Demand Estimation of a Dedicated Shuttle Service for a University

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Abstract: Universities can considerably affect the traffic conditions in their area due to the travel demands of their constituents. UP Diliman, being one of the largest universities in the Philippines, is a significant trip generator inside Metro Manila, with more than 80% of its constituents living off-campus. This research aimed to determine the demand for a dedicated shuttle service for these constituents. Their socioeconomic and trip characteristics were analyzed using a combined RP/SP survey. Binary logistic modeling was conducted to determine the probability of shifting to the shuttle. Results show that for private mode users, **relative trip time, distance of address to campus,** and **arrival location in campus** significantly affect this probability. For public mode users, **relative trip cost**, **distance**, and **sex** are significant. The models estimate around 5,700 UPD constituents will probably use the shuttle, accounting for almost 30% of the off-campus population.

Keywords: UP Diliman, shuttle service, mode shift, binary logistic regression, demand estimation

1. INTRODUCTION

UP Diliman (UPD), the main campus of the University of the Philippines System, is located in one of the busiest parts of Metro Manila. It is bound by national roads, commercial malls, and condominiums. It is also one of the largest universities in the country with a total student population of almost 20,000 as of 1st semester AY 2019-2020, and a workforce of about 3,000 faculty (F), administrative staff (S), and Research, Extension and Professional staff (R).

The current address distribution of UPD constituents shown in Figure 1.1 shows that only 18% live inside the UP Campus. Though 29% live within 3kms, this is still small compared to the 50% living a significant distance from the campus, especially considering the total population of almost 23,000. These portions living far from campus generate a significant number of trips daily, which in turn leads to more private car usage and high demand for public transportation. Longer distances also lead to long travel times and higher costs, especially if no direct routes and/or modes are available. Therefore, there is a need to investigate different solutions to this lack of reliable transport modes for a significant trip generator such as UPD.

This research proposes the use of dedicated shuttle service that can serve as an alternative for both private and public mode users. The challenge is to identify the characteristics that these users consider to be important in choosing their modes such as terminal/ stop location, trip time, and cost. This study is a continuation of the one reported in Peralta et al., (2021) wherein the same constituents and address distribution were analyzed to identify the preferred shuttle service terminals.

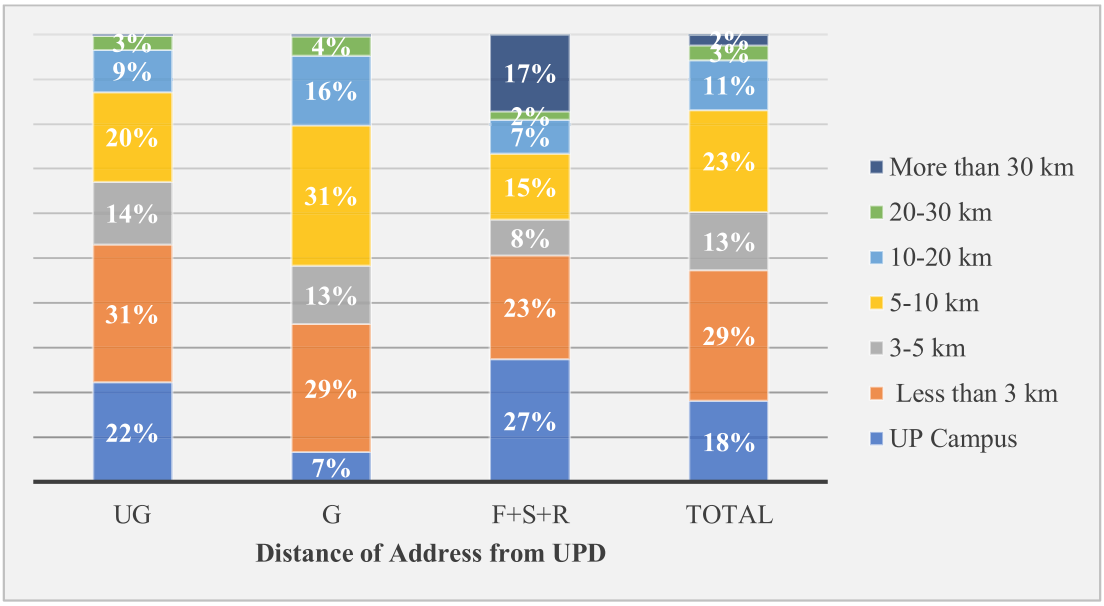

Figure 1.1 Distance Distribution of Current Addresses of Students, Faculty, and Staff (as of 1st Semester 2019-2020)

1.1 Research Objectives

The main objective of the study was to determine the need for a possible shuttle service to cater to the transport needs of the community of the University of the Philippines Diliman, composed mainly of its students, faculty, and staff living outside the campus (from now on, collectively called "potential users"). Specifically, this study aimed to

1. identify the current trip characteristics of potential users such as their transport modes, trip patterns, trip costs, and travel times,
2. determine the significant variables that affect the probability of potential users to shift to the shuttle service, and
3. estimate the number of potential shuttle service users.

1.2 Limitations

Similar to the previous study on terminal locations referred to earlier, this study covered UP Diliman students, faculty, and staff, who regularly go to the campus from their present addresses outside the campus. It did not include those that live within the campus.

This study did not include the traffic analysis of the roads adjacent to and within the campus. The frequency and capacity of the service vehicle was also assumed to be enough to serve the demand based on the assumed maximum waiting time per terminal. The analysis of the addresses means that the estimated trip demands were assumed to be limited to home-based trips only. Comparisons were only made between respondents' current mode (jeep, bus, MRT, etc.) and the hypothetical shuttle service, not among the current modes. The study did not include other hypothetical modes of transport such as the proposed MRT7 line.

Furthermore, this study was conducted prior to the COVID-19 pandemic and did not consider the effects in trip reduction and address changes due to the remote learning and work-from-home set-up.

2. LITERATURE REVIEW

2.1 Trip Characteristics of Off-campus University Trips

Universities and their communities significantly alter the trip patterns in their vicinity (Volosin, 2014). There is a considerable difference between the trip patterns (especially modes) of those living inside and outside campus. College students living inside campuses or within the vicinity have much higher rates of using active transport (cycling and walking) compared to the general population (Pucher, et al., 1999). A travel pattern study on a university in Ohio where 55% of students live outside campus showed that almost 90% of those living outside campus use private cars, usually due to a lack of a bus service to their residential areas (Kaplan, 2015). This distinct difference between travel modes of in- and off-campus students is also seen in a study on a university in Virginia where "*the percentage of walking trips dropped from 79% for on-campus students to 20% for far-from-campus students, and the percentage of driving trips increased from 17% for on-campus students to 78% for far-from-campus students*" (Wang, et al., 2012).

In the Philippines, a study on the trip patterns of students from two private universities in Quezon City showed that for home-based trips, around 40-45% are made using private cars (De Guzman & Diaz, 2005). These studies show that those living off-campus tend to have a higher proportion of car usage which, as discussed earlier, leads to numerous problems.

2.2 Shuttle as a Park-and-Ride Service

Shuttle service, used as both a park-and-ride service and an alternative public transport mode, has been studied for use in trip generating areas such as schools (Shaaban & Kim, 2016; Dave, et al., 2013), central business districts (Asinas, et al., 2017), and parks (Shiftan, et al., 2006). Shuttle services used in park-and-ride facilities encourage private car users to switch from private cars to public transportation (Katoshevski-Cavari, et al., 2018; Zhang, et al., 2018). They lead to reduction of trip costs, reduction of vehicles on the roads, lessening need for numerous public transport routes through consolidation and emission reduction (Mather, 1983).

