Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company’s public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Impact of COVID-19: A radical modal shift from public to private transport mode

Sanhita Das a, Alice Boruah b, Arunabha Banerjee b, Rahul Raoniar b, Suresh Nama b, Akhilesh Kumar Maurya b,∗

a Department of Civil Engineering, Indian Institute of Technology Roorkee, Roorkee, Uttarakhand, 247667, India
b Department of Civil Engineering, Indian Institute of Technology Guwahati, Guwahati, Assam, 781039, India

ARTICLE INFO

Keywords:
COVID-19
Mode choice
Mode shift
Public transport
Car

ABSTRACT

The unprecedented shock triggered by the COVID-19 pandemic has caused significant impact on public transportation services, travel behavior and mode choice preferences. Increasing risk of virus contagion in shared travel modes might result in a systemic shift from public transport to car commute. Such a shift causes increased congestions, emissions with a burden on the existing infrastructure. Given the urgent need of reconsideration of transport in a post-COVID world, this study presents insights into the possible shift from public transport to car use, potential factors influencing the mode shift, with emphasis being also laid on suitable strategies for promoting public transport use in the future world. Based on an online questionnaire survey conducted in India, results of logistic regression model indicate that commuters’ socio-economic characteristics such as age, gender and monthly income tend to significantly influence mode switch preferences. In addition, trip characteristics including travel time, overcrowding and hygiene are strongly associated with mode shift preferences from public transport to car use. Commuters’ perceptions on several strategies for promoting public transport have also been assessed, which will indeed pave the way for the formulation of post-COVID transport policies. In essence, efforts need to be directed towards restoring users’ confidence and trust by providing a safe, secure and healthy environment to the public transport users.

1. Introduction

The outbreak of a novel Coronavirus Disease (COVID-19) with virus strain Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) has struck the global population with its epicenter initiation in Wuhan, China in December 2019 (Huang et al., 2020). Due to lack of initial measures over travel restrictions across different countries, the spreading of the virus has gone unobstructed. Early confirmed COVID-19 cases outside China had travel links to Italy and Iran, and thereafter triggering the rapid spread of virus across 210 countries including India. Owing to alarming rise in virus spread, World Health Organization (WHO, 2020) declared a worldwide emergency on March 11, 2020 to deal with the global pandemic scenario. By May 31st, WHO (2020) had confirmed a total of 62 lakh cases of infection globally, with death toll reaching 3.72 lakhs, and India contributing to 1,82,143 confirmed cases and 5164 deaths.

To curb transmission of the virus, national lockdown restrictions were imposed in India in several phases limiting all non-essential travel. The first phase of lockdown was implemented between 25th March and 14th April, following which Phase 2, Phase 3 and Phase 4 lockdown were continued between 15th April to 3rd May, 4th May to 17th May and 18th May to 31st May respectively. This has led to drastic changes in people’s travel patterns, daily activities, and a significant reduction in road traffic and ridership levels. Public transport ridership in some of the cities of Europe fell by 80% as transport operators reduced their services (Bernhardt, 2020). According to a survey conducted by UITP and World Bank (2020), the ban on bus operations in India had resulted in 90% reduction in ridership, where more than 60% bus operators believed that both demand and service levels would not be more than 50% of a pre-COVID scenario. Pillai (2020) highlighted that the capacity of public transport in Delhi reduced on an average by 73% during the pandemic. A report published by AAOCHAM and Primus Partners also indicated that the ridership of PT reduced by 34% across the Indian cities where out of 55% of the public transport users in the pre-pandemic period, only 21%...
were willing to prefer PT in post-pandemic world. According to the Community Mobility Reports of Google (https://www.google.com/covid19/mobility/), a decline of 32.4% in public transport use was reported in India between February and May 2020, with the maximum reduction being observed as 59.9% in the month of April (Bhaduri et al., 2020). A large decline in mobility was observed across cities due to the fear from COVID-19. This reduction in public transport usage has been the result of personal preferences and government measures to contain the virus spread.

As public transport (PT) brings people in close quarters in a confined space, the users become more vulnerable to the virus, thereby causing serious health concerns which ultimately lead to a loss in ride-shers. A survey conducted in the UK revealed that 72% of the surveyed respondents would not use public transport unless safety and hygiene measures are in place (Transport Focus, 2020), while 18% of the respondents were happy to resume services as soon as the government restrictions are lifted. Even 75% of Indian commuters reported public transport use as unsafe while only 1.7% of the commuters has perceived it as a safe mode of transport (Pawar et al., 2020). As per Troko et al. (2011), the close proximity with which individuals travel in shared travel models could lead to higher chance of getting infected. Although social distancing has become the new norm to reduce the risk of contagion (Tirachini and Cats, 2020), people might rather shift from public transport to car commute due to concerns of hygiene and disease transmission in public transport use. This modal shift has been indicated in the recent literature where 5% of the surveyed respondents in India have shifted from public transport to private mode (Pawar et al., 2020). Buczky (2020) indicated that the dependence on car in Budapest during the pandemic has increased from 43% to 65%. Indeed car commuting in India is expected to increase to as much as 38% by the end of 2020. In particular, the number of car sales recorded in India in the month of July 2020 were found to be 69% higher than that in June 2020. Haas et al. (2020) also revealed that people in Netherlands prefer to use cars and tend to avoid public transport because of the corona crisis. Even a survey conducted in Australia indicated that private vehicle was considered as the most comfortable mode during pandemics and 42% of the respondents referred bus as the least comfortable one (Beck and Hensher, 2020). A recent survey conducted by Pillai (2020) revealed that 55% of Indian shared transport users were more likely to own private cars in the near future, reflecting increase in car sales and skepticism over public transport use. Such a shift and high dependence on car could have negative consequences such as increased congestions, emissions, increased travel times, damage to the environment and accidents. Moreover, rise in car ownership levels in the near future will not only increase transport demand, but also can have negative effects in terms of accessibility and sustainability.

As a consequence, governments are facing challenges to develop a new future for smarter and more efficient public transport system to avert the impending crisis of congestion. In light of this, this paper fills a gap in the understanding of how the COVID-19 pandemic has impacted changes in public transportation and car use in India. It discusses the changes in travel behavior and its subsequent effect on mode switching behavior compared to the situation before the COVID-19 period. Specifically, this paper aims to evaluate the factors influencing commuters’ choice to switch from public transport mode to private cars, their perceptions to associated risks, with proper emphasis being laid on strategies that could be implemented such that our public transportation system remains sustainable and resilient. Recognizing that developing effective policies for a future transport in a post-COVID world requires individuals’ mode choice decisions, this paper also presents several practical implications for public and private policymakers, as they chart a new path to reinstate public transport system post pandemic.

