Influential Factors Affecting Travelers’ Mode Choice Behavior on Mass Transit in Bangkok, Thailand

Phattarasuda Witchayaphong1,*, Surachet Pravinpong1, Kunnawee Kanitpong1, Kazushi Sano2 and Suksun Horpibulsuk3,4

1 Transportation Engineering, School of Engineering and Technology, Asian Institute of Technology, Bangkok 12120, Thailand; spravinpong@ait.ac.th (S.P.); kanitpong@ait.asia (K.K.)
2 Department of Civil and Environmental Engineering, Nagaoka University of Technology, Niigata 940-2188, Japan; sano@nagaokaut.ac.jp
3 School of Civil Engineering, and Center of Excellence in Innovation for Sustainable Infrastructure Development, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand; suksun@g.sut.ac.th
4 Academy of Science, The Royal Society of Thailand, Bangkok 10300, Thailand

* Correspondence: p.witchayaphong@gmail.com; Tel.: +66-2524-5522

Received: 13 October 2020; Accepted: 9 November 2020; Published: 16 November 2020

Abstract: Increasing use of single or fewer occupant vehicles has increased traffic congestion and transport-related emissions. Public transport as mass transit options are increasingly being encouraged amongst travelers to use, as this is an influential strategy to improve the transport network performance. This paper presents a study based on a revealed preference survey conducted on a random sample of 4467 respondents to understand the influential factors affecting the users’ choice of mass transit in Bangkok, Thailand. This study identified an inversely proportional relationship of socio-economic and spatial attributes on public transport mode choice. The binary logit model was employed to compare the utility of private vehicles and mass transit modes. The results showed that gender, age, average income, auto ownership, total travel cost in private transport, total travel time in public transport and distance range from home to mass transit station were the factors that influenced travelers’ mode choice behavior. Moreover, to ascertain the effects of explanatory variables which influence the likelihood of Thai travelers, another binary logit model analysis was utilized by the four distance ranges condition. The studied results showed that there were few significant differences in the propensity to use mass transit. Due to the longer distance of the station, total travel time in public transport was not affected by the Thai travelers mode choice. This research will aid transport authorities and planners to gain knowledge on the impact of socio-economic and spatial behavior of public transport users on their mode choice, resulting in the development in sustainable transport in Bangkok, Thailand.

Keywords: travelers’ mode choice; binary logit model; revealed preference survey; distance ranges condition

1. Introduction

Rapid population growth and economic development have caused a growth in vehicle travel demand in metropolitan areas globally, thus increasing energy consumption and greenhouse gas emission. In fact, the global transport sector was responsible for 31,310 TWh of energy consumption and around 14% of global greenhouse gas (GHG) emissions in 2015 and the demand for this is expected to increase by 260% in 2050 [1,2]. In Thailand, the rapid growth of private vehicles has contributed to emissions as the transport sector emits 59.58 MtCO2 eq or 26.92% of the energy sector in 2013 [3]. The increased amount of burning fossil fuel inside the vehicle’s engine will lead to
the emissions of carbon dioxide and other harmful gasses into the atmosphere. This emission has a negative effect on the world’s climate. Additionally, it contributes to the increase of the global temperature, sea level rise and eventually global warming [4]. The vehicle by itself is responsible for one-third of the greenhouse gas emissions worldwide. In 2018, the Office of Transport and Traffic Policy and Planning [5] identified the common mode of transport in Bangkok as private vehicles (64% private vehicles, 30% public vehicles and 6% nonmotorized vehicles). Bangkok experiences major traffic congestion which leads to air quality problems. As a result, human health will be affected by these emissions; particularly human respiratory system which must be recognised as an important issue of the current transport system in Bangkok. Moreover, the congestion increases blood pressure and chronic stress. Additionally, it has a negative impact on the psychological adjustment, work routine and overall satisfaction with life [6-8]. In 2012, Bangkok was ranked as one of the top 10 most congested cities in the world [7]. The congestion causes travel time delays and increases the number of road accidents [9]. These negative impacts threaten the quality of life and mobility within societies and make transport unsustainable. Shifting from single-vehicle use to shared transport addressed as a promising strategy can reduce traffic congestion and vehicular emissions [10-12]. This can be seen from the introduction of the Mass Rapid Transit (MRT) and Bangkok mass-Transport System (BTS) which has relieved the level of congestion [13]. However, major arterial and connecting roads in Bangkok still suffer from the congestion which requires more effort in promoting the use of public transport. In 2017, Pita et al. [3] stated that public transport would be essential in relieving congestion and meeting Thailand’s policy of reducing greenhouse gas emissions to 20–25% by 2030. It has many benefits for the health and development of cities and people [9].

In order to shift towards a widespread usage of public transport in Thailand, it is essential for planners to provide good management strategies to reduce usage of private vehicles. Decision making on travel mode choice is affected by people behaviors and lifestyle patterns which create varied and complex travel needs. Hence, the planners’ strategies should aim at changing the behavior of travelers and understanding what motivates travelers to use public transport. To do so, investigation and research are required to understand commuters’ influential factors towards travel modes and develop the most attributes required to shift people to the usage of public transport. According to Koppelman and Bhat [14], a transport mode can be characterized by a set of attributes. Attributes can either be generic or alternative-specific. Generic attributes can be applied to all modes equally such as “in-vehicle-time”, while alternative-specific can only be applied for one or some of the modes such as “waiting time in transit stops” which is specific to that transit mode only and will not affect other modes. The main contribution of this paper is to fill a gap in previous literature on empirical studies that analyzed the determinants influencing mode choice for road users in Bangkok, Thailand. Hence, this paper focuses on employing a binary logistic regression model to analyze the influencing determinants for mode choice in Bangkok. This study will be beneficial to the policymakers and transport authorities in carving the path to an efficient transport system solving the issues of the existing public transport systems. Without a better understanding of public users’ needs, the system will not be efficient in pushing the people towards public transport modes. Therefore, a proper understanding of this essential knowledge of users’ response and their socio-economic and spatial characteristics on mode choice will be beneficial to develop the sustainable public transport system.

