00	39%
Driver 5	white (full time), high ratings	2,250.00	3,222.00	5,472.00	41%
Driver 6	white (full time), low ratings	1,655.00	2,566.00	4,221.00	39%
Driver 7	white (part time), high ratings	1,683.00	2,550.00	4,233.00	40%
Driver 8	white (part time), low ratings	1,196.00	1,922.00	3,118.00	38%

Table 3. Results from running the null model to simulate a week of working under no social factor conditions

Even Weight Model

ID	Full Class	Number of High Ratings	No Ratings	Total Rides	Percent high ratings
Driver 1	immigrant (full time), high ratings	147	731	878.00	17%
Driver 2	immigrant (full time), low ratings	117	479	596.00	20%
Driver 3	immigrant (part time), high ratings	95	440.00	535.00	18%
Driver 4	immigrant (part time), low ratings	90	323.00	413.00	22%
Driver 5	white (full time), high ratings	170	661.00	831.00	20%
Driver 6	white (full time), low ratings	181	537.00	718.00	25%
Driver 7	white (part time), high ratings	186	513.00	699.00	27%
Driver 8	white (part time), low ratings	156	305.00	461.00	34%

Table 4. Results from running the even weights model to simulate a day of working under social factor conditions

Even Weight Model (Extended)

ID	Full Class	Number of High Ratings	No Ratings	Total Rides	Percent high ratings
Driver 1	immigrant (full time), high ratings	673	3,511.00	4,184.00	16%
Driver 2	immigrant (full time), low ratings	767	3,152.00	3,919.00	20%
Driver 3	immigrant (part time), high ratings	655	2,750.00	3,405.00	19%
Driver 4	immigrant (part time), low ratings	869	2,796.00	3,665.00	24%
Driver 5	white (full time), high ratings	929	3,868.00	4,797.00	19%
Driver 6	white (full time), low ratings	1,337.00	4,063.00	5,400.00	25%
Driver 7	white (part time), high ratings	1,273.00	3,833.00	5,106.00	25%
Driver 8	white (part time), low ratings	2,062.00	3,437.00	5,499.00	37%

Table 5. Results from running the even weights model to simulate a week of working under social factor conditions

Results of the null model demonstrate an idealistic view of the Uber rating system, with roughly an 8% range in the ratios of high ratings to total rides (Percent high ratings). Those with low ratings struggle to catch up in terms of their ratings over the course of one day of driving. But as seen in the extended null model, one week of driving serves to equalize the ratios more, with at most a 3% difference.

The even weight model however shows a different story, where immigrants and part time drivers struggle to receive consistently high ratings. Low rated drivers, despite the struggle to climb out of low ratings, will actually benefit from them in the face of expectations and bias since low ratings prompt users to think more critically about the experience before giving a rating. In addition, despite full-time drivers often haven provided more rides, they come out with the lower ratio of high ratings to rides. The gap appears to only increase over the extended period, where the difference in ratios increases from 17% to 21%.

This disparity in high ratings per ride given demonstrates a power phenomenon found in networks such as Uber where social groups on the bottom of network hierarchies struggle to mobilize beyond their sub-network. Because of a lean application structure which relies on interpersonal connections with minimal regulation (which is echoed in the network), social issues instantly break down the vision of a shared resource ecosystem, leading people to judge each other's performance and a driver and rider via delivering ratings to one another. In other words, for social groups such as full-time drivers and immigrants, the network does not play in their favor and inhibits them from moving to a more beneficial space in the network (namely, that which allows them higher ratings) (Firmino, 2019).

According to researcher Antonio Chiesi, this makes sense from a network structure perspective. He describes that in negatively connected networks, depending on what happens during an exchange, power dependency relationships may change, leading to continual structural transformations. In the case of Uber, this translates into strengthened bonds between riders and specific driver segments, which results in the increased ratio of high ratings to rides given for more privileged social groups. Chiesi also describes how social mobility is a function of the amount of inequality present in the network. For Uber, the rating system serves as an avenue not to just express inequality, but cyclically propagate it throughout the network.

Limitations

Major limitations extend from a lack of time to explore extended interpersonal factors, interrelationships between said factors, and subsequent network models. More micro-scale, psychological and social factors such as confirmation bias were not explored in this study nor included in the network model. Alternative weightings, or how much each factor really inhibits drivers from receiving high ratings, were also not explored. The simplicity of the network model also restricts any further conclusions to be made given the large number of assumptions made (competition between drivers, estimated rating effect on connecting riders to drivers, objective quality of ride service provided). Lastly, reciprocal rating relationships, as in those which involve drivers and riders rating each other, have not been explored, excluding a bilateral aspect of the network which would increase the density of the network and thus influence analysis of the spread of changes in network. Overall, model complexity serves as the biggest limitation to this research.

In further research, an extended model should be developed, with multiple rider archetypes being randomly generated and assigned to drivers, from which their unique subjectivity can be applied to their probability to giving a rating. Increasing model complexity will allow for deeper conclusions to be made about the extent to which the rating system propagates inequality throughout the Uber network. Professional data scientists and network analysts would also be pivotal in increasing both the efficiency and depth of analysis, allowing for patterns to be identified and subsequently explored in order to identify the largest contributors to inequality and resultant social immobility in the network.

Looking Forward

Three social factors were identified as key to the disenfranchisement of immigrants and full-time drivers to Uber: Racial bias, asymmetric expectations, and lean application structure. These factors do not work independently, but rather together to create barriers to immigrants and full-time drivers from receiving higher ratings, ultimately causing larger disturbances in the uber network. These disturbances over the long run generate power gaps between social groups in the form of weak and strong links between different social groups and the Uber rider base. The continual structural adjustments caused by the strength of social exchanges consequently creates immobility for immigrants and full-time drivers, pushing them to expend extra effort in their line of work to receive the same amount of ratings as other social groups.

Uber has attempted to address many of the issues revolving around its rating system, requiring users for instance to include feedback on why they give a low rating. Prompts like this do help address factors such as cognitive affordance to critically rating drivers (Improved Rating System, n.d.). However, they do not assist in factors which begin expressing at the start of rides, such as asymmetric expectations of the ride experience. These are important to consider moving forward when considering any rating system as they are the social factors which will propagate throughout a system network before ratings are even given. In other words, proactivity becomes key in ensuring that ratings are made in a way which does not systematically disenfranchise large user segments.

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