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A regression-content analysis approach to assess public satisfaction with shared mobility measures against COVID-19 pandemic

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A R T I C L E I N F O

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A B S T R A C T

Introduction: The transportation sector was severely impacted by the COVID-19 pandemic, with shared mobility services being the most affected due to concerns from the public regarding the high likelihood of being a vector of the virus. Although studies have evaluated the impact of the COVID-19 pandemic on shared mobility, a deeper understanding of public satisfaction with the measures adopted during COVID-19 has not been explored.
Methods: This study utilized data collected in the Summer of 2020 across the United States to fill that literature gap. The study applied Ordered Probit (OP) models to explore the factors influencing an individual's confidence in not contracting COVID-19 while using shared mobility modes and Text Network Analysis (TNA) to understand the deeper reasons for their confidence levels.
Results: Results show a significant influence of sociodemographic factors, land-use/built environment, pre- and post-COVID travel behavior, and activity participation on respondents' level of confidence for not contracting COVID-19. Only frequent public transit users showed that they have high confidence in not getting COVID-19 when they use any of the shared mobility options, while people who did not use public transit and those who frequently attend telehealth meetings had low confidence in the measures adopted by shared mobility providers. Furthermore, the text mining results indicated that cleanness was the key theme regardless of the confidence level of the respondents, except for rail and bus transit. However, we observed other patterns of themes across the types of shared mobility.
Conclusions: The study findings can be beneficial in the future to improve ridership during pandemics by considering perceptions and satisfactions of various users.

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1. Background

The transportation sector was among the sectors severely impacted by the COVID-19 pandemic, especially during the lockdown period. Contrary to personal vehicles, transportation modes that promote sharing such as ridesharing, rental cars, public transportation, and bike sharing were severely impacted. The high severity of the impact of COVID-19 on ridesharing was due to concerns on the part of the public regarding the higher likelihood of contracting viruses when using ridesharing since they would act as vectors of the COVID-19 virus. This was because of the fear that a person with COVID-19 who utilized shared modes could easily leave traces of the infection in the vehicle. The viruses could then be easily transmitted to another person who later used the same vehicle. A similar scenario can also be described for ridesharing such as Uber, public transit, taxis, and bikeshare.

Since the emergence of COVID-19, various studies have evaluated its impact on transportation in general and shared mobility in specific (Jenelius and Cebecauer, 2020; Liu et al., 2023; Push, 2022; Rotaris et al., 2022). Studies have shown how detrimental COVID-19 has been to the transportation industry and the ridesharing business (Jenelius and Cebecauer, 2020). Overall, the vehicle miles of travel (VMT) declined significantly during COVID-19 (Liu et al., 2023). Further, shared mobility ridership levels declined significantly during the lockdown period, and it had a direct relationship with the socioeconomic factors of the related community (Qi et al., 2023). Although the ridership for most modes has recovered to near-normal (pre-pandemic levels), bus transit is still struggling in various cities (Dowling et al., 2024; J. Kim and Lee, 2023; Kwon et al., 2023; Parker et al., 2021) and the recovery rate is not uniform (Lizana et al., 2023). Underinvestment and underfunding have been identified as major factors that affected PT in small urban cities during and post-COVID-19, and additional funding would ensure a successful recovery of these systems (Goodland and Potoglou, 2023). Nevertheless, COVID-19 deaths, vehicle hygiene conditions, and income inequality reduced PT ridership, and long waiting times at stops combined with higher transfer rates account for higher reduction rates (Nikolaidou et al., 2023). In addition to that, the domino effects from the pandemic have led to insolvencies as well as liquidations on the part of some shared mobility providers. Although there have been numerous studies on COVID-19 and shared mobility impacts, a deeper understanding of the public perception and concerns with shared mobility during and after the pandemic has not been well explored.

Specifically, the key attributes to consumers' confidence in the measures deployed by the shared mobility providers during COVID-19 have not gathered great attention in the literature despite their importance. Studies have not explored the key reasons for consumers' confidence in the measures using their own words. In most cases, survey questionnaires with stated preference components have been utilized. Such an approach does not allow consumers to express their views compared to an open-ended survey. Understanding consumers' perceptions of the measures deployed in the ridesharing vehicles during COVID-19 would benefit policymakers and planners in case of similar life-altering events in the future. Therefore, this study uses a regression-content analysis approach to explore the key attributes and themes that linked consumers' perceptions of the measures undertaken by shared mobility operators during COVID-19.

The rest of the manuscript is organized as follows; The next section presents the literature review followed by the methodology and data description. Results and discussion are then presented followed by the conclusion, limitations, and implications for future work on this topic.

2. Literature review

The advent of the COVID-19 pandemic has had a profound impact on numerous industries, including public transportation systems. Such impacts prompted a number of studies that targeted various objectives, utilized diverse datasets and methodologies, and provided various insights.

The objectives of various studies on shared transportation models during the COVID-19 pandemic were multifaceted. Dong et al. (2021) aimed to assess passengers' satisfaction and safety perceptions in public transport post-COVID-19 in China, exploring the impact of heightened anxiety and safety concerns on passenger behavior. They conducted a cross-sectional research approach combined with online questionnaires to gather data on passenger experiences and perceptions. Shen et al. (2020) examined the experiences of Chinese individuals regarding preventive measures in public transportation, focusing on the implementation and effectiveness of safety protocols. Their objective was to understand how passengers adapted to new safety measures and whether these measures were perceived as effective in mitigating the risk of COVID-19 transmission. In New York City, Wang and Noland (2021) sought to understand the effects of the pandemic on bike-sharing and subway systems. They aimed to analyze ridership trends, changes in travel behavior, and the resilience of different transportation modes during the pandemic. Bergantino et al. (2021) aimed to enhance the sustainability of mobility infrastructure, particularly focusing on bike-sharing systems in urban areas. Their objective was to identify key factors influencing the adoption and usage of bike-sharing systems and to propose strategies for improving the sustainability and accessibility of shared transportation options in cities. Pourfalatoun and Miller (2023) examined the shifts in e-scooter usage preferences and perceptions amid the pandemic and quarantine behaviors. Findings from shared e-scooter trip data (N = 2604) revealed a decrease in trip frequency but an increase in trip duration. Additionally, survey data (N = 134) suggested a decrease in public transit and ride-hailing usage among those primarily leaving their houses for essential activities, highlighting the potential for hygiene-focused initiatives. Brown and Williams (2023) investigated the impact of COVID-19 on equitable transportation systems in the U.S., particularly focusing on ride-hailing services. Analysis of Uber trip data across four California regions revealed that ride-hail trips declined significantly during the pandemic, especially in higher-income areas and neighborhoods with more transit commuters. However, certain demographics, such as older residents and minority groups, continued to rely on ride-hailing for essential trips, emphasizing the necessity for resilient transportation systems.

