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Factors affecting the mode choice behavior before and during COVID-19 pandemic in Pakistan

Muhammad Abdullah a,*, Nazam Ali a, Atif Bilal Aslam b, Muhammad Ashraf Javid c, Syed Arif Hussain d

a Department of Civil Engineering, University of Management and Technology, Lahore 54770, Pakistan
b Department of City and Regional Planning, University of Engineering and Technology, Lahore, Punjab 54890, Pakistan
c Department of Civil and Environmental Engineering, College of Engineering and Architecture, University of Nizwa, Birkat-al-Mouz, 616, Nizwa, Oman
d Faculty of Civil and Environmental Engineering, Graduate School of Science & Engineering, Saitama University, Saitama 338-8570 Japan

ABSTRACT

The transport sector has been hit hard by the COVID-19 pandemic disrupting travel behaviors and mobility patterns around the globe. The pandemic has also affected mode choice behavior. This research study modeled the mode choice behavior before and during the COVID-19 pandemic in Pakistan. Data was collected through an online questionnaire survey consisting of questions about socio-economic characteristics, factors affecting mode choice, and mode chosen for shorter as well as longer distances for both before and during COVID-19 pandemic situations. The results indicated that public transport use declined, whereas walking and bicycling slightly increased during the pandemic. The respondents placed more priority on safety and security, comfort, cleanliness, infection concerns, personal social status, availability of hand-sanitizers, waiting, and paying more for less congested vehicles during the pandemic. Factor analysis was performed to explore the underlying factors affecting mode choice before and during the pandemic. Discrete choice models were developed to model the mode choice behavior. Monthly household income and pandemic-related underlying factor were significant predictors of mode choice for shorter distances (i.e., < 5 km) during the pandemic. Whereas, gender, car ownership and monthly household income were significant predictors of mode choice for longer distances (i.e., > 5 km) during the pandemic. Understanding the modal shift during a pandemic will surely help urban and transport planners to prepare better for effective transport management in the future. Policy implications are also presented to help policymakers in developing policies for post-pandemic mobility needs, particularly in developing countries.

Introduction

The outbreak of the novel coronavirus (COVID-19) has caused a major disruption to the travel patterns and mobility activities around the globe. Since the first confirmed reported case of COVID-19 from Wuhan, Hebei province of China, at the end of 2019, it spread quickly and was declared a global pandemic on March 11, 2020 (WHO, 2020). In the modern history, the

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* Corresponding author.
E-mail address: muhammadabdullah@umt.edu.pk (M. Abdullah).
universal impacts of pandemics have not been observed on such a large scale on mobilities and societies as in the case of COVID-19 (Beck & Hensher, 2020). In the early and mid-March, many countries launched the attempts to contain or slow down the spread of COVID-19, with travel restrictions as a mandatory countermeasure (Zhang et al., 2020).

The first case of COVID-19 in Pakistan was reported on February 26, 2020, with figures of about 435,056 confirmed cases and 8,724 fatalities on December 12, 2020. Several countries declared national lockdowns to restrict non-essential mobility and travelling. Likewise, Pakistan initiated nation-wide lockdown on April 01, 2020, and extended it twice till May 9, 2020. Lockdown was eased in multiple phases such that some areas of the major cities with severe clusters remained under smart lockdown.

COVID-19 is more than a health crisis that impacted economies, traveling, civil liberties, and social facets. Along with many of the other businesses and industries, the transportation industry has been severely hit by this pandemic. The World Health Organization’s (WHO) guidelines to maintain a necessary social distancing of 6-ft (around 2 m) impacted the mode choice behavior of the public due to the infection and safety concerns. In addition, several countries including Pakistan restricted public transportation use forcing people to reconsider their mode choices. On the other hand, active transport modes, such as bicycling and walking offer better health benefits because of the involvement of physical activity as compared to motorized modes. The ability and affordability to use different travel choices are dependent upon socio-economic factors. Hence, there is a need to understand how this pandemic affected the mode choice behavior.

This paper is aimed at understanding the impacts of COVID-19 on mode choice behavior before COVID-19 and during the COVID-19 pandemic in the major cities of the Punjab province of Pakistan. It is important to assess the perceptions of the commuters regarding mode choices for both shorter (<5-km) and longer (>5-km) distances before COVID-19 and during COVID-19 pandemic. This study fills the gap by providing insights into how mode choices of people changed due to the COVID-19 pandemic in developing countries like Pakistan. This research recognizes that the developing countries especially in the South Asian region have unique socio-economic and social constraints and require special transport-related policies to address the mobility issues during a pandemic situation. This pandemic may prove to be a blessing in disguise to set forth new challenges and opportunities for policymakers in charting out new pathways to meet the needs of travelers.

The rest of the paper is organized in the following manner: Section 2 describes the literature review in two strands of studies pertinent to transport mode choice behavior and COVID-19. Section 3 discusses the survey design and sampling methods. Section 4 presents results and discussions, future research directions, and limitations of the study. Section 5 discusses the policy implications. Finally, conclusions are presented in section 6.

