Impact of Traveler Information on Mode Choice Behavior

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Abstract: This paper analyzed auto commuter’s mode choice behavior under influence of simulated multimodal traveler information by developing two logit models. A combined Revealed Preference (RP) / Stated Preference (SP) travel behavior survey is administered on auto drivers to gather individual commuter’s travel decisions under integrated multimodal traveler information. Two SP scenarios are designed where the first scenario is to test the mode choice preference in a basic situation involving a congested work/school trip with information on several travel options, and the second scenario is to investigate the mode choice decision when certain incentives are given to public transport. Results showed that integrated multimodal traveler information can influence traveler’s mode choice decision. The influence factors that significantly affect the mode choice decision include socio-economic characteristics e.g. gender, age, level of education, and level of income, and multimodal traveler information attributes e.g. access mode to mass rapid transit (MRT) station, access time to MRT station, and transit seat availability. The findings are useful to traffic management agencies to better deign operational policy and information publication strategies.

Key words: integrated traveler information; multi-modal transportation; mode choice; logit model

1 Introduction

Integrated traveler information as provided by traffic control center serves to assist travelers to better plan their trips. By leveraging on the most up-to-date information on network congestion, availability and status of transit modes, opportunities for easy transfer and parking availability, travelers can make smart travel decision, such as adjusting the travel mode, route and departure time, which shall result in saving travel time and alleviating traffic congestion.

A number of studies have attempted to explore the potential of traveler information provisions on influencing the ways commuters normally travel (Bifulco et al., 2011; Parvaneh et al., 2012). Jou et al. (2005) found that the effectiveness of traveler information depends on the types and format of how it is disseminated. Guo (2011) reported that travelers who use public transit had significant tendency to use the public transit information. Chorus et al. (2013) found that travelers pay more attention to the information type and the information cost. Travelers with high level of education spend less money than those with only primary school education for acquiring the traveler information. Research has also been conducted on the impacts of ATIS (Advanced Traveler Information System) on travel behavior, being mainly focusing on the study of auto commuter's route choice behavior. The important factors that influence route choice include system performance attributes such as trip time and congestion; experiential factors such as scheduled delay and familiarity (Buliung et al., 2007) and the nature, extent, and quality of ATIS information (Adler, 2001; Golob, 2003; Qin et al., 2013). ATIS information also indirectly influences route choice through users' expectations of system performance and their perception of feedback on actual performance measures on alternative routes (Bradley, 2006).

However, the afore-mentioned studies did not focus on the impacts of traveler information on commuter's travel choice behavior, as highlighted by Lam and Memon (2003), Zito et al. (2011), and Balakrishna et al. (2013). More specifically, the interactions among mode choices, among others, were not satisfactorily captured in most studies, especially when the dynamic nature of traffic flows on the road network is considered. Furthermore, in most studies, the impacts of traveler information were observed by providing mode-specific information to designated mode users, e.g. the impacts of ATIS were analyzed by providing traveler information regarding the private modes to private mode users only (Farag and Lyon, 2008, 2012; Kenyon, 2003). In such a framework, where the information is provided for specific modes only, the possibility to study the auto's mode choice behavior is very limited (Chorus et al., 2006). Considering the existing multimodal nature of transportation systems, e.g. in urban metropolises like Singapore, where the availability of different modes and the provision of integrated traveler information allows the commuters to plan their trips by integrating different modes or to choose between public and private modes of travel, it becomes relevant to study the commuter's mode choice behavior (Luk and Yang, 2003). As such, this research sets out to explore a more efficient way to estimate the effects of multimodal traveler information, given by an information system like Advanced Multimodal Traveler Information Systems (AMTIS), on commuter's mode choice behavior and how it quantitatively affects the transport network.

The objective of this research study is to improve the understanding on travel characteristics of auto commuters in a multimodal transportation network and their behavior and preferences towards mode choice under integrated traveler information, using Singapore as a case study. The following sections are organized as follows: travel behavior survey is briefly described in Section 2. The preliminary analysis on the mode choice preference is discussed in Section 3. A detailed investigation regarding the influence of integrated traveler information is provided in Section 4. Lastly, conclusions are outlined in Section 5.

2 Travel behavior survey

The commuters' mode decisions are usually dependent on their socio-economic characteristics and travel attributes. It is thus important to understand the sensitivity of these attributes and their influence on individual's mode choice behavior. To achieve such an understanding, a travel behavior survey was conducted. The goal of the survey was to analyze the commuters' travel behavior under the influence of traveler information.