Moreover, numerous reviewed studies utilized various datasets and approaches to gather insights into shared transportation during

COVID-19. Dong et al. (2021) utilized cross-sectional surveys and online questionnaires to capture passengers' perceptions, attitudes, and behaviors regarding public transport safety and satisfaction post-COVID-19. Xu et al. (2023) investigated post-pandemic travel preferences among residents of Alabama, gathering insights through an online survey to discern shifts in behavior such as increased reliance on active travel and potential avoidance of ride-hailing services. Machine learning algorithms were employed to analyze the responses (N = 481) and identify key factors shaping these preferences. Gkritza et al. (2023) conducted three surveys across distinct communities varying in transit and smart mobility usage levels: Indianapolis (low), Minneapolis (medium), and Chicago (heavy). These surveys aimed to gauge public perceptions regarding public transit and emerging technologies like ride-hailing, micro-mobility, and micro-freight delivery services amidst the COVID-19 era. Additionally, the study assessed the correlation between specific demographic factors and travel preferences amid the pandemic. Bergantino et al. (2021) conducted national-level online surveys to collect data on key factors determining the use of bike-sharing systems, including accessibility, affordability, and user experience. Some studies compared pre- and post-pandemic data to evaluate changes in behavior and perceptions (Jabbari and MacKenzie, 2020), while others analyzed specific datasets such as bike-share and subway usage alongside policy responses (Wang and Noland, 2021). Geographic information systems (GIS) were utilized for spatial analysis in some studies (Nian et al., 2020) allowing researchers to assess the spatial distribution of transportation patterns and COVID-19 impacts on travel behavior. Natural language processing (NLP) techniques were applied for data preprocessing and analysis in studies focusing on textual data from online forums and platforms related to shared transportation (Mojumder et al., 2021). The methodologies adopted in these studies were diverse and tailored to address specific research questions. Dong et al. (2021) employed a cross-sectional research approach combined with online questionnaires to gather data on passenger satisfaction and safety perceptions. They used statistical analysis techniques to examine the relationships between safety perceptions, anxiety levels, and satisfaction with public transport services. Similarly, Bergantino et al. (2021) utilized online surveys at the national level to explore factors influencing bike-sharing system usage, employing descriptive and inferential statistical analysis to identify key determinants of bike-sharing adoption. Jabbari & MacKenzie (2020) compared pre- and post-pandemic data using participant questionnaires to assess changes in transportation behavior, preferences, and attitudes towards shared transportation modes. Wang & Noland (2021) analyzed datasets encompassing bikeshare and subway usage alongside policy responses, employing time-series analysis and regression modeling to examine ridership trends and the impact of policy interventions on transportation systems. Additionally, some studies used geographic information systems (GIS) for spatial analysis (Nian et al., 2020), enabling researchers to visualize and analyze spatial patterns of transportation behavior and COVID-19 impacts on travel patterns.

The key findings from these studies provide valuable insights into the impact of COVID-19 on transportation systems and passenger behavior. Dong et al. (2021) highlighted the trade-off between safety perceptions and satisfaction in public transport, emphasizing the need to address passenger anxiety and safety concerns through targeted interventions and communication strategies. Jabbari & MacKenzie (2020), and Pourfalatoun and Miller (2023) noted a shift away from crowded transportation options, indicating changes in passenger preferences and behaviors during the pandemic. Teixeira et al. (2023) and Wang & Noland (2021) found that bike-sharing systems exhibited greater resilience compared to subways, suggesting a potential shift in transportation preferences towards safer and more flexible options. Additionally, Rotaris et al. (2022) observed fluctuations in bike-sharing demand post-lockdowns, indicating evolving transportation behavior in response to changing pandemic conditions. These findings underscore the importance of adaptive strategies, resilience, and sustainability in shared transportation systems, particularly during times of crisis such as the COVID-19 pandemic.

In summary, the literature indicated that the impact of COVID-19 on transportation has been heavily studied. However, the approaches used to evaluate such impacts were not flexible enough to allow respondents to express their views. That being the case, most studies focused on the association but not the reasons for such an association. Also, the results obtained in these studies show various factors that could drive the individual's confidence in not contracting COVID-19 shared mobility, but the reasons behind such confidence are rarely explained using traditional approaches. Thus, this study bridges that gap by accommodating respondents' views in the analysis using text mining in addition to the regression analysis. The next section presents the details of the data used in this study.

3. STUDY data

To understand the factors that may influence the user's confidence that they would not contract COVID-19 while using any shared mobility mode, a web-based stated preference survey was designed, developed, and disseminated to a national panel of United States adults in the Summer of 2020. While it was important to capture the impact of the COVID–19 pandemic on trip-making, activity participation, and travel behavior, it was also important to use a firm foundation from which these impacts could be best measured. Therefore, the research team not only collected data since the onset of the pandemic, but also elicited information from respondents to record their pre-COVID perceptions, opinions, and attitudes to travel, trip-making, and activity engagement. The web-based survey focused on identifying how people's travel patterns (and needs), residential choices, vehicle ownership, mode choice, use of shared mobility systems, trip-making/activity engagement, and use of information and communications technology would change considering the global pandemic (see (Menon et al., 2020) for more details on the survey and its contents).

The University of South Florida Office of Research Integrity and Compliance processed this study and awarded it "Exempt" from the Institutional Review Board (IRB) review (IRB#: STUDY001076). Upon developing the nationwide survey through Qualtrics, pilot deployments were conducted internally before administering the survey through a nationwide panel (Prime Panels) in July–August 2020. Once the pilot testing was completed, the research team further modified the survey questionnaire to reflect the feedback obtained, and the finalized version was submitted for data collection through Prime Panels. Prime Panels, with access to over 50 million Americans, has been an effective panel for collecting survey data in academic research and has been employed by several studies in the field of transportation engineering and urban planning among others. Individuals from all 50 states and Washington D.C. took part in the survey and after employing a series of quality checks, a final useable sample size of 2432 responses was used for this study (see (Barbour et al., 2021; Menon et al., 2020) for more details on the quality control procedures employed to this dataset).

Table 1, below, indicates the descriptive statistics of the variables of interest for this study. As can be seen from the table, the dataset overestimated female respondents (65 percent). 78 percent of the survey respondents were of White ethnicity whereas 45 percent of them possessed at least a bachelor's degree. Technology adoption propensity was elicited in a Likert scale format using statements that classified respondents into tech enthusiasts, tech neutrals, and tech skeptics. Our sample included 25 percent of respondents that could be classified as tech enthusiasts (adopted from *I like new technologies and use them before most people I know*, and *I love new technologies and am among the first to experiment and use them*), and 35 percent of respondents that could be labeled as tech skeptics (adopted from *I am skeptical of new technologies and use them only when I have to*, and *I am usually one of the last people I know to use new technologies*). The

Table 1
Summary of key descriptive statistics for variables of interest used in this study (N = 2414).