However, the benefits of park-and-ride facilities are limited by their location, capacity, and operating performance. For example, these facilities only reduce the number of vehicles plying the road downstream but do nothing to reduce the congestion upstream. They can also cause congestion in the vicinity of the facility if not properly managed. This system may also not perform well if it does not capture enough users. This can be caused by low population density, low demand for the route served, or high amount of "backtracking" needed if the facility is located upstream of the population it tries to serve (Farhan & Murray, 2005).

2.3 Shuttle as a Public Transport Service

Shuttle services also function as a public transportation mode. They are used in different countries in their mobility-to-work programs that provide stops near residential areas and bring workers directly to the place of interest like business districts and education campuses (Victoria Transport Policy Institute, 2015). The type of shuttle service more applicable to UP Diliman would be an employee/student-based commuter van/mini-bus service that shuttles from areas of concentration to and from the campus. For the shuttle service to be economical, there must exist large enough clusters of employees and students in various residential areas (Poole, 1994).

In the Philippines, a Shuttle is defined by the Land Transportation and Franchising Board (LTFRB) as similar to a mini-bus with a capacity of 20-49 per vehicle and can serve a demand of 5,000 persons per hour per direction (DoTr, et al., 2017). It is meant for limited stop routes.

2.4 Factors affecting the Probability of Shifting to a Shuttle Service

Studies on shifting to shuttle services and other public transport alternatives, found different factors affecting the **probability of shifting** such as:

- ❑ **Age -** with the increase of the age, the percentage of travels using active transport (cycling or walking) increases (Li et al., 2015).
- ❑ **Household income -** higher income leads to more use of private cars (Li et al., 2015).
- ❑ **Gender (sex) –** females are more likely to switch to PT (Satiennam et al. 2011)
- ❑ **Trip cost** and **trip time -** higher trip costs and trip times led to a smaller proportion of shifting to public transport (Paulley et al. 2006). Research by Asinas, et al. (2017) on a shuttle service program for a central business district in the Philippines showed that trip time and trip cost are significant for public transport users, but for private vehicle users, only trip time has a significant association with the probability of mode shifting.
- ❑ **Car ownership -** increase in car ownership/availability will, other things being equal, lead to a reduction in the demand for public transport modes (Paulley et al. 2006)
- ❑ **Travel frequency -** respondents that conduct the trip more frequently have a higher probability of shifting to public transport compared to those that do not conduct their trips on a regular basis (van der Waerden, et al., 2008)
- ❑ Time at which the trip is conducted - related to travel costs attributed to private modes (i.e. added fuel cost and parking cost); There is a higher probability of shifting to public transport during peak hours (Albert & Mahalel, 2006)
- ❑ **Number of transfers** (intermodal and intramodal) - increases overall trip time because of the transfer time between modes (Allard & Moura, 2019; Guo & Wilson, 2011; Tapiador, et al., 2009; Wardman, 2004). This variable largely affects public transport modes, especially for long trips that require different modes because of different levels of access. In the Philippines, Tiglao & Patdu (2007) suggested that seamless transfer through the different transport modes is essential not only to maintain, but also improve the attraction of public transit as a mode.
- ❑ **Trip distance -** studies in Australia (Shannon et al., 2006), France (Monchambert, 2020), Germany (Scheiner, 2010), Ghana (Agyemang, 2017), and India (Manoj & Verma, 2016) all indicate that for trips that are longer, the proportion of car usage is higher. This seems to be true regardless of trip purpose. These studies suggest that even though public transport is available for longer trips, the overall trip time is longer due to the number of transfers as discussed earlier. That said, the data from these studies also mean that shorter trip distance leads to higher potential to change from private modes to active transport modes walk, cycling, and public transport.

In this study, both socio-economic characteristics of the trip makers and the trip characteristics were included. The effects on the probability to shifting to the shuttle were analyzed and differentiated between private and public mode users.

3. RESEARCH DESIGN

3.1 Conceptual Framework

The need for a shuttle service is based on two things: (1) location, and (2) demand. Location parameters include the use of existing facilities, distance to activity center, proximity to congested corridors, and spatial distribution of the potential trip makers or service users. This spatial distribution also affects the demand because the decision-making behavior affects the choice to use or not to use the service depending on the travelled distance, travel cost, and travel time associated with the stop. These decision-making parameters were quantified using the concept of utility functions comparing the users currently used mode, and the hypothetical shuttle service with varying levels of attributes including travel cost and travel time. As recommended by (DoTr, et al., 2017), public transport stop studies should include socioeconomic data (present population; distribution by age, sex, occupation, and income level) and trip pattern/ **travel behavior** characteristics (travel frequencies, travel time and cost, trip origin, destination, trip length, modal choice, and time of day).

3.2 Research Methodology

In order to achieve the set research objectives, and in response to the conceptual framework stated, the steps illustrated in Figure 3.1 were performed. Based on the established concepts found in literature, factors affecting the probability of shifting to a shuttle service were identified. These were necessary to be able to estimate the demand and establish the need for such a service. Each step taken is discussed further in the succeeding sections.

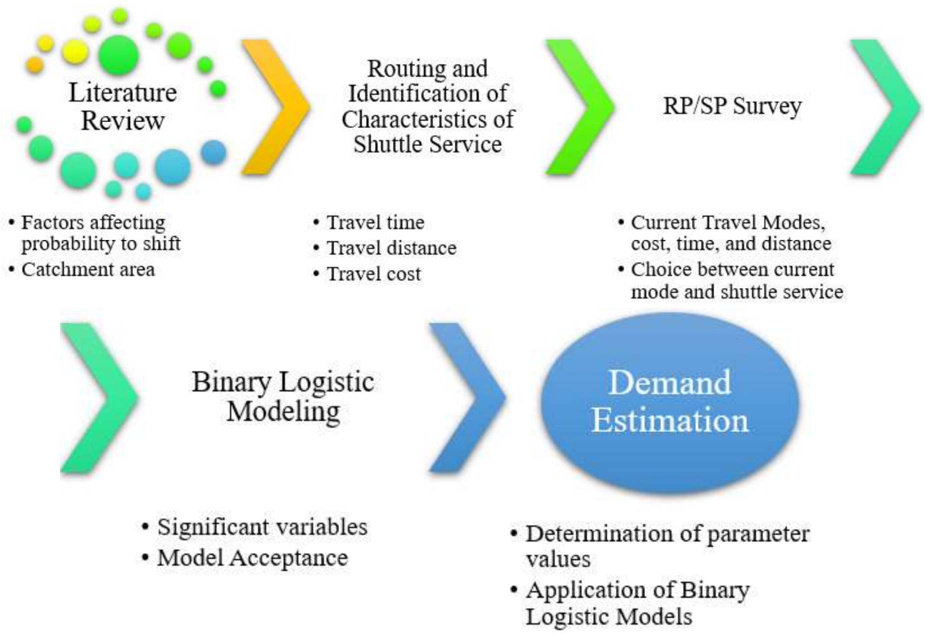

Figure 3.1 General Research Flow

3.2.1 Routing and identification of characteristics of shuttle service

Based on the terminals/ stops identified in Peralta et al., (2021) and illustrated in Figure 4.2, possible routes to serve them were identified using Google Maps. The route per terminal that involved major roads was selected. Trip distances between each terminal and UPD were obtained using Google Maps based on the most frequent route used. Travel time surveys were conducted using Google Maps as well for five (5) weekdays from Monday-Friday. The travel times were obtained every 30 mins for the link connecting each terminal to the corner of E. Jacinto St. and University Ave. These surveys were conducted from 7-10AM, 12-1PM, and 4-7PM, for a total of 17 data points per terminal per day, or 85 points per terminal per week. The route coming from the terminals to UP were considered in the morning and midday surveys, while the route from UP to the terminals were considered for the afternoon trips.