2. Research on mode choice determinants

Transport mode choice behavior is governed by individuals’ characteristics, situational factors, travel characteristics, and a set of personal attitudes, habits, preferences, lifestyle, culture and (dis)abilities (Chakrabarti, 2017). A plethora of literature on mode choice behavior reveals that travel time (Chowdhury and Ceder, 2016; Almasri and Alraee, 2013), trip distance (Nes, 2002; Cho, 2013), cost (Meng et al., 2018), traveler characteristics such as gender (Hanson, 2010; Mahadevia and Advani, 2016; Rosenbloom, 2006), age (Almasri and Alraee, 2013; Liu et al., 2016), income (Mahadevia and Advani, 2016; Ko et al., 2019), access to personal vehicle (Chee and Fernandez, 2013; Chakrabarti, 2017), employment and education (Liu et al., 2016) influence the transport mode choice. Indeed there exists a disagreement in gender-wise mode choice preferences. A study by Mahadevia and Advani (2016) indicated that males prefer using personal commute over transit, while the willingness of males for public transport use was indicated in Chee and Fernandez (2013) work.

Most studies reveal that travel time, speed, comfort, convenience and flexibility of trip making are important for choosing car over public transport (Corpuz, 2007; Nurdden et al., 2007). Factors like accessibility, service and frequency are important for the car users to shift to public transport (Lai and Chen, 2011; Corpuz, 2007). Research also indicates that car dependency increases among families with young children (Ryley, 2006; Scheiner, 2014). Shorter travel time (Eriksson et al., 2008; Vedagiri and Arasan, 2009), subsidized fare (Nurdden, 2007; Gebeyehu and Takano, 2007) have been considered as key factors for making PT more attractive than private mode. A study by Basheer et al. (2019) indicated that car is most commonly used in combination with public transit for work-related travel, where sensitivity for time is high.

In particular, personal commute is often seen to dominate public transit in spaces where automobiles are relatively low-priced. But in places where land use policies are stringent, parking spaces are heavily priced and automobiles are expensive, shared modes of transit often rule (Giuliano and Dargay, 2006). Efthymiou and Antoniou (2017) reported an increase in public transit use due to increased consciousness of environment, improvement in service, and increased costs of buying and maintaining a car. Among other factors, Clark et al. (2016) found that major lifestyle changes such as job change or moving home, as well as a pro-environmental attitude influence shifting from car to public transit use. The commuting policy literature has focused on the promotion of sustainable public transport mode. Indeed integrated planning taking land-use, consideration of all important factors promoting public transport as well as social practices, suitable network level design with introduction of bus rapid transit system, intelligent transportation systems and transits requiring less transfers, can result in a significant shift from car to public transportation services.

The peer-reviewed literature provides evidence that various factors influence the travel mode choice behavior. Very often, car is chosen as a preferred mode because of its speed, flexibility, comfort, and convenience (Beirão and Cabral, 2007). Although the modal shift from public transport to car has been indicated in the literature related to pre-corona period, users’ preferences to choose a mode due to the coronavirus crisis and potential factors influencing such mode choice behavior can vary largely in a complicated manner. Specifically, to provide a comprehensive understanding of mode switching behavior of public transport users to car commute, the characteristics of the users (such as age, gender, income level and employment), trip features (including travel time, access distance, cost, safety, cleanliness and overcrowding) and vehicle characteristics (availability of personal vehicle) are considered in this study. Given the current global public health crisis, several policy measures to reconfigure public transportation services in a post-COVID world have also been discussed.

3. Methodology

3.1. Approach and study area

A stated-preference web-survey was conducted between April 29th
and May 30th 2020, during phase 2 (April 15th to May 3rd 2020), phase 3 (May 4th to 17th 2020) and phase 4 (May 18th to 31st 2020) of nationwide lockdown declaration in India. The first wave of the survey was conducted well after the spread of the virus (more than 24, 75, 723 confirmed cases including 1,69,151 deaths had been reported worldwide on April 22nd). To gauge the impact of coronavirus spread on the transportation sector, the online questionnaire was distributed to the residents residing in different regions of the country via social media platform, email and professional networks. A total of 840 samples was obtained, among which 31% of the surveyed respondents were residing in the north-eastern region of the country, 25% in eastern region, 18% and 10% in northern and southern regions respectively, and the remaining 16% respondents were in the central and western region at the time of response. The survey is designed to collect information about possible changes in travel patterns post pandemic world and perceptions of the respondents to several policy measures that might help in containing the spread of virus on shared mode of transport.

3.2. Survey design

The questionnaire consisted of four sections which included both open-ended and close-ended questions. The first section indicated the purpose of the survey. The second section included current residence and location at the time of response, basic demographic and user characteristics in terms of age group, gender, profession, monthly income, number and type of personal vehicle(s) owned. In order to understand how commuters might change mode of transit post pandemic, trip characteristics before the lockdown is imperative. The third section therefore prompted the respondents to indicate their travel mode preferences during normal commute (before the coronavirus outbreak). In particular, this section inquired about the mode of travel generally used for different trip purposes, trip frequency of such trips (measured on the following scale “no trip”, “daily”, “3-5 times in a week”, “once a week” and “once a month”), approximate travel time to work (indicators included “less than 15mins”, “15-30mins”, “30-45mins” and “greater than 45mins”), distance from home to point of access to public transport services (measured as “0-500m”, “500-1000m”, “1000-2000m”, “2000-3000m” and “more than 3000m”) and factors that encourage respondents to choose cars over public transport during normal commute (considered factors were travel time, cost, personal safety, overcrowding and hygiene, all being measured on the scale of “not important”, “important” and “very important”).

The influence of COVID-19 on mode shift preferences can be assessed based on the dynamic changes on the transport demands, commuters’ preferences in using a particular mode and perceived health risks associated with public transport use. To understand the impact of the pandemic on the mode shift preferences, the fourth section of the questionnaire prompted to indicate the preferred mode of travel post pandemic world for different trips, anticipated safer mode of travel (each travel mode was measured on the scale of “safe”, “unsafe” and “not sure”) and ranking of several possible policy measures for reviving public transportation services post pandemic world. In essence, seven different strategic measures were considered which included “alternate seating arrangement with proper social distancing measures”, “limited passengers allowance”, “provision of personal protective equipment (PPE) kits”, “regular disinfection of buses at end-to-end stoppage”, “cashless fare transaction”, “reduce stoppage at areas attracting large crowd” and “real-time information of seat availability on the buses” and the respondents’ preferences were measured based on the scale of “not important”, “important” and “very important”. It further inquired about preferences of the respondents in using public transport post pandemic, if such strategic measures are implemented and the public transport system is redesigned (measured on the scale of “yes”, “probably yes”, “probably no”, “no” and “definitely not”).

The survey tests respondents’ mode choice preferences during pre-pandemic and post-pandemic world in order to answer questions about mode switching behavior of public transport users to private cars. The possible decline in public transport ridership and different factors influencing the mode shift preferences are indicated by several factors including trip attributes, demographic characteristics, service quality and environment of the public transport system. Most importantly, this survey also attempted to address users’ perceptions to several possible policy interventions which could be implemented for reviving public transport ridership in the post-pandemic world.

