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Post-pandemic shared mobility and active travel in Alabama: A machine learning analysis of COVID-19 survey data

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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

The COVID-19 pandemic has had unprecedented impacts on the way we get around, which has increased the need for physical and social distancing while traveling. Shared mobility, as an emerging travel mode that allows travelers to share vehicles or rides has been confronted with social distancing measures during the pandemic. On the contrary, the interest in active travel (e.g., walking and cycling) has been renewed in the context of pandemic-driven social distancing. Although extensive efforts have been made to show the changes in travel behavior during the pandemic, people's post-pandemic attitudes toward shared mobility and active travel are under-explored. This study examined Alabamians' post-pandemic travel preferences regarding shared mobility and active travel. An online survey was conducted among residents in the State of Alabama to collect Alabamians' perspectives on post-pandemic travel behavior changes, e.g., whether they will avoid ride-hailing services and walk or cycle more after the pandemic. Machine learning algorithms were used to model the survey data (N = 481) to identify the contributing factors of post-pandemic travel preferences. To reduce the bias of any single model, this study explored multiple machine learning methods, including Random Forest, Adaptive Boosting, Support Vector Machine, K-Nearest Neighbors, and Artificial Neural Network. Marginal effects of variables from multiple models were combined to show the quantified relationships between contributing factors and future travel intentions due to the pandemic. Modeling results showed that the interest in shared mobility would decrease among people whose one-way commuting time by driving is 30–45 min. The interest in shared mobility would increase for households with an annual income of $100,000 or more and people who reduced their commuting trips by over 50% during the pandemic. In terms of active travel, people who want to work from home more seemed to be interested in increasing active travel. This study provides an understanding of future travel preferences among Alabamians due to COVID-19. The information can be incorporated into local transportation plans that consider the impacts of the pandemic on future travel intentions.

1. Introduction

In recent years, shared mobility, such as car sharing, ride-hailing, and micromobility, has been widely used as a regular travel mode worldwide. Globally, the number of car/rides sharing users increased from 5936.6 million in 2017 to 6256.2 million in 2019, with 7314.7 million users predicted for 2026 (Statista, n.d.). The number of free-floating fleets is forecasted to increase by 110% from 2020 to 2025 (INVERS, 2021). As a type of emerging travel mode, shared mobility has brought some positive impacts on consumers, the environment, and the transportation system. For instance, shared mobility has excellent spatial and temporal accessibility for people, and it also is a potential solution to the first-/last-mile problems for public transport services (Marsden, 2022). Simultaneously, as an alternative to other travel modes, shared mobility can reduce driving and personal vehicle ownership (Shaheen et al., 2015). However, since shared mobility requires people to share the same hermetic space (e.g., car sharing) or the same vehicle/bike/e-scooter within a short time, the COVID-19 pandemic triggered the crisis in the shared mobility system. For example, in March 2020, the weekly taxi ridership and the number of operating taxis reduced by 95% and 85% in Chicago compared with February 2020 (Ale-Ahmad and Mahmassani, 2020). In this situation,

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examining contributing factors of people's future travel preference for shared mobility is valuable for policy-makers to understand how to make shared mobility more resilient.

Active travel (e.g., walking and cycling) has been proved that it has substantial environmental benefits, such as reducing greenhouse gas emissions (Mindell et al., 2011; Woodcock et al., 2009). Active travel may benefit population health. For example, Laverty et al. (2013) found that active travel was associated with a lower likelihood of being overweight, having diabetes, and having hypertension than private transport. Also, active travel is often related to the highest level of travel satisfaction (de Vos et al., 2019). Lacking relative infrastructure (e.g., cycle lane, sidewalk), safety concerns, abnormal weather, and time-consuming concern became the major issues in the development of active travel (Barajas and Braun, 2021; Luo et al., 2022; Sims et al., 2018). Like the shared mobility system, the COVID-19 pandemic changed people's active travel behavior to some degree. In 2020, the U.K. people walked less than in 2019 on average because of a fall in short walks, but they walked 7% father than in 2019. Different from walking, in 2020, the U.K. people made 20 cycling trips on average and cycled more and farther than in 2019 (U.K. Department for Transport, 2021). Some researchers and countries see that the COVID-19 pandemic might be an opportunity to prompt people to do active travel (Brooks et al., 2021; Nurse and Dunning, 2021). Thus, it is important to investigate which and how factors can affect people's attitudes toward making active travel after they experience the COVID-19 pandemic.

In recent years, machine learning methods have been widely used in studying travel behavior, especially in travel mode choice (Cheng et al., 2019; Ding et al., 2018, 2022; Golshani et al., 2018; Hagenauer and Helbich, 2017; Lhéritier et al., 2019; Lindner et al., 2017; Liu et al., 2021; Rasouli and Timmermans, 2014; Tamim Kashifi et al., 2022; Wang and Ross, 2018; Wang and Wang, 2021; Xiao et al., 2021; Xie et al., 2003; Xu et al., 2021; Zhang and Xie, 2008; Zhao et al., 2020; Zhou et al., 2019). Compared with discrete choice modeling, machine learning methods do not require some assumptions, such as IIA (Independence of Irrelevant Alternatives), on the data. Machine learning methods can capture the nonlinear relationship between independent variables and the dependent variable (Lhéritier et al., 2019; Zhao et al., 2020). Machine learning methods can do better on the multicollinear problem than discrete choice modeling (Lindner et al., 2017). The predictive ability of machine learning methods is also proven to be better than discrete choice modeling in travel behavior research (Lhéritier et al., 2019; Wang and Ross, 2018; Zhao et al., 2020). According to the literature on travel behavior studies, Random Forest (Cheng et al., 2019; Lhéritier et al., 2019; Xu et al., 2021; Zhao et al., 2020; Zhou et al., 2019), Boosting (Ding et al., 2018, 2022; Liu et al., 2021; Tamim Kashifi et al., 2022; Wang and Ross, 2018; Wang and Wang, 2021; Xiao et al., 2021), Support Vector Machine (Hagenauer and Helbich, 2017; Zhang and Xie, 2008), Decision Tree (Lindner et al., 2017; Rasouli and Timmermans, 2014; Xie et al., 2003), and Neural Network (Golshani et al., 2018; Lindner et al., 2017; Xie et al., 2003) were majority adopted to predict travel behavior or investigate the contributing factors of travel behavior. Moreover, Zhao et al. (2020) found that machine learning methods can provide the same behavioral outputs in many aspects as logit models. In other words, using machine learning methods to study travel behavior is a reasonable alternative for discrete choice modeling. The machine learning outputs might differ among various methods (Hagenauer and Helbich, 2017).

Current studies have made extensive efforts to show the changes in travel behavior during the pandemic. However, people's post-pandemic attitudes toward shared mobility and active travel are still under-explored. This study aims to examine Alabamians' post-pandemic travel preferences regarding shared mobility and active travel (i.e., their anticipated post-pandemic travel behavior during the pandemic). An online survey was conducted among residents in the State of Alabama. Survey participants were asked to provide their perspectives about post-pandemic travel behavior changes, e.g., "*whether they will avoid ride-hailing services*" and "*whether they will walk or cycle more after the pandemic*." Over 1,400 Alabamians participated in the survey, and 481 observations are available for modeling the perspectives about post-pandemic travel behavior changes. To reduce the bias of any single model, this study explores multiple machine learning classifiers, including Random Forest, Adaptive Boosting, Support Vector Machine, K-Nearest Neighbors, and Artificial Neural Network. Averaged marginal effects are estimated to quantify the correlates of future travel intentions due to the pandemic. This study provides an understanding of future travel preferences among Alabamians due to COVID-19. The information can be incorporated into local transportation plans that consider the impacts of the pandemic on future travel intentions.

1.1. Literature review

A review of shared mobility and active travel research under the context of the COVID-19 pandemic is provided in this section by demonstrating the shared mobility in COVID-19 and active travel in COVID-19. Table 1 illustrates examples of studies that discussed shared mobility and active travel in the COVID-19 pandemic context.