3.2.2 Preference survey

The revealed/stated preference survey was administered through an online form. The respondents were sampled purposively since the target responders were those working and/or studying in UP Diliman and live outside the campus. The survey was divided into three parts:

1. Socio-economic: age, gender, occupation, car ownership, and household income levels.
2. Current travel behavior for their trips to and from UP Diliman: usual origin, destination within the campus, arrival time, departure time, origin in campus before departing, mode choice, trip time, and if they commute, their travel cost and transfers
3. Stated Preference choice scenarios comparing their current travel mode choice and the proposed shuttle service with varying fare and waiting time. The travel time for the morning, midday, and afternoon peaks for each terminal were shown as reference for the respondent but these were not varied per question since it is controlled by traffic conditions. The fares were based on the current LTFRB approved rates for Utility Vehicles (UV) Express: **₱ 2 per kilometer** (Subingsubing, 2018). The fares where then varied with three levels: ₱ 2/km, ₱ 2.5/km, and ₱ 3/km. The range of waiting times were based on the maximum acceptable waiting time for public transportation: **20 mins** (Arhin et al. 2019), and the shortest waiting time based on the target set in (DoTr, et al., 2017) and the proposed law entitled "The Dignity in Commuting Act (Pangilinan, 2019)": **10 mins**. These 2 factors were selected because they were the easiest to control in practice (i.e., fare is set by simple policies, waiting time is controlled using headway and number of units used). Due to the limited paths created by the targeted locations of the chosen terminals based on population distribution, the passenger assignment was implicitly assumed to be all-or-nothing, and the capacity of the terminals and shuttle units were assumed to be apt for the demand to ensure the stated level of waiting time. This reduces the dependence of the choice to shift on the effects of crowding (Desaulniers and Hickman 2007).

   That said, not all combinations were included in the SP surveys because some were trivial (e.g., highest fare level with longest waiting time). The only scenarios asked in the survey involved comparing their current travel mode and the shuttle with the following characteristics:
   a. fare using ₱ 2/km with a maximum waiting time of 20 mins;
   b. fare using ₱ 2.5/km with a maximum waiting time of 15 mins;
   c. fare using ₱ 3/km with a maximum waiting time of 10 mins;

3.2.3 Binary logistic regression

Like most of transport related choice variables, mode choice is probabilistic in nature Individuals assess the effect of different variables in a different manner. This trade-off in transportation modes is usually measured in terms of a variable called the *Utility* U_i. As shown in Equation 1, it is usually assumed to be a linear combination of parameters associated with the trip maker (such as age, sex, income, etc.) and the attributes of the mode (such as cost, trip time, comfort, etc.). It is composed of a deterministic component and an error term $\boldsymbol{\varepsilon_i}$ to reflect the uncertainty in measuring the utility.

$$U_i = \sum_1^n \beta_n x_{in} + \beta_0 + \varepsilon_i \tag{1}$$

where $\boldsymbol{\beta_n}$: **regression coefficient** associated with parameter $\mathbf{x_{in}}$.

For this study, binary logistic modeling was used because the outcome variable was categorical, and only two outcomes were tested – either choose to shift to the shuttle service or keep using their current mode. For binary logistic regression, the probability P_i of an individual to choose mode i is given by Equation 2 (Field, 2009; Profillidis & Botzoris, 2019).

$$P_i = \frac{e^{U_i}}{1+e^{U_i}} \tag{2}$$

Respondents were distinguished between private car/ motorcycle users (**Group A**) and non-private cars/motorcycles users (**Group B**). For Group A, the independent variables considered were Age, Sex, Occupation, Income, Distance to UPD (based on centroidal distance per barangay to UPD), Frequency of Trips, Arrival Time, Departure Time, Arrival Location, Trip Time Ratio (**TTR**), and Trip Cost Ratio (**TCR**). For Group B, the same set of variables were used, with the addition of the Number of Transfers.

$$TTR = \frac{Usual\ Trip\ Time\ of\ Respondent\ to\ UPD\ (mins)}{Waiting\ Time\ of\ the\ Shuttle\ Service (mins)} \tag{3}$$

$$TCR = \frac{Usual\ Trip\ Cost\ of\ Respondent\ to\ UPD\ (PhP)}{Fare\ of\ the\ Shuttle\ Service\ (PhP)} \tag{4}$$

TTR is meant to measure the relative weight given by respondents to the waiting time of the shuttle compared to their usual trip time. A high TTR means the current trip time of the respondent is relatively high compared to the waiting time of the shuttle. TCR measures the relative weight given by respondents to the fare of the shuttle compared to their usual trip cost. A high TCR means the current trip cost is relatively high to the fare of the shuttle.

Three (3) models were developed for each group. The parameters involved are as follows:

- ❑ Model 1 – All parameters
- ❑ Model 2 – All Parameters with p-value < 0.05
- ❑ Model 3 – Parameters chosen by researcher based on the results of Models 1 and 2

The common method of assessing the goodness-of-fit of binary logistic models is the Hosmer-Lemeshow (HL) test (Canary et al., 2017). A p-value less than the significant value (usually 0.05) means that there is a significant difference between the results obtained by the model and the actual data (Glen, 2016). Therefore, the models developed in this study were deemed acceptable if the HL p-values obtained were greater than 0.05. To compare the models, the McFadden pseudo R^2 index was used. For comparing models with different numbers of predictors, as is the case in this study, the adjusted McFadden R^2 is used to consider the effect of the number of predictors (Smith & McKenna, 2013).

3.2.4 Demand estimation

Based on the terminal assignment of the previous study, the values of the parameters needed by the resulting binary logistic models were determined. These were then subjected to the appropriate model (Group A vs. Group B) to determine the proportion that will shift to the shuttle service. The proportion was then multiplied to the UPD population in the barangay based on University data. It was assumed that the split between Group A and Group B would follow the same proportion for all barangays and was based on the proportion from the survey respondents. This resulted in the total number of shifters from both groups per terminal. The resulting number per terminal was then deemed as the demand that will use the terminal.

4. RESULTS AND DISCUSSION

4.1 Survey Respondents Demographics and Socio-economic Characteristics

A total of **933 (5.0% of the total population living outside campus)** responses were received and accepted. Since the total UPD off-campus population at the time was **18,634**, this sample size represents a **margin of error** of **3.1%** at a 95% confidence level. For reference, the results of the terminal locations obtained previously, together with the population distribution, are shown in Figure 4.2. The terminal IDs corresponding to the terminals are listed in Table 4.2

Table 4.1 Age, Sex, and Occupation Distribution of Survey Respondents

Parameter	Category	Proportion
Age	15-19	19%
	20-29	63%
	30-39	10%
	40-49	4%
	50-59	3%
	60 and above	1%
Sex (assigned at birth)	Male	48%
	Female	52%
Occupation	Undergraduate Student (UG)	51%
	Graduate Student (G)	26%
	Faculty (F)	9%
	Admin. Staff (S)	6%
	Research, Extension, and Professional Staff (R)	8%

4.2 Mode Choice Distribution

Jeepney and private vehicles are the most used trip modes by UPD constituents. Of particular interest is the percentage of semi-private mode users such as TNVS and Taxis with about 5-6% of the respondents using them as their main modes of transport. Like private modes, these modes have a significant impact on traffic (Mirandilla & Regidor, 2019). The groups with the highest usage of these modes are Graduate Students, probably due to two things: 1) traffic during the time they leave work to go to UPD (usually around 5PM) that gives only an hour for travel, and 2) the late departure which limits their mode choices. Active modes are mostly done by faculty and staff, presumably because of onsite or nearby housing opportunities since their relationship with the university is more permanent compared to students.

