Implications of Travel Behavior Determinants on Transportation Planning in the COVID-19 Pandemic

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Abstract

Transportation planning is vital in the current scenario of rapidly growing populations, travel changes, and demand. With the emergence of the COVID-19 pandemic, socio-economic conditions in society are exerting significant strain on transportation infrastructure. These conditions might affect not only the transport demand and infrastructure but also the travel behavior of people. This paper aims to analyze their travel behavior and predict their response to changes in the travel environment, using recent literature on modeling travel patterns in a pandemic. It also analyzes the implications of significant factors to transport planning. Understanding and anticipating travel behavior and its impact on transportation planning in the pandemic condition is crucial in transportation modeling, making decisions, and formulating policies based on travel demands.

Keywords: *Transportation, Transportation Planning, Travel behavior, Pandemic*

1. Introduction

Transportation is an essential component of urban development. Providing access and mobility, enables urban areas to function efficiently. System transportation planning and infrastructure development are the most critical factors, especially in urban areas with solid and rapid urbanization. Transportation demand in urban areas is related to choosing where people live connected to work, shopping, entertainment, school, and other important activities (Sekhar, 2014).

The recent COVID 19 outbreak, on the other hand, has had a significant effect on people, work, and economic development. Travel is considered an important factor in transmitting contagious diseases. Cliff and Haggett (2004) investigated three situations: how measles emerged in Fiji, maladaptive habits after the measles outbreak in Iceland, the cholera outbreak in the United States, and infectious disease transmission rates. Air travel was also a substantial contributor to the 2003 SARS outbreak (Findlater and Bogoch, 2018). The limiting entrance points (such as airports and border crossings) to lower the risk of viral infection is a typical approach to prevent the spread of illnesses (Sun et al., 2020). Individuals, communities, states, and countries must communicate, share information, and coordinate regularly. Human mobility and patterns of interaction significantly contribute to the transmission of the virus, causing travel to be restricted during this epidemic. Depending on local authorities, socio-economic conditions, and ethnic backgrounds, different countries have also proposed or put in place various regulations and safeguards to stabilize and flatten the outbreak. These regulations include school closures, remote or online education, telecommuting, store and restaurant closures, public meetings, social and meeting restrictions, national and city blockades, curfew enforcement. Travel restrictions, including the suspension of public transportation and taxi services, imposition of social distance, border and airport closures were also implemented. These regulations can have an impact on people's health and well-being and on travel movement (De Vos, 2020).

Many researchers report less travel than grocery shopping (Abdullah et al., 2020). They discovered an early shift to panic buying and dry matter in consumer behavior, which affected retail logistics. In other countries, it was reported that the number and distance of trips have decreased significantly. About 60% reduction of the average daily travel distance in Switzerland and 90% of travel by public transport (Molloy et al., 2020). In the Netherlands, the number of trips dropped by 55%, while the distance traveled was reduced by 68% (de Haas et al., 2020). Travels to amusement parks, shopping centers, and malls were found to significantly decrease due to the closures of stores and businesses (Zhang et al. 2021). Most respondents in the study of Anwari et al., (2021) show a declining trend of leisure trips and travels were made only for work reasons. There was a significant decline in the average travel related to work and school from five to two days a week in Indonesia. According to Irawan et al. (2021), shopping trips have reduced from thrice to once a week. It has similar results in India, where most respondents have reduced travel for recreation and shifted to mandatory travel such as work (Aaditya and Rahul, 2021). Additionally, Mayo et al. (2021) in the Philippines have found that low-wage or blue-collar employees have high travel needs for economic considerations. The continued isolation has led to more trips for these purposes after the restrictions were loosen. Moreover, there were more frequent trips for leisure and recreation.

Based on the travel needs of people and the shift of travel demands during this pandemic, it is crucial to understand and analyze their travel behaviors. It can be useful in transportation planning and policymaking. Government authorities and transport planners can use this information in implementing traffic policies to decongest route networks, optimize travel time, and better plan transport services, either public or private. This review paper analyzes the implications of travel pattern determinants to transportation planning during this pandemic. It also discusses the modeling approach in transportation planning and its limitations from existing works of literature. This review paper is outlined in this manner: Section 2 discusses transportation planning and the transport models utilized to analyze different activity patterns of individuals, Section 3 provides factors that influence travel behavior from recent literature and its implications to transportation planning, and finally, Section 4 encapsulates the essential findings and suggests study directions for the future.

2. Transportation Planning and Modelling Approach

The transportation planning process delved into connecting transportation goals to physical use, preservation of culture, socio-economic, ecological, and standard of living in the area covered by the arrangement. It examines current transportation operations and forecasts future transportation needs using data. Transportation planning, according to Garber and Hoel (2015), is a systematic approach for preparing physical facilities and travel mode services to meet transportation needs. It expands into a process of defining future policies, priorities, resources, and innovations to anticipate future transportation needs for people and goods. It entails assessing and selecting roadway or transportation infrastructure to serve current, and future land uses. The construction of a new shopping complex or conference center, for example, will necessitate the expansion of transportation services. In addition, new residential development and industrial parks will increase traffic, necessitating the construction or extension of highways and public transportation. Transportation planning requires more than just identifying highway and transit projects. It is necessary to establish plans for implementing, regulating, controlling, and investing in the transportation infrastructure to meet the long-term goals of the community (McNally, 2008).

This process uses travel demand and supply systems approaches. Demand and supply are essential concepts in economic theory and being commonly used now in the field of transportation economics. These demand and supply concepts in the field of economics is applicable to travel demand and supply of transportation infrastructure. However, transportation need is a derived demand, not a requisite in and of itself. It means that individuals travel not only to go outside but to engage in various activities in various places. Under a set of established land-use, socio-economic, and environmental factors, the number of people or vehicles projected to travel on a specific portion of a transportation system per unit time is known as travel demand. Its forecasts are being used to determine the future vehicle volume or modified transportation system alternatives (McNally, 2008). Travel demand forecasting is used in the transportation planning process to estimate the quantity of traffic in the future.

Forecasting and modeling travel demand is still a helpful strategy for analyzing transportation plans, projects, and policies. The results of modeling can help individuals in the decision-making process, in infrastructure and building design, as well as developing transportation policy (Subbarao and Rao, 2020). The purpose of transportation models is to be as precise as feasible in representing reality. These models can investigate and solve a wide range of transportation issues, including traffic congestion, transportation-related greenhouse gas emissions, economic advantages, and road accidents. Traffic models are commonly used to estimate under uncertainty, support any managerial decisions, build infrastructure, and advise policies on changes in travel patterns (Daisy et al., 2017 & Hafezi et al., 2018). Among the numerous types of travel demand models, the trip-based transport planning models and activity-based transport planning models are widely known. Both can produce relatively accurate travel demand projections from the modeled scenario. Based on their properties, the models can anticipate interim transport consideration (activity intent, time, method of transportation, location, and others) along with protracted transportation plans.