1.2. Shared mobility and COVID-19

The literature about shared mobility in COVID-19 is enriched. Existing studies major focused on how shared mobility affect by COVID-19 during (del Alonso-Almeida, 2022; Bucsky, 2020; Garaus and Garaus, 2021; Kamargianni et al., 2022; Menon et al., 2020; Rahimi et al., 2021; Shokouhyar et al., 2021; Turoń et al., 2021; Zhang et al., 2022) and after the pandemic (Awad-Núñez et al., 2021; Gragera, 2021; Hensher, 2020; Menon et al., 2020; Shokouhyar et al., 2021; Tsvetkova et al., 2022).

Regarding the changes in shared mobility services during the pandemic, the usage of shared mobility is the most mentioned topic by researchers. In general, shared mobility usage and mode sharing declined but not so much during the pandemic (Bucsky, 2020; Heineke et al., 2020; Menon et al., 2020; Shokouhyar et al., 2021; Zhang et al., 2022). For example, Bucsky (2020) reported that bike sharing became more popular because of rapid measures, and other shared mobility services usage dropped slower than traditional travel modes (e.g., transit). More detailed, ride-sharing usage dropped by 15–20%, which is slighter than pedestrian traffic (dropped by around 50%). Some researchers also reported that the usage of some kinds of shared mobility services did not decrease or even grow due to the pandemic (Bucsky, 2020; Shokouhyar et al., 2021). Bike sharing performed well during the pandemic (Bucsky, 2020; Shokouhyar et al., 2021; Zhang et al., 2022). On the contrary, the pandemic seriously affected car-sharing services (Menon et al., 2020; Zhang et al., 2022). Moreover, the strategies of shared mobility services providers are also well-discussed by researchers. The primary strategies include publishing new pricing schemes (del Alonso-Almeida, 2022; Menon et al., 2020; Turoń et al., 2021), developing protective measures for drivers and passengers like maintaining social distancing (del Alonso-Almeida, 2022; Menon et al., 2020; Turoń et al., 2021), and conducting new services (Menon et al., 2020; Turoń et al., 2021). For example, uber (Menon et al., 2020) required all drivers to wear face masks and encouraged drivers to cancel rides with passengers without masks. Also, uber added critical delivery services in selected cities. Some studies investigated the risk perception of shared mobility services during the pandemic (Garaus and Garaus, 2021; Rahimi et al., 2021). Rahimi et al. (2021) found that people with a higher income, who were younger, and who lived in rural areas had a lower risk perception of shared mobility services during the pandemic. In policy-making research, promoting shared mobility, micromobility, and mobility as a service (MaaS) was still one of the prior works for some Europe agencies of large size areas (more than 500,000 inhabitants) during the pandemic (Kamargianni et al., 2022).

Some studies focused on shared mobility services and the potential opportunities after the pandemic. Hensher (2020) and Gragera (2021) indicated that the pandemic offers an opportunity for MaaS to cooperate

Table 1
Examples shared mobility and active travel-related studies under the context of the COVID-19 pandemic.

Literature	Study area	Data	Shared mobility	Active travel	Key finding(s)
Aldred and Goodman (2021)	Outer London, UK	Survey data		√	The emergency low-traffic neighbourhoods and the longer-standing low-traffic neighbourhoods have the same increases in active travel during COVID-19.
del Alonso-Almeida (2022)	Madrid, Spain	Interview data	√		1. COVID-19 did not affect most of the participants' car-sharing usage during the pandemic; 2. 46% of participants kept using car-sharing services but did not trust the cleanliness of the car, and 38% of participants using less car-sharing service because of the decreasing of their travel demand; 3. The advantage of using car-sharing services rather than public transit systems is the probability of keeping social distance.
Awad-Núñez et al. (2021)	Spain	Survey data	√		1. Provided covers for handlebars and steering wheels would increase the willingness of individuals to use shared mobility services; 2. Consumers hope that the prices of shared mobility services would not be changed compared with pre-COVID periods.
Bucsky (2020)	Budapest, Hungary	Multi-source	√	√	1. During the pandemic, bicycle usage grew the greatest compared with other modes; 2. bike sharing became more popular because of rapid measures, and other shared mobility services usage dropped slower than traditional travel modes (e.g., transit).
Garaus and Garaus (2021)	German	Experiment data	√		1. Safety claims cannot reduce the consumers' perceived physical risk during the pandemic; 2. The perceived physical risk is negatively associated with carsharing usage.
Kamargianni et al. (2022)	Europe	Survey data	√	√	1. Promote shared mobility, micromobility and MaaS are the focused strategy for large areas; 2. Smaller areas focused more on promoting active travel.
Menon et al. (2020)	The U.S.	Survey data	√		1. The majority of respondents claimed that they would not be using Uber/Lyft, bicycle/bikeshare, and public transit after the pandemic; 2. During the pandemic, more than 60% of respondents do not trust rail/bus transit, taxi, and Uber/Lyft.
Rahimi et al. (2021)	Chicago, US	Survey data	√		Many factors (e.g., socio-demographic, built environment, and virus spread) are found to be associated with the perceived risk of using shared mobility services.
Scorrano & Danielis (2021)	Trieste, Italy	Survey data		√	1. Cycling increased, but active travel would not increase; 2. There is high substitutability between bikes and buses during the pandemic.
Shaer et al. (2021)	Shiraz city, Iran	Survey data		√	During the pandemic, safe and secure cycling and walking routes and a people-friendly environment strongly impact people's active travel.
Shaer & Haghshenas (2021)	Isfahan, Iran	Survey data		√	1. During the pandemic, the share of walking and cycling modes increased; 2. Active travel is good for older adults' mobility in the post-outbreak.
Thombre & Agarwal (2021)	India	Survey data		√	The bicycle share improved from 31% to 44% because of the provision of bicycle superhighways in some areas of India.
Wali and Frank (2021)	King County Washington, US	Multi-source		√	Using active travel as the commute mode is negatively related to COVID-19 hospitalizations.
Zhang et al. (2022)	Beijing, China	Survey data	√		1. Shared mobility is limited by anxiety about shared spaces; 2. Shared mobility has a lower transmission risk of public transit, and the potential to mitigate the intensity of private car use during the COVID-19 pandemic.

with other shared mobility modes to replace transit and compete with private cars in mode sharing. Menon et al. (2020) and Tsvetkova et al. (2022) also thought that shared mobility had a huge potential after the pandemic. Awad-Núñez et al. (2021) focused on how shared mobility should attract consumers after the pandemic. They proposed that the critical method is maintaining the price the same as pre-COVID-19. Providing covers for handlebars and steering wheels can also make consumers more willing to use shared mobility services.

1.3. Active travel and COVID-19

During the pandemic, some cities improved their active travel systems to make up for the shortages in carrying due to reductions and disruptions in public transit services (Nurse and Dunning, 2021). Several studies indicated that active travel can not only make up for the shortages in carrying due to reductions and disruptions in public transit services but can also help people to avoid social contact with others, maintain health and happiness during the pandemic, reduce the travel cost, and keep a sustainable environment (de Vos, 2020; Koehl, 2021; Laverty et al., 2020). Based on these advantages and the changes in travel behaviors caused by COVID-19, researchers considered that the COVID-19 pandemic might be an opportunity to popularize active travel and decrease the market share of private cars (de Vos, 2020; Koehl, 2021; Laverty et al., 2020; Shaer and Haghshenas, 2021).