2. Literature Review

Travel behavior for mode choice determination affects the efficiency of a transport system. The analysis of the travel behavior differs in each country based on methodology, data collected, attribute variables and units of analysis. This information is essential in creating robust transport facilities in urban areas. Mode choice determinants can be classified into three groups [15–19]; the first group includes subjective determinants that include socio-economic and demographic determinants such as age, gender, income, employment status and vehicle ownership. The second is spatial determinants which focus on population density that can influence the cost, accessibility, time and
suitability of using a transport mode. The third includes determinants of passenger’s perception such as transport policy, law, parking fees, tolls, quality service, etc. The impact of these three types of determinants on mode choice preference is discussed in following subsections.

2.1. Subjective Determinants on Mode Choice

A stated preference survey was conducted in Johor Bahru city using the binary logit model. The study results showed that age, income, vehicle ownership, comfort of a car, reliability of bus service, effective motives and instrumental motives were the main attributes correlated to the travel mode choice [20]. Similar methodology and objectives were conducted in the city of Łódź, Poland [19], which also emphasized that sociodemographic attributes of respondents and household access to a car highly affected transport mode choices. Another analysis was conducted in Croatia to show the preferences for using two modes: cars and public transport. It was evident that the demographic and socio-economic characteristics affected the choice of these modes. The survey data and binary logistic regression analysis were used to identify attributes affecting the mode usage; and they were age, cost, accessibility to public transport and the number of vehicles in the house [21]. A similar study in China applied a hierarchical structure model to forecast mode choice, and a logical relationship to determine the influential factors using existing trip survey data [22]. Another study in China used a binary logistic model to examine the influential factors on travelers choice between the modes of the private car and public transport [23]. It was found that travelers’ gender and auto ownership were the most influential factors on choosing the private vehicle. A study in Brazil used household survey data to analyze mode choice based on socio-economic determinants and geographical position [24]. This study used the decision tree and multinomial logit model to predict the mode choice effectively under the geographical location of the travelers. A study in Spain used a Geographically Weighted Regression (GWR) model to analyze factors affecting daily trips by the metro system of Madrid [25]. This study considered several explanatory variables, including socio-economic characteristics of the population, land use, accessibility and transportation system attributes. The result was evident that seven explanatory variables including the male population, households without a car, population mix, area addressed to residential buildings, active accessibility, resident’s location, and bus lines were affecting trip generations on the metro system of Madrid.

In summary, the most commonly analyzed subjective determinants on mode choice in past literature are factors related to incomes of individuals, i.e., household status and vehicle ownership. The higher income benefitted the travelers to be able to own, maintain and frequently use vehicles. Apart from this, factors such as gender, age, composition of household were considered to estimate the physical condition of the travelers. Furthermore, attributes to analyze travelers’ attitude and perception of safety were considered for analysis in past literature which helps distinguish how peoples’ lifestyle influence on mode choice.

With the complexity of mode choice, subjective determinants that influence the choice are not limited to socio-economic characteristics but also related to socio-psychological factors. Hence, Buehler [26] has completed an interesting study based on Triandis’ theory of interpersonal behavior. This theory allowed Buehler to extract attitude, habitual and other affective factors that influenced people’s mode choice. Buehler found that an individual’s choice on using their vehicle was related to the individual’s strong habitual based on positive emotions on car use.

2.2. Spatial Determinants on Mode Choice

Spatial determinants that influence mode choice usually include land use structure, accessibility to a certain mode from their origin, time and cost factors of using that transport mode. According to Buehler [27], a comparative case study has been conducted to investigate the essential attributes concerning transport mode choice in the United States and Germany. The main differences in the attributes between both countries showed that the United States was more car-dependent amongst all groups of society. Additionally, people living in a dense area in the United States who were close to
Sustainability 2020, 12, 9522

public transport were more likely to use their private vehicles than Germans living in lower-density areas who were farther from public transport. Germans were more likely to walk, cycle and use public transport and robust policies in Germany encouraged the usage of public transport such as increased cost of private ownership, etc. Shen et al. [28] used a latent class model and mixed logit model for transport mode choice based on survey data collected from Japan. The main attributes affecting mode choice were: in-vehicle time, accessibility to public transport, frequency of travel, cost and environmental negative impact [28]. Al-Doori [29] studied on attributes in Yemen that would affect the mode shift of travelers from private vehicles to public transport. It showed that waiting time had a significant impact on mode choice. When public transport’s waiting time was less than 10 min, people would more likely shift to use public transport. Gadziński [30] analyzed the relationship between accessibility of public transport and travel behavior in Poznań city. A correlation coefficient was used to determine that the frequency of travel and travel mode choice were highly correlated with the level of urbanisation. Moreover, integration of discrete choice model and structural equation model were utilised in Chengdu city, China which focused on mode choice on public transport using a latent variable. These latent variables were hidden factors that could not be directly measured or observed, however, these factors had an impact on mode choice. The factors incorporated in the proposed model were modal comfort, personal safety, service environment, convenience and waiting time. It was found that convenience and service environment had higher impacts on public transport mode choice while modal comfort had minimum impact on public transport mode choice [31]. Fu and Juan [32] discovered that the most significant factor which affected public transport usage behavior was behavioral intention using a structural equation model in China while Wang and Zhou [33] focused on relationships between built environment characteristics and mode choice. The compact and clustered developments (higher population densities and high jobs) attracted the usage of public transport. Additionally, if job–house opportunities were balanced, the usage of private vehicles would be reduced. amongst a few researches on medium–long distance trips, LImtanakool et al. [34] conducted an interesting study on the influence of spatial determinants and socio-economic characteristics on home-based trips that are over 50 km based on National Travel Survey data in the Netherlands. This study employed the logit model and identified that spatial determinants of land use arrangement over socio-economic characteristics significantly influenced mode choice on medium–long distanced trips. Moreover, Sanit et al. [35] investigated the factors involved in household choices decisions of multi-worker households with particular emphasis on the role of transport factors, found that rather than transport factors, socio-demographic status played a significant role in explaining their decision mechanism.