3.3. Analytical approaches

Two approaches-logistic regressions and analytic hierarchy process were used to examine the mode choice preferences of the respondents in the post-pandemic scenario. Logistic regression model was considered to explain the mode switching behavior of the public transport users and their shift to car use post pandemic. Accordingly several explanatory variables were considered in the analysis that could potentially influence the decrease in public transport ridership and corresponding shift to car use. On the contrary, an analytic hierarchy process was utilized to rank several policy measures that the respondents considered important for reviving the public transportation system post pandemic. This approach is expected to reveal respondents’ perceptions to several strategic measures that the policy makers might consider for increasing the public transport ridership in the post-pandemic world.

3.3.1. Logistic regression models

Logistic regression model is employed to identify the significant factors affecting the mode switching behavior of public transport users to car commute. Owing to enhanced simplicity in model estimation and translation, and straightforward numerical frame, the model has been widely applied for mode choice decision model development. In the context of mode-switching behavior model, the theory of logistic regression model is that each respondent has a set of mode choice preferences (either selection of original mode or shift from original mode to new mode) and each mode choice preference has its own utility (U\text{in}) which is the ith mode choice preference of the nth respondent. In essence, each respondent chooses the mode with the highest utility and the utility of each respondent is linked to systematic utility (V\text{in}) and an unobserved component or error (e), that is \( U_{in} = V_{in} + e \). The systematic component of utility \( V_{in} \) can be defined as:

\[
V_{in} = \alpha + \gamma_1 Y_1 + \gamma_2 Y_2 + \gamma_3 Y_3 + \ldots + \gamma_K Y_K
\]

where \( \alpha \) represents alternative specific constant in the utility function; \( Y_1, Y_2, Y_3, \ldots, Y_K \) is a set of estimated coefficients of the considered explanatory variables; \( Y_1, Y_2, Y_3, \ldots, Y_K \) is a set of explanatory variables considered in the mode switching behavior choice; \( K \) is the number of attributes. The probability of a respondent choosing a specific mode post pandemic is

\[
P = \frac{1}{1 + e^{-(\alpha + \gamma_1 Y_1 + \gamma_2 Y_2 + \gamma_3 Y_3 + \ldots + \gamma_K Y_K)}}
\]

Fig. 1 shows different explanatory variables used in the logistic regression analysis. The explanatory variables have been categorized into user, vehicle and trip characteristics to help explain mode switching behavior.

3.3.2. Analytic hierarchy process

Concerning potential decline in public transport ridership, a new transport future in the post-COVID world requires provision of safe and quality public transport alternatives. Promoting public transport and implementation of policy measures entail choosing the right alternatives and making rational decisions in such a way that strategic alignment is maintained. The analytic hierarchy process (AHP) developed by Saaty (1980) is considered as one such technique used in decision-making.
process for complex environments, where human judgements, perceptions and consequences have long-term repercussions (Bhushan and Rai, 2004). The AHP technique consists of decomposition of decision making process into a hierarchy of sub-problems and converting subjective assessments of relative importance of each criterion to a set of priority weights or scores.

The top level of hierarchy defines the objective of the decision making process that is, evaluation of several policy measures for promoting public transport in a post-COVID world. The second level of hierarchy defines the criteria and evaluation of their relative priorities, which include (A) alternate seating arrangement with proper social distancing measures, (B) limited passengers allowance, (C) provision of personal protective equipment (PPE) kits, (D) regular disinfection of buses at end-to-end stoppage, (E) cashless fare transaction, (F) reduce stoppage at areas attracting large crowd and (G) real-time information of seat availability on the buses. At the last level, the sub-criteria involve perceptions of the respondents to each criterion, categorized as important, not important and very important.

AHP creates a set of pair-wise comparison matrices between the sub-criteria on the same level, and the relative importance of each sub-criterion was assigned using Saaty scale (Saaty, 1980). The first step involves construction of a comparison matrix and evaluation of relative importance of criterion j compared to k, assigned to (j,k) position of pair-wise comparison matrix. After that, the priority vector (or Eigen vector) for each of the criteria is computed by first normalizing each column of the matrix by summation of all the elements of the same column, and then calculating the mathematical average of all sub-criteria. The AHP then combines the weights and determines an overall score for each criteria, the highest score corresponding to the strategic measure one has to choose. A consistency index parameter is also considered to represent reliability level of the judgement. A step-by-step procedure can be found in Vargas (2010), Longaray et al. (2015) and Sael et al. (2019).

4. Public transit and car use in pre-pandemic and post-pandemic world: descriptive statistics

The descriptive analysis of public transport and car use among commuters during normal commute and post pandemic scenario is discussed in this section. A total of 840 observations were collected and analyzed after removing samples with missing demographics. In particular, the mode switching behavior of the surveyed respondents by different original mode choices and also the travel behavior among the car-owning households are investigated.

4.1. Respondent demographics

Table 1 reports sample demographics, highlighting mode switching behavior of the respondents involving public transport and cars. The data are aggregated by mode choice in the pre-pandemic and post-pandemic world with respect to respondent profile. The sample showed a higher percentage of male respondents, with 89.5% of the respondents aged between 19 and 45 years, 35% being students and reflecting consistent proportion of respondents’ monthly income. Although the gender split in the case study region is 51.54% male and 48.46% female (Census India, 2011), the higher percentage of male
residents can be due to gender-wise travel patterns in India. Also, inadequate responses of the younger and elderly participants can be due to their unwillingness to be surveyed.

The data suggest that females still tend to prefer public transport to cars during normal commute, while the reverse trend follows for males. This is in congruence with the modal choices of females indicated in Srinivasan (2008) and Mahadevia et al. (2012). In both the cases, gender-wise travel patterns indicated drastic reduction in public transport mode choice post pandemic, with higher preferences in selecting car mode. When the respondents are segmented according to age, the data over the 30 group shows a higher preference for cars over public transport, while the under 30 group prefers public transport during normal commute trips. Even public transport is mostly favored by students and respondents with monthly income below ₹75000. According to the Wilbur Smith and Ministry of Urban Development (2008: xii), the public transport accessibility indices in the case study areas lie between 1.22 and 1.67, indicating better accessibility.

Socioeconomic heterogeneities are reflected in the surveyed dataset. Respondents who are mostly women, students, below the 30 age group and monthly income below ₹75000 prefer public transport during normal commute trips. Higher income respondents even show a tendency to use public transport because of better accessibility. Conversely, the mode switching behavior post pandemic indicates that public transport would still be favored by males, students, below the 30 age group and monthly income below ₹30000. This dataset reveals that respondents who are students, below the 30 age group exhibit similar travel patterns in both the scenario, although significant reduction in public transport trips could be observed post pandemic.

4.2. Change in share of overall trips post pandemic

While a reduction in public transport trips and increase in car trips is anticipated post pandemic, it still needs to be answered whether the final mode choice would imply sensitive dependence on the original mode. The dataset presented in Table 2 illustrates distinction in behavior when the original mode choice was shared transport (public transport and carpool) and those when it was not shared (private cars, motorize two-wheeler and cab) and active travel (cycle and walk). The shared modes exhibit large mode switching behavior towards other unshared and active travel modes.

