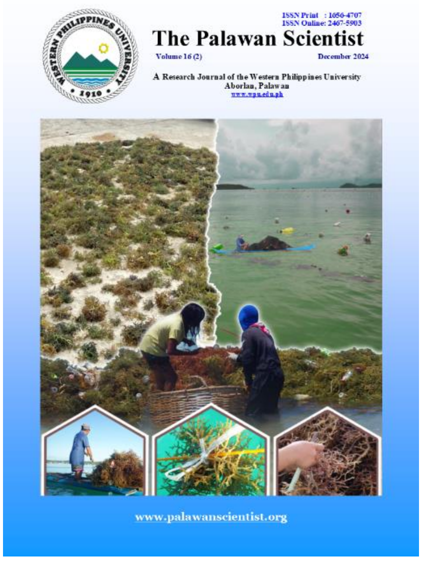
Original Article



Determinants of last-mile travel mode choice under different COVID-19 alert levels: A case study of Batasan Hills, Quezon City, Philippines

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ABSTRACT

The COVID-19 outbreak has led to remarkable changes in the transport sector and people's travel behavior. The suspension of public transport leads to an increase in the number of private car users and the number of walking activities. The last mile, being one of the weakest links in the transport network, has become more challenging to manage with the imposition of different travel restrictions. Using the data collected from the households of Barangay Batasan Hills, Quezon City, Philippines, this study aimed to understand people's travel behavior during the pandemic. Specifically, a binary logit model was used to determine the significant factors that affect the last-mile travel mode choice under different alert levels. Results showed that age during the pandemic, monthly household income, the purpose of travel, travel expense, travel time, departure time, origin, compliance with COVID-19 measures, and trip duration have significant factors in last-mile travel mode choice. In addition, risk perception on public transport was also a determinant of last-mile travel mode under alert levels 1 and 2. Analyzing travel behavior during the COVID-19 pandemic is deemed beneficial in devising strategies and interventions that will help mitigate the spread of the virus while still allowing economic activity and the movement of people to happen.

Keywords: alert levels, COVID-19, last mile, mode choice, travel behavior

INTRODUCTION

The COVID-19 pandemic has emerged as a major concern for the entire world, posing unprecedented risks to the health sector, economy, labor market, food supply, and transportation. Government authorities started implementing lockdowns, community quarantines, curfews, and travel restrictions to curb the spread of the virus. Social distancing and other safety measures are practiced and have become part of the new normal. To prevent people from getting infected, only one person per household is allowed to go outdoors, essentially to buy goods and do activities. Non-essential businesses and service providers were temporarily closed. Schools and workplaces transitioned into a remote environment. Real-life social interactions and social gatherings had abruptly declined due to the imposition of physical distancing rules (Massaccesi et al. 2021). The Philippines, a third-world developing country, reported its first confirmed case on 22 January 2020 (DOH 2020). Since then, the number of infected people continued to grow. Because of its resource and capability limitations, handling the virus has become a big challenge in the Philippines' public health sector.

In September 2020, the government introduced alert-level systems. This alert level system was first implemented in Metro Manila then in the rest of the country months after (Tantuco 2021). During the COVID-19 transmisison, the area is placed under alert level 1, total bed usage, and intensive care unit use were all low or declining (Baclig 2022). Intrazonal and interzonal movements were allowed regardless of age and comorbidity. Establishments are also allowed to operate at maximum capacity (DOH 2021). Under alert level 2, everyone was allowed to go out, but government authorities also imposed additional safety measures and restrictions. It was implemented in areas with increasing hospital admissions even if the number of infected cases were low (Baclig 2022). Gaming establishments were not allowed to operate while other establishments were allowed to open at a maximum of 50% indoor capacity and 70% outdoor capacity. When alert level 3 was imposed residents below 18 years old and belonging to the vulnerable population were restricted from going out, except when buying essential goods or doing essential activities. Areas with a high risk of transmission were not allowed to operate, while those with low to medium risk can open up to 30% indoor capacity for fully vaccinated individuals and 50% outdoor capacity. At least 60% on-site workforce was also allowed in government establishments (DOH 2021). Further, when the area had high cases and hospital admissions, alert level 4 was implemented (Baclig 2022). Intrazonal and interzonal travel was only allowed for individuals without comorbidities, not pregnant, and whose ages were between 18 to 65 years old. A maximum of 10% indoor capacity for fully vaccinated individuals and 30% outdoor capacity was given for service establishments, while at least 40% on-site workforce in the government services. Lastly, alert level 5 signified alarming cases and hospital admissions. The movement of the people was limited to accessing essential goods and services or work only. The strictest rules and guidelines like ECQ were usually implemented in this scenario (Baclig 2022). Mass gatherings were not allowed, and strict home quarantines were imposed. Government officials and authorities were also in a skeleton workforce (DOH 2021).