Descriptive Statistics	Mean	Std. Deviation	Variance
Gender: Female	0.65	0.48	0.23
Race and Ethnicity: White	0.78	0.42	0.17
Race and Ethnicity: Black/African American	0.09	0.28	0.08
Race and Ethnicity: Native American/Alaskan Native	0.05	0.21	0.04
Race and Ethnicity: Asian	0.05	0.21	0.05
Hispanic/Latino Status: Hispanic/Latino	0.07	0.25	0.06
Education Attainment: Respondents with a bachelor's degree	0.26	0.44	0.19
Education Attainment: Respondents with a graduate degree	0.18	0.39	0.15
Education Attainment: Respondents with a high school degree or less	0.21	0.41	0.17
Education Attainment: Respondents with at least a bachelor's degree	0.45	0.50	0.25
Driving License Holders	0.84	0.37	0.14
Tech Adoption Propensity: Tech Enthusiasts	0.25	0.43	0.19
Tech Adoption Propensity: Tech Skeptics	0.35	0.48	0.23
Household Characteristics: HHs with very young children (<5 years)	0.10	0.31	0.09
Household Characteristics: HHs with young children (5–12 years)	0.19	0.39	0.15
Household Characteristics: HHs with elder children (13–17 years)	0.16	0.36	0.13
Household Characteristics: HHs with senior members (>65 years)	0.36	0.48	0.23
Household Characteristics: HHs with members who have an underlying health condition	0.42	0.49	0.24
Household Characteristics: Low Income HH (<$25k)	0.20	0.40	0.16
Household Characteristics: High Income HH (>$100,000 per year)	0.22	0.41	0.17
Household Characteristics: high number of motorized vehicles (3 or more)	0.50	0.50	0.25
Pre-COVID residential location: A large city	0.24	0.43	0.18
Pre-COVID residential location: Suburb	0.38	0.49	0.24
Pre-COVID residential location: Small town	0.22	0.42	0.17
Pre-COVID job sector: Professional/Technical/ITES	0.09	0.29	0.08
Pre-COVID job sector: Health/Pharma/Hospitality	0.07	0.26	0.07
Pre-COVID WFH: had the option to work from home	0.22	0.42	0.17
Pre-COVID WFH: worked from home all workdays in a week	0.03	0.16	0.02
Pre-COVID residential location: A large city	0.15	0.36	0.13
Pre-COVID residential location: Suburb	0.09	0.29	0.08
Pre-COVID residential location: Small town	0.09	0.28	0.08
Pre-COVID commute mode: Drive Alone	0.28	0.45	0.20
Pre-COVID commute: long (30 or more mins one way)	0.10	0.30	0.09
Pre-COVID grocery trip mode: Drive Alone	0.72	0.45	0.20
Pre-COVID grocery trip: long (30 or more mins one way)	0.09	0.29	0.09
Pre-COVID activity participation: frequently attended social gatherings	0.09	0.29	0.09
Pre-COVID activity participation: frequently attended sporting events, concerts or plays	0.06	0.24	0.06
Pre-COVID mode choice: frequently used public transit (bus/rail)	0.17	0.37	0.14
Pre-COVID mode choice: did not use public transit (bus/rail) despite availability	0.56	0.50	0.25
Pre-COVID mode choice: frequently used shared mobility (Uber/Lyft/taxi/cab)	0.15	0.35	0.12
Pre-COVID mode choice: frequently used active modes (bike/bike share/e-bike/e-scooter)	0.10	0.30	0.09
Pre-COVID ICT exposure: frequently attended virtual meetings	0.12	0.32	0.10
Since-COVID vehicle inventory: buying at least one car	0.28	0.45	0.20
Since-COVID vehicle inventory: selling at least one car	0.09	0.29	0.08
Since-COVID change: did not change their residential location	0.85	0.36	0.13
Since-COVID change: residential location is a large city	0.05	0.23	0.05
Since-COVID change: residential location is a suburb	0.05	0.22	0.05
Since-COVID change: in primary job	0.07	0.26	0.07
Since-COVID WFH: do not have the option to work from home	0.16	0.36	0.13
Since-COVID WFH: have the option to work from home	0.28	0.45	0.20
Since-COVID WFH: work from home all workdays in a week	0.04	0.20	0.04
Since-COVID commute mode: Drive Alone	1.00	0.00	0.00
Since-COVID commute: long (30 or more mins one way)	0.05	0.22	0.05
Since-COVID grocery trip mode: Drive Alone	1.00	0.00	0.00
Since-COVID grocery trip: long (30 or more mins one way)	0.06	0.24	0.06

sample included almost equal shares of low-income (<$25,000 per year), and high-income (>$100,000 per year) households. A small but significant share of people (5 percent, respectively) changed their residential location and moved into large cities and suburbs outside large cities since the onset of the pandemic. Table 1 also indicates that while 10 percent of respondents were facing a long commute trip pre-pandemic (30 or more mins, one way), only 5 percent of the survey respondents were making the same kind of trip since the onset of the pandemic.

4. Methodology

As indicated earlier, the objective of this study is not only to identify the key attributes associated with public confidence towards the measures adopted during the COVID-19 pandemic but also the deeper reasons behind their confidence. That being the case, two approaches, regression analysis (via an ordered probit model) and text mining are applied. While the ordered probit model explores the associated factors for the public's confidence in not contracting COVID-19 while using a shared mobility mode, the text network analysis (TNA) uses open-ended responses to expose the deeper reasons behind these levels of confidence.

4.1. Ordered probit model

The dependent variable of interest in this study is the respondents' confidence about not contracting COVID-19 while using the five shared mobility modes (i.e., rental car/car share, rail/bus transit, taxi/cab/Uber/Lyft, UberPOOL/Lyft Share, and bike-share/e-bike/e-scooter). The response categories for each of these dependent variables varied from *strongly disagree* to *strongly agree* in a 5 item Likert-Scale. The dependent variable with 5 response categories was modified into one with three response categories (by combining *strongly disagree* and *disagree* into *disagree*; and by combining *agree* and *strongly agree* into *agree*). With such ordered data (*disagree*, *neither disagree nor agree*, and *agree*), an ordered probability (OP) modeling approach is appropriate (Greene, 2000; Washington et al., 2011). An ordered probability model is derived by defining an unobserved variable, z, which is used as a basis for modeling the ordinal ranking of data. This unobserved variable is specified as a linear function expressed in **Equation (1)**.,

$$z_n = \mathbf{X}_n + {}_n \tag{1}$$

Where $\mathbf{X}$ is a vector of explanatory variables determining the discrete ordering for observation n, is a vector of estimable parameters, and is a disturbance term. Using **Equation (2)**, observed ordinal data, y_n, are defined as (with 1 = *disagree*, 2 = *neither disagree nor agree*, 3 = *agree*),

$$y_n = 1 \text{ if } z_n \, {}_0$$

$$=2 \text{ if } {}_0 < z_n \, {}_1$$

$$=3 \text{ if } z_n \, {}_1 \tag{2}$$

Where 's are estimable parameters (referred to as thresholds) that define y_n and are estimated jointly with the model parameters $\boldsymbol{\beta}$. The estimation problem then becomes one of determining the probability of the three specific ordered responses for each observation n. This is done by making an assumption on the distribution of ε_n in **Equation (1)**. If ε_n is assumed to be normally distributed across observations an ordered probit model results (alternatively, if ε_n is assumed to be logistic distributed an ordered logit model results). Note that without loss of generality ${}_0$ can be set equal to zero requiring the estimation of three thresholds, ${}_1$.

Assuming the disturbance terms are normally distributed (Washington et al., 2011), the ordered category selection probabilities can be written as shown in **Equation (3)** (removing subscripting n for notational convenience),

$$P(y = 1) = \Phi(-\beta\mathbf{X})$$

$$P(y = 2) = \Phi({}_1-\beta\mathbf{X}) - \Phi(-\beta\mathbf{X})$$

$$P(y = 3) = 1 - \Phi({}_{I-1}-\beta\mathbf{X}) \tag{3}$$

Where $\Phi(.)$ is the cumulative normal distribution.