Column (1) in Table 2 presents the percentage share of different travel modes reported by respondents during normal commute (in the pre-pandemic period). On the other hand, columns (2) and (3) indicate the percentage of original mode users preferring to use PT and car respectively post pandemic. While column (4) presents the percentage share of other travel modes excluding PT, car and a particular original travel mode; column (5) specifically indicates the percentage share of a given travel mode adopting the same mode post pandemic.

The unshared mode users and those with active travel mode show a higher preference towards using original mode post pandemic. More than 70% of the motorized two-wheeler (MTW) and car users retain the original mode choice. Interestingly, 24% of the respondents using PT during normal commute show a large shift towards other modes (59%), with only 23% of public transport users being attracted to use the original mode. Similar is the case observed for shared car users, where 18% of the shared cab users prefer using the original mode post pandemic. This indicates that increased exposure to health risks in shared transport could lead to behavioral shift from original mode choice. Those who are accustomed to use shared modes are more likely to adopt other modes of transport, although a small proportion of respondents would still be drawn by shared modes post pandemic. This suggests that suitable preventive measures and alternative strategies need to be followed for ensuring the safe health of the shared mode users post pandemic.

The data indicate that private car draws 18% users from public transport, 24% from cabs and 11% each from active travel mode, although it draws heavily from original car users (80%). This suggests a general trend of the respondents towards avoiding public transport mode and favoring other unshared modes post pandemic. However, preferences of some public transport users towards using the original mode could be attributed to better public transport accessibility and demographic characteristics such as vehicle ownership, profession, income and age group of the surveyed respondents, which might influence the mode choice decisions post pandemic. This provides evidence that although original mode choice influences final mode choice, there will be decreased public transport ridership post pandemic, thereby increasing the demand of other transport modes.

In particular, car commuting seems to be a more stable and attractive alternative to users. Over 80% of car commuters would still commute by cars post pandemic, drawing 18% share from the normal public transport users. This highlights the mode choice behavior of respondents post pandemic.
4.3. Travel behavior of commuters in car owning households

19% of commuters having car in their household reported using public transport as their normal commute mode before lockdown. While the percentage reduces to a large extent in using public transport services post pandemic, leaving the share of anticipated PT users less than 6%.

Table 3 shows that public transport users are generally students, comparatively younger, lower monthly income and lower access to cars in their households.

Respondents having access to cars (35.7%) still choose public transport during normal commute either because household car(s) is/ are not available to them or they prefer using public transport services. Contrarily, 6% of the respondents still consider using public transport post pandemic and is mostly favored by 45% students having lower monthly income and lower average car household access. On average, no significant difference in public transport mode choice is observed between pre pandemic and post pandemic scenario with respect to male and younger respondents. The same hold true for car users.

While there is a significant reduction in PT ridership, the car commuting appears to be a more safe and suitable alternative, increasing the share of car ridership by almost 7% (29.2%–36.3%). Even respondents who are students, have lower monthly income and better car access in their households show a higher preference towards car commuting post pandemic, although no significant differences in their ridership could be observed for younger and male participants. This could be because of the disproportionately smaller number of female participants in the surveyed data. Also, because younger participants may be compelled to use public transport mode either due to unavailability of cars or not possessing driving license, no significant increment in car mode choice could be observed.

The data indicate that public transport users will prefer using the original mode for shorter trip time post pandemic. The relative distribution of trip time, disaggregated by change in commute mode for three different mode switching behavior (shift from public transport to public transport, public transport to car and car to car) is shown in Fig. 2.

39% of public transport users choose the original mode for trips involving lower travel time. Their preferences in selecting the same mode gradually decrease as trip travel time increases. By contrast, there is almost a consistent share of car ridership (24%–31%) across different trip times. This highlights that respondents who generally commute by cars tend to remain a car commuter irrespective of trip travel times.

Most importantly, the public transport users who are more exposed to health risks show a shift in commute mode from public transport to cars (varying from 18% to 32%) post pandemic. The mode shift occurs at all levels of trip times, with the largest share being observed for trips involving higher travel time (greater than 45 min).

5. Modelling results: shift from public transport to cars

The multinomial logistic (MNL) regression model has been considered for analyzing the mode switching behavior of public transport users and their shift to cars post pandemic. MNL is widely used for mode choice modelling due to enhanced simplicity and flexibility in handling multiple explanatory variables. Binary logit regressions were employed which take the value ‘1’ when respondents shift from public transport to cars and ‘0’ when public transport users choose the original mode. Several potential explanatory factors were investigated and the variables with the highest p-values were omitted until the pseudo R² values were found satisfactory.

The explanatory variables include respondents’ demographics, travel patterns during normal commute and perceptions towards mode choice. Within respondents’ demographics, those of age, gender, monthly income, occupation and household vehicle access were defined as categorical variables. Information on travel characteristics such as number of trips usually made by the respondents, access distance to public transport services and average travel time required to make the trips using PT was included in the mode switching behavior model. As a way to investigate the probable factors encouraging users to choose cars over public transport services, five variables including travel time, cost, safety, avoiding crowd and hygiene were added. In particular, the ratings of each factor were considered to understand mode choice preferences of the respondents. Prior to model development, those variables with magnitudes of associations lower than 0.5 were further considered.

Table 4 shows the logistic regression results for the mode switching behavior.

The results strongly suggest that the mode switching behavior of PT users to cars is influenced by distinct set of factors. In particular, it appears that high-income respondents (>75,000) are more likely to use a car. Concerning age and gender, young respondents who are males are found to have a propensity for public transport use. This finding implies that the group of low income respondents who are young and mostly students tend to choose public transport post pandemic, even when they are exposed to increased health risks. Their decisions may be influenced by lower access to private cars in their households. As the degree of car ownership increases, respondents are more likely to switch to car.

Interestingly, the model estimates suggest that respondents prefer to use cars as the number of trips increases. Public transport users appear to be more likely to use private cars for their daily commute, while they still consider using transit for trips with once in a month or longer. Regardless of the accessibility to public transport services, results show that access distance has a significant positive association with the switching preferences to cars. Although better accessibility to transit use appears to exert a positive impact on its use, the results reveal that respondents prefer to avoid transit use, even when the access distance is lower. Another interesting finding is that travel time has a significant positive association with the mode switching choice. Specifically, respondents would mostly prefer to use a private car regardless of the travel time required to reach the destination. This is also supported by Ko et al. (2019).

With respect to respondents’ mode choice preferences, travel time is found to be significant at 0.05 significance level, with increased travel time being positively associated with mode switching choices. Because car-based travel is often considered to be faster than public transport, respondents consider travel time as an important determinant in the transport mode shift from transit to cars. On the other hand, cost of...
Travel is significant at 0.1 significance level, which is somewhat expected because respondents usually rely on public transit because of cheaper costs, thereby reducing its share of commuters as cost increases. Although the variable safety was not found to be significant, the negative association suggests that respondents who are more concerned about personal safety and security still prefer to use public transport over cars. In particular, this variable considers only personal safety and is not related to health risks associated with coronavirus.

