Modelling of pre and post Covid-19’s impact on employee’s mode choice behavior

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Abstract
Public transportation is one of the most affected systems by the pandemic. The utilization of public transit during the pandemic made the people feel unsafe. So, the use of private transportation modes for daily mobility has increased. This study aims to understand the COVID-19 impact on the employee’s mode choice. The survey methodology adopted in this study is a web-based survey in which questionnaires are distributed via various social media platforms and collected respondents' opinions. After collecting the responses, statistical analysis of socio-demographic characteristics, mode choice preferences, and factors affecting the mode choice were performed. From the results, it is observed that there is a mode shift from public transportation to private transportation to avoid the spread of COVID-19, and also there is a marginal increase in non-motorized transportation modes post COVID-19. The finding indicates the factors related to the spread of the infection, are the most important factors to consider when choosing a mode of transportation following COVID-19. Multinomial logistic regression and artificial neural network models were developed to analyze the mode choice of travelers pre and post COVID-19.

Keywords Mode choice · Pre COVID-19 · Post COVID-19 · Employees

Introduction
The coronavirus (COVID-19) pandemic had a significant impact on all aspects of daily lives around the world, including people’s travel patterns and modes of travel. Various counties implemented various methods and measures to stop the spread of COVID-19, including restricting social contacts, having remote teaching, closing shops and malls, restricting functions, meetings, and social events, having lockdown in various parts and shutting down borders, having social distance, and requiring people to wear masks. India is the second-largest populous country in the world. Due to the large population, it is very difficult in controlling the spread of covid-19 and required multiple strategies to tackle the spread of the virus and also the improvement in medical infrastructure for the affected one. The government of India has taken several measures and formulated protocols to achieve the goal of avoiding the spread of the covid-19 virus. The Indian government has made two months lockdown in the first wave, which made a great impact on the country’s economy. All these restrictions may not only be affected travel behavior and mode preferences but also people’s health and well-being. People have reduced their trips and also, they have avoided public transportation due to the fear of the spread of infection and they have shifted to private transportation. Due to the social distancing and lockdown, people have self-isolated and which affected people’s well-being. The public transport operators should focus on making public transport a safer way of traveling, and also, they shouldn’t reduce the frequency of trips or a capacity due to reduced trips but remain to maintain the service so that, people can maintain social distance from each other [8]. Also, the government should temporarily provide financial support to the public transport operators so that they’ll maintain hygiene in the buses. Public transportation mode choice behavior is an important component of transportation planning because it has a direct impact on the layout of...
urban transportation networks and the foundation for urban transportation planning and operation policy decisions [1].

This study focuses on an employee’s primary trip to work. This research aims to assess the influence of socio-demographic characteristics on employee mode choice behavior due to COVID-19. Pre, during, and post COVID-19, the characteristics that determine mode choice, as well as factors that influence them, are explored. Multinomial logistic regression and artificial neural network (ANN) models were developed to analyze the mode choice of travelers pre and post the COVID-19. The developed models will provide a proper relationship between the levels of non-compliance with the pandemic restrictions, the demographic parameters, and the attributes of the respondents that will affect public transport usage in the future.

Literature review

Coronavirus has had a large-scale impact on transportation. The understanding of the urban modal share during a pandemic situation can help the countries better prepare for transport management planning in the future [6]. Given the urgent need for reconsideration of transport in a post-COVID world, many studies were carried out to know the extent to which covid-19 has affected the mode choice behavior [10, 13, 15, 22, 27]. The impact of COVID-19 had decreased shared bike trips and public transport and increases two-wheelers comparison with public transport [21, 22], Sanhita [27]. Instead, people have shifted to personal transportation modes such as personal cars, taxis, and bikes [1, 9]. Post covid-19 due to decreased shared trips, intention to buy a private car or instead of purchasing cars, people would be likely to buy the less expensive electric 2 W increased [18].

To understand the mode choice behavior nested logit model [28], Artificial intelligence [12, 23, 32] is used to assess the behaviors towards mode selection ANN models are easily applicable with their higher capability to identify nonlinear relationships between inputs and designated outputs to predict choice behaviors [2, 7, 16]. COVID spread has increased due to increased mobility, and it can be reduced by restricting inter-country travel [30, 31]. Due to the financial crisis, NMT trips increased in pandemic-affected urban areas, while car use decreased [17, 19]. Most countries encouraged the use of bicycles, e-scooters, and walking as alternate modes of transportation during a pandemic [24].