2.1 Traditional Four-Step Model

Trip generation, trip distribution, mode choice, and route assignment are the four main steps in the traditional four-step model (see Figure 1). The first three steps of the model are intended for forecasting travel demand. Route choice, the fourth stage, balances travel demand and supply by loading tours onto one or even more transport networks.

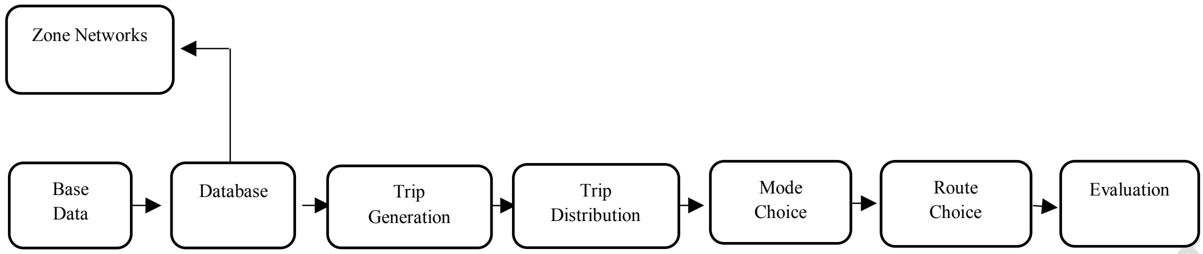


Figure 1. Four-Step Transportation Model
Source: Modified from Modi et al. (2011)

The first phase of the classical first-generation aggregate demand models is trip generation. Trip generation is the analysis and process modeling phase that usually begins with the first step. It is a broad term used in transit planning to refer to the total count of the trip-ends in a specific area. There are two types of trip generation: production and attraction. The number of trips that finish in zone-i is called production (origin). The number of trips that conclude in zone-j is called an attraction (destination) (Sekhar, 2014). The trip generation process presupposes that land activities (e.g., jobs and houses) in each zone produce and attract trips (trip-ends). A production is a trip-end that is developed in an area, whereas an attraction is a trip-end that is drawn to an area. The second stage of travel demand modeling is deciding on a destination from the starting point. When plotted in an origin-destination (O-D) matrix, the trip distribution is the calculated amount of trip ends produced in one zone divided by the total number of the trip-ends drawn to another area (Modi et al., 2011).

The primary notion in modeling trip distribution is that time spent traveling is perceived negatively, and the longer the trip, the more demanding it is. Most trips generated in each zone get attracted to nearby or surrounding zones; some get attracted to moderately distant zones; and very few to highly remote zones. Mode choice is the third stage in travel demand modeling. It is the decision to choose what transport mode to take from origin to destination. These modes of transportation are classified as public transportation riders and personal/private vehicle mode (Sekhar, 2014). One of the most prominent modeling techniques in transportation planning is the modal split/mode choice model. It is because public transportation plays such an essential role in policymaking. An increasing growth rates and income and a growing preference for transport vehicle have all emerged from globalized industrialization. Traffic congestion and environmental difficulties are caused by the increasing volume of various transport modes in the city, resulting in impeded vehicular traffic such as congestion and mishaps, which result in substantial economic damage annually. Shifting passengers of private modes to mass public transportation seems to be a strategy, however, considering the convenience aspect of public transit facilities, it is difficult to achieve. Researchers have done investigations to analyze better the relation between travel modes and the numerous elements that influence it to solve such a declining travel demand. According to current research studies, various socio-economic, cultural, and external factors influence commuter mode choice. Mode choice behavior can be explained using income, car ownership, household characteristics, dwelling location, and other parameters. All supply factors include vehicle duration, waiting period, travel delay, transport costs, transfer time, etc. However, in this situation, where there are travel mobility constraints, more research into other factors determining this behavior is recommended. The fourth and last stage of the four-step modeling process is route assignment. Commuters will choose the route that takes the least amount of time and covers the least amount of distance regardless of the amount of traffic on the road.

The trip-based demand model considers daily travel pattern to be an aggregation of independent trips and uses trips as the unit of analysis. Because of its autonomous behavior, the model ignores the interdependence of several aspects of special trips, such as duration, destination, and transport mode choice. Furthermore, in all stages of the trip-based method, trip schedules and the subsequent interrelationship in the characteristics of multiple trips were ignored. The lack of a behavioral base is another fundamental flaw in the four-step concept. It neglects the behavioral fact that people consider their travel decisions ahead of time by considering the entire trip chain rather than each trip separately. As a result, the model cannot account for the impact of outside and stay-home activities substitutions on overall travel patterns.

2.2 Activity-Based Travel Demand Model

There is a growing amount of literature on activity-based transportation during the previous two decades. Individual and household decisions about activities and travel are better understood using activity-based modeling. The main goal for developing this model for transportation demand analysis is to obtain a better knowledge of individual travel patterns and to construct a model that is sensitive to growing policy challenges like congestion pricing and land use. Compared to trip-based aggregation and disaggregation modeling techniques, the activity-based approach provides a more fundamental and complete foundation for depicting realistic representations of travel behavior. The physical involvement of people in anything that serves their needs or those of their family is defined as an activity. The analysis from the model considers travel as a demand resulting from a movement that was spatially allocated (Subbarao and Rao, 2020).

The fundamental notion is that activities are both in spatial and temporal. Hagerstrand (1970) defined the time-space idea and established the first activity-based model. Individuals live in a temporal-spatial prism, where their involvement in activities is governed by three restrictions. The first type of constraint is capability, which emphasizes physical requirements and available resources which might either enable or limit involvement of people in a particular activity. Second, connection constraints highlight the spatial and spectral requirements for a person who interacts with others to complete an activity. Finally, there are institutional constraints that prevent a person from participating in certain activities at specific time and place. Their choice to engage in each activity at a particular place and time, according to the theory, is the outcome of different situations and settings. (Hafezi et al., 2018).