Literature review

The ongoing COVID-19 pandemic has affected the travel pattern across the globe (Litman 2020). Many of the implications associated with the pandemic are still unfolding which is shaping up the response in terms of various mitigation measures. The relation between the COVID-19 pandemic and the travel behavior is complex resulting in different strand of studies. By now, the dominant strand of studies has investigated the role of travel behavior in spreading the virus (Kraemer et al., 2020). The other strand of studies, which is also growing in number, is focused on the relation between Coronavirus and its effects on the travel pattern in various geographic and sectoral contexts (Abdullah et al., 2021; Musselwhite et al., 2020). It was mainly the former strand of studies, which has shaped up the multi-scaled response towards tackling the COVID-19 outbreak. The results of several studies in this regard have provided an evidence for the spread of the Coronavirus with increased mobility (West et al., 2020). For instance, Yilmazkuday (2020) reported that restricting inter-county travel can reduce COVID-19 weekly cases and deaths as much as by 139,503 and 23,445, respectively in the United States. Keeping in view the findings of such studies, one of the very first mitigation measures in response to COVID-19 was the imposition of the mobility restrictions. Initially, mobility restrictions were imposed on all types of travel modes including active modes (de Bruin et al., 2020) to limit the people's movement to reduce the number of Coronavirus infections (Gostic et al., 2020). Soon other measures such as socioeconomic restrictions, physical distancing, and hygiene measures were also put in place (Transit Center, 2020). Initially, these restrictive measures were imposed in a manner of top-down hierarchy, leaving very limited options for the people with respect to making their travel-related choices. However, it has also been learnt that such top-down measures cannot be much effective in containing the Coronavirus spread without the community’s support. This realization resulted in the widespread risk communication and awareness campaigns to sensitize the communities in adopting precautionary measures (de Bruin et al., 2020). A combination of top-down measures and the desired societal response in accordance with the communicated safety protocols is more successful in curbing the COVID-19 spread across various regions (Anderson et al., 2020).

The lockdown measures have significantly affected travel behavior, notably people’s mode choice behavior. It has also been argued that such travel behavior changes could last for long in the post-COVID-19 world as well (Musselwhite et al., 2020). The number of passenger transport trips has decreased globally, and the major share of these reduced trips comprised of mass public transport trips (Abdullah et al., 2020). The leading reason for the reduction of mass transit trips is the incapacity of these traveling modes for providing a traveling space where social distancing and safety protocols could be adhered, thus significantly increasing the risks for the spread of the infectious diseases (Edelson & Phypers, 2011). However, there are studies which advocate for the continued operation of public transport modes, even during the pandemics, provided the precautionary measures are adopted by its users (Cooley et al., 2011). The evidence emerging from France and Japan shows the
effectiveness of practicing precautionary measures while using public transport as not a single COVID-19 cluster could be spotted and linked to the public transport usage in these countries (O’Sullivan, 2020).

Another trend which has been observed during COVID-19 pandemic is the modal shift from public transport to private vehicles as it is perceived to be safer compared to the public transit during a pandemic (Abdullah et al., 2020). However, it is argued that such transition in the mode choice behavior would be temporary and the pre-COVID-19 travel pattern will resume, once the business-as-usual circumstances will prevail in the post-COVID-19 world (Litman, 2020). With the deteriorating economic conditions, traveling by car would not be a preferred option for long due to its expensive character in comparison to other available modes, and people might opt for the active modes i.e., walking and bicycling (Litman, 2020). Many urban places around the world, particularly those who have been hit hard by the pandemic have seen roads without cars and increased number of cycling and walking trips (Manjoo, 2020). The active modes have come out strong as most compatible with the safety protocols and socioeconomic concerns that may arise during a pandemic. During the lockdown in the United Kingdom, many researchers signed an open letter to the UK government, which advocated for the promotion of cycling and walking by describing them as socially compatible with the social distancing measures (Woodcock et al., 2020). Many health advantages of using cycling and walking as the traveling modes have also been proven (Hamer and Chida, 2008). Many developed world nations have taken extensive measures for the promotion of cycling, e-scooter, and walking as a response to the pandemic crisis (POLIS, 2020). In addition, civil society in many high-income countries has also been affected by the COVID-19 pandemic, which have shaped up many local-level initiatives propagating the usage of cycling and walking as the travelling modes (PBIC, 2020). Nonetheless, there still exists a gap between the studies conducted in the developed and the developing world.

To sum up, enough evidence for the relation between pandemic risks and travel behaviour exists across various contexts. However, it is also important to review the literature to report on the determinants of mode choice behaviour during normal pandemic-free times. Hunecke et al. (2001) found ‘ecological norms’ and ‘fare’ as the strongest factors determining the travel mode choice. Vij et al. (2013) found ‘travel time’, ‘bias for private automobile’ and ‘life-cycle characteristics’ as the significant correlates of travel mode choice decisions while conducting a study in Karlsruhe, Germany. Eluru et al. (2012) also identified ‘travel time’ as a significant determinant of mode choice behaviour of the university staff and students in Montreal, Canada. To draw new travel-related policies for the post COVID-19 world, it is pertinent to study the mode choices before and after the COVID-19 outbreak. It is also important to explore the primary mode choices for addressing the travel needs during the current and any future pandemics. The findings of this research study will surely help policymakers in better understanding the mode choices for finer and improved policy formulations for post COVID-19 world considering the socio-economic and social constraints of the developing world.