In this regard, two kinds of survey technique were used in this paper: revealed preference (RP) survey and stated preference (SP) survey to gather the commuters' travel choice decisions with respect to public versus private modes in congested but information-rich multimodal transportation environment, specifically considering the influence of integrated traveler information. In the RP section, data on actual choices were obtained from the respondents, so as to facilitate the selection of a reference trip for subsequent SP questions. In the SP section, the selected reference trip was customized in different SP scenarios for each individual respondent. These SP scenarios were then presented to the respondent for which the responses were recorded.

Implementing a valid and reliable RP and SP study requires precise definitions of attributes, attention to presentation of preferential information (ratings, rankings, or semantic), efficient experimental design, and rigorous statistical analysis. Given the researchers' intention to use the RP and SP data jointly, the desired data were provided in semantic format, and the choice experiment appeared the most suitable because: (a) preferences are expressed in a context similar to that of an RP survey; (b) choices are perceived to be more realistic than ratings or rankings, and (c) SP method allows in principle to test any discrete choice model structure. In spite of the fact that the choice context was quite typical, in order to ensure greater realism and reliability, a computer-assisted survey instrument was designed. Such an approach provided the facility to customize each SP scenario for every specific respondent, according to the information provided in the RP section during the surveys.

The RP component was divided into four parts in which information about auto commuter's socio-economic characteristics, usual trip preferences, availability and usage of public and private modes were collected. The information gathered in RP component was then presented in the SP component while creating different hypothesized scenarios. The hypothesized scenarios were customized for each respondent based on the information provided in the RP section. This approach resulted in creating realistic scenarios which can be conceptualized by the auto commuters as they reflected on certain parameters which existed in actual situations. There were 2 SP scenarios, which were designed to collect the information on: the mode choice preference (SP1), and the mode choice behavior under certain incentives on public transport (SP2). The mass rapid transit (MRT) which is the railway system spanning the entire island state represented the public transit transport in the survey.

The survey instrument was designed and developed using Visual Basic and Microsoft Access. A pilot survey was conducted to ensure that the survey questionnaire was well designed and to provide training to the survey staff. After the questionnaire was amended to satisfaction, the main survey was conducted. Surveyors were assigned to different locations in Singapore to collect data with portable computer notebooks. The participants were randomly selected within a continuous nine-day period, which served to cover all differential influences (by days of the week inclusive of weekend) of external events. A broad demographic mix of participants was selected to ensure that commuters in all major categories were represented.

The subjects were selected from the driver population located in the northern and eastern sides of Singapore. The selected subjects were required to have valid driving license, and commute regularly by private mode of transport. The central and northern parts were selected due to the reason that the transportation network simulation model mainly covered these parts of Singapore. The participants were contacted by the interviewers at various locations such as petrol stations, car parks of shopping centers, and food centers. The surveys took place when the subjects drove to these locations to fill up petrol, to do shopping or to have their meals. The discussions with the participants were firstly aimed at highlighting the modal choice and travel behavior to give an understanding of the decision-making process for the current modal choices. Then the use and influence of multimodal traveler information on the travel behavior and modal choice was discussed. After which they were required to provide their personal characteristics, and details about their usual travel plans. Later, hypothetical scenarios representing different traveler information schemes were presented to them and their preferences were gathered. Available data were collected from a total number of 479 respondents.

3 Mode choice preference modeling

3.1 Variables selection

To justify the model variables, a general analysis is conducted. The respondents' socio-economic characteristics that were collected in the survey include: gender, age, level of education, level of income, car ownership, stoppage[1], Electronic Road Pricing (ERP), and acceptable delay. The impact of each variable on respondent's mode choice is presented in

[1] Stoppage refers to a regular compulsory stop that the car driver makes to drop off kids at school, spouse at work, or have breakfast before reaching his/her destination.

Table 1, in which the information is provided about the market segment of each socio-economic variable, distribution with respect to each mode of transport, and the details of respondents' mode switching behavior.