The change in people’s behavior is in response to government restrictions, while others are motivated by concerns about personal safety. People’s mode choice behavior among the tougher of these measures is somewhat easy to predict because they have very few options. So far, the limited study has shown that different socio-demographic groups in different nations have changed in different ways in reaction to COVID-19. Nevertheless, very little research has looked into how people changed their travel mode preferences before, during, and after the Covid-19 restrictions. To fill this gap, the present work will assess the influence of socio-demographic variables on mode choice behavior before, during, and after COVID19.

Methods

Survey methodology

The survey was created with the help of Microsoft forms. The questionnaire will consist of the details of socio-demographic characteristics, mode choice preferences, and factors affecting mode choices pre-pandemic, during the lockdown, and after removing all the restrictions. An online survey form was used to collect the responses in Bangalore North, Karnataka, India. In the study area, a survey form has been circulated on numerous social media platforms. Because of the constraints imposed during the pandemic, face-to-face interviews are limited. Snowball sampling is a method used by researchers to generate a pool of participants for a research study by referring people with similar research interest [4]. Responses were collected using the snowball sampling technique, yielding a total of 1158 responses. From the total responses, 87.52 percent of respondents are from the study area, while the remaining 12.48 percent are from outside the study area, which was not considered in the analysis.

Analysis methods

Statistical analysis of socio-demographic characteristics, mode choice preference, and factors affecting the mode choice was performed by using SPSS software. The Wilcoxon signed-rank test is used to evaluate two related samples, or repeated measurements on a single sample to see if their population mean ranks differ [26]. The Wilcoxon signed-rank test was performed to understand the different factors affecting the mode choice. Principal-axis factor analysis was performed to identify the least number of factors that explain the common variance for a set of variables [14]. The purpose of principal-axis factor analysis is to reduce variance among a group of variables. The KMO test was used to determine whether the data is suitable for factor analysis. This test examines whether each model variable, as well as the entire model, has sufficient sampling. KMO values closer to 1.0 are considered ideal, whereas values below 0.5 are deemed unsatisfactory. McNemar’s test is a nonparametric test that compares two correlated dichotomous responses. It is most commonly used to determine the difference between two treatments when the same sample
is used [20]. McNemar test was conducted to observe the variation in the use of public, private, and non-motorized transportation before, during, and after COVID-19. Different analytical models such as multinomial logistic regression and ANN models were developed after examining all of the statistical tests mentioned above. These mathematical models were validated by using Receiver operating characteristic (ROC) curves and Area under Curve (AUC) values.

Results and discussions

The response’s data consistency was checked by using Cronbach’s alpha value, Cronbach’s alpha was a metric used to evaluate the internal consistency or reliability of a set of responses [5]. The survey respondents Cronbach’s alpha value is 0.859, which is higher than 0.7, indicating that the data are internally consistent [25]. The socio-demographic characteristics like gender, age, income, vehicle ownership, etc., of the responses, are shown in Fig. 1. In this survey, around 65% of males and 35% of females responded. Among the respondents, a greater number of respondents is in the age group of 20–45 (87.9%) years.

Figure 2 depicts the mode of transportation used for the primary trip purpose. Before Covid-19, public transportation utilization was 31.89%, but during the lockdown, it was lowered to 5.83% owing to fear of Covid-19 spreading and also due to work from home activity, and then it was increased to 21.31% after Covid-19. Also, after lifting all regulations connected to covid-19, the use of private vehicles has increased, owing to the fear of covid-19 spreading. Following the removal of all restrictions linked to covid-19, it has been noted that the use of non-motorized transportation is marginally increased. It was observed that before Covid-19, only 4.85 percent of respondents worked from home, whereas during the lockdown, it increased to 41.75 percent because most companies offered work from home, and after removing all restrictions related to Covid-19, it decreased to 19.42 percent because companies resumed offline work.