Researchers conducted some studies to investigate the different aspects (e.g., usage, factors related to the usage of active travel) of active travel during the pandemic. Wali and Frank (2021) found that COVID patients with a higher active travel rate are negatively associated with higher COVID-19 hospitalization/fatality rates. Bucsky (2020) reported that, during the pandemic, the usage of riding bikes grew fast in Budapest, Hungary. The modal share of riding bikes increased one more time compared with the pre-COVID period. Thombre and Agarwal (2021) indicated that the bicycle share improved from 31% to 44% because of the provision of bicycle superhighways in some areas of India. Shaer et al. (2021), Shaer and Haghshenas (2021), and Buehler and Pucher (2021) also reported the increase in bicycle usage in non-CBD areas in Iran, the U.S., Europe, and Australia. Buehler and Pucher (2021) believed that bicycle usage would not drop after a few years because bicycle riders were familiar with and got used to traveling by bike. Shaer et al. (2021) found that the duration of riding bikes is positively related to bike-ability, traffic calming, vegetation and aesthetics, intersections safety, design and street pattern, and bike-sharing infrastructures. In addition, walkability, intersection safety, land use density, destination accessibility, traffic calming, security, vegetation, and aesthetics are positively associated with walking duration. Scorrano and Danielis (2021) identified the association between the willingness to make active travel and socio-demographic factors for males in Italy during the pandemic. They summarized that females were more likely to make active travel than males. People who were 35–65 years old, students, and unemployed with a higher willingness to walk. Aldred and Goodman (2021) reported that low-traffic neighborhoods could significantly decrease car usage and increase active travel rates. In policy-making research, promoting active travel was one of the prior works for some Europe agencies of small or medium size areas (50,000 – 500,000 inhabitants) during the pandemic (Kamargianni et al., 2022).

1.4. Summary

In conclusion, some studies provided information on shared mobility services during and after the pandemic, but limited studies discussed active travel in the post-pandemic period. Furthermore, how socio-demographic factors and travel behavior factors affect the willingness to use shared mobility and make active travel after the pandemic is lacking investigated. Some studies provided good insights into investigating the post-COVID travel intentions in Alabama (Adanu et al., 2021; Nie et al., 2022; Shirani-bidabadi et al., 2021). However, no other studies have discussed the post-pandemic shared mobility and active travel wiliness in Alabama. Thus, this study brings a unique aspect of Alabamian's post-pandemic shared mobility and active travel preferences due to the impacts of the COVID-19 pandemic.

2. Data and methodology

2.1. Survey

On April 4, 2020, the Alabama government issued its first Stay At Home order. In the following month, the Alabama Transportation Institute (ATI) developed an online survey to collect travel behavior changes among Alabamians during the pandemic and their future travel preferences by considering the impacts of COVID-19. The survey included two parts. The first part collected respondents' socio-demographic information such as age, gender, education, and household income. The second part asked about respondents' travel behavior before and during the COVID-19 pandemic. Table 2 lists key survey questions and response options.

After receiving approval from the University's Institutional Review Board (IRB), the survey was administered in Qualtrics and distributed via email. The survey was completely voluntary without any incentive. Respondents were informed that they could stop anywhere in the survey or skip questions they did not want to answer. A total of 1,402 respondents from Alabama participated in the survey.

2.2. Data preparation

Before analysis and modeling, the survey data were checked, and cleaned the outlier and missing samples based on the following steps:

- Step 1: Filtering and removing observations outside of Alabama based on their zip code;
- Step 2: Filtering and removing observations which were completed within three minutes;
- Step 3: Labeling observations with missing information (because responders skipped or chose not to answer) with "N.A." values;
- Step 4: Removing observations with "N.A." values in questions "*How has the COVID-19 shelter-in-place order in Alabama reduced your activities and time spent at the following types of places?*" and "*How will your travel behavior change?*";
- Step 5: Using the data imputation method to impute "N.A." values in all left observations.

The purpose of data imputation is to retain a reasonable size of data for analysis and modeling. Among variables of interest, gender, household size, household income, households with children, and fear of COVID-19, only 1% of observations are missing a value. More missing values were found in other variables, including marital status (1.2%), primary commute mode before COVID-19 (4.4%), commute time duration before COVID-19 (10.8%), attitude toward the commute (10.2%), attitude toward working at home (8.7%), and attitude for shopping online (1.5%). The MICE (Multivariate Imputation by Chained Equations) method was used to replace missing values in data for variables of interest. Finally, a dataset of 481 valid samples was prepared for data analysis.

Table 2
Survey items used in data analysis.

Item	Item text	Response Options
Age	*What is your age?*	18 – 25; 26 – 45; 46 – 65; 66 – 75; Older than 75; Prefer not to answer
Education	*What is the highest degree or level of education you have completed?*	Some High School; High School; Bachelor's Degree; Master's Degree; Doctoral Degree; Trade School; Prefer not to answer
Gender	*How do you identify your gender?*	
Income level	*Which of these describes your household income last year?*	\$0; \$1 to \$9,999; \$10,000 to \$24,999; \$25,000 to 49,999; \$50,000 to 74,999; \$75,000 to 99,999; \$100,000 to 149,999; \$150,000 and greater; Prefer not to answer
Short-term travel behavior changes	*How has the COVID-19 shelter-in-place order in Alabama reduced your activities and time spent at the following types of places?*	Grocery & pharmacy (0% – 100%); Parks (0% – 100%); Transit stations (0% – 100%); Retail & recreation (0% – 100%); Residential (0% – 100%); Workplaces (0% – 100%)
Primarily commute mode before COVID-19	*How did you primarily travel to and from work before the COVID-19 shelter-in-place orders?*	My car; Rode in with someone in their car; Bus; Taxi, Uber, Lyft, Via; Bicycle; Walk
Commute time before COVID-19	*How long did you typically spend traveling from home to work before the COVID-19 shelter-in-place orders?*	less than 15 min; 15–30 min; 30–45 min; 45 min – 1 h; more than 1 h
Attitude for commute	*Do you like not having to commute to work?*	Yes; Maybe; No
Attitude for working at home	*Have the COVID-19 shelter-in-place orders made you want to work at home more?*	Yes; Maybe; No
Preference of trip time (not commute)	*When did you most often make trips not related to work (e.g., shopping, errands) before the COVID-19 shelter-in-place orders?*	Before work; During the workhour; After work; Weekends
Attitude for COVID-19 and car crashes	*Are you more afraid of COVID-19 or car crashes?*	COVID-19; Car crashes
Long-term travel behavior changes	*How will it change?*	I will travel to less places; I will travel less often; I will not use public transportation; I will not use taxis, Uber, or Lyft; I will walk more places; I will cycle more places

For modeling purposes, this study re-coded some variables based on the survey responses, such as age groups, education levels, and household income. The dependent variables are the post-pandemic travel preferences or future travel intentions regarding shared mobility and active travel. In the survey, participants were asked to provide their perspectives on post-pandemic travel behavior changes, e.g., whether they will avoid ride-hailing services and whether they will walk or cycle more after the pandemic. Two dependent variables are binary variables – Yes or No, directly extracted from survey responses.

2.3. Machine learning models

The modeling aims to identify the relationship between factors and post-pandemic travel preferences regarding shared mobility and active travel. To eliminate the bias of any single model, this study conducted multiple famous machine learning classifiers, including Random Forest, Adaptive Boosting, Support Vector Machine, K-Nearest Neighbors, and Artificial Neural Network. Except for the Support Vector Machine (tuned by the "e1071" package in R), all machine learning classifiers were tuned hyperparameters by the "caret" package in R using repeated crossvalidation based on predictive accuracy (Kuhn, 2008; Meyer et al., 2019). Averaged marginal effects are estimated to quantify the correlates of future travel intentions due to the pandemic. This study removed each predictor's maximum and minimum marginal effects to minimize the estimation bias before calculating the average marginal effects.

2.4. Random Forest

The Random Forest algorithm (RF) is a basic ensemble learning method that was modified from the bagging tree (Breiman, 2001). The core idea is to aggregate several weak classifiers (i.e., Decision Tree) into a strong classifier (i.e., Random Forest). The Random Forest algorithm employs bootstrapping — a random repeatable selection of samples to build a new training set for each tree in the forest. A random number of trees are built (ntree) based on bootstrapping. The unselected samples are usually called out-of-bag (OOB) observations. Also, to eliminate the potential correlation among each tree, the Random Forest algorithm randomly chose m features (mtry) from all p features. The prediction result of the Random Forest algorithm is based on the prediction result of each tree. In other words, the prediction probability for each class is the proportion of each class in the prediction results of all trees. The Random Forest algorithm is not sensitive to skewed distributions, outliers, and missing values. The "randomForest" package was used to train the Random Forest model (Liaw and Wiener, 2002). The combinations of "mtry" and "ntree" of the shared mobility and active travel models are (5,450) and (5,400).