Table 1. Influence of Socio-Economic Characteristics of Auto Commuters on Mode Choice Behavior

Socio-Economic Variables (Code)		Market Segment (Car Users)	Mode Choice (Number)		Mode Choice (%)	
			Switch to Public	Continue with Private	Switch to Public	Continue with Private
Gender	Female (0)	220	106	114	48.18	51.82
	Male (1)	259	45	214	17.37	82.63
Age (years)	18-35 (0)	48	8	40	16.67	83.33
	36-45 (1)	186	104	82	55.91	44.09
	46-55 (2)	235	37	198	15.74	84.26
	Above 55 (3)	9	1	8	11.11	88.89
Education	A Level[2] (0)					
	Bachelors (1)	75	55	20	73.33	26.67
	Masters (2)	142	67	75	47.18	52.82
	PhD (3)	162	24	138	14.81	85.19
Income (S$) / Month)[3]	Below 1501 (0)	100	5	95	5	95
	1501 -3000 (1)	23	4	19	17.39	82.61
	3001-6000 (2)	69	25	44	36.23	63.77
	6001-12000 (3)	174	56	118	32.18	67.82
	Above 12000	186	59	127	31.72	68.28
Car Ownership	Yes (1)	418	128	290	30.62	69.38
	No (0)	60	23	37	38.33	61.67
Stoppage	Yes (1)	4	0	4	0	100
	No (0)	475	151	324	31.79	68.21
Pay ERP	Yes (1)	285	82	203	28.77	71.23
	No (0)	194	70	124	36.08	63.92
Acceptable Delay (min)	5 (0)	161	43	118	26.71	73.29
	10 (1)	229	82	147	35.81	64.19
	15 (2)	90	27	63	30	70

The mode switching column reflects the comparative percentage of mode switching

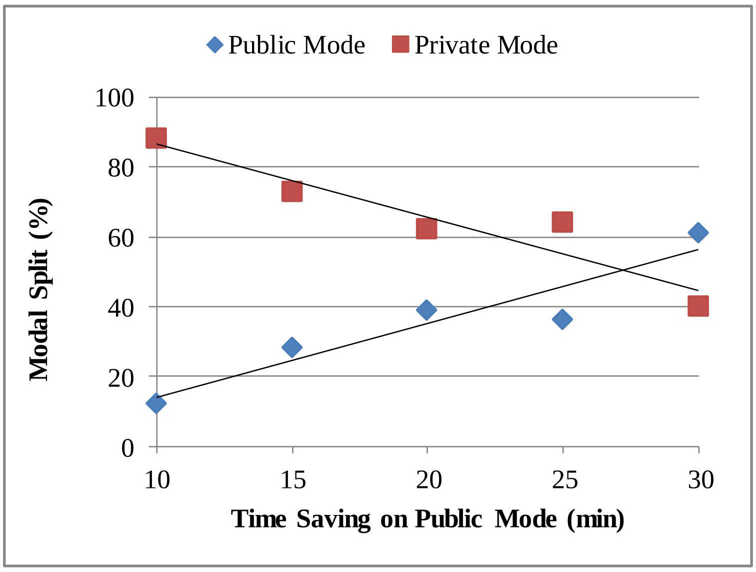
[2] "A" Level in Singapore is pre-university education

[3] The median income in Singapore is S$3480 in 2012 based on the income summary table on Ministry of Manpower's website (http://stats.mom.gov.sg/Pages/Income-Summary-Table.aspx). S$ 1≈ US $ 0.8. Singapore's Big Mac index is -17, popularized by *The Economist.*

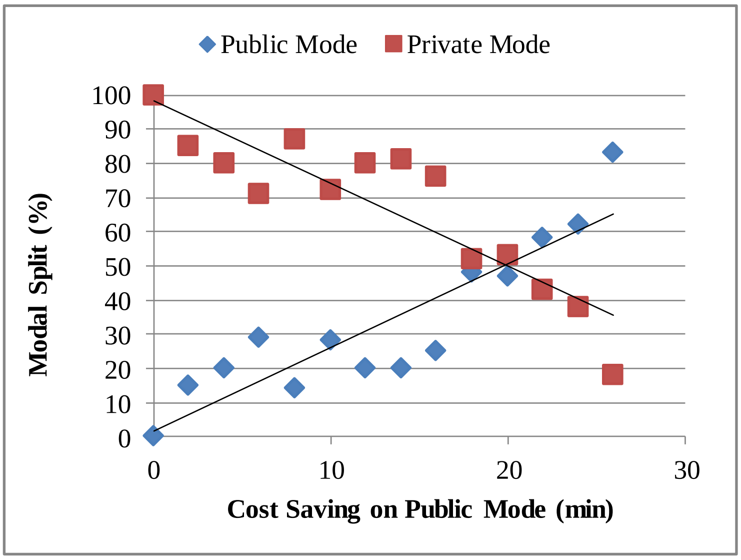
respondents within the specific category, e.g. based on the gender category, about 48% of the females exhibited certain degrees of mode switching behavior, whereas for males only 17% of them had any intention of switching their modes of travel. This may imply that females have higher mode switching propensity as compared to females. Similarly, age, education level and income all seems to influence the mode choice behavior.