Methods

Questionnaire design

The questionnaire had three sections: (1) socio-demographic characteristics, (2) factors affecting mode choice before and during COVID-19 pandemic, and (3) mode choice before and during COVID-19 pandemic. Socio-demographic characteristics consisted of gender, age, car ownership, motorbike ownership, cycle ownership, monthly household income, employment status and education level. Section 2 contained 5-point Likert type items that may affect mode choice before and during COVID-19. For instance, how high a priority people place on cleanliness, infection concern, and social distance etc. while choosing a mode. It was hypothesized that people will consider pandemic-related variables to be more important while choosing a transport mode during the COVID-19 pandemic. For instance, infection concerns and social distance may be more important as compared to comfort and convenience during the pandemic. Therefore, such pandemic-related variables were identified and included in the questionnaire for the respondents to place a priority on each factor when choosing a transport mode. Section 3 contained questions about mode choice for shorter (<5 km) and longer (>5 km) distances before and during the COVID-19 pandemic. For example, which mode did you choose for shorter distances (<5 km) before the COVID-19 pandemic? Which mode do you choose for shorter distances (<5 km) during the COVID-19 pandemic? etc.

Survey and sampling strategy

The survey questionnaire was designed to collect data on mode choice and the factors affecting mode choice both before and during COVID-19 situations. Since face-to-face interviews were difficult due to the social distancing requirements, the partial lockdown in the country and health concerns, an online questionnaire was distributed through emails, social media platforms and personal contacts to the targeted population of the three most populous cities of the Punjab province: Lahore, Faisalabad and Rawalpindi. The objectives and instructions for filling the questionnaire were clearly described at the beginning of the questionnaire to obtain reliable data. The questionnaire was pre-tested through a pilot survey and recommendations were incorporated to ensure the clarity and understanding of each statement to the respondents. The questionnaire was available online for a period of about three weeks from May 09 to 31, 2020. A total of six hundred and seventy-one (671) responses from the targeted cities were received during this period.
Analysis methods

Factor analysis was conducted on section 2 of the questionnaire which consisted of items affecting mode choice before and during COVID-19 pandemic. The purpose of conducting factor analysis was to identify the factors underlying the observed variables affecting the mode choice. Factor scores were then computed using the sum score approach \( \text{DiStefano et al., 2009} \) and used in the mode choice models. Mode choice behavior was then modeled using logistic regression models. Logistic regression models were used to model the probability of using a particular mode for shorter (<5-km) and longer (>5-km) distances both before and during the COVID-19 pandemic. The logit model has the following form:

\[
P(i) = \frac{e^{U_i}}{\sum_{j \in I} e^{U_j}}
\]

\[
U_i = V_i + e_i
\]

\[
V_i = a_i + \sum_{k=1}^{V} b_k \times X_{ik}
\]

where, \( P(i) \) is the probability of mode \( i \) being chosen, \( U_i \) is the utility of mode \( i \), \( U_j \) is the deterministic utility of mode \( i \), \( U_j \) is the utility of mode \( j \), \( e_i \) is the error or unknown portion of utility specific to mode \( i \), \( I \) is the set of modes, \( a_i \) is the mode specific constant, \( b_k \) is the \( k^{th} \) parameter, \( X_{ik} \) is the \( k^{th} \) model variable for mode \( i \), and \( V \) is the number of model variables.

Results and discussion

Transport modes in the major cities of Pakistan

Transport modes in major cities of Pakistan can be broadly classified into four categories: public transport, paratransit services, private transport, and non-motorized transport (Fig. 1). Public transport generally consists of bus and minibus or van. Paratransit services generally consist of taxi (including ridesharing services), auto-rickshaw, and qingqi (motorcycle rickshaw). School or office transport can also be categorized as paratransit services because they are not available for the general public. Private transport mostly consists of private cars and motorbikes. Non-motorized modes are walking and bicycling.

Public transport in major cities in Pakistan has been facing several challenges and is unable to meet the growing demand. Private vehicles (private cars and motorbikes) have been increasing, whereas public transport routes have been decreasing over the years in Karachi, the largest city of Pakistan (Noman et al., 2020). On the other hand, bus rapid transit (BRT) services

![Fig. 1. Transport modes in major cities of Pakistan.](image-url)
have been provided in several cities during the last decade. Intra-city train line has recently been completed in Lahore, the second-largest city of Pakistan. The cities, in general, are lacking appropriate pedestrian and bicycle infrastructure.

**COVID-19 timeline and its impact on transport modes in Pakistan**

The timeline of major events associated with COVID-19 in Pakistan is shown in Fig. 2. In general, road traffic has reduced around the world during the pandemic (Lee et al., 2020; Parr et al., 2020). Since the virus spreads through close contact and by touching the infected surfaces, the pandemic particularly impacted public transport. In addition, the number of outdoor trips reduced during the lockdown causing a sharp decline in public transport demand (Aloi et al., 2020). Fig. 3 shows the mobility trends for places like public transport spots such as bus, and train stations (Google LLC, 2020) as well as the number of cases (OurWorldinData, 2020) in Pakistan. Percent change for transit stations with respect to the baseline indicates that public transport use started declining near the end of March probably because provincial governments implemented lockdowns earlier. Although outdoor trips reduced and public transport use declined during the pandemic, people still need to travel for various primary reasons such as shopping (including grocery), health, and various other compelling reasons. Moreover, essential workers also need to travel during the pandemic. Hence, it is necessary to explore the mode choice behavior during the pandemic.

**Socio-economic demographics of the respondents**

The socio-economic demographics of all 671 respondents are shown in Table 1. The respondents were from the three most populous cities of Punjab province namely, Lahore, Faisalabad and Rawalpindi. Most of the respondents were male (73.3%), between 18 – 30 years old (65.9%). This implies that younger people are more active on social media as compared to older respondents. Female representation was low which might be attributed to the fact that a considerable number of females is housewife in Pakistan and may not have been traveling much before and during the pandemic.