Along with these numerous contagion-related guidelines implemented at both local and national levels, transportation systems and services were also suspended. Restrictions began with the banning of international travel from countries with confirmed cases, followed by visa restrictions and checkpoints at the entry and exit points across every country (Pawar et al. 2020). As a result, the transport industry was greatly shaken on the economic level. Although airlines reacted differently to the implemented restrictions on air travel (Monmousseau et al. 2020), major carriers in the airline industries have experienced a 60% to 80% reduction in their capacity. In the Philippines, public transport was only allowed to operate at full capacity under alert level 1 scenario (Philippine News Agency 2022). Under alert levels 2 and 3, it was allowed to keep 70% of passenger capacity (Philippine News Agency 2022), while full suspension of its usage was imposed under alert level 5 scenario. Further, studies revealed that the mode choice behavior of working Filipinos was affected by the pandemic with the increased shift of respondents from public transportation to using private vehicles, active transportation, and shuttle services (Co et al. 2023). These results complemented the studies from other countries where private transport users gradually increased during the COVID-19 pandemic (Hasselwander et al. 2021; Shakibaei et al. 2021; Zhang et al. 2021; Abdullah et al. 2022), while a minor shift to walking activities for non-commuting was observed (de Haas et al. 2020; Borkowski et al. 2021; Paul et al. 2022). Lastly, non-motorized vehicle users also increased during the pandemic for both commuting and discretionary purposes (de Haas et al. 2020; Abdullah et al. 2022; Paul et al. 2022). These results imply that walking or another active transport mode, motorized and private vehicles lessen the risk of getting infected (Ancheta et al. 2023). There is a need to determine the factors affecting the last-mile travel mode choice under the different COVID-19 alert levels. This can contribute to the extensive studies on the effects of the pandemic on transportation by taking into consideration alert level scenarios and specifically analyzing only the last-mile travel mode of respondents.

The goal of efficiently connecting transportation linkages remains to be a challenge up to this day. Especially, this problem came out worst during the pandemic due to the lack of transportation modes available. The last mile is commonly referred to as the last leg of a transportation journey comprising the movement of passengers from a transportation hub to the destination (Chen et al. 2021) in the context of transport planning and supply chain management. It is frequently the weakest link in a transport network (Stam et al. 2021). A wide range of research investigating the factors that affect travel mode choice has been conducted (i.e. Ben-Akiva et al. 1985; Hensher 1994; Hasnine et al. 2018; Mao et al. 2018; Yang et al. 2018; Mohd Ali et al. 2022). The literature in the context of last-mile transport mode choice has been growing (i.e. Meng et al. 2016; Mo et al. 2018; Guo et al. 2020; Lu et al. 2022). The pandemic-related variables and their effects on travel mode choice are also considered in some research (i.e. Bhaduri et al. 2020; Abdullah et al. 2022; Paul et al. 2022; Zubair et al. 2022). However, there are limited studies on last-mile mode choice behavior for developing countries (e.g. Patil et al. 2020) and studies that incorporate both the pandemic-related factors and last-mile travel mode.