Figure 4.1 Mode Choice Distribution of Respondents

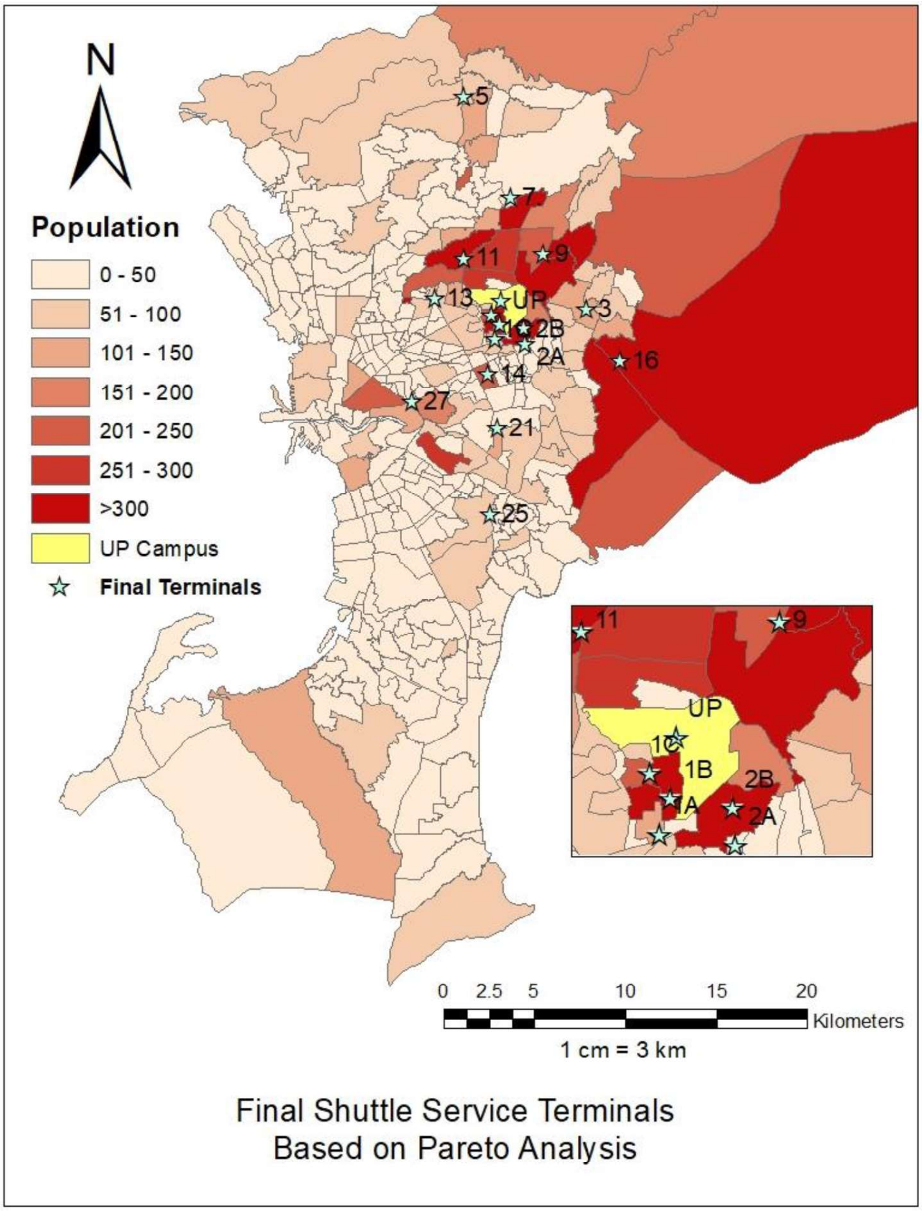

Figure 4.2 Location of Shuttle Service Terminals based on UPD Address Data (Peralta et al., 2021)

4.3 Probability of Shifting based on Survey Results

As mentioned earlier, each respondent was asked to choose between their current transport mode and the shuttle service in three scenarios. If the respondent chose the shuttle service in at least 2 out of the 3 questions, he/she is classified as highly probable to shift. Using this definition, the proportions of those that have a high probability to shift to the shuttle per terminal were obtained and shown in Table 4.2. Majority of respondents that chose the top terminals are willing to shift to the shuttle, with those using the BGC terminal having the highest proportion of 82% in favor of the shuttle. These were mostly composed of graduate students working in the area before going to UPD for their classes. Based on the comments received from the survey, the high proportion of willingness to use the shuttle is due to the lack of viable options and high cost associated with TNVs and taxi use, which is commonly used by this group.

Table 4.2 Stated Preference of Respondents on Shifting to Shuttle Service per Terminal

Terminal ID #	Terminals	No. of Respondents who Chose the Terminal	% of Respondents that Chose to Shift to Shuttle
1A/1B/1C	**Teachers Village**	90	61%
2A/2B	**Katipunan**	93	58%
3	**Concepcion**	43	67%
5	**Almar**	20	55%
7	**Fairview**	27	78%
9	**Don Antonio**	22	55%
11	**Tandang Sora**	33	64%
13	**SM North**	133	56%
14	**Cubao**	35	66%
16	**Masinag**	30	67%
21	**Ortigas North**	22	73%
25	**BGC**	34	82%
27	**Sta. Mesa**	21	81%
	Total	603	63%

4.4 Binary Logistic Models for Group A (Private Car/MC Users)

Group A had a total of 188 respondents. This leads to a total of 564 data points since each respondent was asked three (3) questions each. Upon checking of Model 1, high variance inflation factors (VIF) exist for the TCR and Dist variables. This factor indicates the presence of multicollinearity among variables (Gokmen, et al., 2020). Multicollinearity is defined as "*linear dependence of column vectors of the design matrix in a linear regression model*" (Frisch, 1934). Since the absence of multicollinearity is one of the assumptions of binary logistic regression, its presence must be carefully addressed. For Model 1, the VIF for TCR and Dist variables are 5.83 and 7.17, respectively. These are above the threshold value of 5. This was expected since for Group A, the trip cost per respondent were calculated based on the distance of their residence to UPD. Literature suggests that common ways of addressing multicollinearity is by centering the values (i.e., subtracting the average value from each data point), or by removing one of the variables in question from the regression (Frost, 2017).

Table 4.3 Binary Logistic Regression Results for Group A before Treatment of Multicollinearity

Term	Coef	SE Coef	95% CI	Z-Value	P-Value	VIF
Constant	0.334	0.688	(-1.014, 1.683)	0.49	0.627	
TTR	0.2076	0.0477	(0.1141, 0.3011)	4.35	0.000	1.63
TCR	0.0569	0.0401	(-0.0217, 0.1354)	1.42	0.156	5.83
Age	-0.1242	0.0902	(-0.3009, 0.0525)	-1.38	0.168	1.39
Sex	-0.115	0.180	(-0.467, 0.238)	-0.64	0.524	1.05
Occupation	0.0433	0.0643	(-0.0827, 0.1693)	0.67	0.501	1.52
Income	-0.0237	0.0576	(-0.1367, 0.0892)	-0.41	0.680	1.09
Dist	-0.0507	0.0230	(-0.0958, -0.0057)	-2.21	0.027	7.17
Frequency	0.068	0.113	(-0.153, 0.288)	0.60	0.548	1.54
Arr Time	0.0076	0.0359	(-0.0628, 0.0779)	0.21	0.833	1.59
Dep Time	-0.0041	0.0445	(-0.0913, 0.0831)	-0.09	0.927	1.25
Arr Loc	-0.1366	0.0520	(-0.2386, -0.0346)	-2.62	0.009	1.08

For Model 1, centering the variable did not improve the model since it still led to VIFs of 5.83 and 7.17 for the TCR and Dist variables, respectively. Since both the original and the centered models had high multicollinearity, the option of removing a variable was taken. Because only the Dist variable had a significant p-value in both models, the TCR variable was removed. This resulted in an acceptable VIF of 1.44 for the Dist variable. Multicollinearity was not a problem for both Models 2 and 3. The final models for Group A are shown in Table 4.4.