Interestingly, overcrowding and hygiene/cleanliness were found as the significant factors influencing the mode switching behavior of respondents. One possible explanation is that a crowded bus may lead to increased dissatisfaction (in terms of psychological, emotional distress or loss of privacy) on the passengers during travelling (Li and Hensher, 2011, 2013). Thus, it is more likely that respondents’ preferences on car use will increase in order to avoid crowding in public transport. Moreover, perceptions related to cleanliness are found to have a significant association with the mode switching behavior. Literature highlights that service environment (or cleanliness) has a major impact on mode choice for public transport (Li and Hensher, 2013; Shaaban and Kim, 2016; Chen and Li, 2017), signifying that private cars providing cleaner service environment than public transport attract users to switch to car use.

6. Policy analysis

6.1. Empirical insights

The major empirical findings and their research and policy implications are discussed in this section. In the context of socio-demographic characteristics, respondents who are students below the age group of 30 years with monthly income lower than ₹15,000 show a higher preference for public transport use during both pre-pandemic and post-pandemic scenario. Even higher income respondents who prefer to use public transport during normal commute are more likely to switch to car transportation post pandemic world.

Modelling results suggest that car demand will be primarily driven by travel characteristics and respondents’ preferences towards mode choice. While 80% of car commuters would still commute by cars post pandemic, this study indicates that it would draw 18% share from the normal public transport users. Although socio-demographics do not factor heavily, the car demand will increase with the increase in trip frequency, travel time and respondents’ access to cars in their household. Given the importance of short trips, public transport can still be considered for trips with travel time lower than 15 min. But, respondents who are sensitive to service quality and service environment (such as crowding and cleanliness) show a higher propensity to switch to cars.

Although public transport proves to be an efficient, reliable and cheaper transport mode providing better accessibility, several factors relating to trip characteristics, socio-demographics and respondents’ attitudes influence switching to car commuting post pandemic. Under this circumstance, it would be necessary to promote public transport ridership by providing quality PT services, cleaner and a safe environment, which could possibly reduce health risks.

6.2. Possible strategies to revive public transport systems post pandemic

While public transport is believed to be an efficient, safe and sustainable mode of transport, a significant reduction in public transport ridership is anticipated after resumption of services. Most importantly, public transport provides a lifeline to vast numbers of low and middle-income Indian urban families. This suggests that appropriate policies need to be implemented for building users’ confidence in public transport such that the excessive burden on road traffic is reduced. In particular, developing any effective policies require prior understanding of users’ perceptions and preferences towards the proposed interventions. Recognizing this, this work has further attempted to gain insights into respondents’ preferences to a number of policy measures which, if considered, might revive the public transport system or reduce switching to car transportation.

Based on the questionnaire survey, respondents evaluated the importance of several possible policy measures which could attract them to use the public transport post pandemic. A total of seven strategic measures are considered which include (A) alternate seating arrangement with proper social distancing measures, (B) limited passengers allowance, (C) provision of personal protective equipment (PPE) kits, (D) regular disinfection of buses at end-to-end stoppage, (E) cashless fare transaction, (F) reduce stoppage at areas attracting large crowd and (G) real-time information of seat availability on the buses. Respondents indicated to what extent these proposed strategies are important for using public transport services which in turn might provide a safe and healthy environment to the users.

An analytic hierarchy process (AHP) is used in this study to rank
several considered strategies (Saaty, 1980; Mayo and Taboada, 2020). AHP uses a hierarchical model consisting of goals, criteria and alternatives. It involves pairwise comparisons of the considered strategies at each level with respect to an element from the upper hierarchy level. Based on the principle of hierarchical decomposition, the priority weights are estimated to provide the overall priority of each considered strategy. Prior to understanding users’ preferences to several PT reviving strategies, it is important to demystify which policy strategies can fly and for which segments of population. Accordingly, the priority weights and individual rankings (given in parentheses) of each strategy for each demographic segment are estimated, as presented in Table 5.

The results indicated that factor F ranked the highest in 9 out of 12 sub-segments while factor B and D were the least influential. This implies that respondents seem to be mostly motivated from strategies prioritizing reduced bus stoppage at areas attracting large crowd. This preferred choice is quite understandable because respondents value service quality and environment more for using public transit. This is in line with the significant factors obtained in Table 4. In particular, a higher density of bus stops reduces travel time of the users as well as allows more PT passengers, which impact users’ riding comfort and safety. Concerning socio-demographics, both male and female respondents aged less than 45 years of all professions prioritize factor F. Interestingly, middle to higher income respondents indicated that PT would be preferred if measure F was considered.

Factor E relating to “cashless fare transaction” and factor A favoring “seating arrangement with proper social distancing measures” ranked second and third respectively. One possible explanation is that respondents are usually more concerned about transmission of virus through the exchange of physical money. Therefore, cashless and contactless payment seem to be a more effective public-health measure for middle to high income group respondents aged less than 30 years. On the other hand, both male and female respondents prioritize alternate seating arrangement over cashless payment transaction. A total of 7 in 12 sub-segments rank alternate seating arrangement as the third priority such that social distancing is ensured among the travelers. Although it would be challenging to implement such strategy in Indian contexts where public transport modes are always crowded, such initiatives on social distancing rules would rebuild users’ confidence in using public transport.

Moving beyond, provision of PPE kits (strategy C) and real-time information on seat availability (strategy G) are ranked 4th and 5th respectively. Wearing masks and gloves on public transport are important for the safety of all the travelers and the driver. Moreover, real-time information on seat availability of the transit modes can be made available to the travelers either through an app or occupancy information on the public transport itself. Interestingly, female respondents rank seat availability information as 3rd while reduced bus stops being still considered as the first priority. Conversely, strategy B relating to “limited passengers’ allowance” and strategy D “regular disinfection of buses at end-to-end stoppage” were considered as the least priority strategies among all demographic segments.

To summarize, respondents indicated that the strategy “reduce stoppage at areas attracting large crowd” is the most influential for retaining public transport ridership post pandemic scenario. Cashless and contactless payment was the next priority, followed by alternate seating arrangement with proper social distancing measures, provision of PPE kits, real-time information on seat availability, limited passengers’ allowance and regular disinfection of buses. Furthermore, when the respondents were asked about their likelihood to use public transport if such strategies are implemented, 25.6% of respondents replied “yes” while 53.6%, 16.7%, 3.6% and 0.5% respondents indicated “probably yes”, “probably no”, “no” and “definitely not” respectively. This signifies that implementing such policy measures by reassuring safety to the public transport users can still retain public transport ridership in a post-COVID world.