Managing the last mile will be even more challenging as usage of the transport modes in the country is significantly impacted by the outbreak of the virus. Although the use of various modes of transportation has already been relaxed, the transmission of the virus is still not yet fully managed and controlled. Protocols and restrictions are still changing depending on the type of alert level being imposed in an area. This means that behaviors are still affected by the pandemic. Plans and strategies should also be specific to each area and each alert level. Furthermore, the long-term heterogeneous impacts of the pandemic within different transportation sectors (Mack et al. 2021) will most likely bring transport disruptions and require adjustments from transport system providers and users.

The objective of this study is to analyze and determine the factors affecting the last-mile travel mode choice under different alert levels using the data collected from households in Barangay Batasan Hills, Quezon City, Philippines. This study did not specifically focus on the last-mile problem in passenger transport which refers to the disconnect between public transport and an individual's origin or destination (Tight et al. 2016). However, the study focused simply on the last-mile transport mode choices of individuals during the pandemic and the factors affecting their decision according to various alter level scenarios. The results of this study can be used to understand the travel behavior of the residents. Further, this can be helpful for designing strategies and plans that will help manage the last mile link and mitigate the spread of the virus at the same time.

METHODS

Study Area

Barangay Batasan Hills was chosen as the study area based on a decision criterion that includes the population, existing transport networks, travel demands, and existing establishments. Barangay Batasan Hills is one of the barangays in Quezon City, Philippines (see Figure 1). As of the 2020 Census, Batasan Hills has 166,572 residents which represents 5.63% of Quezon City's total population. Moreover, the barangay has 161,352 families, with an average of 4.67 members per household, according to the 2015 Census (PhilAtlas 2020). There are three major roads in Batasan Hills: Commonwealth Avenue (Radial Road 7/N170), Batasan (IBP) Road, and the Batasan-San Mateo Road. Batasan is also served by the Batasan Station of MRT Line 7 located a few meters south of the junction of Commonwealth Avenue and IBP Road near the Sandiganbayan Centennial Building.

The study area is composed of medium to high-density residential zones, with major and metropolitan commercial zones, institutional zones, and housing zones. Notable buildings and structures within the barangay include the Batasang Pambansa Complex which houses the House of Representatives; and the Sandiganbayan Centennial Building which is home to Sandiganbayan – one of the major courts of the country. Other government establishments in the area include the headquarters of the Civil Service Commission, the Commission on Audit, and the Department of Social Welfare and Development. Also located within the barangay are: Ever Gotesco Commonwealth (a shopping mall); Diliman Commercial Center which has branches of Starbucks and Ministop, and satellite offices of Pag-IBIG Fund and Social Security System; and St. Peter Parish: Shrine of Leaders – all mentioned are along Commonwealth Avenue. On the other hand, available transport modes in the area are bus lines, tricycles, jeepneys, PUVs, and MRT (Batasan Hills undated).

Data Collection

Data used for analysis in this study were collected from households that were randomly selected using the cluster sampling method. A survey questionnaire was designed containing four sections. The first section was intended to capture the socio-demographic and household characteristics of the respondents (gender, age, household position, civil status, educational attainment, number of household members, number of children, elderly members, person with disabilities, vehicle ownership, type and number of vehicles owned, house ownership, residential period, occupation, occupation setup, monthly income). The section on travel characteristics was designed to get the travel behavior and detailed movement of the respondents. The third section captured the variables that are related to risk perceptions, compliance with the pandemic protocols, social responsibility, travel anxiety, fear of infection, and vaccination status. Lastly, the possible factors that they prioritize when choosing their transport mode and their corresponding level of priority were obtained in the last section.

Face to face survey was conducted to obtain data used for analysis in this study. After the survey, data were encoded, checked, and validated. Missing and inconsistent data were removed. A total of 326 valid responses were obtained and coded using the dummy coding technique. Further, stepwise backward elimination was employed to select the independent variables that affect the mode choice of respondents. An initial model containing the initial list of independent variables was estimated. Then insignificant variables were removed one at a time based on their p-values until all the variables left were significant at a 95% confidence level (Washington et al. 2011). All the remaining significant variables were used as the explanatory variables for the final analysis and interpretation of the logit model of last-mile travel mode choice.