2.5. AdaBoost

Adaptive Boosting (AdaBoost) is an ensemble learning algorithm that combines several weak classifiers (e.g., decision tree, logistic regression). This study selected the decision tree as the weak classifier. However, different from R.F., weight plays a vital role in AdaBoost. Initially, each observation has the same weight. If an observation is misclassified, the weight of this observation will be boosted. The next weak classifier will be built based on the updated weights, which are no longer equal. After the iteration convergence, a score will be assigned to each weak classifier. The final classifier is the linear combination of the weak classifiers from each stage (Zhu et al., 2009). AdaBoost has relatively higher accuracy. Compared with R.F., AdaBoost considers each classifier's weight. However, Adaboost is time-wasting and sensitive to outliers. Adaboost models were trained by the "Adabag" package in R (Alfaro et al., 2013). The combinations of "mfinal" (number of iterations) and "maxdepth" (the max depth of each tree) for each model are (400, 15) and (300, 9).

2.6. Support Vector Machine

As a powerful classifier, the primary goal of the Support Vector Machine (SVM) is to find a hyperplane to separate two classes as accurately as possible. It can be presented as an optimization problem: maximize the margin between classes. Simultaneously, at least one margin exists when some violation happens. The formulation and constraints are shown in Eqs. (1)–(3).

$$\min_{w,b,\varepsilon}\frac{\|w\|^2}{2}+C\sum_{i=1}^{N}\varepsilon_i \tag{1}$$

s.t.

$$y_i\left(w^TX_i+b\right)\geq 1-\varepsilon_i \tag{2}$$

$$\varepsilon_i\geq 0 \tag{3}$$

The w is a set of parameters that can define decision boundaries between different classes, C is the penalty parameter. The ε_i is slack variable and the error term to show the margin violation. The y_i is the label of observation i, and b is the intercept of decision boundaries. To deal with the non-linear class boundaries problem, different kernels (e.g., polynomial and radial kernel) are used to enlarge the feature space (James et al., 2013). The SVM model performs well when the feature spaces are high-dimensional. But, the solutions of SVM can not be interpreted easily (Devos et al., 2009). This study adopted radial kernel SVM using the R package "e1071" (Meyer et al., 2019) with two hyperparameters, "cost" (cost constraint violation) and "gamma" (a positive constant that defines how far the influence of a single training example reaches). The combination of hyperparameters (i.e., cost and gamma) of the shared mobility and active travel models are (3, 0.05) and (2, 0.1).

2.7. K-Nearest Neighbors

The K-Nearest Neighbors algorithm (KNN) is a typically non-parametric classification method (Fix and Hodges, 1989). In general, the KNN assumes that similar things are near to each other. Thus, in the KNN, samples are classified by the main votes of their neighbors. The sample will be assigned to the most common class within k_{th} nearest neighbors (k is a positive integer). Different distance metrics can be used to define the distance to distinguish different classes of observations. This study selected the Euclidean metric as the distance metric. The "class" was used to fit the KNN model in this study (Venables and Ripley, 2002). In this study, the best number of neighbors are 20 and 17 for shared mobility and active travel models.

2.8. Artificial Neural Network

The Artificial Neural Network (ANN) was designed to simulate the structure and function of biological nervous systems. An ANN consists of three types of neuro node layers: input layer, hidden layer, and output layer. In general, researchers input data into the model as the input layer. Then, the input data reflects on and processed by the hidden layer. After processing, the probability of each class will be output into the output layer. This study trained single-hidden-layer ANN models by "nnet" packages in R (Ripley et al., 2016). The combination of the number of units in the hidden-layer and the value of weight decay constant for each model are (4, 0.4) and (2, 0.4).

2.9. Marginal effects

Marginal effects represent the estimated changes in predictions for the dependent variable when there is a change in an independent variable (one unit value change for continuous variables or a change of categories for categorical variables) while all other variables are held constant (Williams, 2012; Liu et al., 2015; Liu and Khattak, 2017, 2018). Marginal effects are often calculated after model estimation to show how predictors associate with the dependent variable in the model (Fu et al., 2022; Li et al., 2022; Liu et al., 2016, 2021; Zhang et al., 2022). Different methods of calculating the marginal effects of machine learning models were provided by literature, such as the marginal effect at the mean (Silva Filho et al., 2021; Sun et al., 2020), the marginal effect at the representative value (Silva Filho et al., 2021), and partial dependence (Molnar, 2020). According to the definition of marginal effects introduced by Williams (2012), this study adopted the average marginal effects of variables based on the estimated machine learning models. The average marginal effects can be used to represent the quantified relationships between the COVID impacts on travel behavior (i.e., shared mobility and active travel usage) and associated factors. This study calculated the average marginal effects using the idea of calculating partial dependence (Molnar, 2020) for each variable included in a machine model. In this study, all variables are categorical variables; therefore, this study calculated the average marginal effects for each class or category of a variable except the base category. First, this study used the model to predict the response (i.e., short-term trip reductions or long-term travel preferences) by assuming the variable of interest is in its base class for every observation, and all other variables remain the original values in the training data. The base class predictions from all observations are then averaged, as noted as $\widehat{f}_{Sbase}$. Second, this study replaced the variable of interest with its target class (other than the base class) and kept all other variables with their original values in the training data; then, using the same model, new predictions for the target class were made, noted as $\widehat{f}_{Scategory}$. The difference between these two average values (i.e., $\widehat{f}_{Scategory} - \widehat{f}_{Sbase}$) is the average marginal effect of the specific category. The function, which is estimated by the Monte Carlo method (calculating the average in the training data), is as follows:

$$\widehat{f}_S(x_S) = \frac{1}{n}\sum_{i=1}^{n}\widehat{f}\left(x_S, x_C^{(i)}\right) \tag{4}$$

where, the $\widehat{f}_S$ represents the partial function, and n is the number of observations in the training data. The x_S is feature that needs to be calculated the partial dependence. The x_C is the combination of other features used in the machine learning model $\widehat{f}$, which is treated as random variables here. The $x_C^{(i)}$ is the value of x_C of the i_{th} observations. Furthermore, the partial function requires an assumption that the features in C are not correlated with the features is S.

Usually, Different performance metrics (e.g., Predictive accuracy, recall, Area under the curve) were used to select the best-performed machine learning model. However, different metrics might not indicate the same model as the best-performed model. Also, Lu et al. (2022) and Li and Kockelman (2022) indicated that the estimation of machine learning models could be biased. The very nature of a specific model is a simplified and idealized representation of something. Thus, all models could not be truly correct. To avoid these modeling uncertainties, eliminate the modeling bias, and make the modeling results more credible, this study estimated each predictor's average marginal effects of built machine learning models. This study removed the maximum and minimum marginal effects for each predictor to minimize the estimation bias and get trustworthy results before calculating the average marginal effects.

3. Results

This section first presents the descriptive statistics of key variables in survey data before data imputation, and displays the data distribution after data imputation (Table 3). Then, the modeling results are summarized with estimated average marginal effects of variables on future travel preferences regarding shared mobility and active travel (Tables 4 and 5). The average marginal effects represent the quantified relationships between factors and future travel preferences. Multiple machine learning methods were employed in this study. Both the average marginal effects from individual models and the mean of average marginal effects from multiple models are reported. Fitted models were evaluated using predictive accuracy, defined as the correct prediction rate of a model. For model evaluation, this study divided the data into a training dataset (80% of all samples) and a testing dataset (20%). The predictive accuracy of individual machine learning models is presented along with modeling results. Note that predictive accuracy is only one of the model performance metrics, and different metrics may point to different models for the best performance. To reduce the bias of any single model, the model result interpretation and discussion in this study are based on the averaged marginal effects from multiple models instead of the model with the highest accuracy.