Only the Trip Time Ratio (TTR), Distance (Dist), and Arrival Location (Arr Loc) had a significant effect on the preference of the respondents (p-values ≤ 0.05). This is further illustrated in the factorial plots in Figure 4.3 where only the TTR and Dist variables have a visually significant effect on the stated preference, with the Arr Loc having a less significant effect. The positive coefficient for TTR indicates shorter waiting times or longer current travel times leads to higher probability of choosing shuttle. On the other hand, the negative coefficient for the Dist variable indicates that those that live farther from campus are less likely to shift from their private mode to the shuttle service. As for ArrLoc, the negative sign of the coefficient suggests that those going to the northern areas such as the Shopping Center and SURP areas have a higher probability of shifting than those from the Science and Engineering Complexes. That said, as shown in the factorial plot, this effect is not as significant as the other two.

Table 4.4 Binary Logistic Models for Group A

Group A - Private Car/ MC Users (n = 188x3 = 564)						
Independent Variables	Model 1		Model 2		Model 3	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Intercept	0.435	0.524	0.206	0.467	-0.473	0.007
TTR	0.180	0.000	0.177	0.000	0.185	0.000
Age	-0.119	0.188				
Sex	-0.086	0.631				
Occupation	0.037	0.570				
Income	-0.027	0.637				
Dist	-0.022	0.035	-0.022	0.022	-0.021	0.031
Frequency	0.056	0.619				
Arr Time	0.000	0.995				
Dep Time	0.002	0.958				
Arr Loc	-0.145	0.005	-0.152	0.002		
Regression Parameters						
HL p-value	0.936		0.651		0.693	
Adj. McFadden's R^2	0.042		0.039		0.027	
Accuracy	60.8%		61.7%		58.5%	

Though multicollinearity exists between the distance and TCR variables, only the former had a significant effect (based on p-values) for Group A respondents. This means that the relative cost of the shuttle to their current trip cost is not an important factor in choosing to shift modes. As seen in the regression results before treating the multicollinearity in Table 4.3, the values of the Wald test z-statistic and the p-values indicate that the probability of shifting is more dependent on the relative trip travel time using the shuttle compared to its relative cost. The p-value of TCR based on Model 1 is 0.156, which indicates that there is not enough evidence to conclude that there is a statistically significant association between this variable and the choice to shift. In contrast, the p-value for TTR is significant since it is less than 0.05.

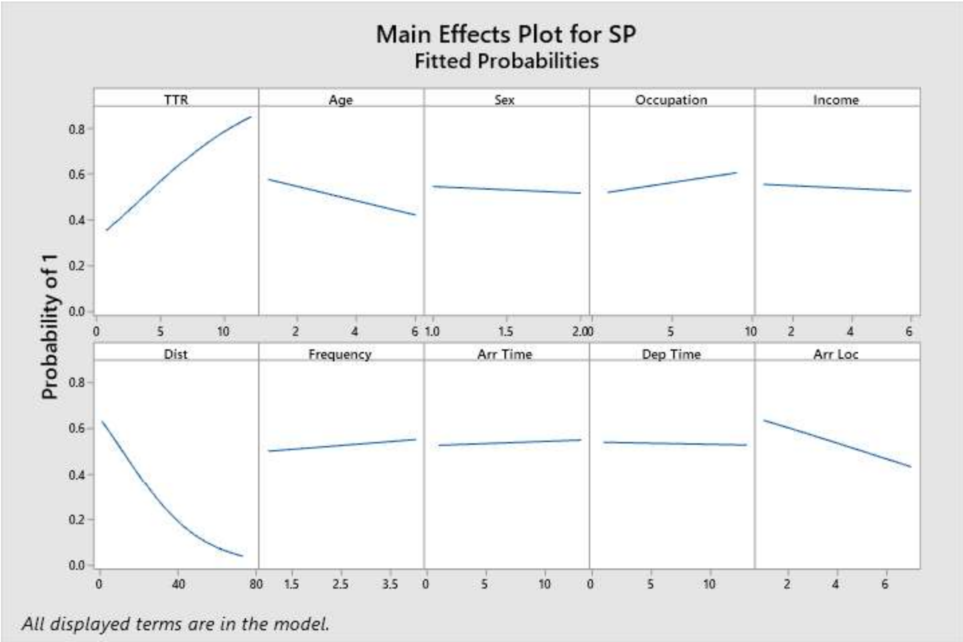

Figure 4.3 Factorial Plot for Group A

The acceptance of each of the models was based on their Hosmer-Lemeshow p-values. The HL p-values of all three models are greater than the significant value of 0.05, suggesting that they are all acceptable, i.e. they produce probabilities that do not deviate significantly from the observed probabilities. The adjusted McFadden's pseudo R^2 values suggest that the models perform at the same level. This is supported by the accuracy values (percentage of correct predictions from the observed values). The small range of accuracy of the three models (59-62%) shows that the performance of the three models is comparable to each other.

4.5 Binary Logistic Models for Group B (Non-private car/MC Users)

Group B had 745 respondents, leading to 2,235 data points. The VIFs of this group indicate that no multicollinearity between any of the independent variables. Hence, no adjustments were made from the original set of variables. The results of the binary logistic modeling for Group B are shown in Table 4.5 while the factorial plots are in Figure 4.4.

For Group B, TCR, Sex, and Dist are significant variables. Income was initially included in Model 2 because its p-value was very close to 0.05. The researchers wanted to find out if the p-value would decrease if the other initially insignificant variables were removed, however its p-value increased to 0.062. Hence, it was removed from the final version of Model 2.

The positive coefficient of TCR suggests that higher current trip costs and/or lower shuttle fares would lead to higher probability of shifting. This is related to the Income variable whose coefficient is positive, suggesting those with higher income have a higher probability of shifting. The rate used in computing for the shuttle fare is based on that for UV Express vans, which is higher than that for other public transport modes. The fact that around 76% of those within the two lowest income groups use either jeepneys, buses, or MRT/LRT/PNR as their main mode leads to only a few of them perceiving the shuttle service to be cheap enough for it to be worth the shift. In contrast, TNVs and taxis which are used by around 10% of those from the two highest income groups, have higher fares, resulting in higher shifting probabilities. The positive coefficient for the Sex variable indicates that males (assigned value = 2) are more likely to shift than females (assigned value = 1). That said, the factorial plot shown in Figure 4.4 indicates that the difference between sexes is rather minor as illustrated by the small slope of the plot.

Table 4.5 Binary Logistic Models for Group B

Group B - Non-private cars/MC Users (n = 745x3 = 2235)						
Independent Variables	Model 1		Model 2		Model 3	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Intercept	-1.295	0.000	-0.693	0.000	-0.095	0.226
TTR	-0.010	0.589				
TCR	0.157	0.000	0.164	0.000	0.159	0.000
Age	-0.030	0.640				
Sex	0.409	0.000	0.406	0.000		
Occupation	-0.002	0.966				
Income	0.050	0.052				
Dist	-0.027	0.000	-0.025	0.000	-0.022	0.000
Frequency	0.007	0.905				
Arr Time	0.013	0.443				
Dep Time	0.008	0.722				
Arr Loc	0.051	0.072				
Transfers	0.079	0.064				
Regression Parameters						
HL p-value	0.14		0.629		0.050	
Adj. McFadden's R^2	0.0374		0.0329		0.0269	
Accuracy	60.7%		59.6%		58.8%	

