Measuring the Impact of the Large-scale Adoption of Ridesharing on the Spread of Infectious Diseases

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16. Abstract

In the near future, ride-sharing vehicles are expected to serve a significant fraction of the transportation demands in cities and urban areas. In the past two decades, there has been an increased occurrence of highly infectious diseases like COVID-19 in the world. The simultaneous increase in ride-sharing penetration in the cities and the occurrence of infectious diseases around the world raise a question about the safety of ride-sharing vehicles amid an infectious disease outbreak. In this paper, we investigate the role of ride-sharing vehicles in the spread of COVID-19 in metropolitan areas. To this end, we considered a compartmental model to capture the progression of SARS-CoV-2 infections in an urban population and an agent-based simulation to capture the ride-sharing exposure to the disease. It is shown through the simulation that in the absence of any within-vehicle disease-control measures, ride-sharing can aggravate the spread of disease. Furthermore, it is shown that effective implementation of disease outbreak control measures at the ride-sharing level can almost nullify this aggravation.

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INTRODUCTION

Recent advancement in information technology and an increment in smartphone ownership has given rise to an alternative mode of intra-city transportation called 'ridesharing' *(1)*. Ridesharing has transformed transportation, making it easier and more affordable to get from one place to another. At present, ridesharing service providers like Uber and Lyft contribute to about 2–12% of total vehicle miles traveled (VMT) in big metropolitan cities like New York and San Francisco *(2)*. In the next two decades, the proportion that ridesharing vehicles represent in the total transportation demand in urban centers is predicted to increase *(3)*.

Widely disseminated national and international transmission of infectious disease outbreaks has increased in recent decades, at least partly due to an increase in domestic and international transportation *(4, 5)*. Usually, long-distance transmission is intercalated with domestic community widespread leading to major worldwide transmission patterns as evidenced in the recent SARS and COVID-19 outbreaks. Of particular concern are highly infectious agents capable of person-to-person transmissions, such as the severe acute respiratory syndrome coronavirus (SARS-CoV) and the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the etiological agents of SARS and COVID-19, respectively. These pathogens can disseminate via airborne transmission during close contact with an infected person and, potentially, from contaminated fomites *(6)*. The aerosols and droplets can remain suspended in the air for several hours within the vehicles *(7)*. Similarly, the viral traces can be found on the surface hours after being expelled from an infected person *(8)*. When the chance of close contact between driver and passenger and the chance of contact with a contaminated surface within the ridesharing vehicle is considered, ridesharing vehicles can act as an additional ground for exposure to the disease *(9)*. In the future, with increased utilization of ridesharing services, people will make more frequent direct or indirect contact with others who are outside their normal social network *(10)*. Therefore, ridesharing is expected to make changes in how infectious diseases are transmitted from person to person.

The two most accepted methods to model the spread of infectious disease are compartmental modeling and agent-based modeling. The aim of disease modeling is to understand the spread of infectious disease and the efficacy of different control measures *(11)*. The equation-based compartmental model assumes a certain level of homogeneity in the population, whereas the agent-based simulation considers the heterogeneity of individual agents in the simulation environment. Moreover, the compartmental models are usually less computationally demanding than the alternative agent-based modeling, which could take days to run on a computer for simulation. In addition to these two methods, a hybrid model that combines both compartmental modeling and agent-based simulation in a single framework has also been used to study the disease progression *(12)*.

In this paper, we evaluate the role of ridesharing on the spread of infectious diseases during an outbreak using a hybrid compartmental/agent-based modeling approach. A novel hybrid simulation model is developed to estimate disease exposure resulting from the use of ridesharing services. A compartmental model is used for macro-level disease transmission among an urban population, including both documented and undocumented cases, while an agent-based model is used to track micro-level disease transmission through ridesharing services specifically. Key simulation parameters are identified from the case of the COVID-19 outbreak in the Tampa Bay area for numerical experiments. Subsequently, several scenarios resulting from studying various values of key parameters are simulated to assess the level of significance of these parameters. Finally, we simulate the application of different outbreak control measures in ridesharing and analyzed their impact on disease transmission.

METHODOLOGY: A HYBRID SIMULATION FRAMEWORK

We develop a two-layered simulation framework that encompasses both a macro-level simulation and a micro-level simulation, as follows (Figure 1). The first layer represents a macro-level simulation, updated at the end of each day. The macro model is built as a modified compartmental model, based on the susceptible-exposed-infected-recovered (SEIR) model *(13)*, and estimates the number of people in each compartment by the end of each day. The output from this first layer is used to find the number of drivers and passengers from each compartment for the next day, and this information is provided to the second layer.