Activity-based transport planning models can effectively simulate individual or stratified travel behavior, resulting in more accurate forecasts of future travel patterns. Because activity engagement is a complex behavior, this inherently raises the difficulty level in the analysis. Traditional travel survey data do not provide enough information on activities. Such data limitations may account for the relatively little concerted efforts to explain travel behavior over time. Modeling travel behavior becomes more complex because it does not only model time allocation into activity categories but also model activity engagement incidents for travel demand analysis. Activity-based transport planning has received much attention in recent years and has achieved substantial advances. A wide range of modeling approaches has been created to simulate multiple aspects of activity-based models, such as type of activity, series of activity, frequency and sequence of activity location, activity duration, and transportation mode for the subsequent trip. A cohesive theoretical framework for an activity-based transport planning model has been developed, which was influenced by previous studies conducted by eminent researchers (see Figure 2).

The framework includes a population synthesizer and a daily activity pattern model. As the base year input, the model uses an aggregate level of data. A population synthesizer converts aggregate level socio-demographic data into disaggregate data. The population oscillator output is loaded in the daily activity pattern model. The method captures if the transactions are performed at home or outside the house, as well as the interactions between household members. Models for forecasting mode of transport, daily schedule, destination, secondary trips, and so on are also included at the scheduling level. Individual records are generated by this model, which can then be aggregated into an OD matrix contingent on the daily schedule and mode. The network assignment acquires the aggregate flow data after assigning it to the network and generates the service level information and other specifications.

Relevant information from the actual activity-travel study specific to the survey area must validate the above framework because its basis are numerous operational activity-based models. Individual activity and travel behavior, especially in developing countries, necessitate changes to the proposed framework.

These transportation models are arguably critical in analyzing the changing travel patterns or behaviors of people given their demographic profile, travel characteristics, and the current pandemic crisis setting. Model parameters, policy actions, and pandemic protocols and measures might influence travel patterns.

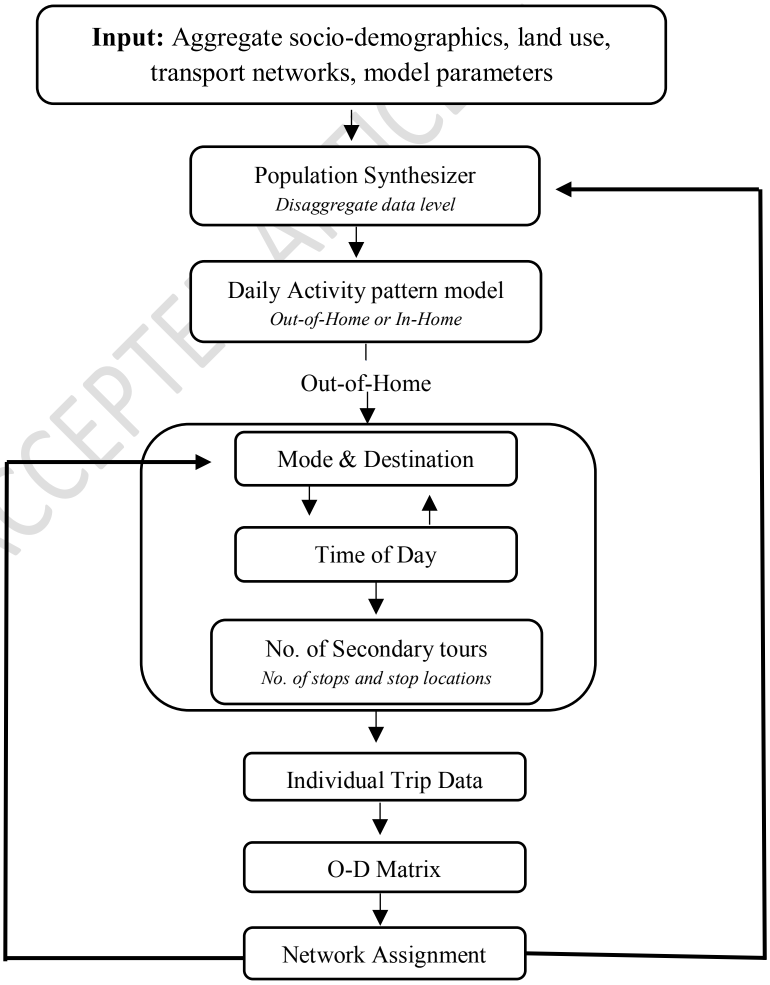


Figure 2. Activity-Based Travel Demand Modelling Framework

Source: Modified from Sekhar (2014)

3. Travel Behavior Determinants and their Implications on Transport Planning

Multiple research works have been undertaken to determine how each factor influences people and household travel behavior. Most of travel behavior research was done for emergency evacuation (Lim et al., 2021; Ramakrishnan et al., 2020; Mostafizi et al., 2019; Nagarajan et al., 2021; Do, X., 2019; Damera et al., 2019, etc.). Lim et al. (2021) identified significant factors in evacuation behavior from the Taal eruption in the Philippines using a discrete choice model. Damera et al. (2019), on the other hand, developed a nested logit model that considers the factors in making decisions in the ability to forecast the comparative order of the location of evacuation and shelter type. Furthermore, Nagarajan et al. (2021) investigated evacuee behaviors and the factors that influence their decision to evacuate.

The emphasis of these extensive studies is on emergency evacuation. Several studies on travel patterns respond to the most recent virus outbreak. De Vos (2020) emphasized how the global epidemic has impacted travel and how alternative modes of transportation, such as pedestrian and biking, are self-sustaining and beneficial to one's health. A significant decline in public transportation use has also been observed in the US cities of Washington and Chicago (Brough et al., 2020; Shamshiripour et al., 2020). In other countries, the trip volume and total distance have decreased significantly (Molloy et al., 2020; de Haas et al., 2020). The closure of shops and business centers has resulted in a significant decrease in visits to theme parks and shopping complexes in Hong Kong (Zhang et al., 2021). Even though several research studies have been conducted to explain behavioral trip changes in the ongoing global epidemic, they have often been undertaken in industrialized nations. Only a few findings in emerging countries were made to identify shifts in travel patterns. According to the findings from the study of Anwari et al. (2021), a substantial majority of their study participants in Bangladesh reduced on leisure activity travel, but only a tiny percentage scale back on work-related travel. In Indonesia, they found a significant decrease in trips, with regular trips lowered from five days to twice per week in career and educational trips (Anwari et al., 2021). Grocery trips have also been reduced from three times per week to once a week. In India, Aaditya and Rahul (2021) revealed similar results, with most of their study participants are eager to lessen their travel for leisure and visits but not for job travel.