**Factors affecting mode choice**

The median values for factors affecting mode choice before and during COVID-19 pandemic, and the corresponding results of Wilcoxon signed rank tests are shown in Fig. 4. The Wilcoxon signed-rank test is a non-parametric test which is used to compare repeated measurements on a single sample (i.e., before and during COVID-19) to determine whether their population mean ranks differ. As expected, most of the respondents placed more priority on pandemic related items during the pandemic.

Wilcoxon Signed Rank tests indicated that respondents put more priority on safety and security, infection concern, cleanliness, social distance, hand sanitizers’ availability, personal social status, waiting for less congested vehicle, and paying for less congested vehicle during the pandemic. However, there was no significant difference between priority placed on comfort before and during the pandemic.

**Exploratory factor analysis on factors affecting mode choice before and during COVID-19**

Exploratory factor analysis (principal axis factoring with Varimax rotation) was carried out on the items which may affect mode choice before (during) COVID-19. The solution for before (during) COVID-19 situation produced two factors (a single factor) based on the eigenvalues criteria (i.e., eigenvalues > 1) which accounted for about 59.554% (61.962%) of the total variance.

The factor loadings are presented in Table 2. A cut-off value of 0.40 was used for item loadings. For before (during) COVID-19 situation, the sampling adequacy was satisfactory, Kaiser-Meyer-Olkin measure = 0.776 (=0.991); Bartlett’s test of
sphericity was significant, 0.000 (0.000); and the determinant of the matrix was 0.044 (0.001). Cronbach’s alpha was adequate for the factors for both before and during the COVID-19 situation (>0.7). Factor scores were computed using the sum score approach and used in the subsequent mode choice models.

**Mode choice modeling**

Logistic regression models were developed to model the mode choice behavior for shorter as well as longer distances both before and during the COVID-19 pandemic (Fig. 5). Since public transport, office/campus transport, and taxi/rickshaw were bound to follow similar instructions from the government during the pandemic, they were combined into a single category called “Public/Paratransit”. In addition, the modal share was quite small for bicycle and walking before as well as during the pandemic; therefore, they were combined into a single category called “Non-motorized” and were removed from the mode choice models. Those who did not mention their salary were removed from the analysis. Age was entered into the models and was found to be insignificant. Also, there was a sample size limitation as well as a weak but significant correlation between age and income level, therefore, age was not entered in the final models presented in the following sections.

**Table 1**

| Items              | Description   | Number of respondents | %    |
|--------------------|---------------|-----------------------|------|
| Gender             | Male          | 492                   | 73.3 |
|                    | Female        | 179                   | 26.7 |
| Age                | 18–30         | 442                   | 65.9 |
|                    | 31–45         | 201                   | 30.0 |
|                    | 46–60         | 22                    | 3.3  |
|                    | Above 60      | 6                     | 0.9  |
| Occupation         | Student       | 248                   | 37.0 |
|                    | Business      | 27                    | 4.0  |
|                    | Government employee | 167             | 24.9 |
|                    | Private employee | 193               | 28.8 |
|                    | Others        | 36                    | 5.4  |
| Income level (PKR) | Less than 50,000 | 193              | 28.8 |
|                    | 50,001–100,000 | 189                | 28.2 |
|                    | More than 100,000 | 189              | 28.2 |
|                    | Prefer not to say | 100              | 14.9 |
| Car Ownership      | Yes           | 288                   | 42.9 |
|                    | No            | 383                   | 57.1 |
| Motorcycle Ownership| Yes         | 343                   | 51.1 |
|                    | No            | 328                   | 48.9 |
| Bicycle Ownership  | Yes           | 86                    | 12.8 |
|                    | No            | 585                   | 87.2 |

**Fig. 3.** Percent change in transit station use, number of cases and deaths.
Fig. 4. Factors affecting mode choice before and during COVID-19.

Table 2
Principal axis factor analysis of the questionnaire items.

| Items                                      | Factor 1 (Pandemic-related-before) | Factor 2 (General-before) |
|--------------------------------------------|-------------------------------------|---------------------------|
| Before COVID-19                            |                                     |                           |
| Social distance                            | 0.733                               |                           |
| Hand sanitizers in vehicles                | 0.710                               |                           |
| Waiting for less congested vehicle         | 0.782                               |                           |
| Paying for a less congested vehicle        | 0.689                               |                           |
| Safety & security                          |                                     | 0.740                     |
| Comfort                                    |                                     | 0.833                     |
| Cleanliness                                |                                     | 0.768                     |
| % of variance explained                    | 32.027                              | 27.527                    |
| Cronbach's alpha                           | 0.831                               | 0.836                     |
| During COVID-19                            |                                     |                           |
| Social distance                            | 0.882                               |                           |
| Cleanliness                                | 0.878                               |                           |
| Infection concern                          | 0.855                               |                           |
| Safety & security                          | 0.820                               |                           |
| Hand sanitizers in vehicles                | 0.795                               |                           |
| Paying for a less congested vehicle        | 0.783                               |                           |
| Waiting for a less congested vehicle       | 0.780                               |                           |
| Comfort                                    | 0.627                               |                           |
| Personal social status                     | 0.613                               |                           |
| % of variance explained                    | 61.962                              |                           |
| Cronbach's alpha                           | 0.931                               |                           |

Fig. 5. Scenarios for mode choice models.
Mode choice for shorter distances (<5 km)

The distribution of responses for mode choice for shorter distances is shown in Fig. 6. The use of public/paratransit reduced, whereas the use of private cars and non-motorized modes increased during the pandemic. Although the proportion of non-motorized modes increased during the pandemic, it is still a small percentage i.e., only 12%.