Car ownership also showed some influence on mode choice behavior. Respondents who did not own cars and drove to work were more inclined to change their mode as compared to those who did own cars. On the other hand, respondents who made regular stops were less willing to change their mode of transport. Such behavior can be due to the commitment that they might have such as dropping their kids at school or dropping their spouses at work. Surprisingly, those who did not have to pay ERP were more inclined towards mode switching. It can be observed that acceptable delay did influence the mode switching behavior, but not in direct relation to the magnitude of delay. By aggregating the data into two groups based on gender i.e. male and female, the influence of age, education, and income on mode choice behavior can be further analyzed.

Two factors regarding the travel characteristics namely estimated time saving and estimated cost saving are recorded in the survey. The empirical findings as presented in Figure 1 show that information on both two factors attracted the respondents to switch from their usual mode. Information on increase in estimated time saving attracted the commuters towards higher degree of mode switching propensity, while the increase in cost saving also attracted the respondents to change their mode of transport.



(a)



(b)

Figure 1. Impact of Estimated Time and Cost Saving on Auto Commuters' Mode Switching Propensity

To further explore the impact of public (transit) mode facility, respondents were given information on transit waiting time and seat availability. The impact of waiting time and seat availability is shown in Figure 2. It can be observed that information on waiting time and seat availability both had significant influence on the mode switching propensity. A high proportion of the respondents i.e. 51% choose transit mode when they were given the information that the waiting time was 1 minute and seats were available, whereas 50% of the respondents chose transit mode with same waiting time, but without the availability of seats. At a lower waiting time, the seat availability did not show any significant impact on mode switching propensity. It reflects that commuters expect a higher level of service when waiting times are longer, and make a trade-off between the transit level of service and their usual mode of travel, while making any mode switching decision.

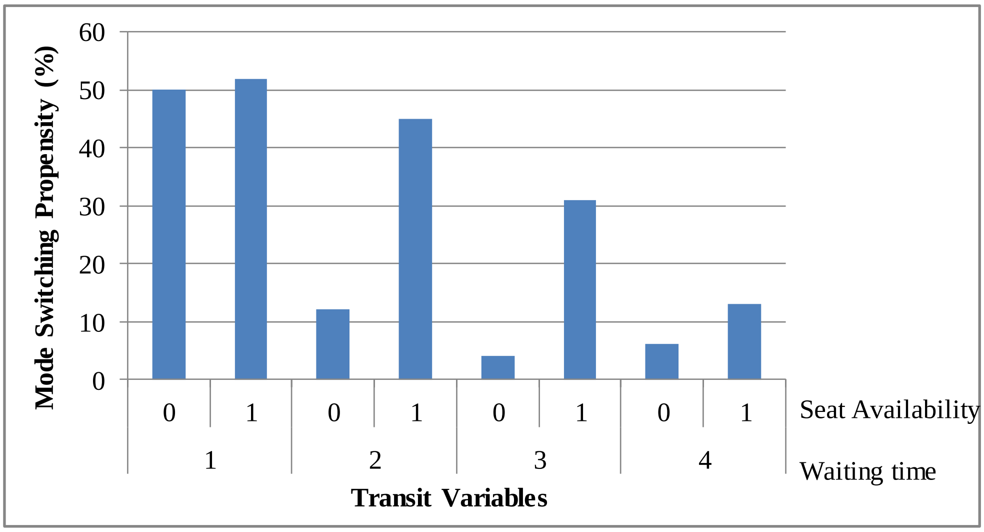


Figure 2. Impact of Waiting Time (min) and Seat Availability (1 if seat is available, else 0) on Mode Switching Propensity

3.2 Binary logit model development

In order to extend the study on the impact of integrated traveler information on auto commuter's mode choice behavior, it is necessary to identify whether the integrated traveler information can influence auto commuter's willingness to switch his/her mode of travel in congested road environment or not. The auto commuter's personal and travel characteristics that may influence the mode choice decisions, under the influence of multimodal traveler information, shall be discussed firstly. With only public and private mode data in consideration, a binary logit model was estimated to analyze the effect of socio-economic and travel characteristics.