For model interpretation, a positive value of $\boldsymbol{\beta}$ implies that an increase in $\mathbf{X}$ will increase the probability of getting the highest response (*agree*) and will decrease the probability of getting the lowest response (*disagree*). In the context of the current study, the independent variables for the ordered probit models estimated were chosen based on engineering judgment as well as an investigation into the pre-existing literature surrounding shared mobility adoption, intentions to use, and their specific influences. While there are the conventional influences of sociodemographic factors – at both the individual and the household level, post-pandemic intentions were also seen to be influenced by pre-pandemic behavior (in this case, specifically trip-making, and travel behavior). Additionally, the COVID-19 pandemic, with its changes to activity patterns, trip making, and travel behavior may have brought about influential factors that could affect the future usage of transportation systems in a post-COVID environment (Menon et al., 2020; Shemer et al., 2022). Therefore, since-pandemic factors were also explored as potential influencing factors regarding respondents' confidence about not contracting COVID-19 while using the five shared mobility modes. The OP models can explain the association between the outcome and predictor variables. However, the reason behind the outcome selected is rarely explained. Such reasons can be obtained from the open-ended responses. The next section presents the text network analysis that was used to explore the open-ended responses.

4.2. Text network analysis

Text network analysis (TNA) is a text mining technique that has recently been utilized to extract meaningful insights from open-ended responses. The insights from the TNA are described based on the keywords, which appear as nodes in the network, and the co-occurrence of the keywords, which appear as the linked nodes. Fig. 1 displays a typical example of the text network (Y. Kim and Jang, 2018; Kutela et al., 2021b; Paranyushkin, 2011).

In this study, the open-ended responses are divided into two categories based how the respondent answered the question related to their confidence for not contracting COVID-19. The first category of open-ended response covers those with high confidence, i. e those who agreed and strongly agreed (rated 5 and 4), while the second category is those with low confidence i.e., those who neither disagreed nor agreed, disagreed, and strongly disagreed (rated 3, 2, and 1).

In the network, the node's size indicates the keyword's frequency, while the link's thickness represents the frequency of the co-occurrence of keywords. The closer the nodes in the network, the closer the keywords in the open-ended responses. The keywords that appear next to each other in the open-ended responses are termed as collocated keywords. Contrary to the cooccurred keywords, collocated keywords provide richer insights. Lastly, keywords with similar themes form a community within the network. The network can have multiple communities.

Three basic processes – (i) normalization; (ii) transformation; and (iii) mapping are involved in creating the text network. Normalization involves converting all responses into lower cases and removing connecting words such as *is*, *the*, *of*, and *he*, that do not provide significant insights. The transformation process involves converting unstructured data into structured data by creating the matrices of keywords. The created matrices result in pairs of keywords and their associated frequencies. Lastly, an algorithm maps each keyword in the structured matrix as a network node (Kim and Jang, 2018; Kutela et al., 2021a, b; Paranyushkin, 2011; Yoon and Park, 2004). This process can be performed in various software, however, in this case, R 4.1.1-environment (R Core Team, 2021), along with the *quanteda* and *igraph* packages (Benoit et al., 2018; Csárdi, 2020) are used for this analysis.

The interpretation of the network can be performed using various measures such as degree centrality, closeness centrality, and betweenness centrality, among others. However, in this case, the objective was to understand the patterns of the reasons for the public's confidence, the network topology, keywords, and collocation keywords were used for interpretation (Y. Kim and Jang, 2018; Paranyushkin, 2011). The following section shows and discusses the results of the adopted methodology.

The next section presents the results and discussion. It covers the ordered probit models results and the TNA results and associated discussions. The ordered probit models unearth the factors influencing individual's confidence about not contracting COVID-19 while using any shared mobility modes, while the text mining results shows the reason for such an association.

5. Results and discussion

To aid better understanding of the results, the ordered probit model results are presented followed by the text mining results.

5.1. Ordered probit modeling results

The results obtained in this study using the ordered probit model are presented in Table 2, below. The table comprises of all variables considered in this study, against the shared mobility options. For the purpose of this study, the five-dimensional Likert scale (1- *strongly disagree*; 2- *disagree*; 3- *neither disagree nor agree*; 4 – *agree*; 5 – *strongly agree*) was converted into a three-dimensional Likert scale (1- *disagree*; 2 – *neither disagree nor agree*; and 3 – *agree*).

Five ordered probit models (one for each of the five shared mobility modes – i.e., rental car/car share, rail/bus transit, taxi/cab/Uber/Lyft, UberPOOL/Lyft Share, and bike-share/e-bike/e-scooter) were estimated to understand the influence of respondents' individual- and household-level attributes, built environment characteristics, travel behavior, and activity participation characteristics (both pre- and since-COVID) on their confidence of not contracting COVID-19 while using shared mobility modes. Model estimates

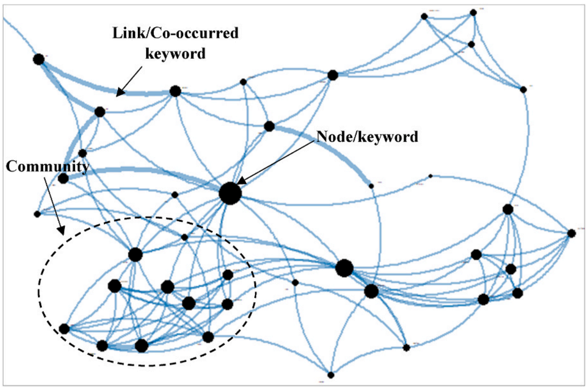


Fig. 1. Skeleton of the text network.

Table 2
Ordered probit estimation of individual's confidence for not contracting COVID-19 while using shared mobility modes (N = 2414).

