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The Effects of the COVID-19 Pandemic on the Modal Shifting Utilising a Latent Class Choice Model with Covariates

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ABSTRACT

The COVID-19 pandemic has posed significant challenges to global public health organisations and governments, leading to countermeasures like hand sanitizer availability, social distancing, and mandatory face mask wearing, which have disrupted the public transportation sector and impacted the virus spread. Anticipating the effects of circumstances like a pandemic on mobility is essential for operators and managers of public transportation systems to effectively and safely manage the system. In this study, the measures taken during the pandemic, such as those mentioned above, were considered as indicators in the latent class model (LCM) for modal shifting. The model incorporates sociodemographic variables as covariates to understand their impact on modal shifting from public transport to private cars. An online survey with 53,973 valid responses was conducted in Istanbul, Turkiye. As a result of the LCM with covariates, a two-latent-class model, the best fit among models ranging from two to six latent classes, emerged. Class-1 participants show increased sensitivity to the pandemic, shifting to private mode, while Class-2 participants are less concerned and tend to maintain their existing mode. The model suggests using LCM with covariates to estimate the modal shift from public transportation to private cars in any given situation.

KEYWORDS

countermeasure; covariates; latent class model; pandemic; survey analysis, modal shifting.

1. INTRODUCTION

The COVID-19 pandemic has posed substantial challenges to public health organisations and governments worldwide [1]. After the World Health Organisation officially declared a pandemic on 11 March 2020 [2], governments around the globe swiftly implemented a range of measures to contain the spread of the newly emerged and relatively unknown COVID-19 virus. Among these measures, mobility restrictions emerged as a prominent strategy. Prior research has consistently demonstrated that social interactions and mobility play pivotal roles in influencing the transmission of infectious diseases, particularly during pandemics [3–4].

These measures encompassed a wide array of actions, including the closure of schools, international border and airport shutdowns, widespread adoption of telecommuting and online learning, remote work arrangements, the shutting down of businesses and restaurants, the cancellation of social gatherings and events, the imposition of lockdowns on entire nations or cities, suspension of public transportation and taxi services to curtail movement and capacity, the enforcement of social distancing norms, and much more [5]. Notably, while some countries, such as the United Kingdom, initially pursued a strategy centred on achieving herd immunity, others, like New Zealand, opted for a comprehensive shutdown of social and economic activities [6]. These measures collectively represent a global response to an unprecedented public health crisis.

Similar to the global scenario, the COVID-19 pandemic has had adverse effects on various facets of daily life in Turkey. As a developing nation, Turkey faced specific vulnerabilities in the wake of the debilitating COVID-19 pandemic [7]. The strategies employed in Turkey to combat the pandemic can be broadly categorised into three key areas: hygiene, social distancing, and mask-wearing. It is worth noting that these measures have had a profound impact on the functioning of the public transportation sector [8].

Due to concerns about virus transmission, individuals who have the means to do so have shown a growing inclination towards using private vehicles for their transportation needs. The research by Ergin et al. (2021) estimates that approximately 9% of public transportation users have shifted to private vehicles in response to the pandemic [9]. Existing studies in the literature support this trend, highlighting that individuals who were once reliant on public transportation have transitioned to private vehicles due to the pandemic [10].

The COVID-19 pandemic has had a profound impact on the demand for public transport, resulting in a significant reduction in passenger numbers. In response, various countermeasures have been implemented, including social distancing measures and enhanced in-vehicle disinfection protocols [11]. Consequently, numerous studies have been conducted and continue to be ongoing, particularly examining passenger behaviour and their mode of transportation choice during the pandemic [5, 6, 12–14]. These investigations encompass areas such as the location and duration of work activities [15], the effectiveness of pandemic-related countermeasures on public transport usage [11], and the impacts of the pandemic on school trips [16].

In literature, some studies focus on the modal shifting from public transport to private vehicle. [17] investigates the probable shift from public transportation to private vehicle commuting owing to COVID-19, identifies variables driving this shift and offers future initiatives for increasing public transportation utilisation. According to the results of a logistic regression model based on an online questionnaire survey conducted in India, commuters' socioeconomic variables such as age, gender and monthly income significantly impact mode switch preferences. Moreover, [18] investigate the primary characteristics that may influence crucial travel mode selections using a multivariate logistic regression model. In this study, investigations into the occurrence of modal shift have explored not only direct influences but also indirect or latent factors. A gap exists in the analysis of factors influencing modal shifting during the pandemic, particularly through the latent class analysis with covariate approach. This study aims to fill this gap by conducting an analysis within the aforementioned framework with a large sample size and strictly focusing on the modal shifting. This study also investigates factors contributing to the increased use of private vehicles during the pandemic, incorporating local and central government measures as indicators with highly responded survey study. LCA is a statistical method utilised to uncover distinct subgroups within populations that share certain common characteristics [19]. In our research, the pandemic-related measures have been integrated as indicator variables in the LCM, while sociodemographic variables have been introduced as covariate variables to gain deeper insights into their influence on modal shifting. This paper's contribution to the field of study lies in the incorporation of sociodemographic attributes as covariates within the LCM, alongside the inclusion of pandemic countermeasures as indicator variables and specific survey study. This approach sheds light on the underlying drivers behind the transition from public transportation to private vehicle usage among individuals who previously relied on public transit. To achieve this, we have employed the LCM with a covariate approach. For the upcoming circumstances such as the pandemic, it is essential for the operator and the manager of the public transportation system to effectively and safely manage the system and estimate the effects of such circumstances on mobility. LCA is a statistical method used to identify hidden or unobservable categorical latent variables based on categorically observed indicators [20]. [21] stated that LCA with a covariate can be defined as an extension of LCA and it gives comprehensive details on model. Because of that, this study is conducted by using the LCM with a covariate through the comprehensive survey study.