The scenario SP1, which refers to a congested work/school trip with information on several travel options, was administered and the respondents were given a choice between private car on expressway, public rail transit, and their usual choices of transport (no inclination to make a choice for the latter). The total number of useable responses was 400, out of which 245 selected private (car) mode of transport, and 115 selected public (transit) mode of transport, and 40 opted for their usual pattern of travel. Excluding the 40 responses, the remaining 360 responses were used for estimating the model. With public and private mode data in consideration, binary logit models were developed based on two types of input parameters; the first was related to the auto commuter's socio-economic characteristics, and the second was related to transport facility characteristics. Different socio-economic and transport facility related variables were considered while estimating the model, and based on their levels of significance some of them were incorporated into the final model, in which the socio-economic variables used were: gender, age, level of education, and level of monthly personal income. The transport facility characteristics were total trip time, and total travel cost. The estimated mode choice model is presented in Table 2.

Table 2. Binary Logit Model Estimating the Commuter's Mode Choice Behavior under Multimodal Traveler Information

Socio-Economic Characteristics	Coefficients (β)	t-Statistics
Constant	11.531	1.941
Gender (ref=female)	2.472	1.863
Age (ref=age group 18 to 35 years)	1.921	1.958
Level of education (ref= "A" level and below)	2.076	2.735
Level of income (ref = income group less than	0.503	1.832

S$1500)

Transport Facility Attributes	Coefficients (β)	t-Statistics
Travel time	-3.36	-2.464
Travel cost (S$)	-0.985	-1.937
Summary Statistics		
Number of observations		360
Log likelihood function		-11.39
Restricted log likelihood		-249.53
Degrees of freedom		354
χ^2		100.665
ρ^2		0.815

All the estimated coefficients were significant at the 10% significance level. The value of ρ^2 was very high, and it implied that the model could describe the mode choice process well. The utility functions for the private (U_{PR}) and public (U_{PB}) modes of transport were:

$$\begin{aligned} U_{PR} = {} & 11.531 - 3.361(\mathit{Travel\ Time})_{PR} - 0.985(\mathit{Cost})_{PR} + 2.472(\mathit{Gender}) \\ & + 1.921(\mathit{Age}) + 2.076(\mathit{Education}) + 0.503(\mathit{Income}) \end{aligned} \tag{1}$$

$$U_{PB} = -3.361(\mathit{Travel\ Time})_{PB} - 0.985(\mathit{Cost})_{PB} \tag{2}$$

The results as presented in Table 2 showed that in a non-congested road environment, auto commuters preferred to take private mode of transport, but with increase in travel time the likelihood of taking private mode of transport decreased. The constant term reflected that, if all the variables in Eq(1) and Eq(2) were equal, the auto commuters would choose private mode of transport, which corroborated with other study results. It may be due to the higher level of comfort and freedom in car mobility (Beirão and Cabral, 2007; De Witte et al., 2013). Among the socio-economic variables, the coefficient for gender had a positive sign, which reflected that males were more inclined to use private mode as compared to females. It may be that men had higher access to vehicles. Similarly, the estimated coefficients for age, income and education had positive sign, which reflected that with the increase in age, income and education the probability of choosing private mode became higher. Thus, it can be concluded that in a congested environment and with higher car cost, auto commuters who belonged to younger age groups, lower income groups and lower level of education might show higher likelihood towards public mode of transport, which is more reliable than private car in Singapore under congestion condition. Higher income commuters have lower probabilities of choosing public transit, which might be attributed to comfort consideration, ready availability of a car and lesser sensitivity to travel cost. The public mode of transport has two main attributes: travel time and travel cost. In a congested environment, the transit mode may be attractive if it has a shorter travel time and lower travelling cost as compared to the private mode of transport. The public mode can become attractive by increasing the travelling cost of private mode. For example, increasing the Electronic Road Pricing (ERP) or parking charges can directly increase the attraction of public mode of transport.

The estimated model shown in Table 2 indicates a potential for multimodal traveler information to influence auto commuters mode switching propensity from private to public mode of transport. In essence, all the surveyed socio-demographic attributes affect the auto commuter's mode switching propensity; these attributes are: gender, age, education, income, travel time and travel cost.