3.1. Descriptive statistics

Trip frequency was directly affected by the pandemic and shelter-in-

Table 3
Descriptive statistic of modeling variables after data imputation (N = 481).

Variable	Description	Code	Percent (%)
Dependent variable			
No longer use shared mobility	No	0	69.4
	Yes	1	30.6
Making more active travel	No	0	82.1
	Yes	1	17.9
Independent variable			
Age	18–25	0	6.7
	26–45	1	44.5
	46–65	2	39.9
	66 or more	3	8.9
Education	Under bachelor's degree	0	13.5
	Bachelor's degree	1	44.5
	Graduate degree	2	42.0
Gender	Male	0	24.1
	Female	1	75.9
HHSize	Household size: 3 to 5	0	49.5
	Household size: 1 to 2	1	48.0
	Household size: 6 to 8	2	2.5
Income	Less than $25,000	0	5.6
	$25,000-$49,999	1	12.5
	$50,000-$74,999	2	17.7
	$75,000-$99–999	3	18.1
	$100,000 or more	4	46.1
Marital status	Single	0	15.8
	Married	1	72.6
	Others (e.g., Widow)	2	11.6
Household with children	No	0	53.6
	Yes	1	46.4
Full-time employed	No	0	31.0
	Yes	1	69.0
Retired	No	0	91.3
	Yes	1	8.7
Using car as the primary commute mode before COVID-19	No	0	5.8
	Yes	1	94.2
Commute time before COVID-19	Less than 15 min	0	34.1
	15–30 min	1	34.1
	30–45 min	2	13.1
	45–60 min	3	8.9
	More than 60 min	4	9.8
Like not having to commute	No	0	18.5
	Yes	1	58.0
	Maybe	2	23.5
Want to work at home more (because shelter-in-place orders)	No	0	26.0
	Yes	1	54.3
	Maybe	2	19.7
Time preference for non-commuting trips	Before work	0	4.6
	During work hours	1	17.9
	After work	2	32.4
	Weekend	3	45.1
Afraid COVID-19 more than car crashes	No	0	43.0
	Yes	1	57.0
Reduction in grocery and pharmacy trips	0–25%	0	10.0
	26–50%	1	23.7
	51–75%	2	23.1
	76–100%	3	43.2
Reduction in park trips	0–25%	0	11.0
	26–50%	1	8.9
	51–75%	2	7.1
	76–100%	3	73.0
Reduction in retail and recreation trips	0–25%	0	2.7
	26–50%	1	4.4
	51–75%	2	6.4

(continued on next page)

Table 3 (*continued*)

Variable	Description	Code	Percent (%)
	76–100%	3	86.5
Reduction in workplace trips	0–25%	0	13.9
	26–50%	1	10.2
	51–75%	2	7.3
	76–100%	3	68.6

place order. Compared with before, participants decreased 48.7% of trips to groceries and pharmacies on average (the standard deviation is 27.3%). Different from grocery and pharmacy trips, they only decreased 21.8% of retail and recreation trips and 22.0% of commute trips (the standard deviations are 28.4% and 27.0%). Experienced the pandemic, 53.4% of participants thought that their trip frequency and destination would change after the COVID-19 shelter-in-place order ended.

The COVID-19 pandemic affected Alabamian's actual usage and attitudes toward using shared mobility and active travel (Figs. 1 and 2). Before the pandemic, 1.2% of respondents reported commuting primarily by active travel. After the shelter-in-place order was issued, the proportion dropped to 0.4%. The usage of shared mobility for commuting had no significant changes between the pre-COVID period (0.4%) and during the pandemic (0.2%). However, 51.4% and 10.6% of respondents indicated that they walked more and rode a bicycle more during the pandemic than during the pre-COVID period. Only considering active travel, more respondents prefer walking during the

Table 4
Correlates on future travel preferences (Whether a person will no longer use shared mobility after the pandemic).

Variables	AdaBoost	KNN	SVM	RF	ANN	Average
Age (base: 18–25)						
26–45	−2.2%	0.4%	−0.5%	−4.7%	−5.1%	−2.5%
46–65	1.5%	1.7%	0.8%	2.1%	8.9%	1.8%
66 +	−0.4%	2.5%	−0.2%	−2.0%	−1.1%	−0.6%
Education (base: Under bachelor's degree)						
Bachelor's degree	−0.1%	−1.4%	0.1%	−0.4%	3.8%	−0.1%
Graduate degree	−1.3%	−2.5%	−0.2%	−3.6%	−2.2%	−2.0%
Gender: Female	1.9%	1.2%	0.4%	3.0%	9.2%	2.0%
HHSize (base: 3–5)						
1–2	0.4%	0.5%	0.3%	0.9%	3.2%	0.6%
6–8	2.9%	1.0%	0.3%	5.7%	1.0%	1.6%
Income (base: Less than $25,000)						
$25,000-$49,999	−2.2%	−0.7%	−0.5%	−0.8%	−7.0%	−1.2%
$50,000-$74,999	0.6%	−2.7%	0.5%	4.3%	5.8%	1.8%
$75,000-$99,999	−0.2%	−5.3%	0.1%	1.5%	1.4%	0.4%
$100,000 or more	−2.4%	−7.4%	−0.8%	−3.3%	−8.0%	−4.3%
Marital status (base: Single)						
Married	0.6%	0.7%	−0.1%	−1.7%	−1.3%	−0.3%
Others (e.g., Widow)	0.6%	1.5%	0.5%	3.5%	0.8%	1.0%
Household with children: Yes	0.0%	−0.4%	0.2%	0.1%	1.0%	0.1%
Full-time employed: Yes	−1.3%	−0.6%	−0.7%	−2.3%	−5.0%	−1.4%
Retired: Yes	0.4%	0.0%	0.0%	2.1%	1.8%	0.8%
Using the car as the primary commute mode before COVID-19 (base: No)						
Yes	0.3%	−0.2%	−0.1%	−0.4%	4.2%	0.0%
Commute time before COVID-19 (base: less than 15min)						
15–30 min	−0.5%	1.0%	−0.1%	1.3%	−1.3%	0.1%
30–45 min	−0.5%	2.5%	−0.3%	0.4%	−2.6%	−0.2%
45–60 min	1.8%	4.0%	0.7%	3.6%	2.1%	2.5%
More than 60 min	1.0%	5.3%	−0.3%	2.3%	2.1%	1.8%
Like not having to commute (base: No)						
Yes	1.1%	0.5%	0.3%	0.5%	3.1%	0.7%
No	−0.4%	0.6%	0.1%	−1.3%	−5.2%	−0.5%
Want to work at home more (base: No)						
Yes	1.2%	0.7%	−0.2%	2.1%	−0.1%	0.6%
Maybe	0.6%	1.1%	0.2%	1.4%	−0.1%	0.6%
Time preference for non-commuting trips (base: Before work hours)						
During work hour	−4.0%	0.7%	−0.7%	−8.0%	−8.9%	−4.2%
After work	0.8%	1.9%	0.4%	−0.7%	10.9%	1.0%
Weekend	−0.9%	3.2%	−0.5%	−3.7%	2.7%	0.5%
Afraid COVID-19 more than car crashes (base: No)						
Yes	2.7%	0.6%	0.5%	4.2%	5.6%	2.5%
Reductions in grocery and pharmacy trips						
26%-50%	−2.8%	0.5%	−0.8%	−2.8%	−2.9%	−2.1%
51%-75%	0.9%	1.0%	0.5%	3.7%	6.5%	1.9%
76%-100%	−0.4%	1.8%	−0.1%	1.0%	3.0%	0.9%
Reductions in retail and recreation trips						
26%-50%	2.1%	0.3%	1.4%	2.9%	11.3%	2.1%
51%-75%	−2.7%	0.8%	−1.1%	−4.2%	−12.6%	−2.7%
76%-100%	1.0%	0.9%	0.1%	−1.1%	1.2%	0.7%
Reductions in workplace trips						
26%-50%	1.3%	−7.3%	1.0%	5.1%	5.6%	2.4%
51%-75%	−3.1%	−13.0%	−0.7%	−6.6%	−7.1%	−5.6%
76%-100%	−4.1%	−15.1%	−1.4%	−8.4%	−12.6%	−8.4%
Reductions in park trips						
26%-50%	−1.2%	2.9%	−0.5%	−1.4%	−6.6%	−1.0%
51%-75%	4.6%	5.1%	1.3%	12.1%	14.7%	7.3%
76%-100%	3.2%	6.1%	0.5%	6.2%	7.0%	5.2%
Accuracy	61.5%	71.9%	66.7%	63.5%	57.3%	

Table 5
Correlates on future travel preferences (Whether a person will make more active travel after the pandemic).