Mode choice before COVID-19

Multinomial logistic regression was applied to model the mode choice for primary trip purpose before the COVID-19 pandemic. The nominal outcome variable was mode choice for shorter distances which consisted of three categories namely, public/paratransit, private car and motorbike. Public/Paratransit was set as the reference category. 517 responses were considered in the analysis. Four demographic variables, namely, motorcycle ownership, gender, monthly household income, and car ownership, and two underlying factors affecting mode choice before COVID-19, namely, Pandemic-related-before and General-before were entered as predictors. The likelihood ratio test was significant indicating that the developed model is a significant improvement over the intercept-only model (Table 3).

Gender, car ownership, motorbike ownership and monthly household income were found to be statistically significant. It is observed that male respondents are more likely to choose private transport (private car and motorbike) relative to public/paratransit when compared to female respondents. It is because females, generally, do not ride motorbikes in Pakistan. Motorbike owners are less likely to use private car relative to public/paratransit when compared to non-motorbike owners. It could be explained by the fact that 55% of the respondents, who owned a motorbike, did not own a car. It is also observed that motorbike owners are more likely to choose motorbike relative to public/paratransit when compared to non-motorbike owners. Car owners have more chance of using private car relative to public transport when compared to non-car owners. Respondents belonging to low-income categories are less likely to use private car relative to public transport when compared to those in the higher income categories. It could be attributed to the fact that most of the respondents (approx. 87%) in the lowest income category (less than 50,000 PKR) did not own a car. Whereas most of the respondents (approx. 74%) in the highest income category (more than 100,000 PKR) owned a car.

Mode choice during COVID-19

Binary logistic regression was applied to model the mode choice for shorter distances during the COVID-19 pandemic. Since public transport use was low for shorter distances during the pandemic, it was omitted from the analysis. Hence, the binary outcome variable (mode choice) consisted of only two categories namely, private car and motorbike. 434 responses were considered in the analysis. Four demographic variables, namely, motorcycle ownership, gender, monthly household income, and car ownership, and one underlying factor affecting mode choice during COVID-19, namely, Pandemic-related-during were entered as explanatory variables. The likelihood ratio test was significant indicating that the developed model is a significant improvement over the intercept-only model (Table 4). Hosmer and Lemeshow test was non-significant ($\chi^2 = 865.441, df = 836, p = 0.233$). The model explained only 5.5% (Nagelkerke R Square) of the variance in mode choice and correctly classified 59.2% of cases.

Monthly household income and the underlying factor i.e., pandemic-related-during were found to be statistically significant. The respondents belonging to the low-income categories are less likely to use motorbike relative to a private car when compared to the high-income respondents. Those who placed more priority on pandemic-related items are less likely to use motorbike relative to a private car when compared to those who placed less priority on pandemic-related items.

Mode choice for longer distances (>5 km)

The distribution of responses for mode choice for longer distances is shown in Fig. 7. As expected, very few respondents chose a bicycle or walking for distances longer than 5 km. The use of public/paratransit reduced, whereas the use of private transport (car and motorbike) increased during the pandemic.
### Table 3
Regression coefficients and model fitting information (before COVID-19).

| Mode                  | Regression Coefficients | Sig. | Odds Ratio | 95% Confidence Interval for Odds Ratio |
|-----------------------|-------------------------|------|------------|---------------------------------------|
|                       |                         |      |            | Lower Bound | Upper Bound                          |
| Private car           | Intercept               | -0.060 | 0.937     |            |                                       |
|                       | General-before          | 0.037  | 0.535     | 1.038      | 0.923                                 | 1.168         |
|                       | Pandemic-related-before | 0.010  | 0.804     | 1.010      | 0.931                                 | 1.096         |
|                       | Motorcycle ownership    | Yes   | -1.500    | 0.001      | 0.202                                 | 0.076         | 0.538         |
|                       |                         | No    | 0         |            |                                       |               |
|                       | Gender                  | Male  | -0.098    | 0.793      | 0.907                                 | 0.438         | 1.880         |
|                       |                         | Female| 0         |            |                                       |               |
|                       | Monthly household income (PKR) | < 50,000 | -1.379 | 0.001      | 0.252                                 | 0.108         | 0.589         |
|                       |                         | 50,0001–100,000 | -0.820 | 0.062      | 0.440                                 | 0.186         | 1.042         |
|                       |                         | > 100,000 | 0         |            |                                       |               |
|                       | Car ownership           | Yes   | 3.734     | 0.000      | 41.852                                | 14.767        | 118.617       |
|                       |                         | No    | 0         |            |                                       |               |
| Motorcycle            | Intercept               | -1.721 | 0.023     |            |                                       |               |
|                       | General-before          | 0.028  | 0.609     | 1.028      | 0.924                                 | 1.144         |
|                       | Pandemic-related-before | -0.009 | 0.823     | 0.991      | 0.919                                 | 1.069         |
|                       | Motorcycle ownership    | Yes   | 2.413     | 0.000      | 11.167                                | 5.581         | 22.343        |
|                       |                         | No    | 0         |            |                                       |               |
|                       | Gender                  | Male  | 1.203     | 0.001      | 3.330                                 | 1.636         | 6.780         |
|                       |                         | Female| 0         |            |                                       |               |
|                       | Monthly household income (PKR) | < 50,000 | 0.026 | 0.952      | 1.026                                 | 0.444         | 2.369         |
|                       |                         | 50,0001–100,000 | 0.400 | 0.363      | 1.491                                 | 0.631         | 3.527         |
|                       |                         | > 100,000 | 0         |            |                                       |               |
|                       | Car ownership           | Yes   | 0.055     | 0.899      | 1.056                                 | 0.455         | 2.454         |
|                       |                         | No    | 0         |            |                                       |               |