The structure of this paper is organised as follows. Section 2 provides an extensive review of the literature pertaining to LCA and transportation. Section 3 outlines the data with countermeasures taken by the government during Covid-19 pandemic, survey and descriptive statistics. Within the methodology section, we elucidate the LCM with covariates, and introduce the model estimation methods. Section 5 subsequently presents the model's results and evaluates them. Finally, in Section 6, we draw conclusions based on the findings and engage in pertinent discussions.

2. LITERATURE REVIEW

In response to the implemented countermeasures, a significant decline in the demand for public transport was observed, as anticipated. For instance, public transport ridership in Budapest experienced a substantial drop of approximately 80% [22], while subway ridership in New York saw a staggering decline of 96% [23]. Similarly, public transport ridership in Stockholm declined by roughly 60% compared to other modes [24]. This abrupt reduction in the number of public transport users placed municipalities in a precarious economic and fiscal situation. It should be noted that there was also a decline in the capacity of the public transit system due to the countermeasures.

[25] conducted an evaluation of long-term policy recommendations and cost-benefit analyses related to public transportation financing during the COVID-19 pandemic. According to their study, the municipality faced substantial financial losses amounting to 19.69 to 24.87 million dollars. However, the proposed policies yielded a net present value ranging from 0.28 to 23.36 million dollars, providing valuable insights into potential strategies for mitigating the economic impact. Reducing the effects of the pandemic on the public transit system is essential to ensure the effectiveness of the system and safety, and to estimate the demand and modal shifting.

COVID-19 has shown varying effects on public transportation passengers with different socioeconomic, and sociodemographic characteristics. According to [26], older adults, and female travellers are more likely to be aware of COVID-19. Furthermore, COVID-19 has had a profound impact on people's behaviour, particularly in the context of public transportation. Low-income populations, as highlighted in the study conducted by [27], were among the most reliant on public transport, leading to smaller drops in ridership compared to other modes and ticket types. Additionally, the research conducted by [28] examines the influence of COVID-19 on commuters' transportation choices and the potential for disease transmission. This study reveals that public transit ridership in metropolitan areas of the United States has been significantly affected, potentially having a disproportionate impact on vulnerable communities.

The impact of the pandemic has been highly variable based on the individual's socio-economic characteristics, resulting in significant changes in their work arrangements, commuting habits, and travel preferences. Cheng et al. (2022) investigated how the COVID-19 pandemic influenced work location and time allocation using a latent class multiple discrete-continuous model [15]. Their findings revealed that men, young adults, and individuals with lower to mid-level incomes faced challenges in transitioning to remote work. In contrast, women, middle-aged individuals, and those with higher incomes experienced increased working hours and productivity loss when shifting from traditional office work. Chen et al. (2022) explored the effects of COVID-19-related countermeasures on the individual's travel decisions, employing the LCM [11]. They discovered that the Dutch central government restrictions significantly impacted transportation mode choices. However, the measures implemented by the public transport sector had varying effects on different demographic groups. Older and more educated individuals were more responsive to enforcement measures, while younger and single Dutch citizens were more open to non-compulsory measures. [29] used a latent class cluster analysis approach to examine modality profiles for non-mandatory trips in the Greater Toronto Area, particularly in response to the pandemic and public health policies. Their study concluded that the importance of public transit declined while private vehicles and active modes gained prominence. Modal preferences were influenced by the individual's pre-pandemic travel behaviour. To promote public health, transportation policies should consider those without access to private vehicles and help non-mandatory trips align with local guidelines. During the pandemic, hospital choice became increasingly important. [30] conducted a patient-based healthcare travel survey in Shanghai to understand variations in healthcare travel among patients. They focused on joint hospital choice and travel behaviour, using an LCM with covariates to identify distinct patient types with specific hospital preferences and travel behaviours.

Additionally, several other studies have utilised LCM to explore various aspects of transportation and behaviour during the COVID-19 pandemic. In the Netherlands, a choice experiment employed LCM to investigate how individuals could adjust their departure times to avoid crowded trains during rush hours.

Real-time crowding data and a rail price discount were introduced. Respondents were categorised into two groups based on their willingness to endure delays. The study found that vaccination significantly reduced the resistance of passengers to board during congestion in the Netherlands [31]. Lee and de Vos (2023) aimed to gain a deeper understanding of the motivations and factors influencing people's decisions to work from home at different stages of the COVID-19 pandemic [32]. Teleworkers were segmented into four groups, and the LCM was applied to each group. The research revealed that attitudes, prior experience with working from home, and specific enabling or constraining factors such as job type, employer support and household size all played a role in influencing the frequency of remote work. Ma et al. (2023) conducted an analysis of non-commuting intentions during the COVID-19 pandemic using online survey data from Nanjing [33]. They employed a hybrid LCM approach. The results categorised respondents as either "cautious" or "fearless." Cautious respondents tended to be older, with higher-income, well-educated, female and full-time employees. In contrast, fearless respondents were more influenced by their perception of the pandemic's severity and their preference for personal protection measures.

3. DATA

In this section, countermeasures and study area will be detailed and the survey study will be described. After that, descriptive statistics of the data that obtained from online survey will be presented.

3.1 Countermeasures

Similar to other countries, various measures were taken in Turkey during the pandemic period. Especially those related to transportation and used within the scope of our work include:

1) *Hand sanitizer (HS)*: As part of the measures taken, it was mandatory to have hand sanitizers inside all public transportation vehicles and at stations or stops. This ensured that passengers could disinfect their hands whenever they wish.
2) *Mandatory wearing of face masks (MASK)*: The use of face masks became mandatory, not only in enclosed spaces but also in outdoor settings. It was compulsory to wear face masks inside public transportation vehicles.
3) *Social distancing (SD)*: There needed to be a certain distance among public transportation users. This distance is generally set at 1.5 meters. To meet this requirement, public transportation vehicles carried fewer passengers at a time but have increased the frequency of trips.