The second layer represents the micro-level simulation built from agent-based modeling, updated every hour. This layer provides the number of people exposed to the disease due to the use of ridesharing. While daily interaction among people is modeled within the macro-level model, the micro-level model tracks interaction from ridesharing specifically. At the end of each day, we aggregate the total ridesharing exposure and feed this information to the upper layer. The cycle repeats for the next day.

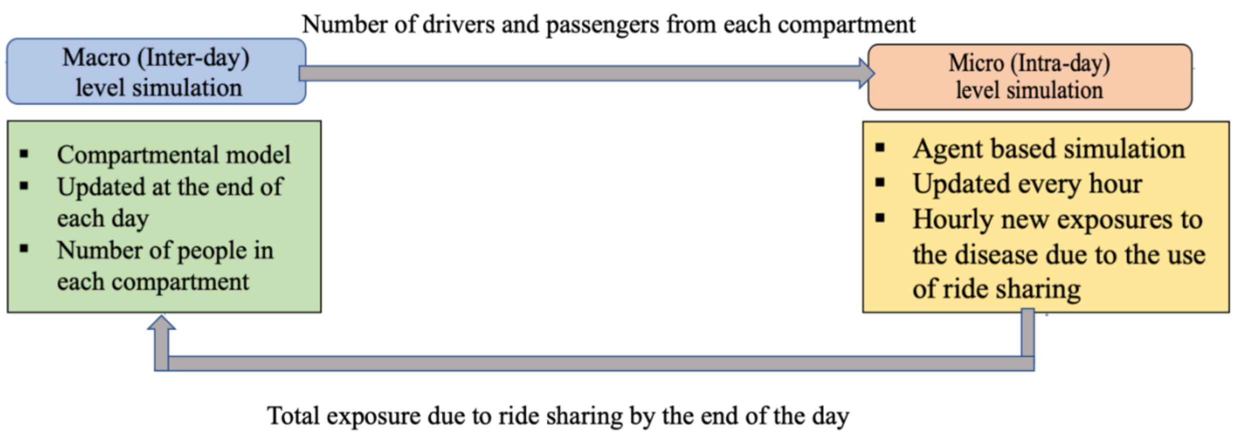

Figure 1 Simulation Framework

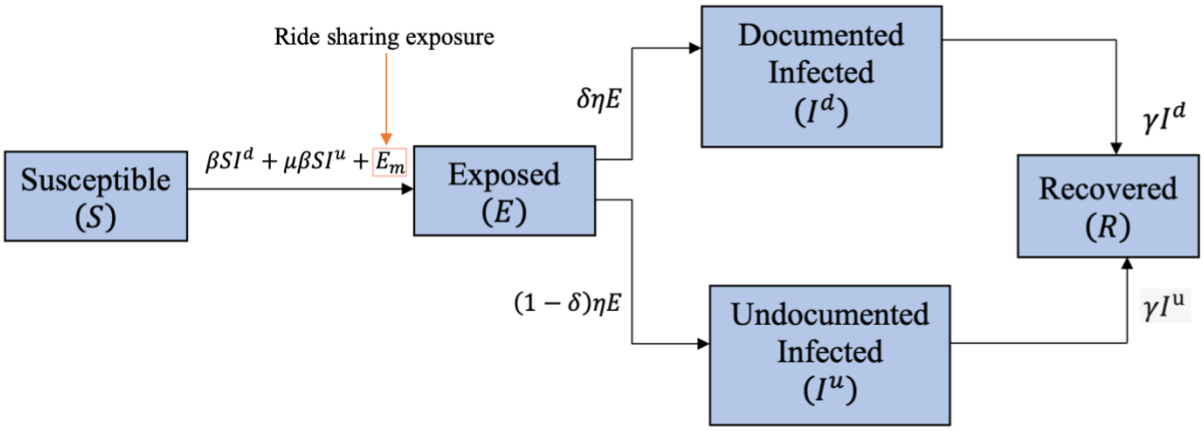

Figure 2 Schematic diagram of the compartmental model

Macro Model

The macro model captures the spread of disease across the city. The whole city is considered a single closed zone. As shown in Figure 2, the population in the city is divided into five different compartments: susceptible, exposed, undocumented infected, documented infected, and recovered. The 'infected' compartment in the SEIR model is divided into 'documented infected' and 'undocumented infected' sub-compartments, and hence the compartmental model is called a modified SEIR model. Susceptible individuals can be infected from an infected person or a contaminated surface at a rate β. Exposed individuals can either develop symptoms (i.e., document infected individuals) at a rate ηδ or remain undiagnosed (i.e., undocumented infected) at a rate η(1 - δ). Undocumented infected individuals are infected by the disease but develop very little to no symptoms. Therefore, the people in this compartment do not get diagnosed, continue their movement in the city, and may continue to spread the disease. Those people who develop acute symptoms and get diagnosed are labeled as documented infected individuals in our model. The individuals of this compartment get hospitalized or isolated and hence play a little to no role in the transfer of disease. People become recovered from the disease at a rate γ and are assumed to develop immunity to the disease. The equations and parameters governing the compartmental model are provided in the appendix.

Micro model

The agent-based model at the micro-level captures the exposure of a susceptible person to the disease due to the use of ridesharing specifically. The ridesharing exposure can be broken down into two modes of disease exposure: Driver to passenger (D2P) exposure and passenger to passenger (P2P) exposure. The exposure of a susceptible passenger to the disease due to contact with an infected driver is D2P exposure, and the exposure due to contact with a contaminated surface within a vehicle is termed as P2P exposure. As we only consider single-passenger rides in this paper, P2P does not include transmission among passengers in ride pooling.