Variable Description	I feel confident that I will not get COVID-19 while using				
	Rental car/ carshare	Rail/bus transit	Taxi/Cab/Uber/ Lyft	UberPOOL/Lyft share	Bikeshare/E-bike/E-scooter
Gender (ref: Male)					
Female	–	–	–	*−2.207*	*−2.382*
Race & Ethnicity (ref: Non-Hispanic/Non-Latino)					
Hispanic/Latino	–	–	–	*−2.237*	–
Household Composition and Family Dynamics					
HHs with adult members (18–64 years)	*2.492*	–	–	–	–
Household Vehicle Inventory					
High number of motorized vehicles (3 or more)	*−2.509*	–	–	–	–
Work location before COVID-19 (ref: Rural)					
Large city	*−2.042*	–	–	–	–
Suburb	*−2.538*	–	–	–	–
Small city or town	**−2.741**	–	−1.964	–	–
Technology adoption propensity					
Tech enthusiasts	*−2.261*	–	*−2.361*	–	*−2.397*
Tech skeptics	–	–	–	–	*−2.526*
Pre-COVID travel behavior and activity participation					
Commute mode drive alone	–	*2.297*	–	–	–
Spend 30 or more mins on grocery trip	–	**3.363**	–	*2.357*	–
Frequently used public transit (bus/rail)	–	**2.596**	–	–	–
Did not use public transit (bus/rail) despite availability	*2.298*	–	–	–	–
Frequently used shared mobility (Uber/Lyft/ taxi/cab)	**3.689**	–	**5.505**	**2.796**	–
Frequently used active modes (bike (share)/e-bike/e-scooter)	–	–	–	–	**3.729**
Frequently used Amtrak	–	**3.024**	*2.235*	**2.842**	–
Frequently attended social gatherings	*2.095*	–	*2.381*	*2.551*	–
Frequently attended church/religious gathering attendance	*2.237*	–	*2.279*	*2.000*	–
Frequently attended sporting events concerts or plays	–	–	*−2.000*	–	–
Household vehicle inventory since COVID-19					
At least 1 vehicle sold	**2.732**	–	–	–	–
Option to work from home since COVID-19	*−2.102*	–	–	–	**−2.953**
Travel behavior and activity participation since COVID-19					
Frequently used public transit (bus/rail)	**4.153**	**2.949**	**3.325**	**3.201**	**3.179**
Did not use public transit (bus/rail) despite availability	**−3.707**	**−3.667**	**−3.194**	**−3.564**	**−3.100**
Frequently used shared mobility (Uber/Lyft/ taxi/cab)	**3.468**	–	*2.735*	*2.538*	–
Frequently used Amtrak	*2.462*	*2.007*	–	–	–
Frequently used Airplane	–	–	–	−1.962	–
Frequent grocery pickup or delivery orders	**−3.578**	**−3.257**	**−3.134**	**−3.147**	*−2.460*
Frequent food pickup or delivery orders	1.982	–	*1.983*	–	*2.418*
Frequently ordering items online for delivery	–	–	*−2.238*	*−2.063*	–
Frequent virtual meeting attendance	–	*−1.986*	–	–	–
Frequent telehealth meeting attendance	**−3.672**	**−4.515**	**−3.766**	**−3.785**	**−2.633**
Threshold (*Disagree*)	−1.370	−1.614	−2.197	−1.443	−2.245
Threshold (*Neither Disagree nor Agree*)	1.853	1.482	0.840	1.830	1.283
McFadden's pseudo R^2	0.081	0.090	0.07	0.079	0.044
2 (Log-likelihood) intercept only	5045.98	4315.52	4663.53	4490.51	5148.88
2 (Log-likelihood) final model	4722.89	3926.22	4336.49	4134.48	4921.45

Estimated Parameter Legend: **Bold font** ~ $p < 0.01$, *Italics font* ~ $p < 0.05$, Normal font ~ $p < 0.1$.

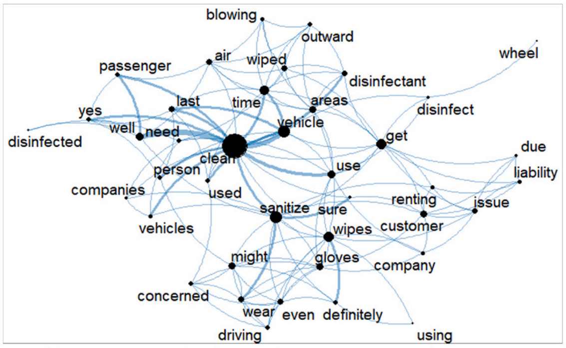
show that female shared mobility users were less likely (than males) to agree that they would be confident about not contracting COVID-19 while using UberPOOL, Lyft share or any bike-based shared modes. Various combinations of race and ethnicity were tested in the OP models before concluding that only Hispanic/Latino individuals displayed skepticism in using pooled-transportation services from the point of infection contraction. On the other hand, households with at least one adult member were likely to feel more confident about using rental car/carshare services. It was interesting to note that educational level and household income had no effect on this aspect. From a built environment perspective, household locations did not seemingly have any significant impacts on respondents' confidence of not contracting COVID-19 while using shared mobility modes. However, work location did influence this phenomenon.

Results from Table 2 show that, in comparison to those that work in rural locations, individuals that worked in a large city, suburb, or small cities pre-pandemic, were less confident of the possibilities of not contracting COVID-19 while using rental car/carshare services. This is very plausibly linked to the plummeting levels of usage of shared mobility services post-pandemic (Delaughter, 2021; Nutley, 2020)– a phenomenon that has led to mergers, acquisitions, fleet reductions (Lynch and Torbati, 2021) as well as liquidations (Push, 2022) among providers. Interestingly, technology adoption propensity (a proxy for tech savviness) was found to have a negative influence over individual's confidence for not contracting COVID-19 while using shared mobility modes. These results need further inspection, as the effects are similar for people that are ahead on the technological adoption cycle, as well as those that lag their peers in adopting technology into their lives.

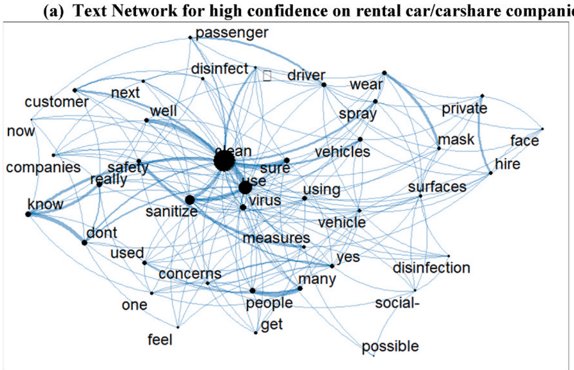
Travel behavior and activity participation pre-COVID have very significant positive influences on an individual's confidence for not contracting COVID-19 while using any shared mobility modes, post-pandemic. For instance, consumers that drove alone on their commute, traveled 30 min or more one way on their grocery trip, frequently used public transit, and Amtrak were more likely to confident about not contracting COVID-19 while using public transit. Similarly, those individuals that did not use public transit despite their availability and instead depended on shared mobility services were more likely to be confident to use rental car/carshare services without fear of infection spread, post-pandemic. In fact, results show that individuals that were frequent users of shared mobility services are more confident in its abilities to protect them from COVID-19. These are the customers that continue to embrace shared mobility modes (like the ones that continue to use public transit, since-pandemic) and will very likely continue to use these services for the foreseeable future. Results from Table 2 also show that individuals that frequented events outside their home (social gatherings, church/religious gatherings) pre-COVID, expressed more confidence on not contracting COVID-19 while using shared mobility modes.

A similar analysis was also done to understand the influence of individual- and household-level changes in travel behavior, and activity participation because of COVID-19, and the results below depict these significant impacts. As discussed before, frequent usage of public transit and shared mobility services since the pandemic (like their levels of usage pre-pandemic) brought more confidence in the minds of respondents about the prospect of not getting infected while using these services. On the other hand, individuals that did not use public transit (despite their availability) since the pandemic expressed greater skepticism about the future of shared mobility usage.

Additionally, those that frequently used shared mobility modes such as the Amtrak, Uber, and Lyft since-pandemic (just like the in the pre-pandemic phase) were likely to feel more confident about the prospect of staying healthy while using shared mobility modes. This is perhaps indicating that many skeptics of shared mobility modes might not be the most frequent users of them, and therefore, maybe suffering from preconceived notions when it comes to potential health concerns in a post-pandemic future. Prior literature around usage, and preconceived notions is an indicator of this possibility (Zajonc, 2001). Lastly, it was very interesting to note that individuals who engaged in behaviors that substituted the long, pre-COVID grocery trips with shorter trips (that involved either picking up after ordering online or getting groceries delivered at home) were more skeptical regarding the ability of these shared transportation modes from keeping them safe.