Users may not be aware of the availability of hand sanitizers inside the vehicle before boarding. Alternatively, passengers may be alerted by other users when someone removes their face mask. Additionally, passengers evaluate whether social distancing is maintained inside the vehicle by observing from the outside. There is no prior information provided at stops or to public transportation users regarding these measures.

3.2 Survey

The study area selected for this research is Istanbul, a unique city situated across both the European and Asian continents, with the Bosporus Strait dividing it and connecting the Black Sea to the north and the Aegean Sea to the south. According to data from the Turkish Statistical Institute (TSI) in 2023 [34], Istanbul boasts a population of 15,907,951 and witnesses approximately 33 million daily trips. Being the economic hub of Turkey, Istanbul faced significant impacts from the COVID-19 pandemic, aligning with similar studies conducted during this period [7, 33, 35–37]. Consequently, an online survey was employed as a data collection method to comply with the pandemic-related measures, mirroring the approach taken by numerous other studies.

The survey comprises three primary sections. The first segment encompasses inquiries concerning individuals' socio-economic characteristics such as age, gender, income, education level and their work/school-related aspects like remote work, remote education, etc. The second part contains travel behaviour, categorised into three groups based on the pandemic period: pre-pandemic, during the pandemic and post-pandemic.

The survey was conducted between 1 June and 12 June 2020 during the pandemic. Questionnaires that were included revealed preference questions to get an idea of the traveller during the pandemic and pre-pandemic behaviour, and stated preferences questions that represent the post-pandemic behaviour of the travel. In the final segment of the survey, individuals were probed for their opinions using Likert scale questions, which include options ranging from 1 to 5 (1 – Definitely do not prefer, 2 – Do not prefer, 3 – Undecided, 4 – Prefer, 5 – Definitely prefer). The Likert scale questions presented were as follows:

- Would you prefer to use public transportation if there were no hand sanitizer available (HS)?
- Would you prefer to use public transportation if social distancing conditions could not be maintained (SD)?
- Would you prefer to use public transportation if mask usage were not mandatory (MASK)?

The responses to these questions were incorporated as covariates in the model. In this study, the variables are categorised, with particular emphasis on dichotomously coded attitudinal variables. In this regard, similarly to Weller et al. (2021), HS, SD and MASK are binary-coded ("Definitely do not prefer" and "Do not prefer" responses are coded as 0, while "Prefer" and "Definitely prefer" responses are coded as 1, and "Undecided" responses are omitted). Linzer and Lewis (2011) noted that the model could also accommodate manifest ordinal variables but would treat them as nominal. In practice, this typically does not meaningfully constrain the analyses [38].

Additionally, for the class allocation model, two dichotomous variables were included: home-based work (HBW) trip purpose (yes=1 or no=0) and private car ownership availability (PCOA) (yes=1 or no=0). Private car ownership availability refers to individuals who have the opportunity to own a private car if they desire and their income level permits it. If a person has a private car or has a high-income level but does not possess a private car, they are coded as 1. Conversely, if they currently do not have a private car and do not have a high-income level, they are coded as 0. If a household's monthly income is at or below the minimum wage, the assumption is made that this household lacks the purchasing power to acquire a private vehicle. This is because, in Turkey, the cost of a private vehicle is approximately equivalent to at least 60 times the minimum wage. In many studies, this aspect is often overlooked and it is assumed that everyone has a private car in their choice set. However, especially in developing or underdeveloped countries, not everyone has a private car included in their choice set.

Similarly, Shah et al. (2021) incorporated household socio-demographic characteristics into their model as covariates [39]. In this study, socio-demographic variables are treated covariates as well. These covariate variables include gender (male or not), age (over 35 or not), work status (employed or unemployed) and education level (higher than high school or not).

The survey was conducted using the online platform Google Forms, and the survey link was distributed via short message service (SMS) to individuals residing in Istanbul, with the support of all GSM operators in Turkey. Since access to technology and the seriousness of survey participation may vary among individuals, the survey does not represent a perfectly random sample. Therefore, the findings of this survey, as is the case with many online survey studies, should not be generalised indiscriminately. However, it is important to note that a substantial amount of data was collected with a high response rate totalling 147,868 responses within a short period.

The responses received in a short period of time were thoroughly examined. Data that did not meet certain criteria were excluded from the study. Incomplete surveys, defined as those where the first questions were answered but subsequent questions were left unanswered, were removed from the dataset. Additionally, due to the survey's design, some questions were not mandatory; hence, certain questions were left unanswered in some surveys. Moreover, for multiple-choice questions, some participants either marked too many options or left options blank, possibly because they did not fully understand the question. These responses were also removed from the dataset. However, responses that were in line with the purpose of this study and had no missing variables used in the model were included in the dataset. After filtering out incomplete or irrelevant responses, a total of 53,973 valid survey responses were included in the modelling study.