The agent-based model keeps track of driver-vehicle pairs for a day. At the beginning of each day, the state of health of drivers is updated based on the proportions of the population in different compartments, extracted from the macro-level model output. The driver-vehicle pair is randomly assigned to fulfill travel demand. After each trip, the state of contamination of each vehicle, as well as the state of health of driver and passenger, is updated. By the end of each day, the total number of people exposed to the virus via ridesharing is fed to the macro-level model.

BASE CASE SCENARIO OF DISEASE SPREAD

We use the case of COVID-19 spread in the Tampa Bay area and its scale in our numerical experiments. The Tampa Bay Metropolitan Area has about 3.2 million population. The first two COVID-19 cases in Florida were reported in the Tampa Bay area on March 1, 2020 (Florida Department of Health, 2020). For simulation purposes, we assume the outbreak starts with 2 documented infected, 12 undocumented infected, and 120 exposed individuals. All the simulations are initialized with the same numbers of individuals in each compartment as mentioned above to ease the comparison between different outbreak mitigation policies at the ridesharing level. We assume that, for a city of size Tampa, 4% of total transportation demand is fulfilled by ridesharing *(2)*. We also assume that ridesharing vehicles transport one passenger at a time and do not support pool transport.

This work aims at investigating the role of ridesharing in the spread of COVID-19 and the effectiveness of different control measures in ridesharing environments rather than predicting the exact spread of the disease in the city. Bearing this in mind, we use a scenario of disease spread in the city as depicted by the parameter values in Table 1.

Table 1 Parameter values over the simulation period

Days	β	μ	η	δ	γ	Rideshare utilization rate
1-10	1.00	0.8	0.25	0.10	0.25	100%
11-29	0.95	0.8	0.25	0.30	0.25	90%
30-55	0.90	0.8	0.25	0.50	0.25	80%
56-70	0.85	0.8	0.25	0.60	0.25	70%
71-90	0.45	0.8	0.25	0.60	0.25	45%
91-135	0.57	0.8	0.25	0.60	0.25	70%
136-160	0.70	0.8	0.25	0.60	0.25	80%
161-300	0.8	0.8	0.25	0.60	0.25	85%

On the first day, the parameters were set as $\beta = 1$, $\mu = 0.8$, $\eta = 0.25$, $\delta = 0.1$, $\gamma = 0.25$ *(13)*. We also assumed that on the first day, there is a 100% utilization of ridesharing service available in the city (i.e., 4% of total transportation demand). As the number of infected cases increases in the city, there is a gradual decrease in movement within the city, reflected by the decline in the value of β and rideshare utilization rate *(14, 15)*. Moreover, there is an increase in disease screening, resulting in an increase in the value of δ. After 70 days, the government imposes a ban on non-essential travels, as a result of which there is a sudden drop in these values. Likewise, after 90 days, government loosens its restrictions, acknowledging the decline in the number of cases. This causes an increase in β and rideshare utilization rate.