People’s travel modes before and after the pandemic for different activities are shown in Figs. 3 and 4. Except for public and private transportation modes, there was little
difference in other modes of transportation preference in people's activities such as shopping, travel to work, recreation, and medicine before and after the COVID-19 norms. People prefer the use of private mode to the public mode for safety reasons.

Figures 5 and 6 indicate the parameters that influence the choice of transportation mode for various trip purposes before and after the removal of all covid-19-related constraints. Following the Covid-19 constraints, the parameters like safety and security, infection concerns, social distancing, door-to-door service, travel time savings, cleanliness, and comfort were shown to be prominent variables influencing mode choice, whereas personal social status and economy were found to be the least relevant considerations.

The Wilcoxon signed-rank test was performed to understand the factors affecting the mode choice before and after COVID-19 and the results was shown in Table 1. The factors like door-to-door service, travel time savings, social distancing, safety and security, infection concern, cleanliness, and comfort have a significant impact on transportation mode selection after COVID-19 when compared to before COVID-19, whereas economy and personal social status have a minor impact after removing all COVID-19-related restrictions. This finding indicates the factors related to the spread of the infection, are the most important factors to consider when choosing a mode of transportation following COVID-19.

The KMO test measure of sampling adequacy is 0.790 before COVID-19 and 0.88 after COVID-19, which is greater than 0.75, indicating that the data set has a significant impact on the results and data can be used for factor analysis. Principal axis factor analysis with varmix rotation was performed on the factors that will affect the choices in Table 2. Based on the Eigenvalues, three factors account for 73.49 percent of the variance in the pre-Covid-19 scenario and two factors account for 69.57 percent of the variance in the post-Covid-19 scenario, both of which are greater than 60%, so these factors can incorporate for future study. The factors loadings for different situations are given in Table 2. Economy, safety and security, cleanliness, comfort, and reducing travel time are general elements that are not related to covid-19 and are loaded in Factor 1. Door-to-door service, personal social standing, social separation, and infectious concerns are all part of Factor 2. After removing all of the restrictions linked to covid-19, the results show that all these
factors have a considerable impact on the mode of transportation choice.

According to the McNemar test results, as given in Table 3, there is a substantial difference in the use of public and private vehicles before, during the lockdown time, and after COVID-19. It was observed that the use of private transportation increased during the lockdown period and after all, limitations linked to COVID-19 were lifted whereas the use of public transportation reduced after removing the COVID-19 restrictions. There is no substantial change in the use of non-motorized transportation before, during, and after Covid-19 restrictions were removed.

### Modelling of mode choice

#### Development of mode choice models

The correlation analysis between mode choice and socio-demographic parameters was performed and the results are given in Table 4. Gender, 2 W ownership, four-wheeler ownership, travel distance and travel time have strong correlation with mode choice before covid-19 whereas income, 2 W ownership, travel distance, and travel time have strong correlation with mode choice after covid-19. All other relations were very weak and have little importance. Multinomial logistic regression and ANN models were developed for mode choice of primary trip purpose before and after COVID-19. In the models, the socio-demographic characteristics were considered as input variables whereas mode choice was considered as an output variable. Multinomial logistic regression test results for before and after COVID-19 were given in Tables 5 and 6. Gender, 2 W ownership, four-wheeler ownership, travel distance, and travel time were significant factors for predicting the mode choice before COVID-19 whereas income, 2 W ownership, travel distance, and travel time were significant factors for predicting the mode choice after COVID-19. From Table 6, it is observed that likelihood ratio tests were significant for the mode choice models developed, which indicates the developed models are a significant improvement over the intercept models only. The overall correct predict percentages of

### Table 1 Comparing the Factors Affecting the Mode Preferences pre and post Covid-19

| Description                  | Mean ranks | Z       | 2-tailed sig |
|------------------------------|------------|---------|-------------|
|                              | Negative   | Positive|             |
| Door-to-Door service         | 44.44      | 63.37   | 6.214       |
| Travel time saving           | 48.24      | 54.49   | 5.183       |
| Economy                      | 41.61      | 53.03   | 0.972       |
| Social distancing            | 34.58      | 64.71   | 8.511       |
| Safety and security          | 26.65      | 34.49   | 3.331       |
| Infection concern            | 33.27      | 63.86   | 8.222       |
| Cleanliness                  | 39.83      | 38.32   | 2.981       |
| Comfort                      | 33.14      | 30.36   | 3.702       |
| Personal social status       | 23.52      | 24.38   | 0.789       |

Fig. 6 Factors affecting mode choice post COVID-19
mode choice multinomial logistic regression models were 79.1% before covid-19 and 78.4% after covid-19, which is more than 50% and represents a good fit for the model.