2.3. Passenger’s Perception Determinants on Mode Choice

As per the past studies, reducing car dependency through volunteer measures has not been successful. Therefore, passenger’s perception measures such as applications of road pricing, congestion pricing, parking costs, introduction of new fuel-efficient transport options and quality service are some of the strategies which can help the shift from single-occupant vehicles to public transport [36–39]. These strategies were shown to result in a significant reduction in congestion [40]. Hence, studies on mode choices based on determinants of passenger’s perception is important. Washbrook et al. [41] analyzed driver response to tolls and other policies that introduced financial disincentives based on revealed preference survey data. It was shown that these policies resulted in a major reduction in single-occupant vehicle usage. Similar implications were taken in China to reduce car dependency and minimize transport-related emissions by Jain and Tiwari [42]. Vrtic et al. [41] conducted a study in Switzerland employing a stated preference survey to support their policy agencies to evaluate the impact of new road pricing schemes on mode choice behavior. The survey was used to analyze the impact of road pricing on mode, route, and departure time choices. Survey respondents tended to avoid costs. For example, people tended to avoid parking costs by choosing longer walking times to get to public transport and tended to avoid toll costs by choosing alternative route options. In Canada,
Hasnine et al. [43] developed a simulation model integrating toll optimization into an integrated framework related to travelers’ departure time choice, route and mode choices. The results showed that travelers tended to change their route choice and departure times when experiencing price policies rather than their mode choices. Irfan et al. [44] developed a model for travel behavior for work-trip mode using data from revealed preferences and stated preferences surveys in Pakistan. The multinomial logistic model was utilized to develop a modal-split model to estimate demand responses to the policies related to transit improvements and congestion pricing. The travel demand was found to be elastic with respect to congestion pricing. A study based on survey data conducted on Australian university students showed that to achieve a mode shift to public transport, transport policy strategies should understand people’s environmental beliefs on transport modes and their situation such as their access to public transport modes at reduced costs [45]. Additionally, Eboli et al. [46] studied transit service quality evaluated at railway stations in the north of Italy, and suggested a methodology for treating spatial variation of service quality attributes. The results showed that studies should consider spatial patterns across the region of the transit service quality attributes for a deeper investigation of passengers’ perceptions on rail services. Another study in Spain applied the structural equation model to examine the influencing passengers’ behavioral intentions towards the use of Light Rail Transit (LRT) services. The result found that behavioral intentions were mostly affected by users’ judgements on quality service and satisfaction level with service [47]. Concluding this discussion, fuel prices, parking fares, toll prices, speed limits, taxes and quality service are identified as influential determinants on mode choice.

3. Materials and Methods

3.1. Concept of Measurement

The question of the research is why Thai traveler households choose to reside near mass transit areas and whether they regularly use mass transit. Specifically, the sub research question is how both the determination of residential location choice as proximity to the mass transit station and travel mode choice behavior is controlled in terms of transport accessibility and socio-demographic factors. Therefore, the research assumption is to determine whether transport accessibility location is a factor to determine mode choice decision.

The primary data from the 4467 respondents were received from a preformatted questionnaire to collect individual opinions of populations who lives near the mass transit area (Figure 2). In a country, the behavior of travelers’ mode choice may be different depending on their living area since the accessibility is different. There may be a large number of factors that would affect travelers’ mode choice behavior and some of them may not be directly measured since they are unobservable factors. There may be an impact on those factors to the results if they could be determined, and the study focused on directly observable factors. Therefore, to understand a traveler’s preference for mode choice and behavior, questionnaire surveys were performed. The survey conducted was based on revealed preference (RP). RP data reveal the actual behavior of an individual and are assumed to be reliable, while at the same time attribute levels have little variability and are highly correlated and the result was analyzed by using the Logit model. In this research, the binary logit function was used to perform 5 models for choice analysis. The first modelling was generated to understand current mode choice behavior without integrating distance range whereas the other 4 models to identify the behavior of different traveler groups within 4 distance ranges in transport mode choice. The procedure of the research is summarized shown in Figure 1.

3.2. Questionnaire Survey

The survey was designed to gather people’s socio-demographic and economic details, travel behavior and their preference on choosing between 2 alternative travel mode choices: private vehicles and mass transit. The collection of modes offered to travelers for home base–work trips has
been established on the topographical location of the trip. The degree of service data was produced for every single accessible mode and all the trips depending on the starting point/destination information of the journey. In terms of private vehicles, cars are the most used vehicle by Thai citizens which was considered as the main private vehicle mode for this research, while public transport represents mass transit mode. Motorcycling, cycling and walking are used as access modes (feeder mode) that connect to mass transit station as well as arrival to destinations. These following modes were not included as the main travel mode used for the research analysis. Therefore, to model the transport mode behavior, the binary logit model was used to explore the factors affecting private car versus mass transit use and also an analytically convenient modelling method in which the level of complexity of binary logit was less when compared to other models proposed.

The data obtained from the RP survey were reliable and this RP survey asked realistic travel information, which focused on home base-work trips. For the household survey, the questionnaire was given to Thai travelers who commute every day. The questionnaire was amended based on the pilot test and was used for collecting the actual data for this research, which was designed consisting of two sections: (1) The respondent’s personal information and (2) travel information. The first part of the survey included social and economic information, demographics of the respondent. Those included questions on gender, age, education level, career, average monthly income, household size and vehicles occupy. The second part contained questions related to the modes of transport which included questions on trip purpose, trip frequency, number of companies, main mode of transport used (private car or mass transit) from origin to destination, mode information of private car and mass transit, feeder mode connect to the main transport mode (motorcycle, walking and cycling), origin-destination station, travel time, travel cost, travel distance and waiting time. Even though the respondents selected the main mode of transport, they were still required need to provide travel information for both types of transport for the home base trips.