We assume that 99% of documented infected individuals, among the non-driver population, are isolated, and they do not play any role in the spread of disease in the city. There are many reported cases where the ridesharing drivers still drive the vehicles even with easily noticeable symptoms *(16)*. This is because the ridesharing drivers work as contractors. For many full-time ridesharing vehicle drivers, avoiding ridesharing means no source of income to support the family *(17)*. Without any compensation packages for the isolated drivers, there will always be some documented infected drivers who are willing to drive. Therefore, we assume that there is a 20% probability that the documented driver still drives a ridesharing vehicle. We also assume that once the vehicle is contaminated, it remains contaminated throughout the day unless the vehicle is disinfected. There is no specific study that quantifies this chance of exposure to SARS-CoV-2 in a ridesharing environment. However, the closed and confined setting of ridesharing with limited ventilation increases the risk of exposure to the disease significantly as compared to the open environment *(18–20)*. Hence, both the P2P and D2P exposure probability were assumed to be 0.3 in the base case scenario, which is then varied in our various scenarios.

RESULTS OF NUMERICAL EXPERIMENTS

We first present our results that demonstrate the role of ridesharing in the base case scenario and test various levels of ridesharing utilization rates and penetration levels. Then we test various control measures that can be used for ridesharing drivers and passengers. The hybrid model was written in Python 3.7, and all the simulations were run on Intel core i7 processor with 16 GB RAM.

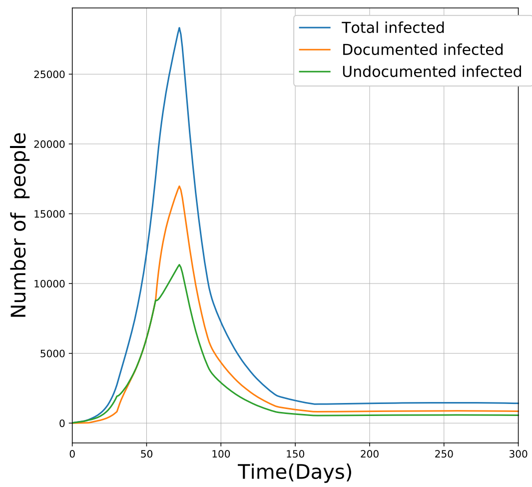

Figure 3 Disease progression over the simulation period

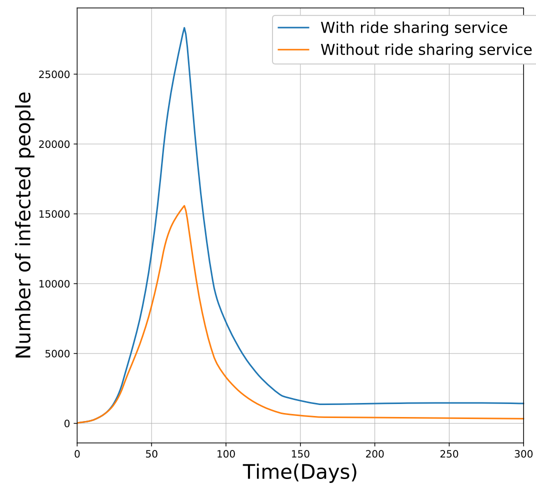

Figure 4 Disease progression with and without the presence of ridesharing service in the city