4 Impact of integrated traveler information on commuter's mode choice behavior

This section examines the impacts of integrated traveler information on auto commuter's mode choice behavior in a congested travel environment. In this regard, the auto commuters were presented with a hypothesized scenario (SP2), which presented the same delayed work/school trips along with the integrated traveler information as in SP1. But in this scenario (SP2), certain incentives were given to public mode of transport. The information provided by the auto commuters regarding the access time to public mode of transport was randomly reduced by 10%, 30%, and 50%. Similarly, the parking cost and ERP charges were randomly increased by 50%, 75%, and 100%. The auto commuters were given a choice between private mode, public mode, and their usual mode of transport. A total of 400 commuters participated, and they were those commuters who had either chosen private mode or public mode of transport in the previous SP. A binary logit model was developed to capture the mode choices based on two types of input parameters; the first one was related to the commuter's socio-economic characteristics, while the second one was related to transport facility characteristics.

Different socio-economic and transport facility related variables were considered while estimating the model, and based on their levels of significance some of them were incorporated into the final model. The levels of each transport facility attribute were entered into the model and were assumed to be provided by an AMTIS according to the SP design. This effort would enable the identification of two important aspects of the disseminated integrated traveler information. First, the usage of the provided information by the commuters, and second the significant attributes that are considered important by the commuters. The sign convention, estimated coefficient values, and their corresponding significance levels, are presented in Table 3. All the included variables were significant at 90% confidence level. The likelihood static ratio shows that the model was significantly different from the null or intercept-only (or know-nothing) model by the χ^2 value (74.8 with 10 degrees of freedom). All the variables have coefficients significantly different from 0, as judged by the size of β relative to its estimated asymptotic standard error, and further indicated by the column labeled

P, which gives the upper bound of the probability of making Type 1 error. The lower value of log likelihood function and the estimated value of ρ^2 reflect the robustness of the estimated model (Cramer, 1999; Rana et al., 2010). These test statistics show that the model can describe the mode choice process well.

Table 3. Mode Choice Logit Model Estimating the Commuter's Mode Choice Behavior, given Integrated Multimodal Traveler Information

Socio-Economic	β	t-Stat	SE	P
Constant	5.731	2.253	2.544	0.024
Gender (ref=male)	-1.97	-1.833	1.075	0.067
Age (ref=age group 18 to 35 years)	1.929	3.016	1.303	0.003
Level of education (ref= "A" level and below)	1.137	2.066	0.55	0.039
Level of income (ref = income group less than S$1500)	1.402	2.287	0.613	0.022
Transport Facility Attributes	β	t-Stat	SE	P
Access mode to MRT station (ref=walk)	2.478	2.108	1.176	0.035
Access time to MRT station	1.759	1.65	1.087	0.105
Waiting time at MRT station	2.514	2.212	1.137	0.027
Seat availability (ref= seat is not available)	-3.161	-2.163	1.462	0.031
Travel time difference (min)	-0.656	-2.172	0.302	0.03
Travel cost difference(S$)	-0.33	-2.585	0.128	0.01
Summary Statistics				
Number of observations				400
Log likelihood function				-56.343
Restricted log likelihood				-225.522
Degrees of freedom				390
χ^2				74.808
ρ^2				0.663

The utility functions for the private (U_{PR}) and public (U_{PB}) modes of transport are:

$$U_{PR} = 5.731 - 0.665(\textit{Travel Time Difference}) - 0.330(\textit{Travel Cost Difference}) \\ -1.970(\textit{Gender}) + 3.929(\textit{Age}) + 1.137(\textit{Education}) + 1.402(\textit{Income}) \tag{3}$$

$$U_{PB} = -2.478(\textit{Access Mode}) - 1.759(\textit{Access Time}) \\ - 2.514(\textit{Waiting Time}) + 3.161(\textit{Seat Availability}) \tag{4}$$

The estimated model consists of one alternative specific constant, four socio-economic variables, and six transport facility attributes. The sign convention of each variable provides the information from which the commuters' mode switching behavior can be analyzed. The positive value of alternative specific constant shows that the commuters' tended more towards the private mode of transport as compared to public mode. The model results show that female commuters were more likely to continue using their usual modes of transport as compared to male commuters. Such behavior can be interpreted as follows: with the provision of information, male commuters showed higher tendency of switching from private to public mode of transport as compared to females. This may be due to a lower tolerance level of congestion among males. Higher age group commuters with high level of education showed higher tendency to use private mode. It could be due to their cohort's value as discussed in Sun et al. (2012), and/or the level of comfort and/or privacy that they may desire with respect to their socio-economic status. The commuters with lower income level tended to switch from private mode to public mode. This may be due to cost saving, as the parking cost and ERP charges were increased in the scenario presented to respondents.