Table 1. Travel behavior determinants from past studies under the COVID-19 pandemic

Author/s	Country & Travel Behavior	Significant Factors
Abdullah et al. (2021)	Pakistan, Mode Choice	Distance, infection concern, social distance, hand sanitizer's availability, and cleanliness
Yang et al. (2021)	China, Travel demand	Employment status/type, income
Tan and Ma (2021)	China, Mode Choice	Employment, commuting mode before the pandemic, travel time, risk perception, confidence in the mode of transport
Ku et al. (2021)	South Korea, Travel usage rate	Traffic, sharing rate, employment type (work-from-home)
Scheffer et al. (2021)	Germany, Mode Choice	Travel time, trip purpose, vehicle ownership, travel distance, destination
Bhaduri et al. (2020)	India, Mode Choice	Trip purpose, trip length, age, income, and working status
Harbering and Schluter (2020)	Mexico, Mode Choice	Gender, income, education, the ratio of children in the household, employment,

		travel cost, travel distance, travel time, car ownership, spatial structure, and transport service
Arreeras et al. (2020)	Thailand, Mode Choice	Gender, age, employment, income, number of transits, travel cost, travel time
Mayo and Taboada (2020)	Philippines, Mode Choice	Safety, availability of mode, cost, comfort, concern for the environment
Devika et al. (2020)	India, Mode Choice	Psychological factors (attitude, behavioral perception, intention)
Keyes and Brown (2018)	England, Mode Choice	Income, attitude to active modes, car use

The different findings from various studies investigating the travel pattern alterations in the pandemic are summarized in Table 1. All of these publications are in the setting of the COVID-19 outbreak. According to recent studies, these factors can be categorized into three groups namely: personal attributes, travel attributes, and risk perception. Other studies refer to socio-demographic variables as personal attributes (Arreeras et al., 2020, Tan and Ma, 2021, Bhaduri et al., 2020). The general framework for this paper shows that each category of travel behavior determinant has specific factors affecting transportation planning. A trip generation or the decision of an individual to go out and their modal choice are influenced by the combination of personal attributes, travel attributes, and risk perception. Meanwhile, trip distribution is controlled by travel attributes and risk perception. Lastly, route choice is mainly determined by travel attributes. The following sections provide a more detailed analysis of how these determinants affect every stage of transportation planning.