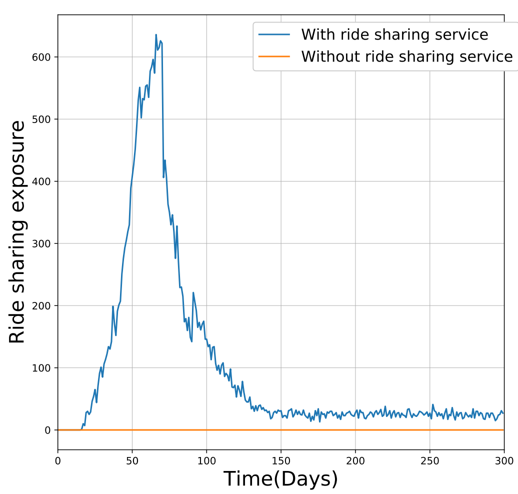

Figure 5 Number of ridesharing exposures

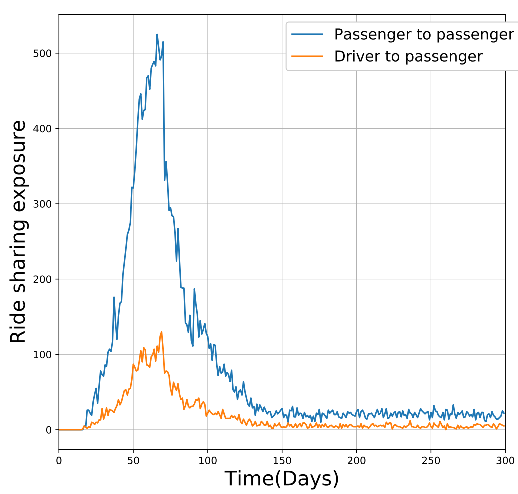

Figure 6 Passenger to passenger vs. driver to passenger exposure

Role of ridesharing in the base case scenario outbreak

Figure 3 shows the progression of SARS-CoV-2 transmission over the simulation period with parameter values as indicated in Table 1. There is an exponential growth of infected individuals after 10 days, and the spread attains its peak on the 74th day. As we assumed that the rideshare utilization rate decreases as the outbreak starts, the infected cases start to decline. Similarly,

Figure 4 shows the differences in the disease progression with and without the presence of ridesharing in the city. In the absence of any kind of ridesharing service in the city, 5.94% of the total population would be infected with the disease. But when 4% of total transportation demand in the city is fulfilled by ridesharing, 11.37% of the total population would be infected. This astounding increase in the number of infected cases in the city is in the absence of any kind of disease control measure at the ridesharing level. Figure 5 provides the number of new susceptible individuals exposed to the disease, due to the use of ridesharing. And even though ridesharing contributes to only about 8.31% of total exposure to the disease, the dynamics of disease progression differs significantly as compared to the disease progression in the absence of ridesharing. Figure 6 provides a breakdown of ridesharing exposure into P2P exposure and D2P exposure. P2P exposure contributes about 81.7% of total ridesharing exposure. We observe that indirect P2P exposure through contaminated vehicles plays a critical role in disease spread.

Since all the documented population and almost all the documented drivers are isolated, the spread of the disease in the city is caused solely by the undocumented infected population. The actual fraction of the SARS-CoV-2-infected population that becomes undocumented (or asymptomatic) is still debatable *(21, 22)*. Given this, Table 2 provides different scenarios of the fraction of infected cases that become documented (δ) and the corresponding change in ridesharing exposure, as well as a percentage of the overall population that becomes infected over the simulation period. As expected, with an increase in the value of δ, the ridesharing exposure decreases and the total number of infected cases in the city also decreases and vice-versa. Even when the majority of the cases are documented, ridesharing vehicles still create new exposures.

Results in Table 3 show that an increase in disease exposure probability also increases the total infected cases in the city. However, a change in P2P exposure probability produces a significant change in both the ridesharing exposure and the infected cases as compared to the same change in D2P exposure probability.

Table 2 Different scenarios of δ and disease progression

Days	δ Scenario 1	δ Scenario 2	δ Scenario 3	δ Scenario 4
1–10	0.15	0.12	0.08	0.05
11–29	0.45	0.36	0.24	0.15
30–55	0.75	0.60	0.40	0.25
56–70	0.90	0.72	0.48	0.30
71–90	0.90	0.72	0.48	0.30
91–135	0.90	0.72	0.48	0.30
136–160	0.90	0.72	0.48	0.30
161–300	0.90	0.72	0.48	0.30
Change in ridesharing exposure in comparison to the scenario in Table 1	-98.36%	-82.30%	+271.40%	+457.82%
Overall population infected	0.52%	2.48%	38.10%	68.47%

Table 3 Different values of P2P exposure probabilities and their effect in disease progression, compared to the baseline scenario (P2P probability=0.3, D2P probability=0.3)

exposure probability		Change in ridesharing exposure in comparison to the baseline scenario	Overall population infected
P2P	0.5	+117.77%	16.21%
	0.1	-70.68%	7.75%
	0.01	-88.41%	6.71%
D2P	0.5	+21.13%	12.36%
	0.1	-26.30%	10.04%
	0.01	-34.71%	9.61%

Table 4 Different scenarios of rideshare utilization rate and disease progression

Days	Scenario 1	Scenario 2	Scenario 3
1–10	100%	100%	100%
11–29	100%	72%	45%
30–55	96%	64%	40%
56–70	84%	56%	35%
71–90	54%	36%	22.50%
91–135	84%	56%	35%
136–160	96%	64%	40%
161–300	100%	68%	42.50%
Change in ridesharing exposure in comparison to the scenario in table 1	+39.05%	-41.53%	13.16%
Overall population infected	13.16%	9.12%	7.36%

Table 5 Rideshare penetration in the city and impact in the spread of the disease

Ridesharing penetration level	Change in ridesharing exposure in comparison to the scenario in table 1	Overall population infected
2%	-73.60%	7.37%
8%	+324.50%	23.68%

Impact of ridesharing utilization rates and penetration levels

Table 4 provides different scenarios of change in ridesharing utilization rate and its influence on disease progression in the city, respectively. The findings in these tables suggest that a rapid decline in the ridesharing utilization rate significantly brings down the number of infected cases in the city.