Among the transport facility attributes, commuters prefer to have MRT stations nearby their residence, within their walking distance, as walk is the preferred access mode. It can be due to the reason that travelling by bus to MRT stations increases the overall waiting time and the number of transfers. Lower access time is preferred, as it can save the effort utilized in travelling. Commuters naturally prefer less waiting times. Increased waiting time at MRT stations decreases the tendency to take public mode of transport.

The negative signs of Travel Time Difference (TTD) and Travel Cost Difference (TCD), which refer to the travel time difference between private and public modes of transport, and travel cost difference between private and public modes of transport, show that commuters' likelihood of mode switching can be increased by increasing the absolute values of these variables. The TTD and TCD can be estimated as:

$$TTD = TT_{PR} - TT_{PB}, \text{ and} \tag{5a}$$

$$TCD = TC_{PR} - TC_{PB}, \tag{5b}$$

where TT_{PR} is the travel time by private mode of transport, TT_{PB} is the travel time by public mode of transport, TC_{PR} is the travel cost by private mode of transport, and TC_{PB} is the travel cost by public mode of transport. Increasing the value of travel time on private mode of transport as compared to public mode of transport would increase the TTD, resulting in less likelihood for the private mode of transport. In other words, increasing the value of TTD would result in higher mode switching as compared to a lower value TTD. Thus, by analyzing the TTD and TCD, it is can be inferred that increasing travel time or cost on any mode will decrease its utility. Furthermore, increase in travel time or cost of private mode would enhance commuters' mode switching propensity.

4.1 Marginal Effect of the Estimated Logit Variables

The exponential values of β give the odds of having an event occurring versus not occurring, per level change in the explanatory variables, other things being equal. The same interpretation applies to both the dummy and the continuous variables. From Table 3, it can be observed that the estimate for gender is -1.97. The resulting exponential value of P, which is exp(1.97)=7.17, indicates that the odds for males are 7.17 times as high as females, to switch their usual mode of travel. Hence, males have higher probability of switching their modes of travel as compared to females.

The level of income has a negative impact on mode switching propensity. Increasing the level of income decreases mode switching, and vice versa. The effect of each stage of income (i.e. 0, 1, 2, 3 and 4) on the odds of maintaining travel usual mode under the influence of integrated traveler information is 1.402.

The transport facility characteristics, the travel time difference and travel cost difference, both affected significantly the auto commuter's mode switching propensity under the influence of the integrated traveler information. It is estimated that each minute increase in travel time difference increases the mode switching propensity by a factor of exp(0.656)=1.927. Similarly, each dollar increase in cost difference increases the mode switching by a factor of exp(0.33)=1.392.

4.2 Predicted Probabilities based on the Explanatory Variables

The predicted probabilities based on the explanatory variables can provide estimates, upon which different policies can be designed and analyzed. It should be noted that variables such as travel time and travel cost can be utilized to design policies which can cause diversion effect on shifting the ridership from private to public mode of transport. There are several measures to reduce travel time by public mode of transport, such as improvement in accessibility or service frequency etc. Similarly, increasing parking cost and ERP charges can directly influence the public mode ridership. To analyze the impact of such policy sensitive variables, pivot point modeling approach was adopted. The results are presented in Table 4.

Table 4. Impact on Modal Split by Increasing Travel Time and Travel Cost of Private Mode of Transport

Unit Change (%)	Travel Time			Travel Cost		
	Private Mode (%)	Public Mode (%)	Diff (%)	Private Mode (%)	Public Mode (%)	Diff (%)
10	80.01	19.99	1.07	80.52	19.48	0.52
20	78.94	21.06	1.07	80	20	0.52
30	77.82	22.18	1.11	79.46	20.54	0.53
40	76.67	23.33	1.15	78.92	21.08	0.54
50	75.48	24.52	1.19	78.36	21.64	0.56
60	74.24	25.76	1.23	77.8	22.2	0.57
70	72.97	27.03	1.27	77.22	27.78	0.58
80	71.66	28.34	1.31	76.64	23.36	0.59
90	70.31	29.69	1.35	76.04	23.96	0.6
100	68.92	31.08	1.39	75.43	24.57	0.61
Average			1.22			0.56

The results in Table 4 reveal that every 10% increase in travel time in private mode, on average, decreased the modal share of private mode by 1.22%. Similarly, every 10% increase in travel cost of private mode decreased its modal share by 0.56%.