3.3 Descriptive statistics

In the online survey, participants were asked about their socio-economic characteristics and transportation behaviours, and their responses were analysed. As shown in *Table 1*, 34% of the participants identified as female, and 81% of them reported being employed or students. The average age of the respondents is 36.45 years. Age groups were determined based on percentile intervals, with the 35–44 age group having the highest participation rate, accounting for 32% of respondents. Income levels were categorised based on the minimum wage policy in Turkey, which was 2,324 TL net in the year 2020. Therefore, an average income figure cannot be calculated. However, it is worth noting that approximately 54% of the respondents reported receiving a salary close to or below the minimum wage. Consistent with the income distribution, private vehicle ownership is relatively low at 35%, however, private car ownership availability is 45%. Only 1% of the respondents reported having no formal education, while 55% are primary or high school graduates, and 32% are university or postgraduate graduates. Unemployed individuals or those not currently enrolled in education make up 12% of the participants. In terms of employment sectors, 67% of the respondents work in the private sector, making it the most preferred sector. Additionally, 15% of respondents are public employees, 2% are students and 3% are retirees. Regarding trip purposes, the highest proportion is home-based work trips, accounting for 86% of trips. Transportation preferences before the pandemic were grouped into two categories: private vehicles (PV) and public transportation (PT). Before the pandemic, 29% of respondents preferred private vehicles, and this figure increased to 39% during the pandemic. Some individuals indicated that they used private vehicles for some of their trips during the pandemic, resulting in a distribution labelled PVPT (private vehicle + public transportation) during this period, which accounts for 2% of preferences. The proportion of public transportation users, which was approximately 71% before the pandemic, decreased to 59% during the pandemic. Additionally, the rate of intercontinental crossings is 8%, whereas before the pandemic, intercontinental trips accounted for approximately 19% of all trips.

Table 1 – Descriptive statistics of dataset (N=53,973)

Variable		*n* (case)	Share (%)	Variable		*n* (case)	Share (%)
Gender	Female	18,189	34	Change in working hours due to pandemic	No	34,667	64
	Male	35,784	66		Yes	19,306	36
Age groups (Average age: 35.95)	13–-27	11,377	21	Working/Studying status	Unemployed	6,734	12
	27–34	13,512	25		Private sector	36,152	67
	35–44	17,192	32		Public sector	8,005	15
	45+	11,892	22		Student	1,243	2
Income groups (Turkish Lira)	< 2,250	12,650	23		Retired	1,839	3
	2,250–3,999	16,462	31	Trip purposes on weekdays	Home-based work	46,532	86
	4,000–5,499	10,167	19		Home-based school	1,913	4
	5,500–6,999	5,260	10		Home-based other	5,528	10
	> 7,000	9,434	17	Mode of transportation (Pre-pandemic)	Private vehicle	15,770	29
Private Car Ownership (pco)	No	35,009	65		Public transport	38,203	71
	Yes	18,964	35	Mode of transportation (During-pandemic)	Private vehicle	21,168	39
Private car ownership availability (pcoa)	No	29,829	55		Public transport	31,680	59
	Yes	24,144	45		Private vehicle + public transport	1,125	2
Do you work/ study?	No	6,734	12	Intercontinental crossing	No	49544	92
	Yes	47,239	88		Yes	4429	8
Education level	Uneducated	498	1	Modal shift (from using public transportation before the pandemic to using private vehicles during the pandemic.)	No	48,257	89
	Primary school	12351	23				
	High school	17025	32		Yes	5,716	11
	Associate degree	6788	13				
	Undergraduate	13357	25				
	Postgraduate	3954	7				

This study places particular emphasis on modal shift and the details are presented in *Table 2*. According to the findings, 10% of the respondents who used public transportation before the pandemic shifted their travel mode to private vehicles during the pandemic. This shift has the potential to worsen traffic congestion in cities. Therefore, the study conducted a detailed analysis of individuals who were public transportation users before the pandemic and shifted to private vehicles during the pandemic.

For a more comprehensive examination of the dependent variable, which is modal shift in this study, the following characteristics of modal shifters (MS) are highlighted:

- The average age of modal-shifted individuals is 37.26 years.
- 37% of them reported receiving a salary close to or below the minimum wage.
- 58% of MS own a private vehicle.
- 37% of MS are female.
- Notably, 49% of these individuals have a university degree or higher level of education, which is relatively high compared to the overall participation rate.
- There is no significant difference in the number of trips based on trip purposes among MS.
- As it is known that Istanbul is located on the Asian and European continents and the intercontinental connection is provided by three bridges, a road tunnel, a rail system line and sea services. 14% of MS changed continent during their daily trips.

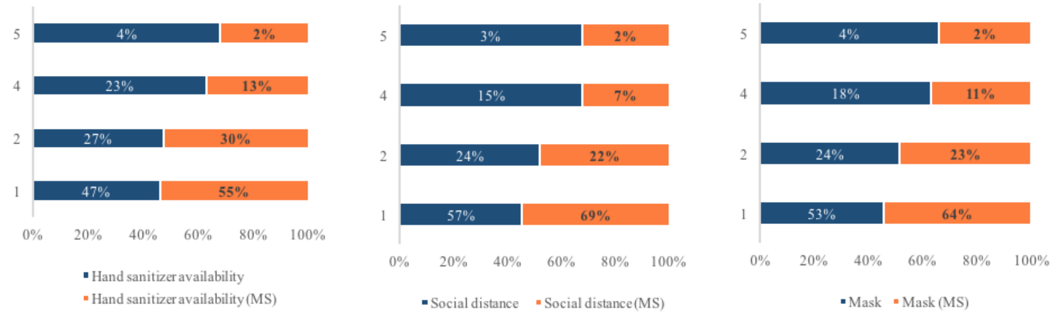
These findings provide valuable insights into the demographic and socio-economic characteristics of individuals who transitioned from using public transportation to private vehicles during the pandemic.

In the final part of the questionnaire, respondents were asked about their opinions regarding countermeasures by using Likert scale questions. The comparison between the responses is presented in *Figure 1*. A notable observation is that MS appear to be more sensitive to COVID-19 and have greater concerns about the pandemic compared to all respondents.