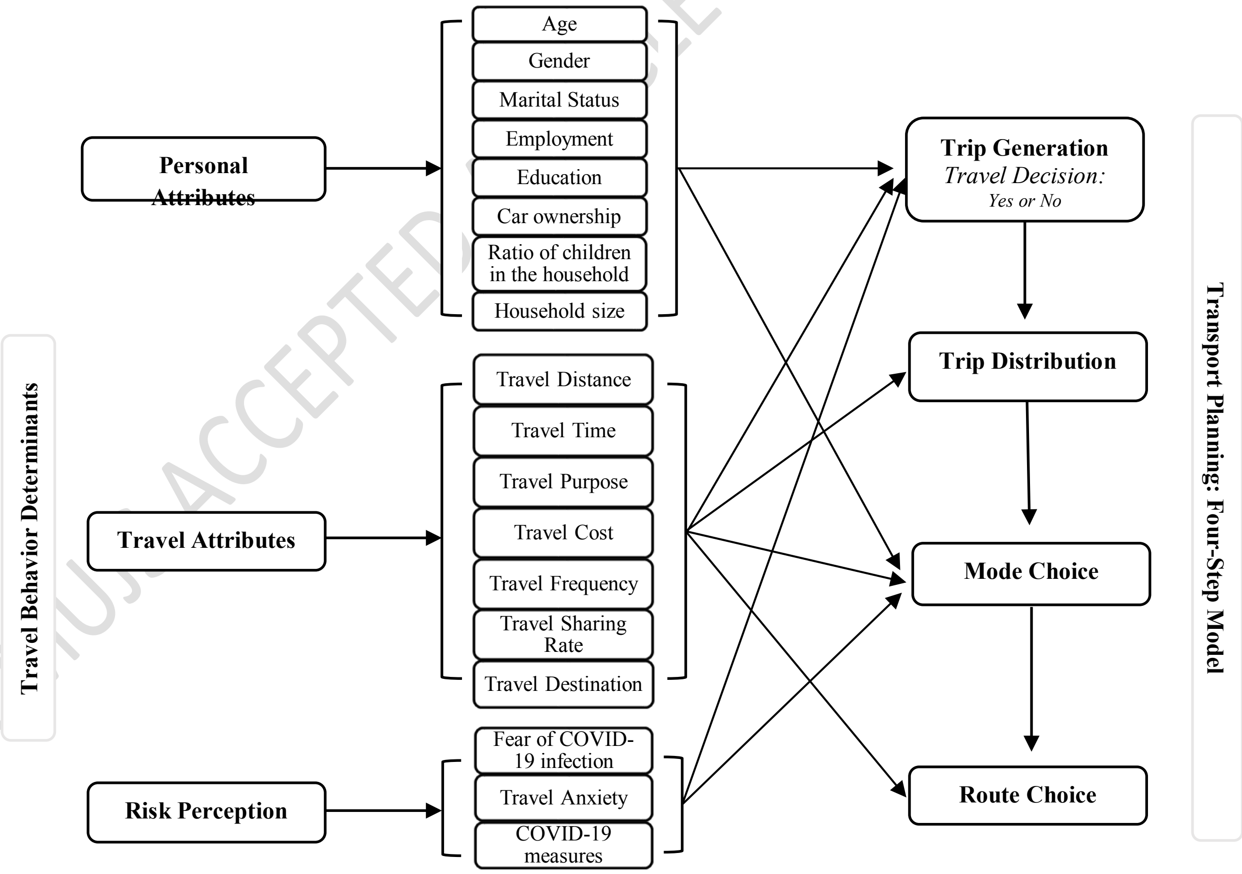


Figure 3. Implications of Factors of Travel Behavior to Transport Planning

3.1 Implications of Travel Behavior Determinants on Trip Generation

Personal attributes considerably affect travel decision and behavior during this pandemic. Specific determinants identified from the existing works of literature include age, gender, marital status, income, education, employment, and household size (Figure 4). In their qualitative study, Yang et al. (2021) investigated how travel patterns changed before and after the pandemic. Travel demand was initially reduced significantly, according to the findings. Second, declining travel reduces activity engagement, impacting both personal health and well-being. The type of employment and income influence travel demand. In terms of income level, Jiao and Azimian (2021) revealed in their study the factors on travel patterns in the next period of the pandemic in the US. The findings show that individuals with an annual income level of lower than 100,000 USD have a lower likelihood of making trips. It is because they can afford other shopping methods such as online shopping, given their easy access to internet service compared to those with an income level of less than 50,000. However, Shin et al., (2022) found out that the highest income category shows a positive effect on the likelihood to go out. Moreover, Ku et al. (2021) assessed the travel pattern in Seoul in the pandemic setting; their findings indicated that the transpo[illegible]nged because of COVID-19. They discovered that the rate of travel usage has [illegible] a large proportion of the population is now accustomed to remote working [illegible] they see it as convenient for them. As the duration spent at work from [illegible] e count of regular commuting trips also decreases (Hensher et al., 2022 [illegible] adults aged 35 or older had higher odds [illegible] because [illegible] iors have shifted to online shopping (J[illegible] d Azimian, 2021). Concerni[illegible] els, individuals without a graduate deg[illegible] ere more likely to go out and [illegible] s (Schaner and Theys, 2020). The findi[illegible] Shin et al. (2022) support t[illegible] gher educational attainment (e.g., coll[illegible] gree) is negatively significant [illegible] d of travel. However, this contradicts tha[illegible] iao and Azimian, 2021), where individuals with higher education levels are more likel[illegible] ld well-paid jobs and afford to [illegible] travel costs. Regard[illegible] nales (Anw[illegible] t was supported b[illegible] ges in tra[illegible] haka City. As fo[illegible] dividual had a higher chance of making trips to stores compared to [illegible] iao and Azimian, 2021). Household size was also seen as significant in deciding to tra[illegible] akibaei et al. (2020) found out [illegible] seholds have a lower probability of going [illegible] the pandemic as they explaine[illegible] ion is that they have fewer needs. Howe[illegible] this [illegible] e result fr[illegible] ao and Azimian (2021) as they indica[illegible] higher likelihood to travel for sm[illegible]

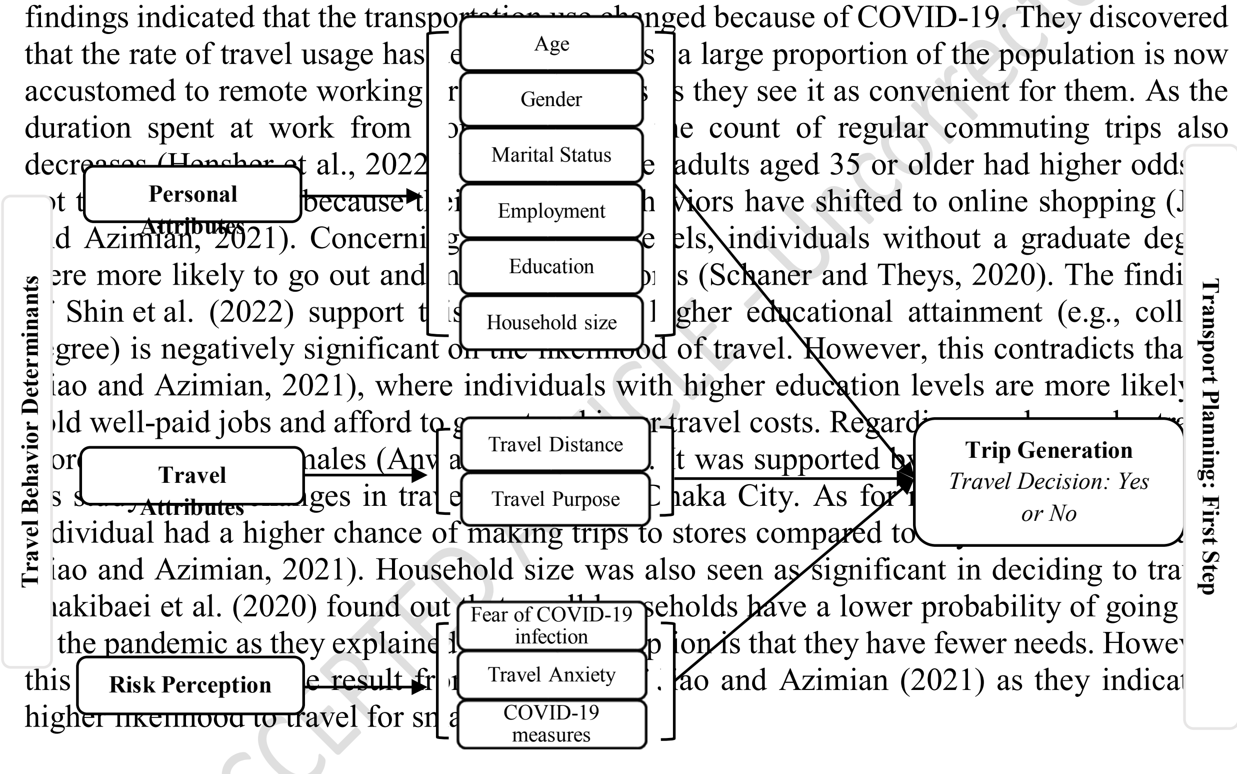


Figure 4. Travel Behavior Determinants on Trip Generation

Travel characteristics or attributes also revealed to have a considerable influence on travel behavior. As indicated in Figure 4, travel distance and travel purpose influenced trip generation. The purpose of their trip influences their travel time, which affects their travel behavior. Abdullah et al. (2021) explores the effect of the global outbreak on travel behavior in Pakistan. The primary intent of travel in the pandemic shifted from education and work to buying groceries. Travel purpose and distance were observed to impact their travel decision and pattern. Abdullah et al. (2020) indicated that people tend to travel when the primary purpose is work or grocery shopping. However, there is a small percentage of respondents who will go out for social or leisure activities. Also, they added that reduced travel distances have a higher likelihood of deciding to go out. A similar finding was obtained by Azimi et al. (2021), where the travel distance has a negative influence on travel decisions.

The last significant variable category is risk perception or behavioral perception. Studies of preventive measures to contain the virus consist of personal preventive measures like hand washing, using hand sanitizer, and wearing a mask, especially in crowded environments (Guner et al., 2020; Girum et al., 2020; Gou et al., 2021), social distancing (Shen et al., 2020; Beck and Hensher, 2021), travel restrictions and lockdowns (Linka et al., 2020; Devi, 2020; Nicola et al., 2020; Sun et al., 2020; Meichtry et al., 2020; Epstein et al., 2007), work from home (Xiao et al., 2021; Okuyan et al., 2021; Macalipis, 2021; Mahajan et al., 2021; Beck et al., 2020; Zafri et al., 2021; Shen et al., 2020), and testing and vaccination status (Moghadas et al., 2020; Chen, 2021; Guner et al., 2020). These measures have a direct effect on the risk perception of people. As these measures are well-implemented and observed, especially in public places and transportation modes, it decreases their risk perception. According to studies, as risk perception increases, they go out less frequently because they are afraid of getting infected, affecting the number of trips generated and distributed. The fear of COVID-19 has resulted in a significant mobility reduction worldwide. A large percentage of people refused to go out because of their fear of getting infected. It has also been reported that people with travel anxiety motivate to make risk-avoidant decisions to minimize the potential dangers of the pandemic (Riad et al., 2020). It leads people to decide to stay at home to reduce exposure to the virus. It complements findings from Beck and Hensher (2020) that their decision to travel and go out has been significantly influenced by their fear about the threat of COVID-19 to the community or the participant.