Similarly, the results in Table 5 provide a different level of ridesharing penetration in the city (i.e., the percentage of transportation demand fulfilled by ridesharing vehicles) and their corresponding effect on disease progression. It is seen that as the level of ridesharing penetration in the city increases, the adverse role of ridesharing in disease progression also increases.

Disease outbreak control measures in ridesharing level

The simulation of different scenarios in the above section gives an insight that ridesharing service as an alternative mode of intra-city transportation can increase the adversity of infectious disease outbreaks in the city. A complete halt of ridesharing service amid an infectious disease outbreak is not a viable option. Instead of a complete halt, we explore different control measures at the ridesharing level.

100% isolation of documented infected drivers

Local authorities become aware of the disease outbreak when there is a noticeable number of documented infected individuals in the city. In our simulation, by the end of 10 days, there are 15 active documented infected cases. At this point in time, the local authorities can make sure that all the documented drivers are isolated. This control measure can be put into practice by implementing compensation packages as well as removing ridesharing service licenses for documented drivers. Isolation of all the drivers with the symptoms decreases the D2P exposure by 22.56% and P2P exposure by 3%. However, this control measure alone only reduces the total infected cases in the city by 0.4%.

Disinfection of vehicles

One of the means to moderate P2P exposure is to disinfect the ridesharing vehicle regularly. Alcohol solutions with at least 70% alcohol and EPA registered microbial products can be used to clean seats, door handles, floor mats, seat belts, light and air controls, and any other parts that can have the remains of virus from an earlier infected passenger *(23)*. We investigated three different vehicle disinfecting policies: disinfecting vehicle after 4 rides, after 2 rides, and after each ride. We assumed that once a vehicle is disinfected, it remains completely virus-free unless the driver is infected, or a new infected passenger gets in the vehicle. As pointed out in Table 6, an increase in the frequency of disinfection reduces the ridesharing exposure significantly. Disinfection of vehicles after each ride eliminates P2P exposure and the overall infected population drops from 11.37% to 6.74%.

Table 6 Different disinfection policies and their effectiveness

Disinfection policies	Change in ridesharing exposure	Change in P2P exposure	Change in D2P exposure	Overall population infected
Disinfection after four rides	-75.30%	-83.00%	-43.30%	8.04%
Disinfection after two rides	-85.94%	-94.74%	-49.65%	7.15%
Disinfection after each ride	-90.90%	-100.00%	-53.40%	6.74%

Table 7 Different level of effectiveness of precaution and hygiene in ridesharing environment and their impact on disease progression

Effectiveness of the precautions and hygiene	Change in ridesharing exposure	Change in P2P exposure	Change in D2P exposure	Overall population infected
50% reduction in both P2P and D2P exposure probability	-67.70%	-67.70%	-67.70%	7.88%
50% reduction in P2P and 80% reduction in D2P exposure probability	-72.17%	-68.76%	-87.38%	7.62%
80% reduction in P2P and 50% reduction in D2P exposure probability	-85.30%	-88.45%	-71.39%	6.90%
80% reduction in both P2P and D2P exposure probability	-89.30%	-89.30%	-89.40%	6.63%