The x-axes of the graphs represent the Likert scale responses as follows: 1 – Definitely do not prefer, 2 – Do not prefer, 4 – Prefer, 5 – Definitely prefer. It is evident that respondents tend to take a stronger and

Table 2 – Descriptive statistics of MS (N=5,716)

Variable		***n* (case)**	**Share (%)**	**Variable**		***n* (case)**	**Share (%)**
Gender	Female	2,134	37	Change in working hours due to pandemic	No	3,180	56
	Male	3,582	63		Yes	2,536	44
Age groups (Average age: 35.95)	13–27	1,040	18	Education level	Uneducated	12	0
	27–34	1,491	26		Primary school	652	11
	35–44	1,812	32		High school	1,446	25
	45+	1,373	24		Associate degree	763	13
Income groups (TL)	<2,250	593	10		Undergraduate	2,131	37
	2,250–3,999	1,517	27		Postgraduate	712	12
	4,000–5,499	1,210	21	Working/Studying status	Unemployed	408	7
	5,500–6,999	863	15		Private sector	3,886	68
	7,000 +	1,533	27		Public sector	1,070	19
Private car ownership (pco)	No	2,367	41		Student	128	2
	Yes	3,349	59		Retired	224	4
Private car ownership availability (pcoa)	No	1,717	30	Trip purposes on weekdays	Home-based work	5,030	88
	Yes	3,999	70		Home-based school	170	3
Do you work/study?	No	408	7		Home-based other	516	9
	Yes	5,308	93	Intercontinental crossing	No	4,918	86
					Yes	798	14



a) b) c)

Figure 1 – All respondents and MS stated opinions on countermeasures: a) HS, b) SD, c) MASK

clearer stance if the COVID-19 pandemic countermeasures are not followed. Here are the key findings from *Figure 1*:

- *HS*: If there is no hand sanitizer in public transportation vehicles, 47% of all participants will definitely not prefer it and 27% will not prefer it. Among MS, 55% will definitely not prefer it and 24% will not prefer it (*Figure 1a*).
- *SD*: In cases where social distancing cannot be maintained in public transportation vehicles, 57% of all participants will definitely not prefer it, while this rate is 69% for MS (*Figure 1b)*.
- *MASK*: If face masks are not used in public transportation vehicles, 64% of MS will definitely not prefer to use public transportation, while 53% of all users will definitely not prefer it (*Figure 1c*).

Overall, MS are more sensitive to the HS, SD and MASK. This suggests that individuals who transitioned from public transportation to private vehicles during the pandemic may have stronger concerns about COVID-19 and stricter expectations regarding safety measures in public transportation.

4. METHODOLOGY

The pandemics was a shock experienced worldwide, and in the face of this unexpected event, different travel behaviours started to emerge. This study aims to investigate whether public transportation users have a tendency towards using private vehicles and, if so, what the factors influencing this tendency are. For this purpose, the key steps in performing LCA was followed:

Step 1: *Indicator Selection*. The selected indicators play a crucial role in determining the characteristics of the latent classes. Aligned with the research question, which seeks to elucidate the influence of countermeasures on model shifting, the chosen indicators are reflective of these countermeasures. In addition to the countermeasures, namely HS, MASK and SD, the selection includes HBW trips and PCOA as indicators. Our study places emphasis on mandatory trips, specifically HBW trips. In addition, PCOA stands out as a significant variable directly influencing the latent class characteristics. PCOA denotes households without current ownership of a private vehicle but with the financial capacity to acquire one. Ultimately, there exist households compelled to utilise public transportation due to financial constraints precluding private vehicle ownership.

Step 2: *Data processing*. According to the research [38], continuous or Likert-scale inputs are converted into categorical variables as aforementioned. Not only the indicators, but the covariates are also converted into categorical variables.

Step 3: In order to determine the number of classes, 2 to 6 classes are evaluated. The same indicators and covariates are used for all of different latent class models.

Step 4: Full information maximum likelihood approach was utilised. Some of the observers did not complete the whole survey. If indicator or covariate questions were not answered, those observations were excluded from the scope of the study.

The methodology followed in this study is showed in *Figure 2*. In alignment with the study's objectives, a survey was designed. The designed surveys were shared online with users as part of the measures taken due to the pandemic. The collected data were cleaned and made suitable for model usage. Concurrently, a literature review was conducted, and coding was performed in accordance with the latent class analysis with covariates approach. Subsequently, models belonging to different latent classes ranging from 2 to 6 were developed, and the most suitable model was selected among them. The structure and variables of the optimal model were examined and the results were evaluated.

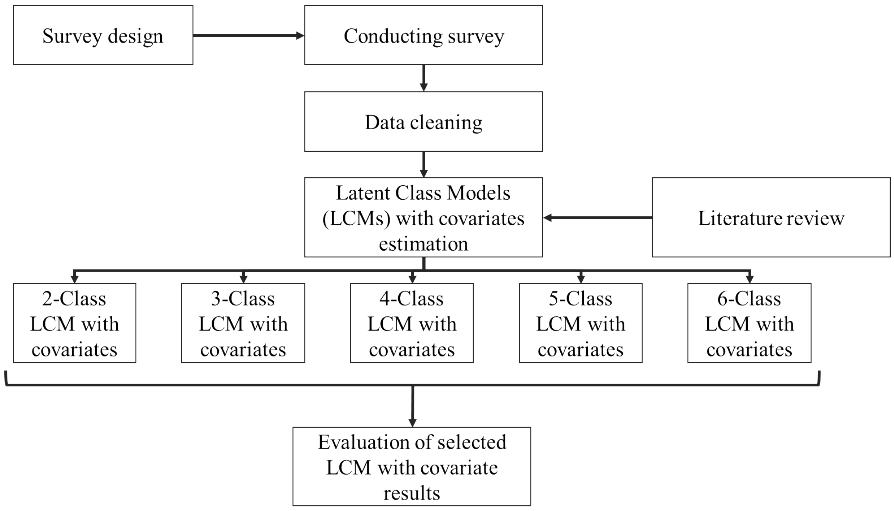


Figure 2 – Methodology of the study

4.1 LCM with covariates

LCA leverages the responses provided by study participants to categorical indicator variables in order to uncover latent categories or groups. When the indicators are continuous variables, a similar statistical technique called Latent Profile Analysis (LPA) is employed [40].