However, based on the existing literature, more research into the travel decision-making mechanisms of people from various cultural backgrounds is required. Different policy responses may result from differences in behavioral intention caused by structural settings, way of life, and traffic conditions. It is observed mainly in emerging areas where bus services are necessary and difficult to maintain social distance (Chen et al., 2022). Continued estimations incorporating more exclusive variables are required to allow people to predict the changes in travel decisions, and behavior as the virus outbreak continues.

3.2 Implications of the Factors of Travel Behavior on Trip Distribution

Studies suggest that travel destination choice is determined by travel attributes and risk perception. This phase of transportation planning forecasts the volume of traffic from the origin zone to the departure point zone, as discussed in the previous section. As a result, trips are plotted in an origin-destination matrix. The specific determinants that shaped trip destinations are depicted in Figure 5. The rate of trip sharing, the purpose of the trip, the distance traveled, and risk perception, specifically COVID-19 fear and anxiety, were all found to have a significant impact on trip distribution.

The assessment on the level of sharing in buses, taxis, railways, which are typical modes of mass transportation, influenced travel decisions, resulting in a lower trip volume (Ku et al., 2021). Travel frequency has also decreased as human mobility has decreased due to the pandemic, affecting the volume of trips generated and the volume of tours to be distributed in each trip (Mayo et al. 2021; Irawan et al. 2021). Longer travel distances may imply more tours in a trip, and thus more trips to be distributed. Poli (2021) discovered in his study of the impacts of the pandemic on trip characteristics that individuals decrease their distance traveled, so they go for destinations closer to their origin. It was supported by Lakatos and Mandoki (2020) in their study of long-distance transportation in Hungary, which revealed that for relatively short distances, 50% of the respondents choose that specific location. This could imply that people are reluctant to travel for an extended period in a pandemic context. It is because there is a high chance of more prolonged exposure to many people during their travel. Furthermore, the purpose of the trip, or why people go out, has a significant effect on the destination. Shaer and Haghshenas (2021) examined the impact of the outbreak on the trips of senior citizens and discovered that travel for work and groceries is more likely to influence the location of their trips.

Furthermore, risk perception and apprehension about COVID-19 have shifted travel destinations of people, with most trips observed to be to workplaces and grocery stores. In the research of Parady et al. (2020) in Japan, they found that level of risk perception was linked to greater reductions in shopping frequency and going out to chain stores and leisure activities. However, Truong and Truong (2021), in their analysis of pandemic travel behavior, suggested that when the loop begins with a decline in the latest reports of cases and deaths from the virus, it will develop a perception in the community that it is safe and secure to go out now because the chance of contracting COVID-19 is relatively low. As a result, residents begin to make short-distance trips, workplaces, vacations, quick visits to relatives and friends, etc.

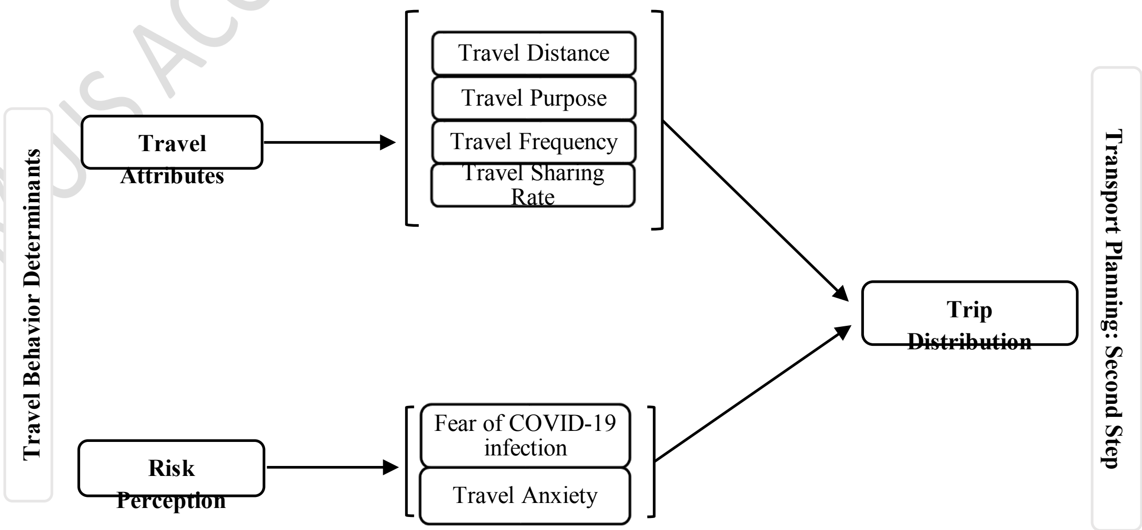
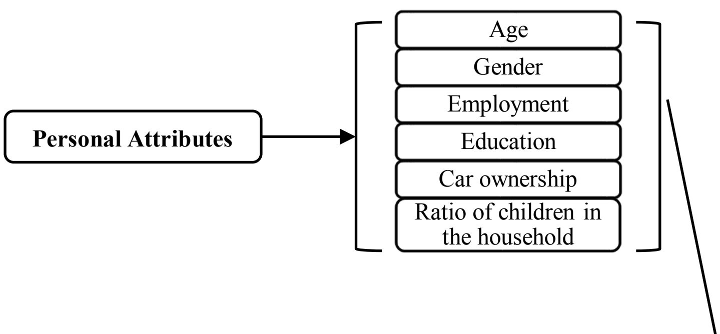


Figure 5. Travel Behavior Determinants on Trip Distribution

3.3 Implications of Travel Behavior Determinants on Mode Choice

In the modal choice behavior assessment of factors, the combination of personal attributes, travel attributes, and risk perception significantly affects choice of transport mode (Figure 6). Specific factors include age, gender, education, employment, income, car ownership, the ratio of children in the household, travel distance, travel purpose, travel time, travel anxiety, infection concern, and COVID-19 measures.