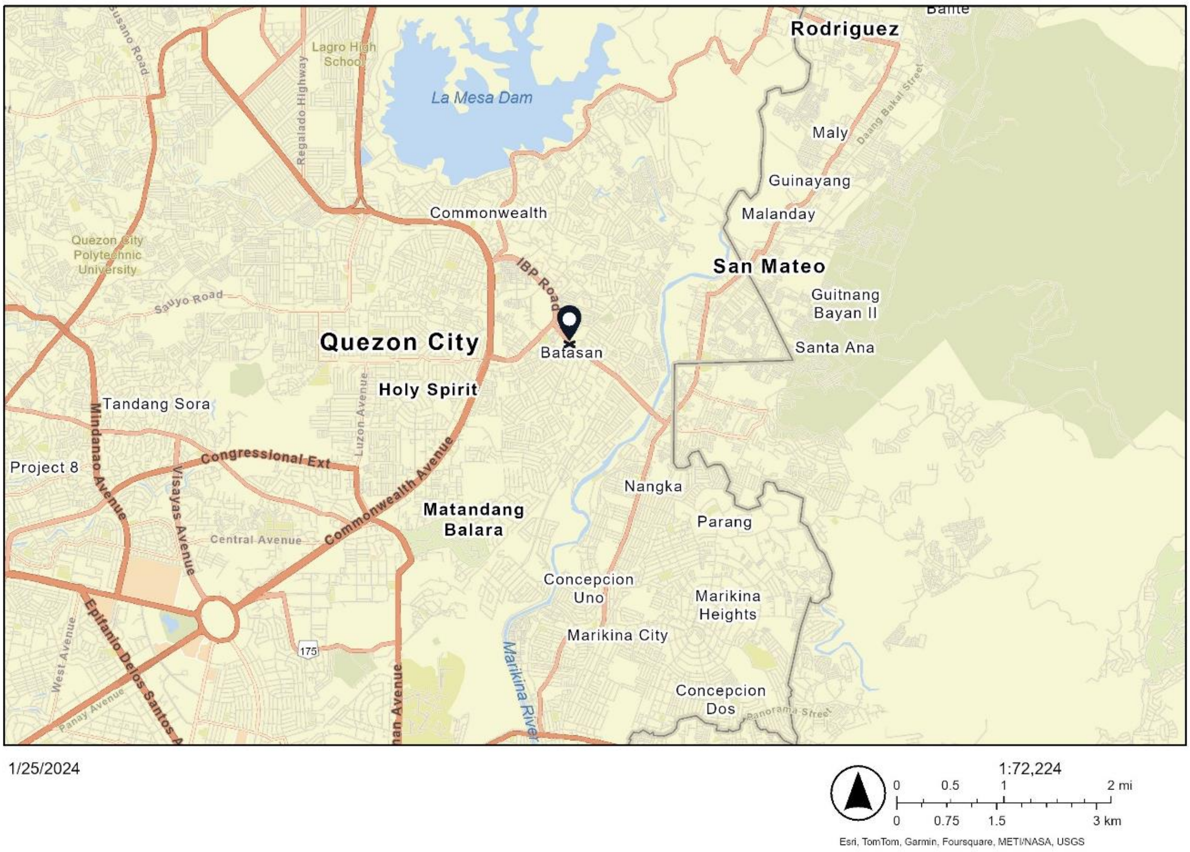

Figure 1. Batasan Hills, Quezon City Map. Source: ArcGIS (2024).