Variables	AdaBoost	KNN	SVM	RF	ANN	Average
Age (base: 18–25)						
26–45	−2.8%	−0.3%	−1.8%	−9.2%	−4.4%	−3.0%
46–65	−2.2%	0.4%	−1.9%	−7.0%	−4.6%	−2.9%
66 +	−5.5%	0.1%	−3.8%	−10.6%	−11.0%	−6.6%
Education (base: Under bachelor's degree)						
Bachelor's degree	1.0%	0.8%	0.6%	1.3%	3.0%	1.1%
Graduate degree	0.1%	0.6%	−0.1%	0.4%	2.7%	0.4%
Gender: Female	−3.7%	−0.9%	−1.9%	−4.5%	−7.0%	−3.4%
HHSize (base: 3–5)						
1–2	−0.5%	0.5%	−1.8%	−0.3%	−7.0%	−0.9%
6–8	7.1%	2.3%	2.9%	9.8%	18.4%	6.6%
Income (base: Less than $25,000)						
$25,000-$49,999	3.6%	−2.7%	0.6%	2.5%	1.6%	1.6%
$50,000-$74,999	−1.8%	−3.8%	−1.8%	−4.0%	−6.1%	−3.2%
$75,000-$99,999	0.6%	−2.4%	−0.3%	−1.6%	−1.0%	−0.9%
$100,000 or more	3.0%	0.1%	1.0%	1.8%	5.1%	1.9%
Marital status (base: Single)						
Married	−5.1%	−0.2%	−4.4%	−9.1%	−12.9%	−6.2%
Others (e.g., Widow)	−2.4%	−0.1%	−0.8%	−3.9%	−2.5%	−1.9%
Household with children: Yes	−2.6%	−1.6%	−2.9%	−4.1%	−13.5%	−3.2%
Full-time employed: Yes	−0.7%	0.1%	−1.4%	−1.4%	−3.0%	−1.2%
Retired: Yes	−0.1%	−0.2%	0.1%	0.0%	−1.0%	−0.1%
Using the car as the primary commute mode before COVID-19 (base: No)						
Yes	1.1%	0.3%	−0.1%	0.0%	1.6%	0.4%
Commute time before COVID-19 (base: less than 15min)						
15–30 min	−0.1%	−1.9%	−0.1%	−1.7%	−2.3%	−1.2%
30–45 min	−0.9%	−2.8%	−0.6%	−3.0%	−5.8%	−2.2%
45–60 min	−0.5%	−3.6%	−0.9%	−4.4%	−4.8%	−2.9%
More than 60 min	−0.2%	−4.1%	0.0%	−3.7%	−5.4%	−2.6%
Like not having to commute (base: No)						
Yes	1.4%	0.5%	−0.2%	1.0%	2.2%	1.0%
No	0.6%	0.6%	−0.7%	1.0%	−1.0%	0.2%
Want to work at home more (base: No)						
Yes	−0.5%	−1.6%	−0.2%	−1.2%	1.6%	−0.6%
Maybe	−0.1%	−1.7%	−0.5%	−0.2%	−2.7%	−0.8%
Time preference for non-commuting trips (base: Before work hours)						
During work hour	1.2%	−0.1%	−0.6%	−1.0%	−1.0%	−0.6%
After work	1.3%	0.0%	0.7%	0.3%	3.5%	0.7%
Weekend	0.4%	0.5%	−0.4%	−1.6%	0.5%	0.2%
Afraid COVID-19 more than car crashes (base: No)						
Yes	−0.6%	0.3%	−0.8%	−1.5%	−4.6%	−1.0%
Reductions in grocery and pharmacy trips						
26%-50%	−4.1%	0.0%	−1.5%	−3.7%	−2.9%	−2.7%
51%-75%	−1.0%	1.5%	−0.1%	−0.4%	0.9%	0.1%
76%-100%	−1.1%	2.7%	−1.0%	−1.8%	−1.6%	−1.2%
Reductions in retail and recreation trips						
26%-50%	−0.5%	1.8%	−0.1%	−1.3%	−1.8%	−0.6%
51%-75%	2.7%	3.2%	1.1%	1.9%	1.7%	2.1%
76%-100%	5.2%	3.7%	1.7%	1.6%	7.7%	3.5%
Reductions in workplace trips						
26%-50%	−6.6%	−5.0%	−1.5%	−7.3%	−6.2%	−5.9%
51%-75%	−2.5%	−7.2%	0.6%	−1.1%	7.1%	−1.0%
76%-100%	−5.3%	−7.0%	−1.2%	−6.3%	−0.8%	−4.3%
Reductions in park trips						
26%-50%	−1.6%	−4.2%	1.2%	0.0%	4.7%	−0.1%
51%-75%	−1.5%	−6.5%	0.6%	−0.8%	0.8%	−0.6%
76%-100%	−4.7%	−7.0%	−2.4%	−7.3%	−6.1%	−6.0%
Accuracy	65.6%	81.3%	79.2%	79.2%	76.0%	

pandemic. Some respondents thought that they would travel less (63.4%), no longer use shared mobility (30.6%), and walk or bike more (17.9%) after the pandemic.

The survey covered the population in almost all age groups, from young to old, while the dominant participants (84.4% of respondents) were between 26 and 65 years old. In terms of education level, 44.3% of participants' highest education level was a bachelor's degree, and 31.4% held a graduate degree. Over 75% of participants were females. Nearly half of the respondents (49.5%) were from households with three to five members. Over 43% of participants reported $100,000 or higher annual income for their household. Concerning respondents' travel behaviors before the pandemic, approximately 33% of respondents indicated that their commuting time was less than 15 min per trip, and the same amount of people reported that their commuting time was between 15 and 30 min per trip. About 11.4% of survey respondents said their community time was longer than 45 min. The survey also captured people's attributes towards working from home and commuting with possible influences of the pandemic. Among the survey participants, 56.3% said they liked not having to commute, and 52.4% said they wanted more opportunities to work from home. When asked about comparing COVID-19 and traffic crashes, 57% of respondents appeared to be more afraid of COVID-19 than traffic crashes.

3.2. Future travel intentions towards shared mobility

The socio-demographic factors are associated with the future travel

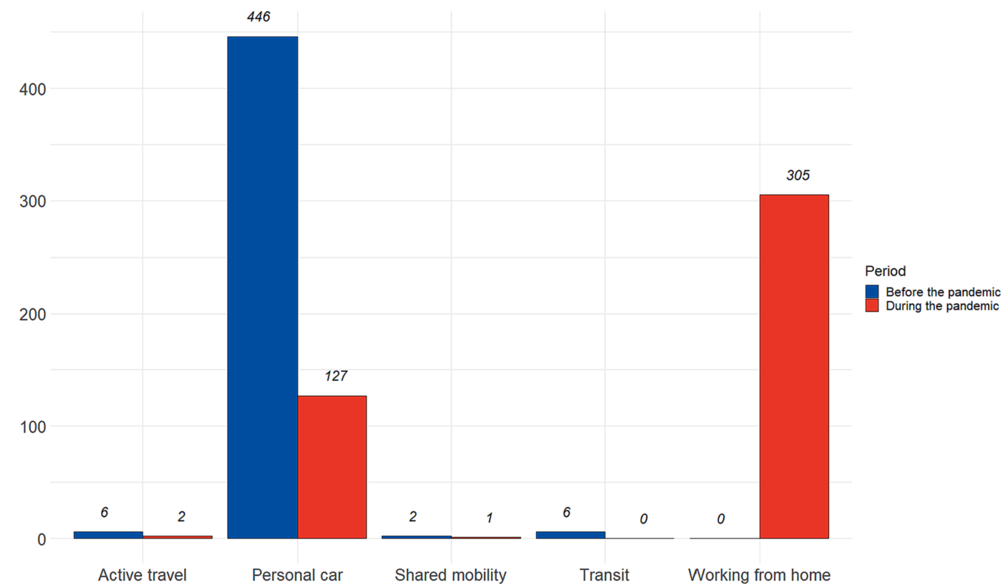

Fig. 1. Primary commuting mode before and during the pandemic.