LCA can be employed to categorise households into latent groups with similar responses and travel patterns, aiming to examine the variations in the impacts of COVID-19 countermeasures and travel behaviour within the community [39]. It is worth noting that the choice of transportation mode is not solely determined by individual characteristics but can also be influenced by psychological factors [33]. Therefore, the preference statements can provide valuable insights for model identification [41].

LCM with covariates is an extension of LCA and is designed to incorporate the influence of external variables not only on the allocation of individuals to latent classes but also on their membership within those classes. In LCM with covariates, it estimates regression relationships that elucidate how the external variables are associated with the latent classes. This enables the evaluation of how external factors impact classification and enhances the understanding of these classes. LCMs, which are a subset of finite mixture models, function similarly to cluster analysis by dividing the sample into different classes or groups. These classes aim to be internally homogenous while exhibiting heterogeneity between classes [42].

In this study, the Apollo package in R was utilised. The model was estimated using the Bunch-Gay-Welsch Statistical Estimation (BGW) algorithm, as outlined by Bunch et al. (1993) [43] and added to the package in R by [44]. Heterogeneity is addressed in an LCM by using several classes with different values for the vector β in each class. When there are S classes, we will have β vectors for each S class (β_1 to β_S). Individual n is a member of class s with the following probability:

$$\sum_{s=1}^{S} \pi_{n,s} = 1, \;\; 0 < \pi_{n,s} < 1 \;\; \forall s \tag{1}$$

$P_{i,n,t}(\beta s)$ represent the likelihood of respondent n selecting option i in choice circumstance t if n falls into class s, where $P_{i,n,t}$ is commonly described as an Multinomial Logit (MNL) model [44]. MNL and LCM have the same class-specific utility function since MNL is an underlying model for LCM [31]. Then, the unconditional (on s) choice probability is given by [44, 45]:

$$P_{i,n,t}(\beta_1,\beta_2,\ldots,\beta_s)=\sum_{s=1}^{S}\pi_{n,s}P_{i,n,t}(\beta_s) \quad [2]$$

In the most basic version, the logit structure of class allocation probabilities $\pi_{n,s}$ are formulated as follows:

$$\pi_{n,s}=\frac{e^{\delta_s+g(\gamma_s,z_n)}}{\sum_{l=1}^{S}e^{\delta_s+g(\gamma_l,z_n)}} \quad [3]$$

where δ_s is an offset and γ_s is a vector of parameters representing the effect of the vector of individual attributes z_n on class allocation probability. Normalisation involves setting δ and γ_s to 0 for one of the S classes, and only estimating the vector of constants δ in a model with constant class allocation probabilities.

The model structure is depicted in *Figure 3*.

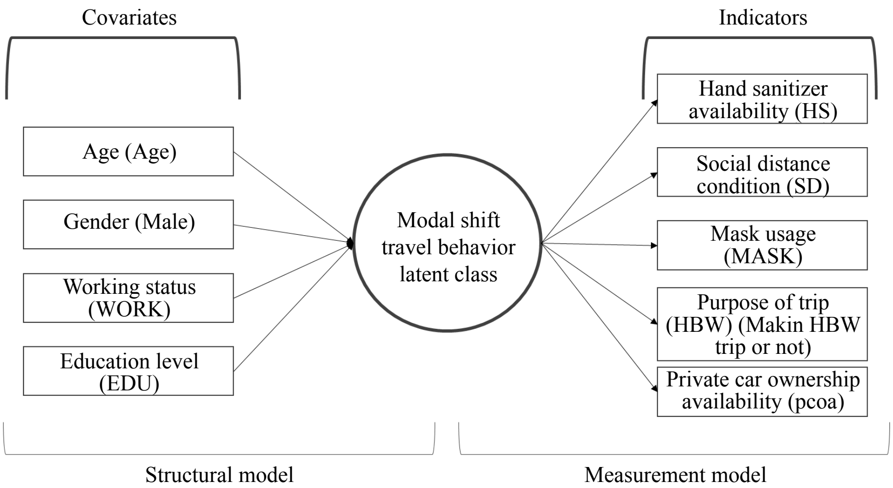


Figure 3 – Model structure

4.2 Model Estimation

Five indicator variables were employed to categorise the MS based on their travel behaviours under COVID-19 countermeasures. These indicators include HS, SD, MASK, making home-based work (HBW) trips and private car ownership availability (PCOA). Additionally, we considered covariates such as gender (GNDR), age (AGE), working status (WORK) and education level (EDU) to represent users' socio-demographic attributes.

Models with different numbers of latent classes ranging from two to six were established. Determining the appropriate number of latent classes that was determined based on criteria such as likelihood ratio statistical tests and information-theoretic approaches [30, 46]. Consequently, we examined several models using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Log-likelihood, and interpretability of results. Lower AIC and BIC values suggest a more accurate and parsimonious model [19, 30]. BIC is preferred over AIC from some of the research as mentioned by [31, 47] in that it penalises the number of parameters more rigorously.

The marginal effect or elasticity of the variables is also considered. However, an elasticity pertains to a percentage change and is therefore applicable solely to continuous explanatory variables. Moreover, the marginal effect can be applied to both continuous and categorical variables [45]. These parameter estimates are created for all characteristics, which are designed as dummy variables and are binary-coded. Therefore, the marginal effect of the parameter in the model is the coefficient of the specified parameter itself.