The conventional computations, which find it difficult to solve problems, can be substituted with neural networks, which are simplified versions of human brain processes. ANNs are computational systems with an input layer, hidden layer, and a layer of neurons for the output. ANN is an effective method for mimicking numerous real-world problems [29]. For the development of ANN models, different modes were grouped into three categories such as public transport, private transport, and NMT based on similar

| Table 2: Rotated Factor Matrix |
|--------------------------------|
| Pre Covid-19 | Post Covid-19 |
| Factor 1 | Factor 1 | Factor 2 | Factor 2 |
| Economy | 0.862 | Infection concern | 0.864 |
| Safety and security | 0.810 | Social distancing | 0.858 |
| Cleanliness | 0.720 | Cleanliness | 0.720 |
| Comfort | 0.698 | Door-to-door service | 0.558 |
| Travel time saving | 0.560 | Travel time saving | 0.488 |
| Door-to-door service | 0.489 | Safety and security | 0.658 |
| Personal social status | 0.468 | Economy | 0.618 |
| Social distancing | 0.240 | Comfort | 0.617 |
| Infection concern | 0.128 | Personal social status | 0.615 |
| Percentage of variance | 47.006 | 14.501 |
| Cronbach’s alpha value | 0.774 | 0.777 |

| Table 3: McNemar Test Results on travel mode Preference for Primary Trip Purpose |
|-----------------------------------------------|
| Descriptions | Chi-Square value | Asymp. Sig. value | Result |
| Before and during lockdown | Before and after covid-19 |
| Public–Private | 16.173 | 0.000 | Significant |
| Public–Non-motorized transport | 0.125 | 0.774 | Insignificant |
| Private–Non-motorized transport | 7.230 | 0.093 | Insignificant |

| Table 4: Correlation analysis between mode choice and socio-demographic parameters |
|-----------------------------------------------|
| Socio-demographic parameters | Pre Covid-19 | Post Covid-19 |
| | r | P | r | P |
| Gender | -0.044 | 0.02 | -0.031 | 0.61 |
| Age | 0.019 | 0.53 | 0.007 | 0.72 |
| Educational qualification | 0.159 | 0.47 | 0.060 | 0.57 |
| Income | -0.082 | 0.44 | -0.086 | 0.00 |
| 2 W ownership | 0.079 | 0.01 | 0.045 | 0.02 |
| Four wheeler ownership | -0.049 | 0.00 | -0.063 | 0.31 |
| Employment status | 0.198 | 0.06 | 0.172 | 0.51 |
| Travel distance | -0.045 | 0.01 | -0.069 | 0.04 |
| Travel time | -0.039 | 0.02 | -0.003 | 0.01 |

| Table 5: Multinomial logistic regression model parameters significance information |
|-----------------------------------------------|
| Variables | Pre Covid-19 | Post Covid-19 |
| | Chi-Square | Sig | Chi-square | Sig |
| Gender | 13.77 | 0.001 | 2.08 | 0.352 |
| Age | 2.65 | 0.265 | 3.48 | 0.175 |
| Educational qualification | 6.65 | 0.354 | 13.25 | 0.039 |
| Income | 14.83 | 0.022 | 24.91 | 0.000 |
| 2 W ownership | 14.76 | 0.022 | 10.36 | 0.110 |
| Four wheeler ownership | 13.04 | 0.221 | 5.29 | 0.871 |
| Employment status | 25.18 | 0.004 | 28.80 | 0.001 |
| Travel distance | 24.12 | 0.002 | 25.25 | 0.001 |
characteristics. For the development of the best ANN models, different trials were conducted by changing the different types of training and optimization algorithms. For before covid-19 ANN model, batch type of training and scaled conjugate gradient algorithm show the best fit with a percentage of incorrect training predictions as 14.0% and 17.3% as incorrect testing predictions. For after covid-19 ANN model, batch type of training and Gradient Descent Algorithm shows the best fit with a percentage of incorrect training predictions of 12.0% and 13.2% as incorrect testing predictions. Table 7 illustrates the network information details, such as input, hidden and output layers details, for before and after the covid-19 condition. The number of hidden layers is one, and there are five sets in each hidden layer. A hyperbolic tangent was employed as the activation function for the hidden layer. The dependent variable in this model is the mode, which is employed for work purposes and has many units of three for both before and after the Covid-19 condition. Softmax was utilized as the output activation function, with cross-entropy as the error function. The overall correct predict percentages of ANN mode choice models were 85.2% before covid-19 and 89.5% after covid-19, which is more than 50% and represents a good fit for the model.