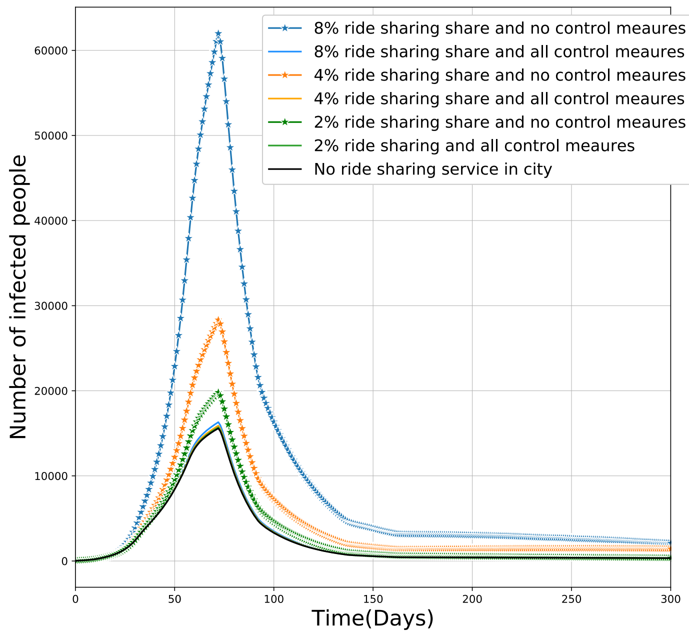

Figure 7 Effectiveness of combined control measures with different penetration of ridesharing service in the city

Proper precaution and hygiene

Both the driver and passengers can adopt proper precautions and proper hygiene to reduce the chance of ridesharing exposure. Some of the act of proper precaution and hygiene in ridesharing practice during an outbreak are mentioned below *(23)* :

- Proper use of face-covering clothes such as mask
- Creation of a partition between driver and passenger compartment, if possible
- Avoiding contact with the surfaces touched by passengers before cleaning and disinfection
- Avoiding touching eyes, nose, or mouth
- Sanitizing/washing hands after every ride

The actual reduction in ridesharing exposure depends on the effectiveness of these precautions and hygiene *(24)*. In Table 7 we provide a different level of effectiveness of precaution and hygiene and their corresponding impact on outbreak control. An 80% effective implementation of preauction and hygiene from both driver and passenger reduces the ridesharing exposure by almost 90% and the total infected population in the entire area drops from 11.37% to 6.63%.

Combination of the different control measures and their effectiveness

When each of the proposed control measures is put in practice alone, the ridesharing service still contributes to a substantial number of exposures to the disease. Nevertheless, the combination of all the above-mentioned control measures can aid to decrease the ridesharing exposure further. Assuming that the ridesharing service fulfills 4% of total transportation demand and the proper precaution and hygiene from both the drivers and passengers are 80% effective, the combination of all the control measures reduces the ridesharing exposure by 98% and 6.05% of the overall population become infected with the disease (Figure 7). In comparison to the scenario where there is no ridesharing service in the city, even with the combination of all the control measures, ridesharing adds 600 ridesharing exposure. This number can be reduced by implementing the effectiveness of proper precaution and hygiene practices that further reduce D2P exposure probability.

Similarly, when ridesharing fulfills 2% of total transportation demand in the city, the combination of all the control strategies decreases the ridesharing exposure by 97.3% and 5.98% of the total population become infected.

Likewise, when 8% of total transportation demand in the city is fulfilled by ridesharing, the joint effect of all the control measures lowers the ridesharing exposure by 99.1% and 6.21% of the total population become infected.

DISCUSSION

Ridesharing services may aggravate the spread of highly infectious diseases like COVID-19, especially in big cities with large ridesharing penetration. We have presented a study of the role of ridesharing during an infectious disease outbreak in a city. Our simulation results suggest that within vehicle infection control measures can reduce the risk of ridesharing-associated disease transmission. However, the level of the increase in infected cases due to ridesharing depends on several key factors. Almost all the documented infected individuals in the city are isolated, and only undocumented infected individuals are responsible for the spread of disease. Owing to this fact, the fraction of exposed cases that become infected (δ) largely determines the severity of disease progression in the city as well as the role that ridesharing plays during the outbreak. When only a small fraction of infected cases is identified and isolated, there is an overall increase in both ridesharing exposure as well as the total number of infected cases in the city as compared to the situation when a large fraction of infected cases is identified and isolated. Similarly, the level of ridesharing penetration in the city also determines the intensity of its role in the disease spread in the city. For instance, as the penetration of ridesharing service increases from 2% to 8%, the infected cases in the city increase by almost 220%. Vehicular movement within the city decreases as the number of documented infected cases increases.

Our result in

Table 4 suggests that a rapid drop in the ridesharing utilization rate during the disease progression decreases the gravity of the ridesharing service's role in disease spread. In addition to this, the value of P2P and D2P exposure probability also drastically affect the ridesharing service's role in disease spread. Even though the decrease in both P2P and D2P exposure probability decreases the ridesharing service's role in disease progression, a small change in P2P exposure probability results in a pronounced change in infected cases as compared to a small change in D2P exposure probability. To sum up, even with a small penetration, ridesharing service can drastically exacerbate the progression of disease in the city.