#### Model Fitting Information

| Model                  | Model Fitting Criteria | Likelihood Ratio Tests |
|------------------------|------------------------|------------------------|
|                       | -2 Log Likelihood      | Chi-Square             | Df | Sig. |
| Intercept Only         | 1022.357               |                         |    |      |
| Final                  | 585.431                | 436.927                | 14 | 0.000 |

### Table 4
Regression coefficients and model fitting information (during COVID-19).

| Variables              | Regression Coefficients | Sig. | Odds Ratio | 95% C.I. for Odds Ratio |
|------------------------|-------------------------|------|------------|-------------------------|
|                       |                         |      |            | Lower | Upper |
| Car ownership (Yes)    | -0.138                  | 0.553 | 0.871      | 0.553 | 1.374 |
| Motorbike ownership (Yes) | 0.255               | 0.238 | 1.290      | 0.845 | 1.968 |
| Gender (Male)          | 0.236                   | 0.323 | 1.266      | 0.793 | 2.022 |
| Monthly household income, PKR | 0.009           |      |            |       |       |
| Monthly household income, PKR (<50,000) | -0.709 | 0.011 | 0.492      | 0.284 | 0.853 |
| Monthly household income, PKR (50,001–100,000) | -0.746          | 0.004 | 0.474      | 0.286 | 0.785 |
| Pandemic-related-during | -0.022              | 0.046 | 0.978      | 0.957 | 1.000 |
| Constant               | 1.039                   | 0.047 | 2.828      |       |       |

![Fig. 7. Modal share for longer distances before and during COVID-19 pandemic.](image-url)
Mode choice before COVID-19

Multinomial logistic regression was applied to model the mode choice for primary trip purpose before the COVID-19 pandemic for longer distances. The nominal outcome variable was mode choice for longer distances before COVID-19 pandemic which consisted of three categories namely, public/paratransit, private car, and motorbike. Public/paratransit was set as the reference category. 565 responses were considered in the analysis. Four demographic variables, namely, motorcycle ownership, gender, monthly household income, and car ownership, and two underlying factors affecting mode choice before COVID-19, namely, Pandemic-related-before General-before were entered as predictors.

The likelihood ratio test was significant indicating that the developed model is a significant improvement over the intercept-only model (Table 5). The goodness of fit tests, i.e., the Pearson's chi-square test ($\chi^2 = 861.429$, df = 904, $p = 0.842$) and the chi-square test based on deviance ($\chi^2 = 639.202$ df = 904, $p = 1.000$) were non-significant indicating that the data and the model predictions were similar. The McFadden R-square value of 0.350 indicated an excellent fit. The multinomial logistic regression model classified 70.8% of the cases correctly.

Gender, car ownership, motorbike ownership and monthly household income were found to be statistically significant. It is observed that male respondents have more chance of using motorbike relative to public transport when compared to female respondents. As explained earlier, female motorbike ridership is almost non-existent. It is also observed that private transport owners (private car and motorbike owners) are more likely to use private transport relative to public transport when compared to non-private transport owners. Respondents belonging to low-income categories have fewer chances of using private cars relative to public transport when compared to those in the higher income categories.

Mode choice during COVID-19

Multinomial logistic regression was applied to model the mode choice for longer distances during the COVID-19 pandemic. The nominal outcome variable was mode choice which consisted of three categories namely, public/paratransit, private car and motorbike. Public/Paratransit was set as the reference category. 562 responses were considered in the analysis. Four demographic variables, namely, motorcycle ownership, gender, monthly household income, and car ownership, and one underlying factor affecting mode choice during COVID-19, namely, Pandemic-related-during were entered as predictors.

The likelihood ratio test was significant indicating that the developed model is a significant improvement over the intercept-only model (Table 6). The goodness of fit tests, i.e., the Pearson’s chi-square test ($\chi^2 = 541.119$, df = 538, $p = 0.178$) and the chi-square test based on deviance ($\chi^2 = 400.718$ df = 538, $p = 0.000$) were non-significant indicating that the data and the model predictions were similar. The McFadden R-square value of 0.350 indicated an excellent fit. The multinomial logistic regression model classified 70.8% of the cases correctly.