Logit Model Parameter Estimation and Validation of Model Specification

The binary logit model was used for data analysis. Any household, h, traveling his last mile by walking, w, or through a vehicle (public/private), v, is represented by a utility function as presented in Equations 1, and 2, respectively. $\beta' wh$, and $\beta' vh$ are vectors of parameters that are estimated for the model for households, h, choosing walking, w, or vehicle, v, as last-mile travel mode, respectively. X_{wh} and X_{vh} are vectors of the determinants that households prioritize when choosing last-mile travel mode choice of either walking, w, or by vehicle, v, respectively. ε_{wh} and ε_{vh} are vectors that account for the effects of unobserved attributes and preferences on observed alternatives w and v, respectively.

$$U_{wh} = \beta'_{wh} X_{wh} + \varepsilon_{wh} \tag{1}$$

$$U_{vh} = \beta'_{vh} X_{vh} + \varepsilon_{vh} \tag{2}$$

P_{wh}, and P_{vh}, indicate the probability that a household chooses walking, w, or by vehicle, v, as last-mile travel mode choice, respectively. These can be determined using Equations 3 and 4, respectively.

$$P_{wh} = \frac{e^{\beta'_{wh} X_{wh}}}{e^{\beta'_{wh} X_{wh}} + e^{\beta'_{vh} X_{vh}}} \tag{3}$$

$$P_{vh} = \frac{e^{\beta'_{vh} X_{vh}}}{e^{\beta'_{wh} X_{wh}} + e^{\beta'_{vh} X_{vh}}} \tag{4}$$

The coefficients β, X, and ε were determined using the maximum likelihood estimation. STATA version 15.0 was used in estimating the parameters of the binary logit model. The significance of the independent variables to the last-mile travel mode choice was determined using the t-statistics (p-value). The final model includes determinants whose p-value is less than 0.05 (significant at 95% confidence level) or 0.01 (significant at 99% confidence level). Also, model fit was assessed using the McFadden pseudo R^2. The values of McFadden pseudo R^2 ranging from 0.2 to 0.4 indicate that the model fits the data well (McFadden 1997).

RESULTS

Socio-Demographics and Travel-Related Variables

From the 326 valid responses collected from the residents of Barangay Batasan Hills, Quezon City, it was revealed that 196 respondents traveled by foot

(60.12%), and 130 used public transportation (39.88%) in their last mile travel during the pandemic. Table 1 provides a summary of the description and frequency of the socio-demographic and travel-related variables. The descriptive analysis showed that most of the respondents have ages ranging from 15 to 50 (73.62%), have at most 4 household members during the pandemic (73.62%), and it is also worth noting that 60.43% have a monthly household income of more than Php10,000. All the interviewees indicated that they have traveled during the pandemic. During their first-mile trip, 43.56% depart from their houses at 9 AM or earlier, while 56.44% depart after 5 PM. Most of them pay at most PHP 20 which accounted for 81.29%, while 80.66% travel for at most 20 minutes, 46.94% go to the workplace, barangay hall, or school, 43.01% go to a grocery store, shopping mall, or public market, and 10.04% go to other locations such as hospitals, churches, and relatives. Also, most of the last-mile travelers originate from their workplaces/barangay halls/schools accounting for 40.80%. In addition, 288 of the last-mile travels was within 20-minute travel (88.34%).

Table 1. Descriptive summary of socio-demographic and travel-related variables used in the analysis.

Variables	Classifications	Frequency	Percent
Age of the respondents during pandemic (AGED)	15- 50	240	73.62
	>50	86	26.38
Number of household members during the pandemic (MEMD)	≤4 members	240	73.62
	>4 members	86	26.38
Household monthly income during the pandemic (MINCOMED)	≤ 10,000	129	39.57
	> 10,000	197	60.43
Travel Mode (Last Mile) (MODELM)	Walking	196	60.12
	Public Transport	130	39.88
Travel expense (First Mile) (EXPENSEFM)	0-Php20	265	81.29
	>Php20	61	18.71
Travel time (First Mile) (TRAVTIMEFM)	1min - 20mins	263	80.67
	>20 mins	63	19.33
Departure Time (Last-Mile) (TIMELM)	9 am and earlier	142	43.56
	After 5 PM	184	56.44
Origin (Last-Mile) (ORIGLM)	Others (Hospital/Relatives/Church)	34	10.43
	Workplace/Brgy. Hall/School	133	40.80
	Grocery/shopping mall/Market	159	48.77
Travel time (Last-Mile) (TRAVTIMELM)	1min - 20mins	288	88.34
	>20 mins	38	11.66