Different control measures can be implemented at the ridesharing level to diminish the ridesharing exposure to the disease. 100% isolation of documented drivers reduces the D2P exposure but still does not create much difference in overall ridesharing exposure. Another, control measure, disinfection of vehicle after each ride eliminates the P2P exposure and hence drastically reduces the ridesharing exposure. Similarly, proper precaution and hygiene from both driver and passenger brings down the chance of both P2P and D2P exposure and eventually lowers the total ridesharing exposure. But the overall effectiveness of this control measure depends on the efficiency of the precautions and hygiene practices adopted by both parties. However, when each of the above-mentioned control measures is put in practice, rideshare still contributes to a considerable number of exposures and this increases the number of infected cases in the city. Nevertheless, the combination of all the proposed control measures eliminates the P2P exposure and remarkably reduces the D2P exposure. This helps to make ridesharing service almost a safe mode of transportation even during an infectious disease outbreak in urban settings.

LIMITATIONS

Among various assumptions that we made in this study, our model assumes uniformity in transportation demand among different age groups as well as the length of trips. We also single-passenger rides only. Consideration of the heterogeneity of these factors can give a more comprehensive result. Given the computational complexity, the agent-based simulation in this study keeps track of each driver-vehicle pair, only for the day. Our model assumes lifelong—at least long-term—immunity, which is still debatable.

CONCLUDING REMARK

With an increase in the acceptance of ridesharing as a major transportation source in urban areas, ridesharing services can exacerbate the spread of highly infectious diseases like COVID-19. While the simulations in the study do not exactly replicate the progression of disease in the Tampa Bay area, the purpose of this model is to help public health officials and policymakers understand the potential role of ridesharing in the spread of highly infectious diseases. The control measures proposed in this study can be an aid for the local authorities and the policymakers to make ridesharing service a safe mode of transportation during an outbreak of infectious disease. Furthermore, this paper opens a new field of study in the intersection of transportation and disease spread.

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APPENDIX

Discrete compartmental model

A set of difference equations are used to model the transition of the population from one compartment to the other. The difference equations used for the modeling purpose are:

$$S(t+1) = S(t) - \mu\beta S(t) I^u(t) - \beta S(t) I^d(t) - E_m(t)$$

$$E(t+1) = E(t) + E_m(t) + \mu\beta S(t) I^u(t) + \beta S(t) I^d(t) - \eta E(t)$$

$$I^u(t+1) = I^u(t) + (1-\delta)\eta E(t) - \gamma I^u(t)$$

$$I^d(t+1) = I^d(t) + \delta\eta E(t) - \gamma I^d(t)$$

$$\mathrm{R}(t+1) = \mathrm{R}(t) + \gamma I^u(t) + \gamma \mathrm{I}^{\mathrm{d}}(t)$$

$$N(t) = S(t) + E(t) + I^u(t) + I^d(t) + R(t)$$

where, $S(t)$, $E(t)$, $I^u(t)$, $I^d(t)$, $R(t)$ and $N(t)$ represent the number of susceptible, exposed, undocumented infected, documented infected, recovered and the total population of the city in the day t respectively. $E_m(t)$ represents the number of new ridesharing exposure by the end of the day t.

The parameters in the compartmental model are:

i. β: Transmission rate of documented infected individuals

$$\beta = \text{(number of close contacts with the susceptible population in a day)} \times \text{(probability of exposure to the disease)}$$

ii. μ: The rate by which the transmission rate of undocumented infected is reduced as compared to the documented infected. $(0 < \mu < 1)$

iii. η: The fraction of exposed population that become infected. If z is the mean latency period of the disease, then $\eta = \frac{1}{z}$

iv. δ: The fraction of infected population that become documented. So, (1-δ) is the fraction of the infected population that becomes undocumented. ($0 < \delta < 1$)

v. γ: Recovery rate. If d is the average duration of infection for infected patients, then $\gamma = \frac{1}{d}$

Simulation Framework

for day = *1, 2, ..., N* **do**

Find the hourly travel demand for the day;

Assign the compartment to each driver based on the proportion of the population in each compartment;

for time in day = *1, 2, ..., t* **do**

Randomly assign the vehicle-driver pair to fulfill the hourly travel demand;

Update the state of health of passengers, drivers, and the vehicles;

end

Feed the total ridesharing exposure to the compartmental model;

Update the compartmental model for the day;

end

Algorithm 1: Algorithm for agent-based simulation