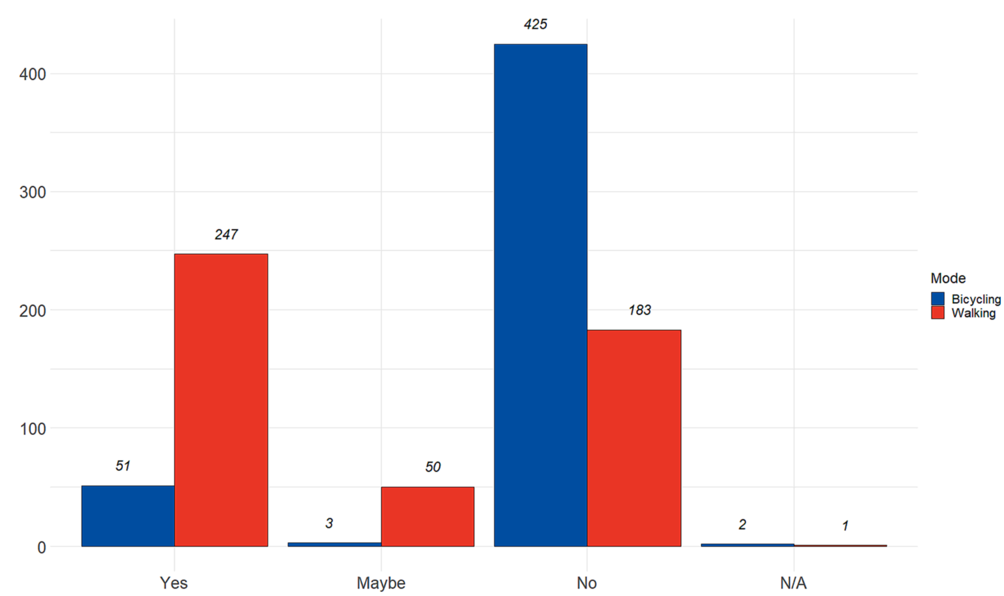

Fig. 2. Changes of walking and riding a bike during the pandemic.

preference of using shared mobility after the pandemic. Compared with the youngest age groups (18–25 years old), 26–45 years old respondents were 2.5% more likely, and 46–65 years old respondents were 1.8% less likely to keep using shared mobility. There is no significant difference between the youngest age group and the oldest age group. Regarding the highest education level, respondents with a graduate-level degree were 2.0% less willing to no longer use shared mobility after the pandemic. Females are more likely to no longer use shared mobility after the pandemic than males. Respondents who lived in large household-size families (6–8) were more willing to no longer use shared mobility than medium household (3–5) members. Compared with the lowest household income level (less than $25,000), respondents with $25,000-$49,999 and $100,000 or more household income are 1.2% and 4.3% more likely to keep using shared mobility in the future. However, respondents with $50,000-$74,999 were less likely to keep using shared mobility in the future. Full-time employees are 1.4% more willing to keep using shared mobility than other types of employees.

Travel behavior factors show slight correlates with the future travel preference for shared mobility. Whether using private cars as the primary commuting mode before the pandemic did not affect respondents' future travel preference of using shared mobility. Compared with short commuters (less than 15 min per trip), respondents who spent more than 45 min per trip before the pandemic were more likely to no longer use shared mobility after the pandemic, especially for respondents who spent 45 to 60 min commuting per trip before the pandemic (the average marginal effect is 2.5%). Respondents who preferred to make non-communizing trips during work hours seem more likely to keep using shared mobility.

As shown by the magnitudes of marginal effects, the short-term travel impacts are found to have strong relationships with the future travel preference of using shared mobility. Compared with respondents who reduced 0–25% of their grocery and pharmacy trips, respondents who reduced 26–50% and 51–75% of grocery and pharmacy trips were 2.1% less and 1.9% more likely to no longer use shared mobility. Respondents who reduced 26–50% and 51–75% of retail and recreation trips were 2.1% more and 2.7% less willing to no longer use shared mobility than respondents who made the same number of retail and recreation trips (reducing 0–25% of retail and recreation trips). Compared with respondents who reduced 0–25% of their workplace trips, respondents who reduced 26–50% are positively associated with no longer using shared mobility after the pandemic. On the contrary, respondents who reduced more than 50% of workplace trips seem to have negative and linear relationships with no longer using shared mobility. Respondents who reduced more than 50% of park trips were less willing to keep using shared mobility than respondents who reduced 0–25% of park trips.

3.3. Future travel intentions towards active travel

Similarly, the socio-demographic factors are associated with the future travel preference of active travel after the pandemic. Compared with the youngest age groups (18–25 years old), 26 or older respondents were less willing to make more active travel after the pandemic, especially for respondents who were older than 65 years old. The highest education level did not show strong relationships with the future travel preference of active travel. Females are associated with a lower likelihood of making more active travel after the pandemic than males. Respondents who lived in large household-size families (6–8) were 6.6% more willing to make more active travel than medium household (3–5) members. Compared with the lowest household income level (less than $25,000), respondents with $25,000-$49,999 and $100,000 or more household income are 1.6% and 1.9% more likely to make more active travel in the future. However, respondents with $50,000-$74,999 were 3.2% less likely to make more active travel in the future. In terms of marital status, married respondents were less willing to make more active travel than single respondents. Respondents who lived in households with children are associated with a lower likelihood of making more active travel.

Travel behavior factors show slight correlates of the future travel preference of making more active travel. Whether using private cars as the primary commuting mode before the pandemic did not affect respondents' future travel preference of making more active travel. The future preference impacted by COVID-19 for active travel seems to have approximately linear relationships with commuting time before the pandemic. Compared with short commuters (less than 15 min per trip), respondents who spent more than 15 min per trip before the pandemic were more likely to make more active travel after the pandemic, especially for respondents who spent 45 to 60 min commuting per trip before the pandemic (the average marginal effect is −2.9%).

As shown by the magnitudes of marginal effects, the short-term travel impacts are found to have strong relationships with the future travel preference of making more active travel. Compared with respondents who reduced 0–25% of their grocery and pharmacy trips, respondents who reduced 26–50% of grocery and pharmacy trips were 2.7% less likely to make more active travel after the pandemic. Respondents who reduced more than 50% of retail and recreation trips show a greater likelihood of making more active travel than respondents who made the same number of retail and recreation trips (reducing 0–25% of retail and recreation trips). Compared with respondents who reduced 0–25% of their workplace trips, respondents who reduced 26–50% and 76–100% of their workplace trips were 5.9% and 4.3% less willing to make more active travel after the pandemic. Respondents who reduced more than 75% of park trips were less willing to make more active travel after the pandemic than respondents who reduced 0–25% of park trips.