3.3. Participants

This research focused on extra details on private car users’ mode choice behavior in different areas to better understand the likely measures that would have to be taken to encourage greater mass transit use. This research was conducted in congested areas in Bangkok due to the existence of huge number of cars registered, accessibility of mass transit available and the adequate reflection of travelers. In the

![Figure 1. Research procedure.](image-url)
2019 population, there were more than 66.59 million people in Thailand, which included 5.67 million people in Bangkok [48]. Especially, the respondents from the household survey along mass transit locations were randomly selected, depending on a simple random sampling technique, to accomplish a representative sample, which demonstrates demographic and socio-economic information. Therefore, due to the reasons mentioned above, these areas were envisioned to be an exceptional case study, which represents Bangkok. The 4467 samples in this research were collected from 2 main mass transit railway areas (Figure 2) within Bangkok, Thailand. The 2 areas were located at: (1) Airport Rail Link (ARL) area and (2) Bangkok Mass Transit System. The ARL is a Mass Transit System owned by State Railway of Thailand (SRT) and operated by SRT Electrified Train (SRTET). ARL first consisted of 2 express services (one service runs nonstop between Makkasan station and airport, and the other runs between Phayathai station and airport) and the city line, a commuter line that services with 8 stations. Bangkok Mass Transit System area, commonly known as the BTS or the Skytrain, is an elevated light rapid transit system or known as medium-capacity rail transport system in Bangkok, Thailand. In addition to serving businesses, shopping districts and residential areas in the heart of Bangkok, an extension project is also in the plan to reach the broader community of potential passengers in suburban Bangkok. The samples in these 2 areas totaled 3241 and 1226, respectively. For each area, the data were gathered within 4 distance ranges, which were indicated by circular shapes including (1) within 400 m, where the travelers could walk to get access to the main public transport stations. (2) 400–1000 m, where feeders could be used by travelers to get access to the main public stations. (3) 1000–10,000 m, where the feeders have to be used by travelers to get access to the stations, and (4) more than 10,000 m, from the station where it is too far to select transit services and private cars might be used by travelers. The number of samples within the 4 distance ranges from each area is presented in Table 1.

Figure 2. Sample locations within Bangkok.
Table 1. Samples from different stations.

| Area | Station Name | Samples within 4 Distance Ranges |
|------|--------------|----------------------------------|
|      |              | within 400 m | 400–1000 m | 1–10 km | >10 km | Total |
| ARL  | Phayathai    | 83           | 105        | 111     | 107    | 406   |
|      | Ratchaprarop | 107          | 88         | 99      | 107    | 401   |
|      | Makkasan     | 93           | 109        | 88      | 108    | 398   |
|      | Ramkhamhaeng | 43           | 109        | 131     | 113    | 396   |
|      | Huamark      | 122          | 107        | 79      | 114    | 422   |
|      | Ban Thap Chang | 104        | 118        | 75      | 110    | 407   |
|      | Ladkrabang   | 128          | 24         | 145     | 112    | 409   |
|      | Suvarnabhumi | 0            | 1          | 298     | 103    | 402   |
|      | Total        | 3241         |            |         |        |       |
| BTS  | Aree         | 100          | 100        | 100     | 118    | 418   |
|      | Siam         | 2            | 193        | 104     | 99     | 398   |
|      | Bearing      | 98           | 100        | 94      | 118    | 410   |
|      | Total        | 1226         |            |         |        |       |
|      | Total samples by distance | 880 | 1054 | 1324 | 1209 | 4467 |

3.4. Sample Characteristics

The socio-economic characteristics and travel information of the survey respondents were classified per chosen mode (Table 2). The percentage of male respondents were 47.93%, while 52.07% were female. In terms of age, 6.87% of respondents were between 18 and 22 years old. 30.11% of respondents were between 23 and 30 years old. Most of them (34.61%) were aged between 31 and 40 years old, followed by 21.65% of respondents aging between 41 and 50 years old, 5.75% were aged between 51 and 60 years old, while 1.01% were older than 60 years old. For the education level, most applicants held bachelor’s degree and diploma with percentage of 53.57%, and 21.89%, respectively. 20.37% of respondents were high school, while 4.16% of applicants were postgraduate. In terms of career, 49.12% of the respondents were private employees, while 18.47% owned a private business, 8.87% were students, 16.77% were government employees and 6.78% were other careers. This research also observed differences in average monthly income and the results showed that 56.35% respondents had monthly income between THB 15,000 and 25,000 (1 USD = 31.59 THB), 29.04% had income less than THB 15,000, while 10.92% of applicants had income between THB 25,001 and 35,000, 2.87% had income of THB 35,001–50,000 per month, and 0.83% reported higher income THB >50,000. As per the household size, 35.62% of respondents had 2 people within their house, 34.12% had 3 people, 23.10% had more than 3 people, and 7.16% had only 1 person per household. The last section of the socio-economic characteristics part of the survey discussed details for the vehicle occupied, 51.24% of the respondents had at least 1–2 vehicles within their house, followed by 47.93% who did not own any, and 0.83% had more than 2 vehicles in their house.