Arreeras et al. (2020), in their study of mode choices of people under pandemic, revealed that age, gender, and occupation significantly affect transport mode choice decisions in Nakhon Ratchasima. When gender and occupation characteristics are considered, the 35-44 age group is more likely to use private than others. It is supported by Jiao and Azimian (2021), who found that people aged 35 and up are much less inclined to utilize public transport. They also added that in terms of gender, men have a lower likelihood to travel by public transportation. This result is similar to the studies before, such as Shakibaei et al. (2020) and Harbering and Schluter (2020). They revealed that females are more likely than males to take public transportation and walk instead of driving. The negative coefficients associated with income had a significant impact on mode choice decisions. In addition, low and middle-income households show that they are more inclined to use public transit as they cannot afford to purchase a personal vehicle (Jiao and Azimian, 2021). This finding is similar to another study in which a group with higher incomes (15,000-30,000 baht per month) is more likely to use public transportation than low earners. The capacity of high earners to own a private car is linked to socio-economic factors. If all other factors are considered, income and car use correlate with each other, with greater income linked with a lower probability of deciding to take public transport or active mode rather than a car. (Keyes and Brown, 2018, Arreeras et al., 2020). Tan and Ma (2021) also discovered, using a logit model of the choice behavior of commuters during the pandemic, that occupation is a significant variable in the mode of transportation that they will use when going out. Self-employed and contract workers have a lower likelihood of using rail transit. The study of Harbering and Schluter (2020) in Mexico yielded similar results. If an individual is an employee or contractual worker, there is an additional distinction in mode decisions throughout the week. The employee has a higher probability of commuting by car during the week than by any other mode of transportation. They also discovered that having a car is a significant factor in what mode of transportation individuals choose. Significant heterogeneity and changes in travel mode choices are revealed in India based on respondents' age, income, and employment status (Bhaduri et al., 2020). Furthermore, the education and child ratio were found to be significant. The car is more likely to be used by commuters who are better educated (Ton et al., 2020). It was backed up with the findings of Jiao and Azimian (2021) as they argue that those with higher educational attainment are most probably have a well-paid job and afford a private vehicle. Also, the number of children in the household leads to a positive attachment to the car. They demonstrate that there are more determinants than previously thought in the formation of choice sets. While many research findings identify the choice of transport mode set established on ownership and trip attributes, only a few have tried to include personal features in the availability of mode determination (Ton et al., 2020).



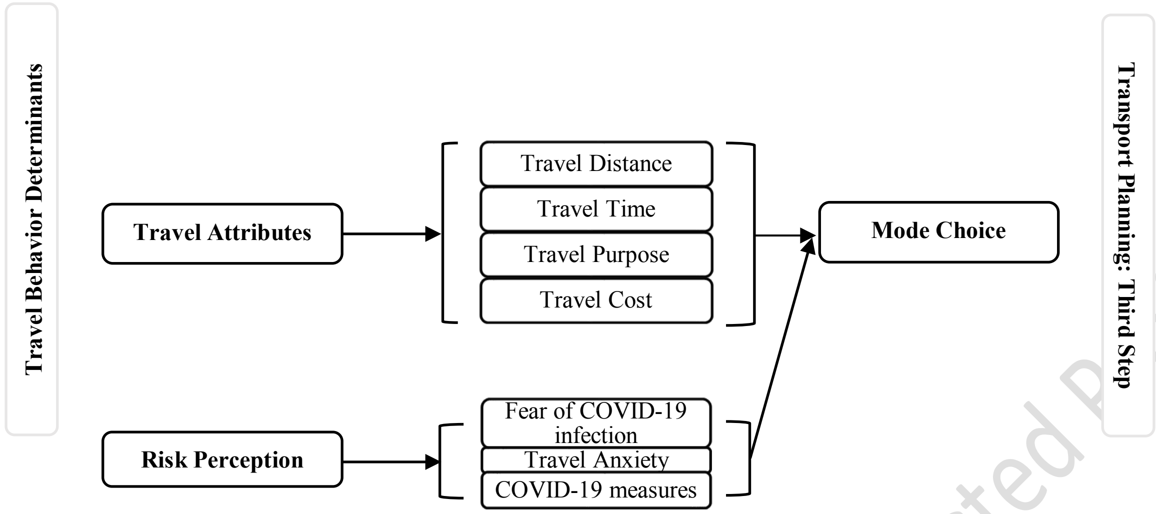


Figure 6. Travel Behavior Determinants on Mode Choice

The amount of non-commuting travels taken before and during outbreak has also changed significantly. There was a notable modal switch from motorized to non-motorized transport mode for distances lower than 5km. They switched from mass transit to personal transport if travel distance is longer.

These are backed up by the results of Bhaduri et al. (2020), who discovered that travel purpose and travel duration impacted the shift from shared modes to personal modes. However, it contradicts the findings of Harbering and Schluter (2020) in Mexico. They indicated that as trip distance tends to get longer, the decision to go for cheaper transport modes becomes much more highly probable than driving. In contrast, expensive taxis, bicycles, and walking modes have a lower likelihood of being used than a car. In addition, commuters prefer to drive their car as travel times lengthen (Harbering and Schluter, 2020). This complements the findings from Nakhon Ratchasima, where the travel time variable influenced mode choice. It demonstrates a high likelihood of selecting the private modes. This finding implies that public transportation may take a longer travel time than private transportation. As a result, when travel time is limited, people prefer private transportation over public transportation (Arreeras et al., 2020). However, this contradicts the findings from Bautista-Hernandez (2021), where the bike, walk, and other-NMT all negatively correlated with travel time. As a result, they claim that trips taken in these modes take less time than trips taken in a car. It might be because of the spatial environment of the community. Other research has discovered that related costs have an impact on mode decisions. Commuters are more likely to choose a mode of travel other than a private vehicle as travel costs increase. Arreeras et al. (2020) affirmed that travel expenses factors are connected with a coefficient value that represents the likelihood of deciding private car when traveling on a limited budget. One probable explanation is that frequent use of public transportation results in higher costs, notably for public transportation operations, whereas private cars can make a direct trip from a starting point to the destination.

On the other hand, risk perception can also affect the transportation mode choices of commuters. The study of Mayo and Taboada (2020) identified the factors that have significant impacts on travel behavior in Metro Cebu, Philippines. Their key findings show that safety takes precedence over accessibility, transport cost, convenience, and environmental awareness, regardless of other socio-demographic factors. When all factors are considered, privately owned for-hire vehicles outrank various mass transit systems, despite rapidly deteriorating traffic situations and rising travel costs. It is interesting to note how each group ranks factors second after safety. It could imply that the safety of the mode of transportation boosts their confidence while lowering their risk perception. This is confirmed in the study of Abdullah et al. (2021). The study results indicate that during the pandemic, respondents prioritize their fear for infection, observance of social distancing protocols, hand sanitizer use, availability, and cleanliness, among others, as it increases their perception of the risk of infection. In addition, there is a lower probability of using public transport mode when commuters perceive that their chance to be infected is higher on this type of mode. It reflects the confidence of passengers in mass transit like buses, taxis, and other ride-sharing services (Tan and Ma 2021). A similar finding of Jiao and Azimian (2021) backed this up where commuters are less likely to travel with public transport services when they develop travel anxiety.