4. Discussion

According to Tables 4 and 5, some similarities between participants' future travel preferences of shared mobility and active travel are revealed in this study. First, factors such as "retired," "like not to commute," "want to work at home more," and "afraid of COVID-19 more than car crashes" did not show significant relationships with future travel preferences (i.e., no longer using shared mobility and making more active travel). These results indicated that, in this dataset, Alabamians' future preference was not affected by whether they had already retired or their attitudes toward the COVID-19 pandemic. Their future preferences depended more on their socio-demographic characteristics, commuting time before the pandemic, and different types of trips' decreasing rates during the pandemic. Then, some factors are strongly associated with the future travel preferences of shared mobility and active travel and show the same influence trend. Gender is identified as an important factor in both models. Females are associated with a lower likelihood of making more active travel and a greater likelihood of no longer using shared mobility after the pandemic than males. That might be because of females' safety concerns (Loukaitou-Sideris, 2014). Compared with the lowest income level (less than $25,000), respondents with $25,000-$49,999 and $100,000 or more household income are more likely to travel more actively and keep using shared mobility after the pandemic. However, respondents with $50,000-$74,999 were 3.2% less likely to make more active travel and 1.8% more willing to no longer use shared mobility after the pandemic. The low-income respondents included a large number of students. The highest-income level respondents and students have a higher probability of using shared mobility before than pandemic (Alemi et al., 2018; Winter et al., 2020). Also, high-income level respondents might consider their health more than the cost of active travel, and student travelers might be concentrated near or on the campus convenient for active travel (Lundberg and Weber, 2014). Other respondents might prefer to travel by their own vehicle(s) because of the potential cost of shared mobility and time consumption. Respondents who spent more than 45 min commuting per trip before the pandemic were less likely to make more active travel and more likely to no longer use shared mobility. They might live away from the working and commercial areas. In terms of the situation in Alabama, driving might be the most efficient travel mode in rural areas.

Not every factor performed similarly in these two models. Compared with the youngest age group (18–25 years old), respondents who were 26–45 years old were more likely to keep using shared mobility after the pandemic, and respondents who were 46–65 years old were less likely to keep using shared mobility. That might be because older people have a lower usage rate of ride-hailing services (Clewlow and Mishra, 2017). No longer using shared mobility will not affect their daily life and will decrease the exposure rate to the potential risk of disease. However, roughly, older respondents were likely to make more active travel. Physical disadvantage and lack of related facilities might be the key reasons. The highest education level relates slightly to the future preference for active travel. However, compared with responders without a bachelor's degree, graduate degree holders are more likely to keep using shared mobility, which is consistent with Sikder (2019). Large household-size members were more likely to no longer use shared mobility and make more active travel than medium household-size members. Large household-size members can share vehicles with other family members rather than using shared mobility (Sikder, 2019). The finding of active travel is consistent with Plaut (2005). Married respondents are less likely to abandon using shared mobility and make more active travels after the pandemic. Married people are proven to be highly associated with the perceived severity of COVID-19 (Rosi et al., 2021), which seems inconsistent with this result. However, the rate of using shared mobility by married respondents is unknown in the pre-COVID stage. It is hard to say that married respondents are willing to use shared mobility frequently after the pandemic. The lack of related infrastructures might be the reason for the unwillingness to make more active travels than before. Respondents with kid(s) are less willing to make more active travels after the pandemic. Traveling by walking or bicycling is not as convenient as personal cars under space–time constraints (Schwanen, 2011).

During the pandemic, because of the spreading ability of the virus and the economic pressure on many families, the limitations of shared mobility, such as being prone to virus transmission and related high costs, exposure to the pandemic might prevent some Alabamians from keeping using shared mobility in the future. After experiencing the pandemic, some people became aware that walking and riding bikes are good ways to make a trip that can avoid the virus, save money, reduce carbon emissions, and exercise to keep healthy. In addition, some objective factors also limited Alabamians' long-term travel behavior. For instance, Uber and Lyft only served a small part of Alabama (Lyft, n.d.; Uber, n.d.). Also, Alabama is primarily rural, so the bicycle lanes and sidewalks might not be enough. The limited service and facilities might be a shackle to using shared mobility and making active travels for Alabamians. These limitations may plague some groups with unique socio-demographic characteristics, such as low-income people and people with disabilities (Cochran, 2020; Parker et al., 2021).

As a summary of each model, age, gender, and income level contributed significantly to modeling Alabamians' near- and long-term impact of the pandemic and shelter-in-place orders on travel behaviors. In more detail, the heterogeneity of different categories within each factor led to the different modeling results. Take age as an example. The variance of different age groups' social experience, living pressure, and mental and physical conditions might lead to different behaviors when respondents face the pandemic and shelter-in-place orders and further affect their travel behaviors (e.g., whether using online shopping to replace offline shopping trips). Likewise, the variation in risk perception and safety concerns between males and females could result in various travel behaviors and future preferences. The occupational categories represented by different income levels and the risk perception of different income levels determined respondents' diverse travel behaviors during the pandemic.

5. Limitations

Because of the quality of survey data and sample size, this study may not represent the true population in Alabama. As shown in Table 3, females, high-education level, and high-income households are over-represented in the data, so selection bias may exist in modeling results. Also, to keep as much information as possible, this study applied data imputation to replace some N.A. values, which can also affect the modeling results. Moreover, all responses are voluntary. It is unknown to the authors whether a respondent gave truthful and accurate responses when answering the survey questions though the observations with obvious outliers and from subjects who completed the survey within three minutes were removed from the data for modeling. Last, this study employed several machine learning classifiers to capture the correlates of variables of interest. The model performance could be further improved with balanced data and a larger dataset.

6. Conclusions

This study surveyed Alabamians about their travel behavior changes during the COVID-19 pandemic and future travel preferences after the pandemic. This study aimed to provide a unique perspective of people's future travel preferences (i.e., whether respondents no longer use shared mobility and make more active travel) due to the pandemic in Alabama. Methodologically, this study adopted five machine learning classifiers, including Random Forest, Adaptive Boosting, Support Vector Machine, K-Nearest Neighbors, and Artificial Neural Network, to capture the correlation of the COVID-19 pandemic on future travel preferences. Average marginal effects were calculated based on machine learning models to quantify the correlates of COVID-19 impacts on future travel preferences. This study combined multiple machine learning classifiers to avoid bias from any single model results by averaging their marginal effects.

Key results from future travel preference of shared mobility and active travel models showed that 26–45 years old respondents were more likely, and 46–65 years old respondents were less likely to keep using shared mobility than younger groups (18 to 25 years old), and 26 or older respondents were less willing to make more active travel after the pandemic than younger groups, especially for respondents who were older than 65 years old. People with a graduate degree were more willing to keep using shared mobility than people with a lower-level degree. Females are associated with a lower likelihood of making more active travel and a greater likelihood of no longer using shared mobility after the pandemic than males. Compared with the lowest income level (less than $25,000), respondents with $25,000-$49,999 and $100,000 or more household income are more likely to make more active travel and keep using shared mobility after the pandemic. Respondents with $50,000-$74,999 were less likely to make more active travel and more willing to no longer use shared mobility after the pandemic. Respondents who spent more than 45 min commuting per trip before the pandemic were less likely to make more active travel and more likely to no longer use shared mobility. Large household-size members were more likely to no longer use shared mobility and make more active travel than medium household-size members. Married respondents are less likely to abandon using shared mobility and make more active travels after the pandemic.

This study provides an understanding of the impacts of COVID-19 on future travel preferences in Alabama. The information is valuable for developing local transportation plans that incorporate the impacts of COVID-19 on future usage of shared mobility and active travel. An expanded survey sample size within Alabama is needed. As the world is transitioning out of the COVID pandemic, a follow-up survey may provide improved information about post-pandemic travel behavior and compare Alabama residents' future preferences and actions. More machine learning classifiers could be tested in future research, and it would be worthwhile to examine the variation of model estimates using different machine learning classifiers.

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.

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Author contributions

The authors confirm contribution to the paper as follows: study conception and design: Ningzhe Xu, Qifan Nie, Jun Liu; data collection: Steven Jones; analysis and interpretation of results: Ningzhe Xu, Qifan Nie, Jun Liu, Steven Jones; draft manuscript preparation: Ningzhe Xu, Qifan Nie, Jun Liu, Steven Jones. All authors reviewed the results and approved the final version of the manuscript.

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