6.3. Policy implications

Due to the ongoing pandemic, transport policy makers are facing myriad of challenges to reconcile social safety and protection with global economic growth. Clear directives and formulating new policies based on users’ preferences provide an opportunity to reinforce the new transport future in a post-pandemic world. In particular, the impact of individual behavioral changes and their perceptions to travel choice has

---

**Table 4**

Logistic regression model of mode switching from public transport to car.

| Variables                        | Coefficient | p-value |
|----------------------------------|-------------|---------|
| **Gender and age**               |             |         |
| Constant term                    | -2.755      | 0.001   |
| Male                             | 1.682       | 0.032   |
| Age                              | -0.632      | 0.043   |
| **Monthly income (%) and employment** |             |         |
| 15,000-30,000                    | 0.983       | 0.011   |
| 30,000-45,000                    | 0.861       | 0.046   |
| 45,000-75,000                    | 0.896       | 0.042   |
| More than 75,000                 | 1.964       | 0.031   |
| Ref: Less than 1500              |             |         |
| Student                          | -0.774      | 0.082   |
| Ref: Employed                    |             |         |
| **Trip frequency**               |             |         |
| Trip frequency: once a month     | -0.236      | 0.321   |
| Trip frequency: once a week      | 0.368       | 0.152   |
| Trip frequency: 3-5 times a week | 0.541       | 0.067   |
| Trip frequency: Daily            | 0.888       | 0.040   |
| **Access distance to PT services (m)** |             |         |
| Access distance: 500-1000         | 0.242       | 0.063   |
| Access distance: 1000-2000        | 0.495       | 0.019   |
| Access distance: 2000-3000        | 0.512       | 0.015   |
| Access distance: greater than 3000 | 0.432   | 0.021   |
| Ref: Access distance: less than 500 |           |         |
| **Travel time (minutes)**        |             |         |
| Travel time: 15-30                | 1.642       | 0.043   |
| Travel time: 30-45                | 1.856       | 0.041   |
| Travel time: greater than 45      | 2.020       | 0.035   |
| Ref: Travel time: less than 15    |             |         |
| **Household access to cars**      |             |         |
| Travel time: important           | 1.493       | 0.007   |
| Travel time: very important      | 1.621       | 0.012   |
| Ref: Travel time: not important  |             |         |
| Cost                             |             |         |
| Cost: important                  | 0.127       | 0.087   |
| Cost: very important             | 0.236       | 0.078   |
| Ref: Cost: not important         |             |         |
| Safety                           |             |         |
| Safety: important                | -0.487      | 0.308   |
| Safety: very important           | -0.442      | 0.381   |
| Ref: Safety: not important       |             |         |
| **Hygiene**                      |             |         |
| Hygiene: important               | 0.617       | 0.042   |
| Hygiene: very important          | 0.819       | 0.037   |
| Ref: Hygiene: not important      |             |         |
indicated an unprecedented decline in public transport ridership. Recognizing that reconfiguring or formulating transport policies should be based on users’ perceptions and mode choice preferences, several possible policy implications obtained from this research are summarized below.

6.3.1. Safeguard safety

During the pandemic the onus of responsibility has been placed on the individuals for their own and others’ health and wellbeing. Although shared trips run a significant risk in such a public health crisis, several policy measures targeting public transport users will be effective to reassure users’ safety during operation. In this line, reconfiguring the layout of seats with alternate seating arrangement, cashless and contactless fare transaction, provision of PPE kits and hand sanitizer dispensers can be considered to safeguard safety to the public transit users. Even respondents considered reconfiguring seating arrangement of buses as one of the influential strategies to retain the PT ridership in a post-COVID world, followed by provision of PPE kits (or wearing masks and gloves, etc.).

6.3.2. Service environment

Modelling results showed that overcrowding and hygiene/cleanliness are the significant factors influencing switch of public transport users to car commuting. This suggests that policy formulations designed with careful consideration of service environment are more likely to be effective in the context of promoting safe and healthy journeys to the travelers. Some of the interventions might include limited allowance of passengers prohibiting overcrowded public transit, frequent cleaning of vehicles and handgrips in buses, social distancing markers to guide the onboard passengers and separating bus drivers from the boarded passengers.

6.3.3. Service innovations

The provision of quality transit service and technological innovations can be effective in ensuring healthy and safe service to the public transport users. Results of analytic hierarchy process indicated real-time digital information on seat availability as the fifth influential strategy that respondents might prefer to use public transport in a post-COVID world. In essence, respondents are more likely to switch to private car commute when the travel time on public transport increases. As indicated in the analytic hierarchy process results, strict public transport restriction measures such as eliminating stoppage at bus stops attracting large crowd might be needed to ensure limited passengers entry on the buses, thereby reducing their average travel time. The policy measures need to suit users’ attitudes and behavior, and build confidence about returning to public transportation in a post COVID world.

6.3.4. Reliable system

Results showed that respondents’ mode switching behavior is strongly associated with travel time. In essence, respondents are more likely to switch to private car commute when the travel time on public transport increases. As indicated in the analytic hierarchy process results, strict public transport restriction measures such as eliminating stoppage at bus stops attracting large crowd might be needed to ensure limited passengers entry on the buses, thereby reducing their average travel time. The policy measures need to suit users’ attitudes and behavior, and build confidence about returning to public transportation in a post-COVID world.

Given the global pandemic, integrating cashless and contactless payments, real-time information data, ensuring safety measures, reconfiguring the internal layout of the transit services with provision of a healthy service environment, can be effective and attractive for reviving public transport ridership in the face of global public health crisis. Additionally, several interventions at the tactical and operation level such as changes in time tables, redesigning PT services to avoid crowding, real-time information of vehicles and crowding at stations, communication and awareness to the passenger, accessibility and safe operation of PT, service frequencies and rigid hygienic routines can improve the long-term resilience of public transport sector and customer retention in the post-covid world.

7. Conclusions

This study attempted to explore to what extent the COVID-19 pandemic and government’s policies to curb the transmission of the virus in India will impact the mode switching behavior from public transport dependence to car use. Recognizing that developing effective policy measures should be based on travelers’ mode choice behaviors, an online questionnaire survey is conducted from approximately 840 Indian residents aged 16 years and older. The survey data coupled with statistical approaches provided an understanding of behavioral patterns, attitudes, mode choice preferences and perceptions of the survey participants.