According to the travel information of respondents, the most common trip purpose for Thai commuters was for work, school, business and shopping, which was 80.70%, 7.97%, 5.89% and 5.44%, respectively. The travel frequency of Thai commuters less than 6 times a week was 63.38%, followed by 35.73% being 6 to 9 times a week and 0.90% of respondents were travelled more than 9 times a week. The survey also showed the number of travelers within their trip, where 55.36% of respondents travelled alone, 37.97% travelled with a company, 5.55% travelled with a few companies and 1.12% travelled with more than 3 people. For the total travel time of commuter journey, most people, approximately 64.32%, spent within 30 min, 31.72% travelled between 30 to 60 min and 3.96% spent more than 1 h on their journey. According to the total travel cost, 91.18% of the respondents mostly spent less than THB 100 per trip, 8.10% spent between THB 101 to 200 per trip and 0.72% spent more than THB 200 per trip. Regarding the travel distance information, the highest number of respondents (86.14%) travelled within 15 km, followed by 10.57% who travelled between 15 to 25 km and 3.29% who travelled more than 25 km per trip. Lastly, the data of the total waiting time (only for those commuters who use mass transit) during trips showed that 53.93% of the respondents spent less than 10 min in regards to waiting time of their journey, while as 45.12% waited between 10 to 20 min and 0.91% waited more than 20 min during their travel journey.
Table 2. Socio-economic characteristics.

| Choice | Private Car | Mass Transit | Total |
|--------|-------------|--------------|-------|
| Quantity (Percent) | 2601 (58.23%) | 1866 (41.77%) | 4467 |

SOCI-ECONOMIC CHARACTERISTICS (Classification per chosen mode)

| Gender | Male | 1387 (64.78%) | 754 (35.22%) | 2141 (47.93%) |
|        | Female | 1214 (52.19%) | 1112 (47.81%) | 2326 (52.07%) |
| Age | 18–22 years | 74 (24.10%) | 233 (75.90%) | 307 (6.87%) |
|        | 23–30 years | 607 (45.13%) | 738 (54.87%) | 1345 (30.11%) |
|        | 31–40 years | 1014 (65.59%) | 532 (34.41%) | 1546 (34.61%) |
|        | 41–50 years | 694 (71.77%) | 273 (28.23%) | 967 (21.65%) |
|        | 51–60 years | 186 (72.37%) | 71 (27.63%) | 257 (5.75%) |
| Education level | Older than 60 years | 26 (57.78%) | 19 (42.22%) | 45 (1.01%) |
| High school | 476 (52.31%) | 434 (47.69%) | 910 (20.37%) |
| Diploma | 625 (63.91%) | 353 (36.09%) | 978 (21.89%) |
| Bachelor | 1353 (56.54%) | 1040 (43.46%) | 2393 (53.57%) |
| Postgraduate | 147 (24.24%) | 300 (75.76%) | 396 (8.87%) |
| Career | 454 (60.61%) | 295 (39.39%) | 749 (16.77%) |
| Employee | 577 (69.94%) | 248 (30.06%) | 825 (18.47%) |
| Private business | 1307 (59.57%) | 887 (40.43%) | 2194 (49.12%) |
| Private employee | 167 (55.12%) | 136 (44.88%) | 303 (6.78%) |
| Average Income | THB <15,000 | 542 (41.79%) | 755 (58.21%) | 1297 (29.04%) |
| THB 15,000–25,000 | 1519 (60.35%) | 998 (39.65%) | 2517 (56.35%) |
| THB 25,001–35,000 | 391 (80.12%) | 97 (19.88%) | 488 (10.92%) |
| THB 35,001–50,000 | 114 (89.06%) | 14 (10.94%) | 128 (2.87%) |
| THB >50,001 | 35 (94.59%) | 2 (5.41%) | 37 (0.83%) |
| Household Size | 1 person | 88 (27.50%) | 232 (75.50%) | 320 (7.16%) |
| 2 persons | 844 (53.05%) | 747 (46.95%) | 1591 (35.62%) |
| 3 persons | 970 (63.65%) | 554 (36.35%) | 1524 (34.12%) |
| 4 or more | 699 (67.73%) | 333 (32.27%) | 1032 (23.10%) |
| Car Ownership | None | 990 (46.24%) | 1151 (53.76%) | 2141 (47.93%) |
| 1–2 | 1584 (69.20%) | 705 (30.80%) | 2289 (51.24%) |
| 3 or more | 27 (72.97%) | 10 (27.03%) | 37 (0.83%) |

TRAVEL INFORMATION OF RESPONDENTS (Classification per chosen mode)

| Travel Frequencies | Less than 6 times/week | 1602 (56.59%) | 1229 (43.41%) | 2831 (63.38%) |
|                   | 6–9 times/week | 986 (61.78%) | 610 (38.22%) | 1596 (35.73%) |
|                   | More than 9 times/week | 13 (32.50%) | 27 (67.50%) | 40 (9.00%) |
| Number of companies | 1 person | 1223 (49.45%) | 1250 (50.55%) | 2473 (55.36%) |
|                   | 2 persons | 1173 (69.16%) | 523 (30.84%) | 1696 (37.97%) |
|                   | 3 persons | 169 (68.15%) | 79 (31.85%) | 248 (5.55%) |
|                   | 4 or more | 36 (72.00%) | 14 (28.00%) | 50 (1.12%) |
| Total Travel Time | Less than 30 min | 1978 (68.85%) | 895 (31.15%) | 2873 (64.32%) |
|                   | 30–60 min | 590 (41.64%) | 827 (58.36%) | 1417 (31.72%) |
|                   | More than 60 min | 33 (18.64%) | 344 (81.36%) | 377 (8.46%) |
| Total Cost | THB 0–100 | 2207 (54.19%) | 1866 (45.81%) | 4073 (91.18%) |
|                   | THB 101–200 | 362 (100.00%) | - (0.00%) | 362 (8.10%) |
|                   | THB More than 200 | 32 (100.00%) | - (0.00%) | 32 (0.72%) |
| Total distance | less than 15 km | 2271 (59.02%) | 1577 (40.98%) | 3848 (86.14%) |
|                   | 15–25 km | 256 (54.24%) | 216 (45.76%) | 472 (10.57%) |
|                   | More than 25 km | 74 (50.34%) | 73 (49.66%) | 147 (3.29%) |
| Waiting time | Less than 10 min | - (0.00%) | 1007 (100.00%) | 1007 (53.97%) |
|                   | 10–20 min | - (0.00%) | 842 (100.00%) | 842 (45.12%) |
|                   | More than 20 min | - (0.00%) | 17 (100.00%) | 17 (0.91%) |