From the existing recent works of literatures on the transport mode choice, researchers suggest that the subsequent studies should elaborate on the actual behavior and choices of people using revealed preference data.

3.4 Implications of the Factors of Travel Behavior on Route Choice

On the other hand, route choice analysis showed that travel attributes significantly influence their route choices. As shown in Figure 7, these specific factors consist of travel destination, travel distance, travel time, and travel cost.

Chen et al. (2020), in their study of vehicle route planning during a pandemic, found that the trip destination, travel distance, and travel time all imply vehicle route choices. It implies that people who travel a shorter distance will have a relatively short travel time, which results to taking that route. Anwari et al. (2021) corroborated this previous study. Long-distance trips are closely attributed to the road a commuter will consider taking unless a shorter route can be accessed. These findings support those of Shelat et al. (2022), who studied route choice behavior in the Netherlands under pandemic environments. Their decision-making models indicated that respondents choose routes with shorter travel times and lower costs because they sense a lower risk. Marra et al. (2022) give the same results as other studies, indicating that the significant distinction in travel patterns under this outbreak depends on how people consider travel expenses and trip duration. Also, commuters do not have a definite best route for a regular trip, but they frequently take routes that will provide cheaper alternatives. However, they have suggested that this phase of transport planning needs more attention of studies and findings to understand better the factors in choosing their route alternatives.

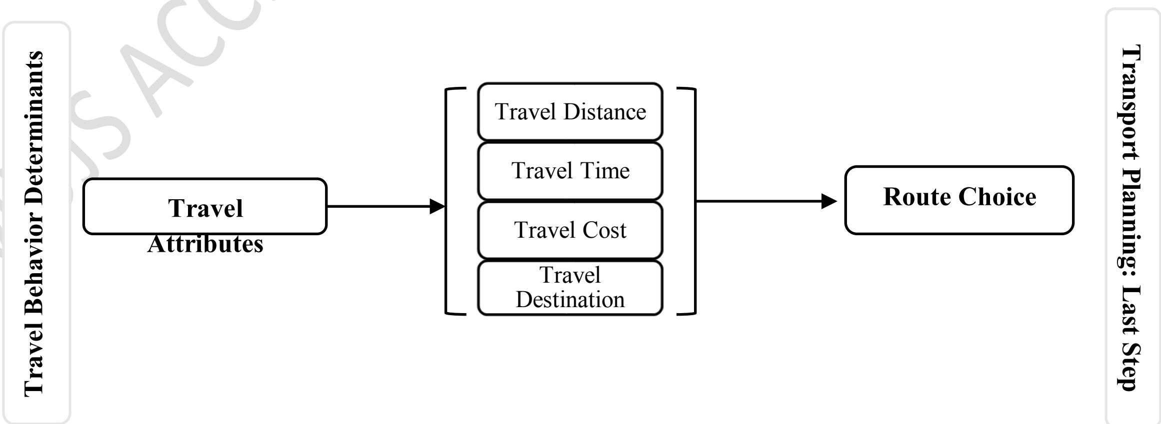


Figure 7. Travel Behavior Determinants on Route Choice

These existing works of literatures showed us the different significant determinants that influence travel behavior. Personal attributes such as socio-economic and household attributes, travel attributes such as trip purpose, distance, cost, and so on are critical factors in determining their travel behavior. Also, the risk perception and their concern about virus spread can be seen in their decision to travel and the mode of transportation they use. However, recent research findings found that the variables in the choice set of these studies were insufficient. According to the literature, other factors influencing travel behavior should be considered, including a broader range of variables in the choice set specification, such as psychological, social, environmental, and latent factors. Furthermore, because the focus of the study is on the travel pattern changes before and under the pandemic outbreak, replicating the investigation after the pandemic will help determine whether these changes will persist or not. To represent the study area, transit mode should be subdivided into categories; for instance, other transport modes that are accessible in a specific area could have been considered and contributed to mode choice forecasts.

4. Summary and Recommendations

During a health crisis, such as an outbreak, there are expected changes in transport or mobility of people. Primarily, this is because of the innate drive to protect individuals from the virus. Preventive measures such as travel bans and other protocols to avoid infection from spreading have been implemented. This pandemic did not only change the intention to travel to a specific place, but it also affects the decision of individuals to travel or not. Changes in travel behavior include lessened travel frequency, transport mode shift, the purpose of traveling, and others.

The paper discovers that travel behavior has changed significantly in a pandemic setting. Alternative transport modes like walking and cycling have been used by commuters as they found it to be sustainable. The number of people using public transit has declined substantially. The number of trips and distance traveled have also decreased significantly due to the closing of local physical businesses. Adventure Park and shopping center visits have also dropped considerably. Several factors that have an influential impact on these changes in travel behavior were also identified. The findings demonstrated the interdependence of variables such as personal attributes comprised of socio-demographic and household characteristics, trip attributes, and risk perception or concern for virus spread. Furthermore, these travel behavior determinants have specific implications for transportation planning. The paper discussed that a combination of these factors affects the four-step of transport planning model.

Moreover, the national government and local government units can plan ahead of time by forecasting the pattern of travel behavior during these times. Appropriate transportation interventions can be used to prioritize socio-demographic groups that need to travel urgently. Local government officials, for instance, may work with existing industrial businesses, companies, and institutions to identify workforce who need to travel for work, mainly that income is less than the basic wage. The government can then subsidize public buses or other forms of mass transportation to cover worker fares. Also, a transportation schedule can be created to match the work schedules of employees. Furthermore, prolonged home isolation stimulated people to leave from home when restrictions were lifted, leading to higher recreational or entertainment trip frequencies. As a result, the government must impose stricter travel health protocol execution to reduce the virus propagation. It can be enforced by issuing fines to commuters who wear face masks improperly or not at all, as well as public transport operators who exceed the fifty percent passenger capacity limit. During curfew hours, more enforcement officers should be observable in heavily populated areas with high foot traffic. Non-essential travel after curfew hours can be handled similarly.

Future research can examine travel behavior using a broader range of variables in the choice set specification, such as psychological, social, environmental, and latent factors. Furthermore, the focus of the study can be shifted to after the pandemic to determine whether these changes will persist or not. Another interest for further study can explore the travel behavior of people with the combination of stated and revealed preference data.

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