Validation of mode choice models

The percentage of responses for which the test's outcome is positive that it correctly identifies is known as the test's sensitivity. The percentage of responses for which the test correctly identifies that the outcome is negative is known as the specificity [3]. The sensitivity and specificity can be calculated over all feasible threshold values when the results are reported on an ordinal scale or continuous scale. As a result, sensitivity and specificity vary depending on the threshold, and they are inversely connected. The plot between sensitivity and 1-Specificity is known as ROC curve. Then, the area under the curve (AUC), as a useful indicator of accuracy, has been taken into consideration with a relevant interpretation [11]. The developed multinomial logistic regression and ANN models were validated by plotting ROC curves and AUC values. The ROC curves for multinomial logistic regression models and ANN models as shown in Figs. 7 and 8 respectively. The AUC values
are also estimated for the developed mode choice models as given in Table 8. From the ROC curves, it is observed that all the lines are above the diagonal or reference line hence the developed mode choice models were validated. From AUC values, it is also observed that the values are more than 0.5 for the developed mode choice models. So,

![ROC Curve for multinomial logistic regression before and after covid-19 models](image1)

**Fig. 7** ROC Curve for multinomial logistic regression before and after covid-19 models

![ROC Curve for ANN before and after Covid-19 models](image2)

**Fig. 8** ROC Curve for ANN before and after Covid-19 models

| Table 8 | AUC values |
|---------|-------------|
|         | Multinomial logistic regression | ANN models |
| Before Covid-19 | 0.756 | 0.867 |
| After Covid-19  | 0.733 | 0.894 |
the developed mode choice models were validated based on AUC values also.

Conclusion

This study presents the findings of an online questionnaire survey conducted to investigate changes in the mode choice of employees as a result of the ongoing COVID-19 pandemic. Pre Covid-19, only 4.85 percent of respondents worked from home, whereas during the lockdown, it increased to 41.75 percent because most companies offered work from home, and after removing all restrictions related to Covid-19, it decreased to 19.42 percent because companies resumed offline work. Except for public and private transportation modes, there was little difference in other modes of transportation preference in people's activities such as shopping, travel to work, recreation, and medicine before and after the COVID-19 norms. People prefer the use of private mode to the public mode for safety reasons. The respondents gave a high priority to infection concern, safety, security, and social distancing as their priority for the mode of transport they choose after the restrictions of COVID-19 were lifted whereas economy and personal social status gave the least priority. This indicates the factors related to the spread of the infection, are the most important factors to consider when choosing a mode of transportation post covid-19. The KMO test measure of sampling adequacy is 0.790 before covid-19 and 0.88 after covid-19, which is greater than 0.75, indicating that the data set has a significant impact on the results. Multinomial logistic regression and ANN models were developed for mode choice of primary trip purpose before and after COVID-19. The overall correct predict percentages of mode choice multinomial logistic regression models were 79.1% for pre covid-19 and 78.4% for post covid-19, which is more than 50% and represents a good fit for the model. The overall correct predict percentages of ANN mode choice models were 85.2% for pre covid-19 and 89.5% for post covid-19, which is more than 50% and represents a good fit for the model. There are some methodological limitations of this study. The questionnaire is in English language, only those who understand the language could fill the questionnaire.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Consent for publication This work is the authors' own original work, which has not been previously published and not currently being considered for publication elsewhere.

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