The distance range area between household location to the main mass transit station by the proportion of 4467 respondents is shown in Figure 3. The information depicts that, on average, Thai respondents tended to use private cars (58.23%) rather than mass transit commute (41.77%). Additionally, it is evident that the further away a residential location is from a mass transit station, the higher the proportion is for private car users. For instance, when the distance to the station was less than 400 m, 50.34% of Thai respondents preferred to use mass transit while 49.66% preferred the usage of the private vehicle. When the distance increased up to 1000 m, 53.98% commuters avoided the usage of public transport while 46.02% were likely to use mass transit. Similarly, when the distance increased up to 10 km, 56.19% of respondents preferred to use their private vehicles while 43.81% chose the usage of mass transit. Meanwhile, when the distance to the station was larger than 10 km, the number of respondents who would rather use their private car increased significantly to 70.39% of respondents,
compared to 29.61% of respondents selecting the usage of mass transit. Therefore, the survey results showed that there were few significant differences in the propensity to use mass transit due to the residential location at the longer distance to the station.

Figure 3. Station distance range proportion of respondents.

3.5. Model Specification

A binary logit model is commonly used in the field of transport planning and it describes the probability of choosing one transport mode out of 2 alternatives. The ability to represent complex aspects of individual traveler decision choices by incorporating important demographics can be interpreted by the logit model which is implemented for logistic regression. When the probability of selecting one alternative is \( P(a) \) and the other alternative’s probability is \( P(b) \), it can be written as \( P(b) = 1 - P(a) \). The binary logit model consists of the utility theory, which means that a traveler’s preference towards a specific transport mode is based on the value, is called utility (U) [49]. According to the binary logit model, the probability of selecting a transport mode, ‘\( m \)’ by an individual ‘\( i \)’ can be written by considering only the observed component of the utility function as follows:

\[
P_{mi} = \frac{e^{V_{mi}}}{1 + e^{V_{mi}}} = \frac{1}{1 + e^{V_{ni}-V_{mi}}} \quad (1)
\]

where

- \( P_{mi} \) is the probability of mode, ‘\( m \)’ being selected by individual ‘\( i \)’
- \( V_{mi} \) is the utility function of mode, ‘\( m \)’ for individual ‘\( i \)’
- \( V_{ni} \) is the utility function of mode, ‘\( n \)’ for individual ‘\( i \)’

The mode utility is a mathematical function based on the attractions which are associated with a traveler related to a specific trip [50]. This discrete choice model predicts an individual’s choice based on utility or relative attractiveness [51,52] when the public transport is considered, utility functions are related with attributes such as waiting time (for the mode to arrive), in-vehicle travel time, travel cost, etc. A utility function can be written for a transport mode, ‘\( m \)’ for an individual ‘\( i \)’ as follows:

\[
U_{mi} = \beta_0 + \beta_1 X_{mi1} + \beta_2 X_{mi2} + \beta_3 X_{mi3} + \ldots + \beta_n X_{mi n} \quad (2)
\]

where

- \( U_{mi} \) is the utility function of transport mode (\( m \)) for individual ‘\( i \)’
- \( n \) is the total number of attributes
- \( X_{mi 1,2,3,\ldots, n} \) is attributes of transport mode (\( m \)) for individual ‘\( i \)’
- \( \beta_0 \) is intercept value (constant)
- \( \beta_1, \beta_2, \beta_3, \ldots, \beta_n \) is coefficients for attribute values
A binary logit model for Bangkok commuter trips was developed for 2 alternatives, namely, mass transit and private car, to compare the utility of these travel modes and identify the factors which influenced car users to move from travelling by car to public transport as mass transit. In this model, the dependent variable was “0” if the commuters’ travelled by private vehicle and “1” for mass transit commuter. According to the questionnaire survey, the RP survey focused mainly on current condition. The coefficients were estimated by fitting the data to the model using the maximum likelihood estimation method. The selection model was selected based on the highest value for percentage correct, the highest value for Nagelkerke R square and the lowest value for -2 log-likelihood and in the Hosmer and Lemeshow test, the (sig.) value should be greater than 0.05.

4. Results and Discussion

In this research, some specific variables were estimated to impact the behavior of Thai travelers when they were exposed to various transport modes. The important variables (e.g., travel cost and travel time) identified in the literature are significant, whereas other variables are proposed exclusively to address this research problem. Moreover, to understand the behavior of commuters who lived in the four different residential location distance ranges further from the mass transit station, the logit models were applied to check the influential factors within these ranges.

4.1. Modelling of Current Mode Choice

Several variables, found in earlier studies, have been attempted during the calibration process. Some of the models, which were tested, have demonstrated inadequate statistical goodness-of-fit and/or unproductive signs and consequently were denied. Amongst all the model specifications tested, the most acceptable model is presented in Table 3. In the data set, there were both continuous and categorical variables. Some of the explanatory variables such as gender, age (range), average individual income and distance range were categorized. For instance, the gender was categorized as 0 for male and 1 for female. The age was categorized as; 18–22, 23–30, 31–40, 41–50, 51–60, and older than 60 years old. The average individual income was categorized as: less than THB 15,000, THB 15,000–25,000, THB 25,001–35,000, THB 35,001–50,000, THB 50,000–100,000 and over than THB 100,000. The distance range was categorized as; within 400 m, 400–1000 m, 1000–10,000 m, and more than 10,000 m from the station. On the other hand, the total travel time of mass transit, the total travel cost of private vehicles, and household car ownership were considered continuous variables. The Spearman’s correlation coefficient, appropriate for both types of the above variables, was used in this analysis. After correlation testing at a p-value of < 0.05, a summary of estimations using the binary logit model for Bangkok’s travelers by private vehicle versus public transport. All the variables presented in the table have significant parameter estimates and logical signs. The utility functions from the parameter estimates obtained from model are shown in Equation (3).