Moreover, as shown in Table 2, most of the respondents have a high perception of the risk of public transport, high compliance with COVID-19 measures, high COVID-19 fear, and high travel anxiety for all alert levels. About 80.06%, 80.06%, 87.12%, 84.66%, and 86.20% of the respondents have high perceptions of the risk of using public transport under alert levels 1, 2, 3, 4, and 5, respectively. High compliance is also observed on COVID-19 measures for alert levels 1 to 5 with proportions of the responses equal to 97.24%, 88.04%, 87.73%, 88.04%, and 90.18%, respectively. Likewise, around four-fifth of the respondents have a high level of fear of COVID-19 under alert level 1 (83.13%), alert level 2 (78.83%), alert level 3 (80.06%), alert level 4 (84.05%), and alert level 5 (80.37%). The number of respondents with high travel anxiety also increased with alert levels, with proportions of 76.07%, 80.37%, 87.42%, 88.65, and 88.96% for alert levels 1 to 5, respectively.

Table 3 shows the result of the model estimation of last-mile mode choice in all alert levels. The models are attributed from alert level 1 to alert level 5. All the models show significance at (*p = 0.000*) which indicates that there is an established relationship between independent and dependent variables. The area under curves (AUCs) calculated at 75.83 for alert level 1 and 74.53 for alert levels 2, 3, 4, and 5, indicating that the models have an excellent ability to discriminate. McFadden *pseudo*-R^2 assessed the model's goodness of fit. The model's *pseudo*-R^2 is within 0.16 to 0.17. The Correct Classification Rate (CCR) for the alert level models (alert levels 1-5) ranges from 69.02 to 70.25, and their CCR base rates are 52.05. This implies that there is an improvement in the predictive accuracy with the addition of significant variables in the model.

The model specification was further validated using the Likelihood Ratio (*LR*) test. The binary logit model for alert level 1 yielded LL_{Whole}, $LL_{Sample1}$, and $LL_{Sample2}$ values of -181.19, -86.04, and -92.77, respectively. The resulting value of *LR* with 5 degrees of freedom is 4.76. The critical value χ at a 5% level of significance and 5º of freedom, χ2 0.05, 5, is 11.07. The lower value of calculated *LR* compared to $\chi^2_{0.05,5}$ indicates that the null hypothesis that there is

Table 2. Descriptive summary of scenario-based variables used in the analysis for different alert levels. F- frequency.

Variables	Classifications	Alert Level									
		1		2		3		4		5	
		F	%	F	%	F	%	F	%	F	%
Risk in Public Transport Use (PTL)	Low	65	19.94	65	19.94	42	12.88	50	15.34	45	13.80
	High	261	80.06	261	80.06	284	87.12	276	84.66	281	86.20
Compliance to COVID-19 measures (COMPL)	Low	9	2.76	39	11.96	40	12.27	39	11.96	32	9.82
	High	317	97.24	287	88.04	286	87.73	287	88.04	294	90.18
COVID-19 fear (CFL)	Low	55	16.87	69	21.17	65	19.94	52	15.95	64	19.63
	High	271	83.13	257	78.83	261	80.06	274	84.05	262	80.37
Travel Anxiety (TAL)	Low	78	23.93	64	19.63	41	12.58	37	11.35	36	11.04
	High	248	76.07	262	80.37	285	87.42	289	88.65	290	88.96

no significant difference between the parameters across different samples is accepted. Lastly, the LL_{Whole} of the logit models for alert levels 2, 3, 4, and 5 is equal to -183.79. The $LL_{Sample1}$ for alert levels 2 to 5 is equal to -92.81, while $LL_{Sample2}$ is equal to -88.77. From these values, the calculated *LR* for alert levels 2, 3, 4, and 5 is 4.42. The critical value χ at a 5% level of significance and 4 degrees of freedom, $\chi^2_{0.05,4}$, is 9.49. All the values of *LR* for alert levels 2, 3, 4, and 5 are less than the $\chi^2_{0.05,4}$, which means that there is no significant difference between the parameters of the whole data and the parameters across different samples.