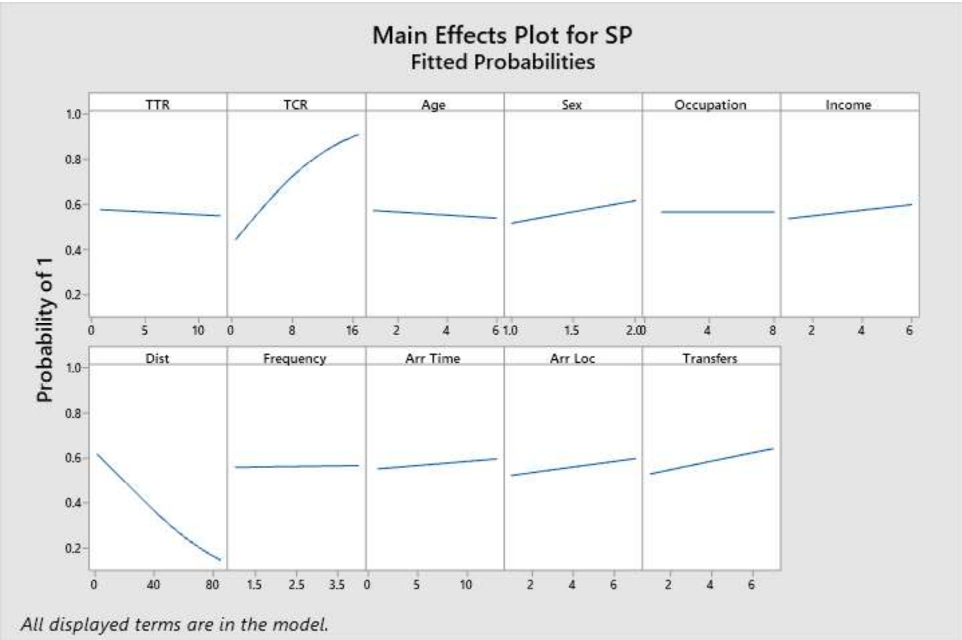

Figure 4.4 Factorial Plot for Group B

Like in the models for Group A, the Dist variable has negative coefficients for the models for Group B. This implies that respondents who live farther from the campus tend to choose to retain their current mode, rather than shift to the shuttle. That said, the magnitude of the coefficient is different between the groups: 0.0507 for Model 1 of Group A, and 0.0266 for Model 1 of Group B. This means that it has a larger effect on private mode users than for others. The resulting p-values also indicate that in choosing between the shuttle and their current modes, Group B values relative travel cost more than the savings in travel time.

The Hosmer-Lemeshow p-values suggests that all three models for Group B produce probabilities that do not deviate significantly from the observed probabilities (≥ 0.05). Like the models for Group A, the pseudo R^2 and the accuracy values of the three models suggest that the models perform similarly. Hence, reducing the variables from those in Model 1 to those in Model 3 does not significantly change the performance of the model.

4.6 Demand Estimation

Model 3 for both Groups A and B were chosen as appropriate models for demand estimation. The third models had the least number of indicators and were the easiest to measure on a per barangay level. The waiting time and trip fares used were the mid-level rates (waiting time: 15 mins, trip fares: PhP 2.5/km). Upon tabulation of the results, the probability of shifting, and the expected numbers of users per terminal are shown in Table 4.6 and Table 4.7, respectively.

Table 4.6 Proportion of Barangay Population Probable to Shift to Shuttle Based on Binary Logit Models per Group

Terminal	Group A	Group B	All
Teachers Village	45.6%	68.6%	**57.1%**
Katipunan	50.4%	69.3%	**58.7%**
Concepcion	53.2%	58.1%	**55.7%**
Almar	63.4%	50.2%	**56.8%**
Fairview	58.8%	53.7%	**56.6%**
Don Antonio	56.0%	64.7%	**61.2%**
Tandang Sora	50.2%	60.7%	**56.2%**
SM North	56.4%	64.1%	**60.0%**
Cubao	52.8%	66.3%	**59.5%**
SM Masinag	52.9%	51.4%	**52.4%**
Rob. Galleria	61.1%	52.8%	**56.1%**
BGC	59.5%	51.4%	**55.5%**
Sta. Mesa	55.2%	58.5%	**56.7%**

Table 4.7 Demand Estimates for Each Terminal per Group

Terminal	Group A	Group B	TOTAL
Teachers Village	135	982	**1117**
Katipunan	149	787	**936**
Concepcion	50	274	**324**
Almar	39	152	**191**
Fairview	58	165	**223**
Don Antonio	38	259	**297**
Tandang Sora	62	494	**556**
SM North	160	845	**1005**
Cubao	38	234	**272**
SM Masinag	89	210	**299**
Rob. Galleria	9	85	**94**
BGC	39	162	**201**
Sta. Mesa	37	197	**234**
TOTAL	**903**	**4846**	**5749**

The proportion that is expected to shift ranges from 52-61% for the combined groups. The proportion for Group A is higher for that of Group B in the five farthest terminals from UPD (Almar, Fairview, SM Masinag, Rob. Galleria, and BGC). This reinforces the findings from the binary logit modeling that car users are more affected by trip distance than public transport users. The proportions from the analysis of the survey responses in Table 4.2 show that the model results are generally lower by an average of 9% and a maximum of 27%. The largest difference is from those that are assigned to the BGC terminal. Survey responses estimate 82% shifting, while the model estimates around 56%. This is because the model uses address data as basis for the population assigned to a terminal while survey respondents can choose the terminal based on origin before going to UPD. The main difference can be seen in the case of graduate students who go to UPD from work, instead of from their residence. Graduate students have a higher likelihood of shifting than other occupation groups because of the increased trip distance and the time of their usual trips to UPD wherein not many options are available. Since the model assumes that these are home-based trips, it does not consider the cases wherein the origin is from work. The terminals with the lowest differences between the survey and model results for proportions for shifting are the Katipunan and Teachers Village terminals. Trips from these areas are mostly home-based, as assumed by the model.

The terminals with the most expected demand are Teachers Village, SM North, and Katipunan. The Teachers Village terminals has one of the highest numbers of UPD residents among all barangays and are nearest to UPD. Group B members from this area have a much higher probability of shifting at 69% compared to 45% of Group A. This is because public transport from the area usually involves tricycle rides with a higher average cost per person per trip than other public transport modes. The SM North terminal has a high demand not necessarily because of the population of UPD constituents around the terminal, but because of its accessibility from far areas. The Katipunan terminal enjoins a mix of the two: high UPD population and good accessibility from other areas via public transport.

The terminal with the lowest demand is the Robinson's Galleria terminal in Ortigas. This is another manifestation of the model only considering home-based trips, which are low in the case of this terminal. The model is more likely underestimating the demand for this terminal since a good part of the demand for this terminal come from graduate students working in the adjacent CBD. The same is true for the BGC terminal. This demand will increase if the demand from the working graduate students in the area is added.

The total expected demand for the top 13 terminals is 5,749, which is about 30% of the current off-campus population of UPD, or about 25% of the total UPD population. This would make the shuttle service the top mode used going in and out of campus. The results expect a total of 903 person-trips that currently use private modes to shift to the shuttle service to access the campus. There are also 4,846 person-trips that are expected to shift to the shuttle from public transport modes. This does not mean that they will use the shuttle solely since they will still use different modes to access the terminals, but the shuttle will serve as the main mode.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The first objective of this study was to identify the current trip characteristics of potential users. Majority of the respondents use jeepneys as their main mode of transportation. For those that live relatively far (> 10km), private mode usage is high while use of active modes is highest for those living within 3km, and significantly decreases with distance.

The next objective was to determine the significant variables that affect the probability of shifting to the shuttle service. For private mode users, the probability is significantly affected by the Trip Time Ratio (TTR), Distance, and Arrival Location. Shorter waiting times and/or longer current travel times increases the probability. Those living farther from campus are more likely to shift. For non-private mode users, Trip Cost Ratio (TCR), Sex, and Distance significantly affects this probability. Lowering the shuttle fare would increase the probability, and like the private mode users, those that live farther from campus are more likely to shift.