\[ U_{\text{PUB}} = 2.025 + (0.381 \times G) - (0.395 \times \text{Age}) - (0.638 \times \text{INC}) - (0.675 \times \text{Car}) + (0.009 \times \text{TC}_{\text{PRI}}) - (0.004 \times \text{TT}_{\text{MassTransit}}) - (0.228 \times \text{Dist}_{\text{Range}}) \]  

(3)

In Table 3, the Sig. < 0.05 represents the significant contribution of the variable in the model. The variables influencing the travelers’ mode choice behavior on mass transit included: gender, age, average individual income, household car ownership, the total travel cost of a private vehicle, total travel time of mass transit and distance range from mass transit station. The analysis showed that the estimated coefficients for the age, average income, household car ownership, total travel time of mass transit and distance range came out negative whereas the estimated coefficients for the gender and total travel cost of the private car came out positive. These can be explained as follows:
Table 3. Estimation results using binary logistics models (first model).

| Variable Code | B    | S.E.  | Sig. | Exp(B)  | 95% C.I. | Lower | Upper |
|---------------|------|-------|------|---------|----------|-------|-------|
| Gender        | G    | 0.381 | 0.067| 0.000** | 1.463    | 1.282 | 1.670 |
| Age (Range)   | Age  | -0.395| 0.034| 0.000** | 0.673    | 0.630 | 0.720 |
| Individual Income | INC  | -0.638| 0.055| 0.000** | 0.528    | 0.474 | 0.588 |
| Household car ownership | Car  | -0.675| 0.061| 0.000** | 0.509    | 0.451 | 0.574 |
| Travel Cost of Private Vehicle | TCPRI | 0.009 | 0.001| 0.000** | 1.009    | 1.007 | 1.101 |
| Total travel time of Mass Transit | TT_MT | -0.004| 0.002| 0.022 * | 0.996    | 0.992 | 0.999 |
| Distance Range | DistRange | -0.228| 0.031| 0.000** | 0.796    | 0.749 | 0.847 |
| Constant      |      |       |      |         |          | 2.012 | 7.478 |

-2LL  5207.479
Model chi-square  863.609
Cox & Snell R Square  0.176
Nagelkerke R Square  0.237
Hosmer and Lemeshow Chi-square  14.686
Number of observations  4467

** significant at 1% level; * significant at 5% level.

For the variables with the negative sign of coefficients, the result on the age implied that the elderly were less likely to use mass transit, similar to the results of Mackett and Ahen [53], while the younger generation drove less and preferred to take public transport, rather than the elderly. With higher average income, the travelers were less likely to use mass transit similar to the previous research in the United States [54] indicating that high-income travelers were less sensitive to travel costs and they were more likely to cars for intercity travels. The estimated coefficients for total travel time of mass transit and household car ownership were negative, implying that an increase in travel time for the mass transit was likely to increase the probability of car users to continue choosing the car as the preferred mode of transport. Additionally, when the number of car ownership increased, people were less likely to use mass transit. This study agreed with the research findings that an increase in household car ownership was likely to decrease the resistance to a mode change [55]. Resistance to switching was found to be lower amongst respondents whose household vehicle ownership was more than two vehicles, whereas respondents from households that owned one vehicle were highly resistant to the mode change. Lastly, the distance range between residential location to the main mass transit station directly affected mode choice decisions. The distance range variable is expected to have negative coefficients, which was statistically significant with respect to mode choice of the mass transit. This indicated that the probability of choosing the mass transit decreased, as access distance range from home to the main station increased. This study agreed with the research findings that the people residing near the transport terminal were more likely to choose those modes operating; and people located far away from the terminal might use other modes [55].

Focusing on the positive sign of coefficients, the gender and total travel cost of the private car were presented in this model. According to the results, the estimated coefficients for gender came out positive, implying that females would use mass transit instead of driving a car [56]. Generally, expense cost or travel cost was one of the main factors affecting intercity mode choice. The total travel cost by private car of Thai travelers primarily includes the fuel price and tollways, whereas the total cost of travelling by mass transit is represented by the fares paid. Total travel cost as an independent variable affected the choice of private car users, which had a positive coefficient. This implied that it had a positive
relationship; when the travel cost of private transport increased, travelers became more likely to use public transport.

4.2. Identifying Behavior of Traveler Groups in Different Distance Ranges from Station

Another binary logistic regression analysis was performed with an iterative procedure for model calibration, to ascertain the effects of explanatory variables which influence the likelihood of Thai travelers. The final analysis was conducted on the set of variables that were tested to have no correlations amongst these variables. The Table 4 describes the estimated coefficient and the outputs of four different models which utilized the four different distance ranges condition. The conditions were based on distance from residential locations, i.e., less than 400 m (second model), 400 m–1 km (third model), 1–10 km (fourth model) and more than 10 km (fifth model). All the variables indicated in Table 4 had considerable parameter estimates and logical signs. The coefficients for the six explanatory variables, including gender, age, average individual income, household car ownership, total travel time and total travel cost, were performed as the significant contributors at a 95% level of confidence ($p < 0.05$) to Thai traveler’s mode choice behavior for the first two distance ranges within 1 km (the second and third models). The logical signs of the estimated coefficients are worthy of attention and indicated that the estimated coefficients for the age, average income, household car ownership and total travel time of mass transit came out negative whereas the estimated coefficients for the gender and total travel cost of the private car came out positive. The model results summarized the estimated coefficients from the binary logit model for four residential locations in different distance ranges by private car versus mass transit.