Our findings show that over 80% of car commuters would commute by cars post pandemic, drawing 18% share from the public transport users. Although 19% respondents of car-owning households reported using public transport as their normal commute mode, a significant decline in public transport use has been reported post pandemic, leaving the share to only 6%. Yet, younger participants below 30 age group would still prefer using PT services either due to unavailability of cars or not possessing driving license. Interestingly, travel time has been found as an influential factor in the understanding of mode switching behavior. While 39% of public transport users would still choose the

---

**Table 5**

| Segments | A     | B     | C     | D     | E     | F     | G     |
|----------|-------|-------|-------|-------|-------|-------|-------|
| Gender   | 0.146 (2) | 0.138 (6) | 0.144 (4) | 0.135 (7) | 0.145 (3) | 0.148 (1) | 0.142 (5) |
| Age (years) | 0.145 (3) | 0.138 (6) | 0.142 (5) | 0.132 (7) | 0.147 (2) | 0.149 (1) | 0.144 (4) |
| Less than 29 | 0.146 (3) | 0.138 (6) | 0.142 (7) | 0.136 (7) | 0.144 (4) | 0.147 (1) | 0.145 (3) |
| 30–45 | 0.149 (1) | 0.136 (6) | 0.148 (2) | 0.133 (7) | 0.145 (3) | 0.144 (4) | 0.143 (5) |
| More than 45 | 0.145 (3) | 0.138 (6) | 0.144 (4) | 0.135 (7) | 0.145 (2) | 0.149 (1) | 0.143 (5) |
| Profession | 0.145 (3) | 0.138 (6) | 0.144 (4) | 0.135 (7) | 0.147 (2) | 0.149 (1) | 0.144 (4) |
| Student | 0.144 (3) | 0.139 (7) | 0.142 (5) | 0.137 (7) | 0.146 (2) | 0.149 (1) | 0.144 (4) |
| Others | 0.144 (3) | 0.139 (6) | 0.142 (5) | 0.137 (7) | 0.147 (2) | 0.149 (1) | 0.144 (4) |
| Monthly income (1) | 0.144 (3) | 0.139 (6) | 0.142 (5) | 0.137 (7) | 0.147 (2) | 0.149 (1) | 0.144 (4) |
| Less than 15,000 | 0.144 (3) | 0.139 (6) | 0.142 (5) | 0.137 (7) | 0.147 (2) | 0.149 (1) | 0.144 (4) |
| 15,000–30,000 | 0.144 (3) | 0.139 (6) | 0.142 (5) | 0.137 (7) | 0.147 (2) | 0.149 (1) | 0.144 (4) |
| 30,000–45,000 | 0.144 (3) | 0.140 (6) | 0.144 (4) | 0.137 (7) | 0.146 (2) | 0.149 (1) | 0.144 (4) |
| 45,000–75,000 | 0.144 (3) | 0.135 (6) | 0.143 (5) | 0.137 (7) | 0.146 (2) | 0.149 (1) | 0.144 (4) |
| More than 75,000 | 0.144 (3) | 0.137 (6) | 0.143 (4) | 0.137 (7) | 0.145 (2) | 0.150 (1) | 0.142 (5) |
| Overall | 0.145 (3) | 0.138 (6) | 0.144 (4) | 0.135 (7) | 0.146 (2) | 0.148 (1) | 0.143 (5) |
same mode for shorter trips (less than 15 min), they show a large shift in commute mode from public transport to cars as trip time increases, with the largest share being observed for trips greater than 45 min.

Public transport services being the most impacted transport sector, several potential explanatory variables that could influence the mode switching behavior of public transport users from PT to car use were further investigated. Respondents’ socio-economic characteristics are found to be significantly associated with mode shift choice. In particular, high-income (>75000) and elderly respondents, with access to private cars in their households are more likely to use a car. Regardless of the accessibility to PT services, PT users show a stronger propensity to car use for their daily commute as travel time to work increases. Most importantly, overcrowding and hygiene/cleanliness are the significant factors influencing the mode switching behavior to cars, as crowding and unhygienic service environment increase the risk of exposure to the virus. These findings reflect that the COVID-19 crisis might show a behavioral shift on travel preferences, which can have long-lasting effects on people’s mobility with increased burden on road infrastructure.

In this light, the crisis might form a window of opportunities for policy makers to revamp the public transport services by implementing suitable policy measures.

This research has explored several policy strategies based on respondents’ perceptions and behavioral attitudes in the near future. Utilizing analytic hierarchy process, several proposed policy measures were ranked and the priority weights indicated that reducing frequency of bus stops at areas attracting large crowd is the most influential factor for retaining public transport ridership post pandemic scenario. Cashless and contactless payment was the next priority, followed by alternate seating arrangement with proper social distancing measures, provision of PPE kits, real-time information on seat availability, limited passengers’ allowance and regular disinfection of buses. It is important for the policy makers to address the expectations of the users and build users’ confidence in public transport use by providing a safe and healthy service environment. Given the governmental policies to restrict public transport use, it is important to closely observe the changes in mobility patterns and the negative impact of the pandemic on the existing road infrastructure as the car dependence continues to rise in a post-pandemic world.

**Author’s Contribution**

Sanhita Das: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization, Alice Boruah: Investigation, Resources, Writing – original draft, Arunaba Banerjee: Investigation, Resources, Writing – original draft, Rahul Rao: Investigation, Resources, Suresh Nama: Resources, Akhilesh Kumar Maurya: Writing – review & editing, Visualization, Supervision.

**References**

Almairi, E., Alzaa, S., 2013. Factors affecting mode choice of work trips in developing cities—gaza as a case study. J. Transport. Technol. 3 (4), 247–259.

Bashker, M.A., van der Waerden, P., Kochan, B., Bellmanns, T., Shah, S.A.R., 2019. Multi-stage trips: an exploration of factors affecting mode choice combination of travelers in England. Transport Pol. 81, 95–105.

Beck, M.J., Hensher, D.A., 2020. Insights into the impact of COVID-19 on household travel and activities in Australia—The early days under restrictions. Transport Pol. 96, 76–92.

Beirac, G., Cabral, J.S., 2007. Understanding attitudes towards public transport and private car: a qualitative study. Transport Pol. 14 (6), 478–489.

Berhardt, 2020. Decline in ridership, adapted templates and disinfection-robots – the impact of Corona/COVID-19 on public transport. Retrieved on 02 August 2020 from https://www.urban-transport-magazine.com/en/decline-in-ridersh-adopted-templates-and-disinfection-robots-the-impact-of-corona-2019-2020-public-transport/.

Bhaduri, E., Manj, B.S., Wadud, Z., Goswami, A.K., Choudhury, C.F., 2020. Modelling the effects of COVID-19 on travel mode choice behaviour in India. Transportation Research Interdisciplinary Perspectives 8, 100273.

Bhusan, N., Rai, K., 2004. Strategic Decision Making: Applying the Analytic Hierarchy Process. Springer, New York.

Bucky, P., 2020. Modal Share Changes Due to COVID-19: the Case of Budapest. Transportation Research Interdisciplinary Perspectives, p. 100141.

Census India, 2011. Gender Composition, India Series 1, Office of the Registrar General and Census Commissioner. New Delhi. Retrieved from. https://censusindia.gov.in/census-and-you/gender_composition.aspx.

Chakrabarti, S., 2017. How can public transit get people out of their cars? An analysis of mode choice for commuters in Los Angeles. Transport Pol. 54, 80–89.

Chen, W.L., Fernandez, J.L., 2013. Factors that influence the choice of mode of transport in Penang: a preliminary analysis. Procedia-Social and Behavioral Sciences 91, 1–7.

Chen, J., Li, S., 2017. Mode choice model for public transport with categorized latent variables. Mathematical Problems in Engineering, 2017. https://doi.org/10.1155/2017/7861945. Article ID 7861945.