(a) Text Network for high confidence on rental car/carshare companies



(b) Text Network for low confidence on rental car/carshare companies

Fig. 2. Text Network for high and low confidence for not contracting COVID-19 from riding in Rental Car/Carshare.

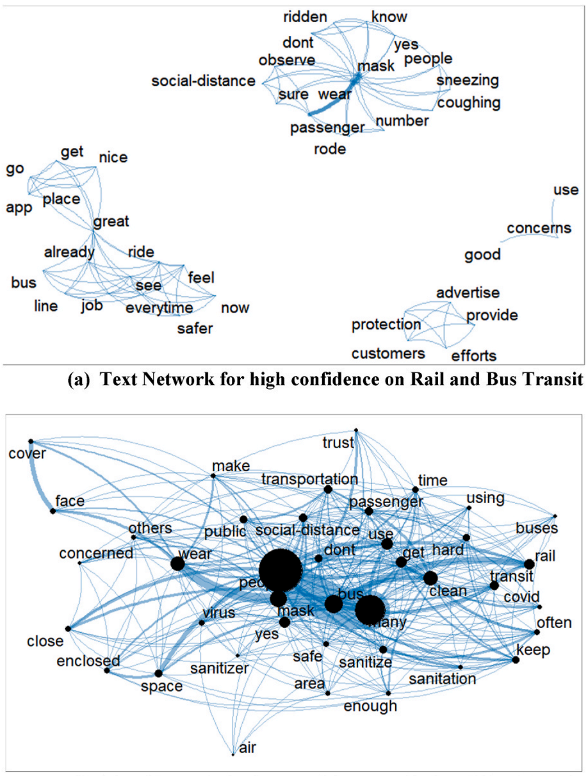
This behavior was also noticed in cases of those that frequently ordered items online for delivery as well as those who have attended virtual meetings and telehealth appointments more frequently, since the pandemic. It seems like the added convenience as well as comfort features afforded since the onset of the pandemic have negatively impacted the demand and usage of shared mobility services. As indicated earlier, the regression results normally provide the association between predictor and response variable. However, in most cases, researchers and the general public may be interested in the reason for such association. Thus, this study applied text mining to understand the reasons for high and low confidence of the measures. The next section presents the text mining results.

5.2. Text network results

The text network for two categories of outcomes for each shared mobility mode was developed. The two categories of the text networks were generated from the open-ended responses associated with high confidence (those who responded *agree* and *strongly agree* – rated 5 and 4) against others (those who responded *neither disagree nor agree*, *disagree*, and *strongly disagree* – rated 3, 2, and 1). The next section presents the text network results and discussion, which covers five modes of shared mobility, rental cars/carshare, Rail and Bus Transit, Taxi/Cab/Uber/Lyft, and UberPOOL/Lyftshare.

5.2.1. Rental cars/Carshare

Fig. 2 presents the text networks for high confidence and other segments in the measures adopted in the rental car/carshare companies. It can be observed that both networks are centered on the keyword *clean*, which implies that whether a person has high confidence or otherwise, they feel confident about not contracting COVID-19 while using rental cars/carshare, if the vehicle was clean. Our results also reveal that those who felt high confidence were satisfied with the cleanliness while others were not. Further, sanitization was one of the topics mentioned by several respondents. Although respondents might have used *clean* and *sanitize* interchangeably, clean implies the clarity/clearness/freshness, while *sanitize* involves the use of disinfectants. People with high confidence used words like well *cleaned*, *clean areas*, *clean person* among others to express their satisfaction. Typical responses for this group of people include *Clean and sanitize well*, *I would still disinfect handles doors*, *steering wheel* , *buttons brake lever* etc., and *But figure they would clean well as to not be sued.* On the other hand, the people with low confidence looked at cleanness from the other angle. For instance, one response stated that "*I am not sure how complete the clean would be done*". Further, several people were concerned with the way operators sanitize these rental cars. Typical responses include *How they are sanitized?* And *They won't* and *cannot be properly sanitized.*



(a) Text Network for high confidence on Rail and Bus Transit

(b) Text Network for low confidence on Rail and Bus Transit

Fig. 3. Text Network for high and low confidence for not contracting COVID-19 from riding in Rail and Bus Transit.

5.2.2. Rail and bus transit

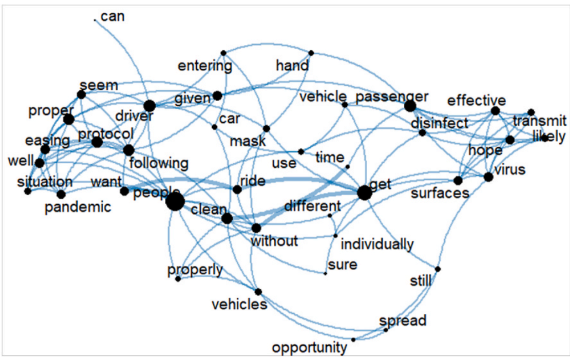
Fig. 3 presents the text network results for high and low confidence regarding not contracting COVID-19 while riding rail and/or bus transit. Contrary to rental car/carshare services, the responses for low and high confidence on rail and bus transit are distinguishable. Topologically, Fig. 3 (a) is relatively less dense compared to Fig. 3 (b), which implies that relatively a few people had high confidence of not contracting COVID-19 in the rail and bus transit. In fact, among 707 open-ended responses, only 68 showed high confidence in this regard. According to Fig. 3 (a), the positive responses focused on the app used by buses, customer protection efforts, mask wearing, and social distancing. Typical responses included "*They are good no concerns*", "*Great place to go to get a nice app*", "*Individual seats*", "*partition*", "*Number of passengers but all were wearing mask when I rode*".

Contrastingly, Fig. 3 (b) is very dense, which implies that most of responses were from people that expressed low confidence about not contracting COVID-19 while in bus and rail transit. The collocated keywords "*many people*" have the thickest link implying the high frequency in the responses (n = 70). In fact, this keyword has multiple implications. While some respondents used it to show the number of people using this mode of transportation "*too many people use this type of transportation to be safe*", "*too many people at the same time difficult to use social-distance*", *and* "*too many people in transit, it's not worth the risk*", others used it to show the number of people that got sick using this mode, "*many people have gotten sick from riding the train*". Further, a relatively large number of respondents were concerned about mask wearing as indicated by the keywords "*wear mask*". Typically, this group of individuals provided these kind of responses "*people who don't wear mask*", "*other bus riders not wear mask*".