For the last-mile mode choice under alert level 1, the variable indicator for the departure time for the last-mile trip during the pandemic has a positive coefficient (β = 1.08), indicating that those who depart from their places after 5 PM are more likely to use public transport mode. The positive coefficient (β = 1.01) obtained for the variable indicator of COVID-19 fear under alert level 1 implies that the higher the perception of risk for COVID-19, the lower the chances that the respondents will ride public transport mode. Interestingly, those who are fully vaccinated and with high compliance with COVID-19 safety measures are less likely to choose public transport. This is derived from the coefficient β = -1.67. This only shows that despite the providence of vaccination, people are not yet lenient in complying with safety protocols and have avoided using public transport to ensure safety and curb virus spread. Lastly, the trip duration variable indicator has a negative coefficient (β = -0.74), suggesting that if the respondents highly prioritize trip duration, the higher the chances they will travel by foot in their last-mile travel.

In addition, for alert levels 2, 3, 4, and 5, positive coefficients were observed for the variable indicators for last-mile departure time (β = 1.10), and travel anxiety for those with booster shots (β = 1.53). This indicates that last-mile travelers who depart from their last-mile origin later than 5 PM and those who have booster shots but with travel anxiety tend to ride public transport. On the other hand, negative coefficients were obtained for variable indicators for compliance with COVID-19 measures for those fully vaccinated (β =-1.67), and trip duration (β = -0.68). From these coefficients, it infers that those who are fully vaccinated with high compliance with COVID-19 measures, and those who highly prioritize trip duration are more likely to walk in their last-mile travels. This may be attributed to the imposition of stringent regulations, such as travel restrictions, in response to the increasing number of infected residents and hospital admissions, which may affect the accessibility and availability of public transportation.

DISCUSSION

With the impacts of the pandemic, stretching the last mile and managing it becomes more challenging. Thus, this study examined the last-mile travel mode preferences of the households in Barangay Batasan Hills, Quezon City, Philippines under different alert level systems. Data were validated and coded. Variables were analyzed. A binary logit model was estimated to analyze the significant factors affecting the last-mile travel mode choice during the pandemic.

Table 3. Parameter estimation and model validation results of binary logit model for public transport at different alert levels. ** significant at 99%; * significant at 95%.

Parameters	Alert Level			
	1		2 to 5	
	β	P > |z|	β	P > |z|
Departure Time Last-Mile (TIMELM) indicator variable (1 for > 5 PM, 0 otherwise)	1.08**	0.000	1.10**	0.000
COVID-19 Fear Alert Level 1 (CFL1) indicator variable (1 for High, 0 for Low)	-0.95*	0.028		
Compliance to COVID-19 measures of Fully Vaccinated (COMPFV) indicator variable (1 for High, 0 for Low)	-1.67**	0.004	-1.67**	0.004
Travel Anxiety of those with Booster (TAB) indicator variable (1 for High, 0 for Low)	1.28**	0.000	1.53**	0.000
Trip Duration as a priority during pandemic (TDD) indicator variable (1 for High Priority, 0 for Low Priority)	-0.74**	0.009	-0.68*	0.014
Constant	-0.77	0.277	-0.20	0.760
LR chi^2	76.10		70.89	
Prob > chi^2	0.000		0.000	
Pseudo R^2	0.17		0.16	
Base CCR	52.05		52.05	
Correct Classification Rate (CCR)	69.02		70.25	
Area Under Curve (AUC)	75.83		74.53	
Log-Likelihood whole sample (LL_{Whole})	-181.19		-183.79	
Log-Likelihood sample 1 ($LL_{Sample1}$)	-86.04		-92.81	
Log-Likelihood whole sample 2 ($LL_{Sample2}$)	-92.77		-88.77	
Likelihood Ratio (LR)	4.76		4.42	
Degrees of Freedom	5		4	
Critical value, $\chi^2_{0.05}$	11.07		9.49	