The last objective was to estimate the number of potential shuttle service users. It is estimated that about 30% of the total off-campus population will shift to the shuttle if implemented. The proportion for Group A (private mode users) is higher for that of Group B (public mode users) in the five farthest terminals from UPD (Almar, Fairview, SM Masinag, Robinson's Galleria, and BGC) since car users are more affected by trip distance than public transport users. The model results are generally lower than that from the survey results. The largest difference was seen in the BGC terminal where the survey responses indicate that the demand would be significantly higher than what the model predicted. This is because the model assumes that all these trips are home-based trips, and therefore it does not take into account the cases wherein the origin is from work.

The total expected demand for the top 13 terminals (5,749) includes 903 person-trips that currently use private modes, and 4,846 person trips that use different public transport modes. This reduction of car usage is seen to lead to a reduction of car usage in between buildings as well. This in turn will increase the trips done through active modes and/or the jeepney services inside the campus. As for those that would shift from other public transport modes, the shift has the potential of increasing their trip level of service in terms of trip time due to reduced transfers and stops, and over-all comfort due to the higher vehicle standards compared to current modes.

The study was able to use the analysis of spatial distribution of user origins (addresses) together with their socioeconomic and trip characteristics, as basis for demand estimation. The methodology implemented can be applied in other studies regarding terminal location planning depending on the target sector to be served by the service such as hospitals, government offices, large public corporations These analyses can help tailor different aspects of the service such as seating capacity, schedule of service, route, fare, and terminal location.

5.2 Recommendations for Project Implementation

Based on the results of the study, it is recommended that a shuttle service for UPD be implemented since it would be beneficial to a significant amount of UPD personnel. With more than 80% of the total population living outside the campus, the number of trips to and from UPD is a substantial factor in the travel demand inside and adjacent to the university. If a staggered approach is needed, it is recommended to start with the Teachers Village, Katipunan, and SM North terminals since they are expected to have the highest demand. Based on peak hour demand, the operation of these three terminals would need 17-20 shuttle trips. During the average operating hours, about 12 shuttles is needed for the three terminals to operate at the desired level. To shift more users currently using public transport, the fare must be set to as low as possible. To convert more private mode users, the waiting time or the time headway between shuttles must be reduced by using more units and proper scheduling based on demand distribution. The initial implementation would help serve as baseline studies to see how much of the expected demand is realized and understand what can be done to improve the services.

Another recommendation is to increase the number of available student, faculty, and staff housing within the campus. Not only will it help reduce off-campus trips, but the results of the study also show that the resulting shorter trips will encourage more active transport usage.

In reaction to the current COVID-19 pandemic, the government has promoted the use of shuttle services to prevent students and employees from contracting the virus (Department of Transportation, 2020). The mandates of physical distancing will reduce the capacity of the shuttle service per vehicle. This will increase the number of units needed to maintain the assumed waiting time in between vehicles. That said, the demand may also be reduced because of the work-from-home and distance learning policies developed in response to the pandemic.

5.3 Recommendations for Further Studies

The next logical study to conduct would be a willingness to pay study to determine the fare at which users are comfortable of paying without a significant decrease in willingness to shift. Studies on route selection and scheduling could also be conducted. These would help determine optimal routes by looking at different scenarios such as multi-stop service versus point-to-point service. The access of each user from their specific home to the terminals in terms of trip distance and mode can also be studied. Studies on other terminals can also be conducted. Of particular concern are the other CBDs such as Makati and Alabang where some graduate students work before going to UPD. This could be part of a study that focuses on work origins instead of home-based trips as basis. Determining the number of shuttles needed per terminal at different times of day based on an analysis of the temporal distribution of trips would also be an important step in improving the shuttle service.

The logistic regression models could also be further studied by varying different aspects of the shuttle service such as comfort level, available seating, and other levels of time headway. Different parameters can also be added such as parking availability, time of day and day of the week at which the trip is conducted, and weather condition to see their effect on the probability of shifting to the proposed service. These can also help fine tune the models if these added parameters are found to be significant. The accuracy of the input variables such as trip time, trip cost, and current mode choice can also be improved by using travel diary and travel time surveys.

The effect of the implementation of the shuttle such as on the number of cars, percentage of parking spaces occupied, number of riders in jeepneys from outside the campus, and boarding and alighting patterns, air quality, noise levels, and active mode usage can also be investigated.

The effects of the “new normal” or the change in travel demand and patterns brought about by the current pandemic for the UPD community should also be studied to update the results of this research. The University setting is particularly affected due to the implementation of work-from-home and study-from-home programs. The willingness to shift could be affected since the general attitudes towards distancing and mode availability have changed. The fare rates might also change due to reduced capacity from operating the physical distancing policies.

REFERENCES

Agyemang, E. (2017). Mode choice for long distance trips: Evidence from the Greater Accra Metropolitan Area of Ghana. *Journal of Transport Geography, 64*, 150-157.

Albert, G., & Mahalel, D. (2006). Congestion Tolls and Parking Fees: A Comparison of the Potential Effect on Travel Behavior. *Transport Policy, 13*(6), 496-502.

Allard, R. F., & Moura, F. (2019). Effect of transport transfer quality on intercity passenger mode choice. *Transportation Research Part A: Policy and Practice, 109*, 89-107.

Arhin, S. A., Ptoe, P. E., Gatiba, A., Anderson, M., Ribbisso, M., & Manandhar, B. (2019). Acceptable Wait Time Models at Transit Bus Stops. *Engineering, Technology & Applied Research, 9*(4), 4574-4580.

Asinas, R. J., Diaz, C. E., & Lidasan, H. S. (2017). Designing Employee Shuttle Service Program for Employees in Makati Central Business District. *Journal of the Eastern Asia Society for Transportation Studies, 12*, 2362-2375.

Canary, J. D., Blizzard, L., Barry, R. P., Hosmer, D. W., & Quinn, S. J. (2017). A comparison of the Hosmer–Lemeshow, Pigeon–Heyse, and Tsiatis goodness-of-fit tests for binary logistic regression under two grouping methods. *Communications in Statistics - Simulation and Computation, 46*(3), 1871-1894.

Dave, S. M., Raykundaliya, D. P., & Shah, S. N. (2013). Modeling trip attributes and feasibility study of co-ordinated bus for school trips of children. *Procedia - Social and Behavioral Sciences, 104*, 650 – 659.

De Guzman, M., & Diaz, C. E. (2005). Analysis of mode choice behavior of students in exclusive schools in Metro Manila: the case of Ateneo De Manila University and Miriam College. *Proceedings of the Eastern Asia Society for Transportation Studies, 5*, 1116 - 1131.

Department of Transportation. (2020, May 29). *Public Transport Guidelines and Protocols for the 'NEW NORMAL'.* Retrieved May 2020, from http://dotr.gov.ph/55-dotrnews/1558-read-as-various-areas-in-the-country-prepares-to-shift-from-modified-enhanced-community-quarantine-mecq-to-general-community-quarantine-gcq-the-new-normal.html

DoTr, DILG, & LTFRB. (2017). *Local Public Transport Route Plan Manual Volume 1.*

Farhan, B., & Murray, A. T. (2005). A GIS-Based Approach for Delineating Market Areas for Park and Ride Facilities. *Transactions in GIS, 9*(2), 91– 108.

Field, A. (2009). *Discovering Statistics using SPSS* (3rd ed.). London: SAGE Publications Ltd.

Frisch, R. (1934). *Statistical Confluence analysis by Means of Complete Regression Systems* (5th ed.). Oslo: Universitetets konomiske Instituut.