### Table 5
Regression coefficients and model fitting information (before COVID-19).

| Mode                   | Regression Coefficients | Sig. | Odds Ratio | 95% C.I. for Odds Ratio |
|------------------------|-------------------------|------|------------|-------------------------|
|                        |                         |      |            |                         |
|                        | Intercept               | -0.225 | 0.714      |                         |
| General-before         |                         | 0.033 | 0.463      | 1.034                   |
| Pandemic-related-before|                         | -0.005 | 0.866      | 0.995                   |
| Motorcycle ownership   | Yes                     | -0.543 | 0.081      | 0.581                   |
|                        | No                      | 0     | .          | .                      |
| Gender                 | Male                    | -0.208 | 0.927      | 0.533                   |
|                        | Female                  | 0     | .          | .                      |
| Monthly household income (PKR) | < 50,000 | -1.012 | 0.004      | 0.363                   |
|                        | 50,001–100,000          | -0.244 | 0.494      | 0.784                   |
|                        | > 100,000               | 0     | .          | .                      |
| Car ownership          | Yes                     | 3.536 | 0.000      | 34.327                  |
|                        | No                      | 0     | .          | .                      |
| Motorcycle             | Intercept               | -2.536 | 0.001      |                         |
| General-before         |                         | -0.002 | 0.971      | 0.998                   |
| Pandemic-related-before|                         | 0.009 | 0.797      | 1.009                   |
| Motorcycle ownership   | Yes                     | 1.221 | 0.000      | 3.389                   |
|                        | No                      | 0     | .          | .                      |
| Gender                 | Male                    | 1.799 | 0.000      | 5.523                   |
|                        | Female                  | 0     | .          | .                      |
| Monthly household income (PKR) | < 50,000 | -0.069 | 0.866      | 0.934                   |
|                        | 50,001–100,000          | 0.043 | 0.919      | 1.044                   |
|                        | > 100,000               | 0     | .          | .                      |
| Car ownership          | Yes                     | -0.425 | 0.397      | 0.654                   |
|                        | No                      | 0     | .          | .                      |

**Model Fitting Information**

| Model | Model Fitting Criteria | Likelihood Ratio Tests |
|-------|------------------------|------------------------|
|       |                        | Chi-Square | df | Sig. |
| Intercept Only | −2 Log Likelihood | 1088.971 | 400.718 | 14 | 0.000 |
| Final       | 688.253                |            |     |     |

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\( p = 0.454 \) and the chi-square test based on deviance \( \chi^2 = 575.842 \text{ df } = 538, p = 0.126 \) were non-significant indicating that the data and the model predictions were similar. The model explained only 4\% (Nagelkerke R Square) of the variance in mode choice and correctly classified 57.7\% of cases.

Gender, car ownership, and monthly household income were found to be statistically significant. Male respondents are less likely to use a private car relative to public transport when compared to female respondents. A possible reason could be the fact that females have been reported to experience significantly greater fear of the COVID-19 pandemic (Broche-Pérez et al., 2020). It is also observed that respondents belonging to low-income categories are less likely to use motorbike relative to public transport when compared to those in the higher income categories. Income inequality is relatively higher in Pakistan indicating that those in the lower-income category might be belonging to low education levels (Shahabadi et al., 2018). In addition, people with low education levels have been reported to be less able and less willing to self-isolate (Atchison et al., 2020). Furthermore, conspiracy beliefs related to COVID-19 are prevalent among those with lower education levels (Georgiou et al., 2020). It can be further supported by the fact that the pandemic-related-during score was low for the respondents in the lowest income category (Mean = 34.52, SD = 9.31) when compared to those in the highest income category (Mean = 36.98, SD = 8.21). Contrary to the expectations, car owners are less likely to use private cars relative to public transport when compared to non-car owners. Non-car owners might be renting cars during the pandemic. Nonetheless, future studies should include “rented cars” as another transport mode while modeling the mode choice behavior.

The logistic regression models for during the COVID-19 scenario explained a small amount of variance in the response variable. There are likely to be other factors affecting mode choice behavior during the pandemic. For instance, mode choice could depend on the purpose of travel, lockdown or government restrictions, the number of COVID-19 cases, and perceptions about the severity of COVID-19 pandemic, etc. In addition, a nonlinear relationship between mode choice and explanatory variables should also be explored in the future studies.

**Policy implications**

The results of this study indicated that private car use increased, whereas public transport use decreased during the pandemic. Since the respondents placed more priority on pandemic-related items while choosing a mode during the pandemic, public transportation needs to be made safer and healthier from the pandemic viewpoint. For instance, the number

### Table 6
Regression coefficients and model fitting information (during COVID-19).

| Mode                  | Regression coefficients | Sig. | Odds ratio | 95\% Confidence Interval for the Odds ratio |
|-----------------------|-------------------------|------|------------|-------------------------------------------|
|                       |                         |      |            |                                           |
| **Private car**       |                         |      |            |                                           |
| Intercept             | 1.756                   | 0.005|            |                                           |
| Pandemic-related-during | 0.006                   | 0.641| 1.006      | 0.981, 1.032                             |
| Motorcycle ownership  |                         |      |            |                                           |
| Yes                   | 0.159                   | 0.506| 1.172      | 0.734, 1.871                             |
| No                    | 0                       |      |            |                                           |
| Gender                |                         |      |            |                                           |
| Male                  | -0.841                  | 0.005| 0.431      | 0.241, 0.771                             |
| Female                | 0                       |      |            |                                           |
| Monthly household income (PKR) |                       |      |            |                                           |
| < 50,000              | -0.300                  | 0.351| 0.741      | 0.395, 1.391                             |
| 50,0001–100,000       | 0.023                   | 0.938| 1.023      | 0.579, 1.808                             |
| > 100,000             | 0                       |      |            |                                           |
| Car ownership         |                         |      |            |                                           |
| Yes                   | -0.713                  | 0.007| 0.490      | 0.293, 0.820                             |
| No                    | 0                       |      |            |                                           |
| **Motorcycle**        |                         |      |            |                                           |
| Intercept             | 1.810                   | 0.011|            |                                           |
| Pandemic-related-during | -0.024                  | 0.103| 0.976      | 0.949, 1.005                             |
| Motorcycle ownership  |                         |      |            |                                           |
| Yes                   | 0.300                   | 0.288| 1.350      | 0.776, 2.349                             |
| No                    | 0                       |      |            |                                           |
| Gender                |                         |      |            |                                           |
| Male                  | -0.253                  | 0.488| 0.776      | 0.379, 1.589                             |
| Female                | 0                       |      |            |                                           |
| Monthly household income (PKR) |                       |      |            |                                           |
| < 50,000              | -1.166                  | 0.002| 0.312      | 0.148, 0.654                             |
| 50,0001–100,000       | -0.691                  | 0.040| 0.501      | 0.260, 0.968                             |
| > 100,000             | 0                       |      |            |                                           |
| Car ownership         |                         |      |            |                                           |
| Yes                   | -0.597                  | 0.054| 0.551      | 0.300, 1.010                             |
| No                    | 0                       |      |            |                                           |