Descriptive Summary of Variables

The descriptive analysis result of the study showed that most of the respondents in Batasan Hills, Quezon City travelled by walking during the pandemic instead of using public transportation. This result complements the study of Co et al. (2023) where they indicated that most travellers are shifting away from using public transport during the pandemic and some shift to walking activities for non-commuting (Borkowski et al. 2021). Most of their travels are for the purpose of going to their workplaces or going to school. Moreover, many of the respondents have high risk perception in using public transportation. The result of high-risk perception for public transportation use indicates that the vehicle characteristics including the number of passengers allowed, social distancing inside the vehicle, and service environment (crowding, cleanliness, comfort) are driving factors to risk perception. Previous studies revealed that most respondents perceived public transport as a high risk of infection due to its poor sanitization, ventilation, and high occupancy rate disregarding physical distancing at most times compared to private vehicles (Co et al. 2023; Abdullah et al. 2020).

Factors Affecting Last-Mile Travel Mode Choice under COVID-19 Alert Levels

The model estimation for the last-mile travel mode choices under alert levels 1 to 5 are affected by their travel characteristics such as their last-mile departure time and trip duration during the pandemic. Those who depart after 5 PM are more likely to travel with a public vehicle. When the respondents highly prioritize the trip duration, then they are more likely to travel on foot. Abdullah et al. (2020) and Zubair et al. (2022) emphasized that variables like cost, comfort, and trip duration become less priority during the pandemic compared to pandemic-related factors such as the usage of facemasks, social distancing, cleanliness, safety, and security. Risk-related variables such as COVID-19 fear, compliance with safety measures and protocols, and travel anxiety also influence their last-mile mode choices. Those who are fully vaccinated and have high compliance with pandemic protocols are also more likely to walk when stretching their last mile to avoid risk of infection. This contrasts with the study on 16 European countries regarding the influence of COVID-19 risk perception and vaccination status on the number of social contacts which revealed that vaccinated individuals were reported to have a higher number of contacts than non-vaccinated, showing leniency of compliance and safety protocols (Wambua et al. 2023). Moreover, the increasing rate of transmission in public transportation, making it unsafe to ride has reduced the chances that it will be chosen (Paul et al. 2022). On the other hand, the model estimation showed that those who received booster shots and with travel anxiety are more likely to use public transport denoted with a positive coefficient (β = 1.28). Further, the choice of mode of transportation is influenced by personal preferences for public transit, willingness to use it, and belief in its security (Aaditya and Rahul 2021; Lee et al. 2022). Further, coefficients from the parameter estimation of the logit models for last-mile travel mode under alert level 1 show that those who show fear of COVID-19 infection are less likely to use public transport.

The findings of this study can provide useful insights into creating and devising strategies and plans that will benefit both transport service providers and consumers during the COVID-19 pandemic. It can also provide information that can be used in the development and improvement of transport systems in the country, specifically on last-mile transport. On the other hand, policies on riding public transport can also be regulated. It can also be beneficial to revise the travel guidelines under different alert levels. Although the study is deemed beneficial to understanding travel behavior during the pandemic, it can still be subjected to some limitations. It is recommended that the study area should also be expanded to nearby barangays or cities to capture a detailed analysis of the travel mode choice during last-mile travels. The study made use of two alternatives namely walking and traveling in a vehicle (private/public). To capture the specific effects of the socio-demographic and travel characteristics on different travel modes, it is suggested that public transport and private transport be analyzed as two separate alternatives. The addition of other travel modes can also be done. The last mile is as weak as the first mile in terms of transport links. Thus, it is highly recommended that the first mile should also be studied. Other travel decisions such as trip generation, destination choice, and route choice can also be a focus of future research.

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ETHICAL CONSIDERATIONS

In the conduct of data collection, participants informed consent was provided and sought. Only those who were willing to participate were interviewed. The personal information of participants is kept confidential. Only the results of the data analysis are published in this paper.

DECLARATION OF COMPETING INTEREST

We declare no competing interests in this work.

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