5. RESULTS

The LCM fit statistics for latent class models established in this study, ranging from two to six are presented in *Table 3*. As seen in the table, the two-class model provides the best fit for our dataset. It is important to clarify that, given the model we have estimated and the observed choices in our dataset, there is a 78.4%

posterior probability of belonging to Class 1 and a 21.6% posterior probability of belonging to Class 2. The characteristics of each class were determined based on the individuals' behaviours, particularly in their home-based work trips and their transportation mode choices under COVID-19 countermeasures.

Table 3 – LCM goodness-of-fit statistics for two to six numbers of latent classes

Model	BIC	AIC	Likelihood (final, whole model)	Adj. Rho-squared vs equal shares	Adj. Rho-squared vs observed shares
2-class	34,253.79	34,111.45	-17,039.72	0.5441	0.0647
3-class	34,282.24	34,050.94	-16,999.47	0.5449	0.0664
4-class	34,416.36	34,096.09	-17,012.05	0.5443	0.0651
5-class	34,395.97	33,986.74	-16,947.37	0.5458	0.0681
6-class	34,484.68	33,986.49	-16,937.24	0.5458	0.0681

The sociodemographic variables of gender, age, working status, and education level were considered and included in the modelling as covariates. The covariate coefficients for Class 1, concerning to Class 2, are presented in *Table 4*. In the class allocation model, the covariate variable "male" is statistically significant at the 10% level and has a positive effect on Class 1 membership. This suggests that being male increases the likelihood of belonging to Class 1. Regarding age, while it was found to be positively related to shifting to a private car for individuals aged 35 and older, the effects of age groups on class membership appear to be limited, consistent with the results of [30]. Regarding working status, individuals in Class 1 who are working or studying have a negative effect on class membership. This indicates that individuals in Class 1 are less likely to be employed or students compared to Class 2. Similarly, the level of education has an impact on class membership. As the level of the last school individuals graduated from increases, the probability of being in Class 1 decreases. This implies that individuals with higher education levels are more likely to belong to Class 2.

Table 4 – Class allocation model covariates (Reference class: Class 2) (N = 53,973)

		Estimate	SE	t-ratio
Covariates	$\delta_{Class\ 1}$ (Class allocation model)	1.85804***	0.13695	13.5669
Male (dummy)	$\gamma_{GNDR\_Class\ 1}$	0.07018*	0.03781	1.8559
Age group: 35 and above (dummy)	$\gamma_{AGE\_Class\ 1}$	0.03933	0.03551	1.1076
Working status: worker or unemployed (dummy)	$\gamma_{WORK\_Class\ 1}$	-0.40615***	0.09475	-4.2865
Education level: greater than high school (dummy)	$\gamma_{EDU\_Class\ 1}$	-0.55808***	0.03971	-14.055

, *, and * indicate statistical significance respectively at 10%, 5% and 1% level.*

Class-conditional membership probabilities for indicators by each class are presented in *Table 5*. Respondents in Class 1 demonstrate a high sensitivity to the pandemic and take precautions to protect themselves from the virus. As expected, they are less likely to use public transport if hand sanitizer is unavailable in vehicles, with 74.01% of Class 1 users preferring not to use public transportation in such cases. Similarly, when social distancing cannot be maintained in public transport vehicles, 82.6% of Class 1 participants indicate a preference for not using public transportation. Wearing a facemask is considered one of the most effective measures against the spread of the pandemic. In cases where masks are not used, 79.14% of individuals in this class state that they would prefer not to use public transportation. Moreover, 87.7% of Class 1 users engage in home-based work travel. Additionally, 48.9% of participants in Class 1 either own a private car or have the financial means to purchase one.

In the second class, there are individuals who generally do not take the pandemic seriously or appear not to take it seriously due to their inability to change their travel behaviour based on economic constraints. Therefore, 27.8% of participants in Class 2 do not shift from using public transportation to private cars even when hand sanitizer is unavailable. Additionally, 23.1% do not shift even if social distancing cannot

Table 5 – Class-conditional membership probabilities for indicators by each class (N = 53,973)

		Class 1	Class 2
Class share		0.784	0.216
Would you prefer to use public transportation if there were no hand sanitizer available?	Yes	0.2599	0.2784
	No	0.7401	0.7216
Would you prefer to use public transportation if social distancing conditions could not be maintained?	Yes	0.1754	0.2314
	No	0.8246	0.7686
Would you prefer to use public transportation if mask usage were not mandatory?	Yes	0.2086	0.2852
	No	0.7914	0.7148
Trip purpose (HBW or not)	HBW	0.877	0.8063
	Others	0.123	0.1937
Private car ownership availability	Yes	0.4886	0.2922
	No	0.5114	0.7078

be maintained, and 28.5% do not shift even if wearing a mask inside public transportation vehicles is not mandatory. A significant portion of Class 2 participants, 80.6%, also engage in home-based work travel. Moreover, in Class 2, 70.8% of participants do not have a private car or the financial means to purchase one.

Additionally, it is worth noting that 51.1% of the participants in Class 1 do not have the means to buy a private car, which implies that they are obliged to use public transportation. This information sheds light on the factors influencing class membership and travel behaviour under COVID-19 countermeasures. As highlighted by [40], due to the complexity of these classes, there is a risk of falling into the "naming fallacy", where the name assigned to the class may not accurately represent its membership. Therefore, we have opted not to assign names to the classes. Although it is possible to name them "COVID Conscious" and "Infection Indifferent" as suggested by [26], we have refrained from naming the classes due to the latent nature of these categories.