**Model Fitting Information**

| Model Fitting Information | Likelihood Ratio Tests |
|---------------------------|------------------------|
|                         | Model Fitting Criteria |       | Chi-Square | Df | Sig. |
| Intercept Only           | –2 Log Likelihood      | 801.291| 44.603 | 12 | 0.000|
| Final                    |                        | 756.688|        |    |      |
of passengers using public transport vehicles at a time may be reduced to maintain the social distance within the vehicle. It might be acceptable for the passengers since they are willing to wait and pay for a less congested vehicle. This suggestive measure could also be implemented through increasing the frequency of the public transit service. Also, hand sanitizer’s availability and cleanliness may further help in addressing the concerns of the passengers about using public transport during the pandemic. Other options such as proper ventilation, contact-free (online) fare system, and mandatory face masks inside public transport may also attract passengers towards public transport. However, as the results of this study suggest that respondents belonging to a low-income category are more likely to use public transport relative to a private car during the pandemic when compared to those belonging to higher income categories. The high-income people generally own a private vehicle and would prefer to use it as habitual users regardless of the circumstance, a similar result has been found by Vij et al. (2013). The possibility of a correlation between low-income level, low education level and conspiracy beliefs about the COVID-19 pandemic should also be explored. Furthermore, pandemic associated risks awareness campaigns need to be commissioned to sensitize the masses, particularly the low-income groups as a desired community response are equally pivotal and important to curtail the spread of pandemic risks.

Although the use of non-motorized modes increased during the pandemic, overall, it still has a low modal share. Non-motorized modes of travel are relatively safer from the pandemic viewpoint. The use of non-motorized modes is related to the land use pattern and availability of the grocery markets in the vicinity. In addition, walking and bicycling are healthy activities for self-isolation lifestyle. Therefore, they need to be promoted during the pandemic, especially for shorter distances. Pakistani cities generally lack pedestrian and bicycle infrastructure, however, the space created by the reduction in traffic levels during the pandemic may be utilized for non-motorized modes of travel.

Further, the mode choice models suggested that the factors which were significant for predicting mode choice before the COVID-19 pandemic may not be significant for predicting mode choice during the pandemic. Hence, urban transport planners need to determine those previously unexplored factors which are likely to affect mode choice during the pandemic. For instance, the unavailability of certain modes during the pandemic, government restrictions, lockdown implementation, and travel purpose are some additional factors that might affect mode choice during the pandemic and need to be explored.

Conclusions

This study explored the mode choice behavior for shorter as well as longer distances both before and during the COVID-19 pandemic in three major cities of Punjab province of Pakistan. The data was collected through an online questionnaire which consisted of three sections: demographic characteristics, factors affecting mode choice before and during COVID-19 pandemic, and mode choice for shorter and longer distances for both before and during COVID-19 situations. The respondents placed more priority on safety and security, cleanliness, infection concern, social distance, personal social status, waiting for, and paying for a less congested vehicle while choosing a mode during the pandemic. Public transport use decreased during the pandemic, whereas walking and bicycling increased during the pandemic particularly for shorter distances. However, the modal share for walking and bicycling was still small. The mode choice model for shorter distances during the pandemic indicated that monthly household income and the underlying pandemic-related factor are the significant predictors of mode choice. Whereas, the mode choice model for long distances during the pandemic indicated that gender, car ownership, and monthly household income are significant predictors of mode choice. The mode choice models for during pandemic situation had low Pseudo r-square values. It could be due to some other factors which may affect the mode choice behavior during the pandemic or due to a non-linear relationship between mode choice and the explanatory variables. Nonetheless, further studies are required to model the mode choice behavior during the pandemic.

This study had some methodological limitations. The questionnaire was designed in the English language; therefore, it is likely that only those respondents filled it who could understand the language. Since, an online questionnaire was preferred over face-to-face interviews due to the social distancing requirements, only those with internet access could fill the questionnaire which could lead to biased results. The sample was skewed towards the younger population possibly because of the lower presence of older people on social media. In addition, the cross-tabulation tables for dependent variable and the explanatory variables showed that a small number of cells had zero frequency which can be dealt with by collecting a larger and more diverse sample. Since the pandemic situation is still evolving and the second wave has hit several countries, additional studies on mode choice behavior with more representative samples are recommended. Furthermore, advanced mode choice models such as mixed logit models should be developed to overcome the limitations of multinomial logit models presented in this study.

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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