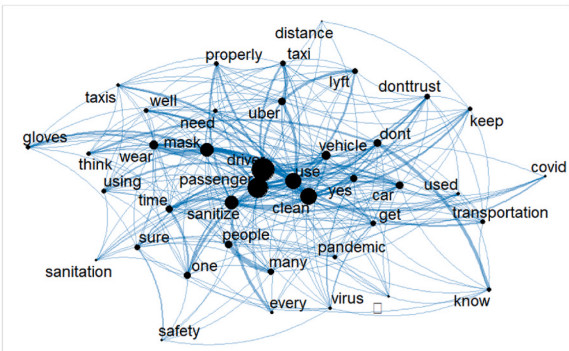
5.2.3. Taxi/cab/uber/lyft

Fig. 4 presents the text network for responses from respondent with high and low confidence for not contracting COVID-19 from Taxi/Cab/Uber/Lyft. The network for low confidence is relatively denser than the network for high confidence. This indicates that, less people were confident that they would not get COVID-19 from Taxis. In fact, only 91 out of 668 respondents expressed high confidence. Although this number is low, it is relatively higher than that seen in bus and rail transit. According to.

Fig. 4 (a), people showed high confidence due to the drivers who followed protocols effectively and disinfected their vehicles. Typical statements include "*…. All of the drivers that have given me rides seem to be following proper protocol as well which is easing during the pandemic situation when some people be stubborn and careless to an extent*." On the other hand, cleanliness of the vehicle was the main issue for individuals that had less confidence with regard Taxi/Cab/Uber/Lyft. This is revealed by the keywords "*driver*", "*clean*", "*sanitized*", and "*use*". Typically, respondents stated that "*They are supposed to wipe down the car between passenger, but you cannot really tell if they do or how thoroughly they do it.*" and "*Maybe have sanitizer available for clean seatbelt buckles door handles etc*".



(a) Text Network for high confidence on Taxi/Cab/Uber/Lyft



(b) Text Network for low confidence on Taxi/Cab/Uber/Lyft

Fig. 4. Text Network for high and low confidence for not contracting COVID-19 from riding in Taxi/Cab/Uber/Lyft.

5.2.4. UberPOOL/lyftshare

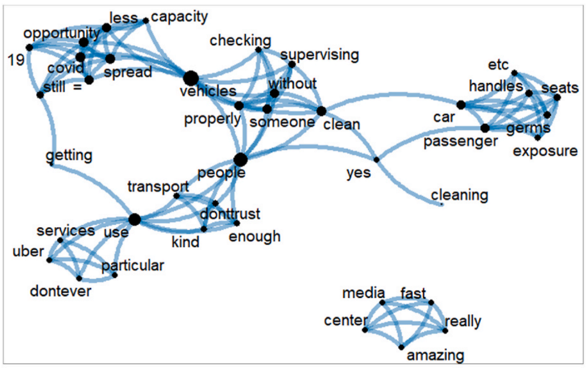
Fig. 5 presents the text network results for pooled ride hailing services, UberPOOL and Lyftshare. Similar to previously investigated modes, a relatively small number of respondents showed high confidence for not contracting COVID-19 from these services. Although respondents had higher confidence ratings, their comments reflect otherwise. In fact, most of the comments were negative although the ratings were positive. For instance, respondents talked about exposure to germs, distrust in the transport system etc. The typical narratives include *" …. Exposure to other passenger and germs on car seats, handles, etc".*

Furthermore, as expected, respondents' low confidence focused on the number of passengers and mask wearing as indicated by the keywords "*many passengers*" and "*wear mask*". Further, some considered risky sharing a ride with strangers as indicated by the keyword *"strangers"* in the network. For instance, one of the respondents mentioned *"I would not want to share with strangers",* and *"I would personally not even consider using this service, due to it entailing sharing a vehicle with strangers at close proximity."* Also, several respondents mentioned that "*they do not know*" about many aspects of the pooled ride hail, which made them feel uncomfortable using it. For instance, some respondents mentioned that *"Yes, I would not be get in a car with more strangers during a pandemic. I don't know what their routine is, I don't know their habits."* and *"I don't know who used this type of transportation before me"*.

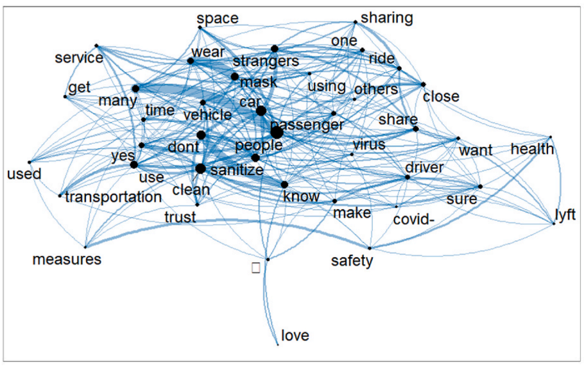
5.2.5. Bicycle/bikeshare/E-bike/E-scooter

Lastly, Fig. 6 shows the text network results for bicycle/bikeshare/e-bike/e-scooter. As has been the trend so far, a relatively small percentage of respondents expressed high confidence for not contracting COVID-19 from these modes. This is observed from the topology of the two networks, whereby the high confidence network is less dense, in comparison to the low confidence network. People with high confidence focused on cleanliness as indicated by the size of the keyword "*clean*". Other keywords such as "*use wiped*", "*sanitize bikes*" were used to indicate the way respondents considered these services. Further, a few responses preferred these services due to their open-air nature. The comment read as "*an open-air device would likely be safe*" and *"not many concerns as it would be in the open air", "sanitize the vehicle between clients",* which indicate their confidence in these modes.

On the other hand, the network for the low confidence has similar keywords but pointed to different usages. For instance, the keyword "*use*" which may indicate that the respondents either used or did not use these shared mobility options. The same keyword may also point toward the use of sanitisers to clean bikes as indicated by the co-occurred keywords "*use sanitizer", "clean bikes*". The actual comment from the respondents shows that, some did not use it because they are afraid of contracting COVID-19, while others did not use it although they were. The typical comment states that "w*on't use afraid of get COVID*" and "*I didn't use this service though it was available …*". The comment on cleanliness stated that "*need full clean between used*" and "*health and cleanliness concerns*", among

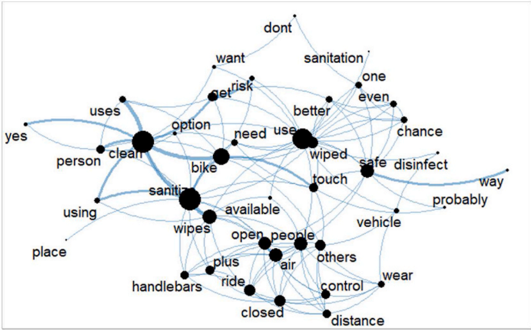


(a) Text Network for high confidence on UberPOOL/Lyft Share

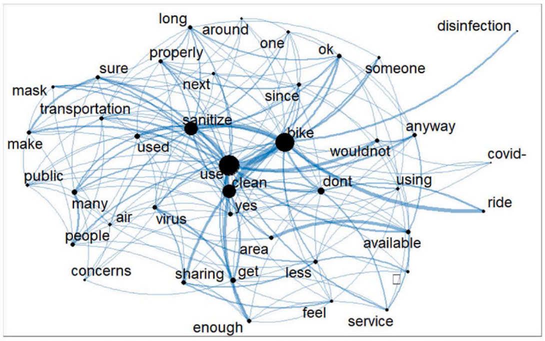


(b) Text Network for low confidence on UberPOOL/Lyft Share

Fig. 5. Text Network for high and low confidence for not contacting COVID-19 while riding in UberPOOL/Lyft Share.