Frost, J. (2017). *Multicollinearity in Regression Analysis: Problems, Detection, and Solutions.* Retrieved May 2020, from Statistics By Jim: https://statisticsbyjim.com/regression/multicollinearity-in-regression-analysis/

Glen, S. (2016, August 28). *Hosmer-Lemeshow Test: Definition.* Retrieved June 2020, from Elementary Statistics for the rest of us!: https://www.statisticshowto.com/hosmer-lemeshow-test/

Gokmen, S., Dagalp, R., & Kilickaplan, S. (2020). Multicollinearity in measurement error models. *Communications in Statistics - Theory and Methods*.

Guo, Z., & Wilson, N. H. (2011). Assessing the cost of transfer inconvenience in public transport systems: A case study of the London Underground. *Transportation Research Part A, 45*, 91-104.

Kaplan, D. H. (2015). Transportation sustainability on a university campus. *International Journal of Sustainability in Higher Education, 16*(2), 173-186.

Katoshevski-Cavari, R., Bak, N., & Shiftan, Y. (2018). Would free park-and-ride with a free shuttle service attract car drivers? *Case Studies on Transport Policy, 6*(2), 206-213.

Li, M., Song, G., Cheng, Y., & Yu, L. (2015). Identification of Prior Factors Influencing the Mode Choice of Short Distance Travel. *Discrete Dynamics in Nature and Society*.

Manoj, M., & Verma, A. (2016). Effect of built environment measures on trip distance and mode choice decision of non-workers from a city of a developing country, India. *Transportation Research Part D: Transport and Environment, 46*, 351-364.

Mather, J. J. (1983). Guidelines and Standards for the Planning, Design, and Operation of Bus Park-and-Ride Facilities. *Transportation Research Record 908*, 1-6.

Mirandilla, C. S., & Regior, J. R. (2019). Assessment of Transportation Network Vehicle Services from the Drivers' Perspective. *Journal of the Eastern Asia Society for*

Transportation Studies, 13, 2369-2389.

Monchambert, G. (2020). Why do (or don't) people carpool for long distance trips? A discrete choice experiment in France. *Transportation Research Part A: Policy and Practice, 132*, 911-931.

Pangilinan, F. P. (2019, July 24). Senate Bill No. 775. *An Act Providing for a Magna Catra for Dignified Commuting, Creating the National Office of Commuter Affiars, Appropriating Funds Therefor, and for Other Purposes*. Pasay.

Paulley, N., Balcombe, R., Mackett, R., Titheridge, H., P. J., Wardman, M., . . . White, P. (2006). The Demand for Public Transport: The Effects of Fares, Quality of Service, Income and Car Ownership. *Transport Policy, 13*(4), 295-306.

Peralta, M. H. T., Castro, J. T., Fargas, D. C., & Martinez, K. P. (2021). *Locating Off-campus Shuttle Service Terminals for a University using Address Cluster Analysis*. Manuscript submitted for publication.

Poole, R. (1994, April 1). *Shuttle Vans.* Retrieved May 2020, from reason Foundation: https://reason.org/policy-study/shuttle-vans/

Profillidis, V., & Botzoris, G. (2019). *Modeling of Transport Demand* . Amsterdam: Elsevier.

Pucher, J., Komanoff, C., & Schimeck, P. (1999). Bicycling renaissance in North America? Recent trends and alternative policies to promote bicycling. *Transportation Research A, 33*, 625-654.

Satiennam, T., Jaensirisak, S., Natevongin, N., & Kowtanapanich, W. (2011). Public transport planning for a motorcycle dominated community. *Journal of the Eastern Asia Society for Transportation Studies*, 970-985.

Scheiner, J. (2010). Interrelations between travel mode choice and trip distance: trends in Germany 1976–2002. *Journal of Transport Geography, 18*(1), 75-84.

Shaaban, K., & Kim, I. (2016). The influence of bus service satisfaction on university students' mode choice. *Journal of Advanced Transportation, 50*, 935-948.

Shannon, T., Giles-Corti, B., Pikora, T., Bulsara, M. S., & Bull, F. (2006). Active Commuting in a University Setting: Assessing Commuting Habits and Potential for Modal Change. *Transport Policy, 13*(6), 240-253.

Shiftan, Y., Vary, D., & Geyer, D. (2006). Demand for park shuttle services—a stated-preference approach. *Journal of Transport Geography, 14*, 52-59.

Smith, T. J., & McKenna, C. M. (2013). A Comparison of Logistic Regression Pseudo R2 Indices. *Multiple Linear Regression Viewpoints, 39*(2), 17-26.

Subingsubing, K. (2018, October 24). *LTFRB: UV Express overcharging riders.* Retrieved from inquirer.net:https://newsinfo.inquirer.net/1046250/ltfrb-uv-express-overcharging-riders

Tapiador, F. J., Burckhart, K., & Martí-Henneberg, J. (2009). Characterizing European high speed train stations using intermodal time and entropy metrics. *Transportation Research Part A, 43*, 197-208.

Tiglao, N. C., & Patdu, I. T. (2007). Issues and Directions on Integrated Public Transport in Metropolitan Manila. *Proceedings of the Eastern Asia Society for Transportation Studies. 6.* Eastern Asia Society for Transportation Studies.

van der Waerden, P., Timmermans, H., & Bérénos, M. (2008). Trip Characteristics and Travelers' Willingness to Change Transport Mode in Favor of Public Transport. *Bijdrage aan het Colloquium Vervoersplanologisch Speurwerk.* Santpoort-Noord.

Victoria Transport Policy Institute. (2015, September 29). *Campus Transport Management.* Retrieved May 2020, from TDM Encyclopedia: https://www.vtpi.org/tdm/tdm5.htm

Volosin, S. E. (2014). *A Study of University Student Travel Behavior.* Tempe: Arizona State University. Retrieved June 2020, from https://repository.asu.edu/attachments/143315/content/Volosin_asu_0010E_14461.pdf

Wang, X., Khattak, A. J., & Son, S. (2012). What Can Be Learned from Analyzing University Student Travel Demand? *Transportation Research Record Journal of the Transportation Research Board, 2322*, 129-137.
Wardman, M. (2004). Public transport values of time. *Transport Policy 11*, 363–377.
Zhang, J., Wang, D. Z., & Meng, M. (2018, December). Which service is better on a linear travel corridor: Park & ride or on-demand public bus? *Transport Research Part A: Policy and Practice, 118*, 803-818.

ANNEX – Variables used in Binary Logistic Models

Table A.1 [Age] Age Brackets Used

Age Bracket
15-19
20-29
30-39
40-49
50-59
60 and above

Table A.2 [Occupation] Numerical Code Equivalent for Occupation

Occupation	Code
Undergraduate Student (UG)	1
Graduate Student (G)	2
Faculty (F)	3
Admin. Staff (S)	4
Research, Extension, and Professional Staff (R)	5

Table A.3 [Income] Average Annual Household Income Cohorts

Income
Less than ₱ 150,000
₱ 150,000 - 300,000
₱ 300,000 - 450,000
₱ 450,000 - 600,000
₱ 600,000 - 750,000
More than ₱ 750,000

Table A.4 [Frequency] Numerical Code Equivalent for Frequency of Trips

Frequency	Code
1-2 days a week	1
3-4 days a week	2
5 days a week	3
More than 5 days a week	4

Table A.5 [Arr Time/ Dep Time] Arrival and Departure Times

Time
7-8 AM
8-9 AM
9-10 AM
10-11 AM
11-12 NN
12-1 PM
1-2 PM
2-3 PM
3-4 PM
4-5 PM
5-6 PM
6-7 PM
7-8 PM
8-9 PM

Table A.6 Arrival and Departure Modes Considered

Trip Mode
Own car/ family car/ motorcycle
Jeepney
Bus
UV Express
Tricycle
TNVS (e.g. Grab, Angkas, etc.)
Taxi
MRT/ LRT/ PNR
Bicycle/ Walking