6. CONCLUSIONS

In this study, measures such as hand sanitizer availability inside the vehicles, social distance, face mask wearing during the pandemic were considered as indicators and sociodemographic variables were included as covariates in the LCM for modal shifters. This study conducted a thorough analysis of how the individuals' travel behaviours were affected by pandemic measures, specifically focusing on the factors that prompted people who were previous users of public transportation to switch to using private cars.

Estimating the impact of upcoming circumstances, such as the pandemic, on mobility is crucial for the effective and safe management of public transportation systems by operators and managers. Not only do the countermeasures make a distinction between groups, but sociodemographic attributes may also affect the transportation choices of individuals. This study has shown the feasibility of including sociodemographic data as covariate variables in the model and that sociodemographic characteristics are factors that affect membership in latent classes. Additionally, this study contributes with its unique results. Here are some notable findings from this aspect of the study:

- *Gender Influence*: Males and individuals over the age of 35 were more likely to shift to private vehicles. In contrast, younger individuals, especially females, were more inclined to continue using public transportation.
- *Age:* Age did not show a significant impact on the likelihood of shifting transportation modes. This implies that age alone may not be a decisive factor in the individuals' mode choice changes.
- *Work and Education*: Interestingly, individuals who were working and had higher levels of education tended to continue using public transportation. This observation is particularly relevant for developing countries, where economic conditions may limit the availability and affordability of private vehicles. In such contexts, having a job and a higher level of education could be associated with a greater reliance on

public transportation. Employed individuals were more likely to stick with public transportation, while non-workers were more likely to shift to private cars.
- *Economic Conditions*: The economic conditions within a country also play a significant role in the individuals' mode choice. In some cases, people may not shift to private vehicles due to factors such as the belief that the pandemic will not last long or the recognition that their city, in this case, Istanbul, is heavily congested with traffic, making private car usage less attractive.
- *Trip Type*: The nature of the trip, particularly whether it was mandatory, played a significant role in mode choice. Those with mandatory trips, who may not have the option to work from home or afford a private vehicle, tended to continue using public transportation.

These findings highlight the complexity of mode choice during the pandemic, where individual circumstances, socioeconomic factors and the necessity of trips all interact to influence transportation decisions.

Tailored policies and interventions should take the abovementioned factors into account to effectively manage transportation systems during similar events in the future. On the other hand, for some users, it does not matter whether there is a high risk for health, they stick to the current mode due to economic conditions and uncertainty.

Local or central authorities need to ensure the implementation of the countermeasures. For example, in Turkey, a change in working hours was implemented to manage traffic efficiently. The purpose of this measure was to reduce peak-hour traffic. However, the results did not meet expectations because individuals were still in a rush to reach their workplaces, and some offices did not change their work hours. Additionally, urban memory should not be overlooked, as the individuals' habits are not easily overcome, and actions should be taken accordingly.

One of the shortcomings encountered in practical implementations is the lack of knowledge or sharing of information with users regarding the occupancy rates of public vehicles. Moreover, when users are unaware of when the next public transportation service will arrive, they tend to continue using crowded routes. Particularly in cities experiencing heavy traffic congestion, information dissemination should be considered a fundamental infrastructure.

The study has limitations, primarily related to the online survey's potential bias toward younger and tech-savvy respondents. Future research should aim for a more diverse sample, including older individuals. Expanding the scope to include geographical data and additional travel-related variables could enhance the analysis. Consideration of factors like walking, cycling, and para-transit modes is essential for a comprehensive understanding of transportation choices. Despite these limitations, the study provides a foundation for understanding how people adapt their transportation choices during pandemics, offering insights for future research and policy recommendations.

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COVID-19 Pandemisinin Kovaryans Değişkenli Gizli Sınıf Seçim Modeli ile Modal Değişim Üzerindeki Etkileri

COVID-19 pandemisi, global kamu sağlığı kuruluşları ve yerel ve merkezi yönetimler için önemli zorluklar doğurmuş ve el dezenfektanı kullanılması, sosyal mesafenin sağlanması ve zorunlu olarak maske takılması gibi tedbirlerin alınmasına yol açmıştır. Bu önlemler toplu taşıma hizmetini önemli ölçüde bozmuş ve virüsün yayılmasını etkilemiştir. Pandemi gibi durumların mobilite üzerindeki etkilerini önceden tahmin etmek, toplu taşıma sistem işletmecileri ve yöneticileri için sistemini etkin ve güvenli bir şekilde yönetmek için elzemdir. Bu çalışmada, pandemi sırasında alınan yukarıda bahsi geçen önlemler, türel değişim üzerindeki etkilerini incelemek adına gizli sınıf modelinde (LCM) değişken olarak ele alınmıştır. Model, toplu taşıma kullanımından özel araç kullanımına geçişin üzerindeki etkileri anlamak adına sosyodemografik değişkenleri kovaryatlar olarak ele almaktadır. İstanbul genelinde 53,973 geçerli geri dönüşün alındığı geniş kapsamlı bir online anket çalışması yapılmıştır. Kovaryat değişkenli ikiden altıya kadar farklı gizli sınıf sayılarında modeller üretilmiş ve bunun sonucunda 2 gizli sınıflı modelin en iyi seçenek olduğu ortaya çıkmıştır. Sınıf-1 katılımcıları pandemiye karşı artış eğiliminde bir duyarlılık gösterirken toplu taşımadan özel moda geçiş eğilimi gösterirken, Sınıf-2 katılımcıları ise pandemiye karşı daha az endişeli olmakta ve mevcut ulaştırma türünü kullanmaya devam etme trendi göstermektedir. Model, herhangi bir beklenmeyen durum karşısında toplu taşımadan özel araçlara modal değişimi tahmin etmek için kovaryatlarla birlikte LCM kullanılmasını önermektedir.

Anahtar kelimeler

tedbir; kovaryat; gizli sınıf modeli; pandemi; anket analizi, türel geçiş.