(a) Text Network for high confidence on Bicycle/Bikeshare/E-Bike/E-Scooter



(b) Text Network for low confidence on Bicycle/Bikeshare/E-Bike/E-Scooter

Fig. 6. Text Network for high and low confidence for not contracting COVID-19 while riding Bicycle/Bikeshare/E-Bike/E-Scooter.

others.

6. Conclusions and implications

This study was conducted to assess the perceptions and concerns of the consumers/public on shared mobility modes during and after the COVID-19 pandemic based on their confidence in not contracting COVID-19 while riding any of these modes. To assess this, respondents were categorized into low and high-confidence groups. The shared mobility modes considered for this analysis included Rental car/Carshare, Bus/Rail Transit, Taxi/Cab/Uber/Lyft, UberPOOL/Lyft Share, and Bicycle/Bikeshare/E-bike/E-scooter. The analysis used data collected from a national panel of U.S. adults in the Summer 2020. In carrying out the analyses, this study used Ordered Probit (OP) models, and then a Text Network Analysis (TNA) technique to explore the deeper reasons for the observed relationships.

The OP model estimations show that female users were less likely (than males) to be confident about not contracting COVID-19 while using shared mobility modes. The locations of households did not show significant impacts on respondents' confidence of not contracting COVID-19 while using shared mobility modes. On the contrary, travel behavior and activity participation in the pre-COVID positively influenced an individual's confidence in not contracting COVID-19 while using any of the shared mobility modes. People who frequented public transit and shared mobility services since the pandemic had more confidence in not contracting COVID-19, while those who did not were suspicious of their prospects of shared mobility usage. The same was observed for those who frequently ordered items online for delivery as well as those who frequently attended virtual meetings and telehealth appointments. Based on these findings, the authors utilized the TNA technique to extract deeper insights.

The confidence in rental cars/carshare services was mostly based on cleanliness – people with high confidence of not contracting COVID-19 were satisfied with the cleanliness of the vehicles, unlike those who expressed low confidence. The confidence in rail and bus transit showed that customer protection efforts, wearing masks, and social distancing were the main factors for the high confidence among this group. On the other hand, low levels of confidence in this mode were mostly influenced by "*many people*" who either rode with them, affecting social distancing, or getting sick. In the case of taxi/cab/Uber/Lyft, the high confidence was due to the drivers who followed protocols effectively and disinfected, while the low confidence demographic was a consequence of poor sanitation/cleanliness onboard. In pooled ride-hailing (UberPOOL/Lyft Share), a smaller proportion of the respondents showed high confidence in not contracting COVID-19, although their comments still showed low confidence, especially regarding the usage of masks and sanitation, an opinion shared by their low-confidence counterparts. Lastly, regarding bicycle/bikeshare/e-bike/e-scooter, the high-confidence group based their assessment on the cleanliness of bikes, and their use in the open air – both of which reduced the probability of contracting the virus. On the contrary, the low-confidence group had more concerns about sanitizing and cleaning the bikes. The analysis identified the significant impact of enhanced sanitation protocols on user confidence, especially in rental cars and carshare services, suggesting that stringent cleaning protocols and transparent communication are crucial. For public transit, the study underscores the necessity of permanent safety measures like enforced mask-wearing and social distancing. In ride-hailing services, driver adherence to health safety protocols emerged as vital, recommending continuous training and compliance checks. Additionally, the positive perception of bicycles and other active mobility options linked to open-air use and personal cleanliness control suggests expanding and maintaining bike lanes and bikeshare facilities. These targeted strategies can increase user confidence, ensuring safer shared mobility usage and contributing to a resilient post-pandemic transportation network.

Based on the results of the ordered probit modeling as well as the text network analysis, it is evident that a lot of positive attitudes towards not contracting COVID-19 on shared mobility modes come from the demographic that are either frequent users of shared mobility modes (both pre-and since-COVID), or those that frequented public events, and generally more crowded settings pre-COVID. This indicates potential geographic-level influences for the success of shared mobility modes. For instance, from a shared mobility provider's perspective, exposure and usage are clear indicators for positive outcomes – shared mobility providers could leverage this to enhance service offerings in these locations instead of diversifying to areas where people have lesser and lesser exposure to their fleet. Pandemic-related challenges are unique, and therefore, operators need to make custom-made, creative solutions to enhance ridership in the short term. Within the modes, it is evident that while there is more discussion among users regarding legacy shared mobility modes (rental car and transit), not much is known about the prospects for emerging offerings (UberPOOL, Lyftshare, e-bikes, e-scooters, etc.). This may point to a need to temporarily focus on current offerings while not necessarily creating newer options for users until the period of skepticism with the concerns of infection spread is behind them.

The outcomes from this study show that the choice of transportation mode was greatly affected by COVID-19. Across all shared mobility modes, a smaller proportion showed high confidence in not contracting COVID-19, and a larger portion was concerned about this possibility, which could have impacted ridership, and prospects of these service options. These outcomes are helpful to understand the behaviors of the community during a life-altering event, which is the basis for improving the level of service, and the creation of newer business models for future operations. The analysis shows that positive attitudes towards not contracting COVID-19 correlate with frequent use of shared mobility, suggesting providers should focus service enhancements in areas with established user bases. This could involve increasing service frequency, improving connectivity, or offering loyalty incentives. Additionally, the pandemic highlights the need for operators to implement creative, customized solutions to boost ridership in the short term, particularly in regions that already demonstrate high usage. Moreover, understanding user behavior during such disruptive events can guide the improvement of service levels and the development of future business models, emphasizing the importance of incorporating factors like cost, travel time, and availability in future research to gain a holistic view of user confidence in shared mobility choices.

While OP models quantify the impact of various factors on user confidence during the COVID-19 pandemic, TNA explores the underlying reasons behind these trends through qualitative analysis of open-ended texts. This approach provides deeper insights that complement the quantitative data, revealing specific concerns like sanitation and preventive measures that structured data alone might miss. Together, these methods offer a holistic view of user perspectives, enhancing the study's findings by linking numerical trends with real-world experiences.

The current study is not without limitations. This study was limited to the user confidence in not contracting COVID-19 and their preferences on shared mobility usage, regardless of the perceived costs of these modes in terms of travel time, out-of-pocket costs, schedules, and availability. Future studies in this aspect should consider these (and other) factors in more detail to extract the overall confidence of users in the shared mobility choices. Despite the success of the text mining approach used in this study to provide more insights, some limitations exist for researchers who intend to use a similar approach. First, the efficacy of this approach is contingent upon the quality of the underlying data. Secondly, interpreting textual data may inherently involve subjectivity, potentially introducing unobserved biases into the analysis. Thirdly, some text may produce a complex network, which may be difficult to interpret. Future studies can utilize advanced modeling techniques, such as large language models, to overcome these limitations.

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CRediT authorship contribution statement

Boniphace Kutela: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Nikhil Menon:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Jacob Herman:** Writing – review & editing, Writing – original draft. **Cuthbert Ruseruka:** Writing – review & editing, Writing – original draft. **Subasish Das:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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