Cho, H.D., 2013. The Factors Affecting Long-Distance Travel Mode Choice Decisions and Their Implications for Transportation Policy. University of Florida.

Chowdhury, S., Coder, A.A., 2016. Users’ willingness to ride an integrated public-transport service: a literature review. Transport Pol. 48, 183–195.

Clark, B., Chatterjee, K., Melia, S., 2016. Changes to commute mode: the role of life events, spatial context and environmental attitude. Transport. Res. Pol. Pract. 89, 89–105.

Corpa, G., 2007. September. Public transport or private vehicle: factors that impact on mode choice. In: 30th Australian Transport Research Forum, 11.

Efthymiou, D., Antoniou, C., 2017. Understanding the effects of economic crisis on public transport users’ satisfaction and demand. Transport Pol. 53, 89–97.

Erikson, L., Friman, M., Garling, T., 2008. Stated reasons for reducing work-commute by car. Transport. Res. F Traffic Psychol. Behav. 11, 427–433.

Transport Focus, 2020. Growing Safety Concerns Among Public Transport Users – Survey, Express & Star News, 21 May 2020.

Gebevaya, M., Takano, S., 2007. Diagnostic evaluation of public transportation mode choice using AHP. Journal of Public Transportation 10 (4), 27–50.

Giuliano, G., Dargay, J., 2006. Car ownership, travel and land use: a comparison of the US and Great Britain. Transport. Res. Pol. Pract. 40 (2), 106–124.

Haas, M., Faber, R., Hamersma, M., 2020. How COVID-19 and the Dutch ‘Intelligent Lockdown’ change Activity and Travel Behaviour. Evidence from Longitudinal Data in the Netherlands. Transportation Research Interdisciplinary Perspectives, p. 100150.

Hanson, S., 2010. Gender and mobility: new approaches for informing sustainability. Gender Place Cult. 17 (1), 5–23.

Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., et al., 2020. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet 2020 395, 497–506. https://doi.org/10.1016/S0140-6736(20)30183-5.

Ko, H.L., Byun, M., 2018. Exploring factors associated with commute mode choice: an application of city-level general social survey data. Transport Pol. 75, 36–46.

Lai, W.T., Chen, C.F., 2011. Behavioral intentions of public transit passengers—the roles of service quality, perceived value, satisfaction and involvement. Transport Pol. 18 (2), 318–325.

Li, Z., Hensher, D.A., 2011. Crowding and public transport: a review of willingness to pay evidence and its relevance in project appraisal. Transport Pol. 18 (6), 880–887.

Li, Z., Hensher, D.A., 2013. Crowding in public transport: a review of objective and subjective measures. Journal of Public Transportation 16 (2), 6.

Liu, Y., Hong, Z., Liu, Y., 2016. Do driving restriction policies effectively motivate commuters to use public transportation? Energy Pol. 90, 253–261.

Long, A.A., Gois, J.D.D.R., da Silva Munhoz, P.R., 2014. Proposal for using AHP method to evaluate the quality of services provided by outsourced companies. Procedia Computer Science 55, 715–724.

Mahadevia, D., Advani, D., 2016. Gender differentials in travel pattern—the case of a mid-sized city. Rajkot, India. Transit. Res. Environ. 40, 292–302.

Mahadevia, D., Joshi, R., Daset, A., 2012. Accessibility and Sustainability of Bus Rapid Transit in India. UNEP Rise Centre on Energy, Climate and Sustainable Development, Technical University of Denmark, Roskilde.

Mayo, F.L., Taboada, E.B., 2020. Ranking factors affecting public transport mode choice of commuters in an urban city of a developing country using analytic hierarchy process: the case of Metro Cebu, Philippines. Transportation Research Interdisciplinary Perspectives 4, 100078.

Meng, M., Rau, A., Mahardhika, H., 2018. Public transport travel time perception: effects of socioeconomic characteristics, trip characteristics and facility usage. Transport. Res. Pol. Pract. 114, 24–37.

Nes, V.R., 2002. Design of Multimodal Transport Networks: A Hierarchical Approach. Birkhäuser, Boston, 365 pp.

Rahmat, R.A., Ismail, A., 2007. Effect of transportation policies on modal shift from private car to private car in public transport in Malaysia. J. Appl. Sci. 7 (7), 1013–1018.

Pawar, D.S., Yadav, A.K., Akolekar, N., Velaga, N.R., 2020. Impact of physical distance due to novel coronavirus (SARS-CoV-2) on daily travel for work during transition to lockdown. Transportation Research Interdisciplinary Perspectives 1000203. https://doi.org/10.1016/j.trirp.2020.1000203.

Pillat, S., 2020. Public Transport Use Likely to Fall Sharply after Lockdown: Study. Hindustan Times, 29 May 2020.

Rosenbloom, S., 2006. Is the driving experience of older women changing? Safety and mobility consequences over time. Transport. Res. Pol. Pract. 114, 24-37.

Ryley, T., 2006. Use of non-motorised modes and life stage in Edinburgh. J. Transport. Technol. 3 (4), 247–259.

Saaty, T.L., 1980. The Analytic Hierarchy Process. Planning, Priority. Resource Allocation. RWS publications, USA.

Sael, N., Hamim, T., Benabbou, F., 2019. Implementation of the analytic hierarchy process for student proficiency. International Journal of Emerging Technologies in Learning (IJET) 14 (15), 78–93.
Scheiner, J., 2014. The gendered complexity of daily life: effects of life-course events on changes in activity entropy and tour complexity over time. Travel Behaviour and Society 1 (3), 91–105.

Shaaban, K., Kim, I., 2016. Assessment of the taxi service in Doha. Transport. Res. Pol. Pract. 88, 223–235.

Srinivasan, S., 2008. A Spatial Exploration of the Accessibility of Low-Income Women: Chengdu, China and Chennai, India. Gendered mobilities, pp. 143–158.

Tirachini, A., Cats, O., 2020. COVID-19 and public transportation: current assessment, prospects, and research needs. Journal of Public Transportation 22 (1), 1.

Troko, J., Myles, P., Gibson, J., Hashim, A., Enstone, J., Kingdon, S., et al., 2011. Is public transport a risk factor for acute respiratory infection? BMC Infect. Dis. 11 (1), 1–6.

UITP, World Bank, 2020. Bus operations in India: what has been the impact of COVID-19? Retrieved on. https://www.uitp.org/news/bus-operations-india-what-has-been-impact-covid-19. (Accessed 2 August 2020).

Vargas, R.V., 2010. Using the Analytic Hierarchy Process (Ahp) to Select and Prioritize Projects in a Portfolio. Paper presented at PMI® Global Congress 2010—North America. Project Management Institute, Washington, DC. Newtown Square, PA.

Vedagiri, P., Arasan, V.T., 2009. Estimating modal shift of car travelers to bus on introduction of bus priority system. Journal of transportation systems engineering and information technology 9 (6), 120–129.

WHO, 2020. Coronavirus disease (COVID-19) dashboard. https://covid19.who.int/.