4.3 Marginal Effect on the Probability of Commuter's Mode Switching Propensity

Instead of examining the marginal effect of an *x* variable on the odds, one can also examine the marginal effect of the variable on the probability of the event. Such marginal effect is given by the following equation:

$$\frac{\partial \text{Prob}(y=0)}{\partial x_k} = \frac{e^{-\sum_{k=1}^{K}\beta_k x_k}}{\left(1+e^{-\sum_{k=1}^{K}\beta_k x_k}\right)}\beta_k \tag{6}$$

Table 5 present the marginal effects of the variables on the probability of auto commuter's mode switching propensity. Observing the marginal effect column, it can be seen that among the socio-economic variables, the most significant effect is gender and age, followed by income and education respectively.

Table 5. Effects of the Variables on the Probability of Commuters' Mode Switching Propensity

Variable	Coefficient (β)	Mean	Marginal Effect
Socio-economic			
Gender	1.970	0.543	0.725
Age (years)	-1.930	1.491	-0.710
Level of education	-1.137	1.750	-0.418
Level of income (S$)	-1.402	2.241	-0.516
Transport facility			
Access mode to MRT station	-2.479	0.578	-0.912
Access time to MRT station	-1.760	0.750	-0.647
Waiting time at MRT station	-2.514	0.664	-0.925
Seat availability	3.162	0.690	1.163
Travel time difference (min)	0.656	2.414	0.241
Travel cost difference (S$)	0.330	2.202	0.122

Among the transport facility, the sensitive variable is the waiting time for transit service. Each single minute increase in travel time reduces the mode switching propensity by a factor of 0.925. This analysis can also be viewed in another perspective i.e. any improvement in the waiting time reduction can cause a significant impact on transit ridership, such that 1 minute reduction in waiting time will increase the mode switching propensity by a factor of 0.925. A similar kind of effect can be observed for the access time variable. The time difference and cost difference, which in this case represent the time savings and cost savings on public mode of transport respectively, also show positive effect on auto commuter's mode switching propensity.

It can be concluded from this analysis that auto commuters show a certain level of mode switching propensity under the influence of integrated traveler information. Younger male auto commuters with lower level of income are more willing to switch their usual mode as compared to richer and better educated auto commuters. The cost factor also influences the mode choice, such that if the auto commuter belongs to a lower level income group he/she may show higher mode switching propensity. Richer auto commuters with a higher level of education are less willing to switch. The time and cost saving is appreciated by all auto commuters. In time context, auto commuters are more sensitive to waiting time than travelling time. They choose modes with overall shorter journey times. The cost saving enhances the attraction of public mode, which the auto commuters compare with higher private mode cost. Thus, the provision of integrated information regarding the transport facility variables can enhance the mode switching propensity in the auto commuters.

5 Conclusions

The main objective of the travel behavior survey was to determine the factors that influence the commuter’s mode choice decision. It is clear from the estimated travel behavior models (2 SP scenarios) that the socio-economic characteristics that significantly influence the mode choice decision are: gender, age, level of education, and level of income. The attributes related to multimodal traveler information that significantly influence the mode choice decision in congested road environment are: access mode to MRT station, access time to MRT station, and transit seat availability. Estimated time saving, estimated cost saving and waiting time at MRT station also have certain influence on the travel mode choice decision. The information regarding delayed travel time generated the desire in commuters to access multimodal traveler information, and information on estimated time saving allowed the commuters to analyze different modes of travel. Information about transit facility, also significantly influenced the mode choice decision, such that improved transit level of service can increase the transit ridership. The knowledge gathered from the travel behavior survey provides valuable expertise to select variables that significantly influence the mode choice decision.

However, the model still has several limitations. There are also cases where the proposed model could not properly describe the traveler behavior under other situations. For instance, different cities may have different influence factors; certain policy may strengthen or eliminate the effect from certain influence factors. A model cannot be perfect and provide the best fit for all possible cases. Future studies will contribute to better understanding of the traveler behavior in more cases.

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