**Table 4. Summary of the model for each distance range.**

| Variable                          | Dist. Range 1 (2nd Model) | Dist. Range 2 (3rd Model) | Dist. Range 3 (4th Model) | Dist. Range 4 (5th Model) |
|----------------------------------|---------------------------|--------------------------|--------------------------|--------------------------|
|                                   | B            | Sig | B             | Sig | B            | Sig | B            | Sig |
| Gender                           | 0.363        | 0.014 * | 0.446        | 0.001 ** | 0.449        | 0.000 ** | 0.282        | 0.046 * |
| Age (Range)                      | -0.274       | 0.000 ** | -0.352       | 0.000 ** | -0.353       | 0.000 ** | -0.606       | 0.000 ** |
| Average Individual Income        | -0.447       | 0.000 ** | -0.681       | 0.000 ** | -0.818       | 0.000 ** | -0.644       | 0.000 ** |
| Household car ownership          | -0.736       | 0.000 ** | -1.150       | 0.000 ** | -0.460       | 0.000 ** | -0.519       | 0.000 ** |
| Travel Cost of Private Vehicle   | 0.007        | 0.000 ** | 0.016        | 0.000 ** | 0.008        | 0.000 ** | 0.008        | 0.000 ** |
| Total travel time of Mass Transit| -0.008       | 0.045 *  | -0.017       | 0.000 ** | 0.002        | 0.589    | -0.001       | 0.730    |
| Constant                         | 1.322        | 0.001 ** | 1.760        | 0.000 ** | 1.321        | 0.000 ** | 1.545        | 0.000 ** |

**-2LL**: 1081.662, 1213.285, 1600.169, 1242.475

Model chi-square: 138.236, 241.168, 214.919, 226.543

Cox & Snell R Square: 0.145, 0.205, 0.15, 0.171

Nagelkerke R Square: 0.194, 0.273, 0.201, 0.243

 Hosmer and Lemeshow Chi-square: 13.881, 6.371, 11.921, 12.571

Number of observations: 880, 1054, 1324, 1209

**significant at 1% level; * significant at 5% level.**

The results in the second and third model, where the residential location was within the distance ranges of 1 km, showed that socio-economic determinants as household car ownership had the highest impact on mode choice behavior and followed by the attributions of average individual income, gender, and age. Even though the variables relating to transport factors (travel time and travel cost) were significantly below the 95% confidence level, the parameter estimates that these two variables within these two residential location distances range had slightly less impact on the mode choice behavior for the respondents compared to the socio-economic factors (gender, age, average income and household car ownership). On the other hand, the total travel time of the mass transit factor was not significant at the 0.05 level (the sig. value is greater than 0.05) for the fourth to fifth model. In the fourth model where the distance range was between 1 km to 10 km, the average individual income created the highest impact, followed by household car ownership, gender and age. This was also observed in the case of the fourth distance range (the fifth model), where the respondents lived more than 10 km away to the mass transit stations. The average individual income, age and car ownership attributes were strong factors and had the highest impact on the mode choice, followed by gender.
From the research assumption mentioned above, the study explored potential factors to understand the decision-making on mode choice in different distances range from residential location to the main mass transit station for Thai travelers. The result showed that there were different impacts on traveler’s choices decisions among these 4 models. In addition, the variables related to transport factors had less impact on the mode choice behavior for Thai’s traveler compared to the socio-economic factors. This result also indicated that householders had less likely to relocate near the mass transit station and use this mode to commute even though the travel cost and travel time of mass transit could be reduced. This result agrees with the Sanit et al. [35] findings which reported that transport factors were considered less important towards the location and travel choice behavior. The result also showed that the travelers who lived far away from the mass transit station (distance higher than 1 km), rarely used the public mass transit. This was due to the inconvenient access to the main mass transit station and hence they preferred to drive. Also, a study by Charoentrakulpeeti et al. [57] stated that incomplete and small networks were the main reason for the failure to attract public transit ridership in Bangkok.

The findings illustrated that considerable differences exist between males and females both in terms of access to and usage of the travel mode choices. The model results implied that females would use mass transit instead of driving a private car even though the distance from the residential location to access mass transit station is quite far this implies that females prioritize affordability when compared to access to private vehicles. In the model, a demographic variable such as age was identified to substantially explain the transport mode choice decisions. The results identified that the increased age was related to less use of mass transit which illustrated that the young people drove less and preferred to take public transport, rather than the elderly. These findings can be attributed to lower mobility as people age, which limits the use of public transport.

Considering the individual income group, the effect of average income on mass transit was negative, implying that with the increase in income, the usage of public mode will reduce. Specifically, travelers with higher average income were less likely to use mass transit. The income was noted to have a significant influence on a traveler’s choice of mode, where a rise in the level of income increased the utility of private vehicles while the utility for public modes of transport decreased.

The coefficient of household car ownership in these models was significant for the travel mode choice decision which also tended to increase the utility for private vehicles. A negative parameter for car ownership indicated that mass transit users do not have access to private vehicles. Therefore, the traveler prefers to drive rather than using mass transit even though their residential location is close to the public transit station.

5. Conclusions

Mode shift from single-occupant vehicles to shared transport is important for effective use of road supply as congestion is a major problem to transport planners in Bangkok, Thailand. Therefore, this work developed an analysis based on the binary logit model to identify influential factors affecting travelers’ mode choice behavior on mass transit as public transport uses. The majority of the survey respondents were female, and mostly fell in the age group of 31 to 40 years old. Moreover, most respondents held bachelor’s degree and were private sector employees. With regards to the income, most of the respondents earned THB 15,000 to 25,000 monthly. Amongst the respondents, there were a few who earned more than THB 50,000 monthly. The majority of the respondents lived in a small household with only two members. The respondent group mainly took their regular trips to work and preferred to use private transport. The results showed that the influential factors affecting Thai travelers’ mode choice behavior on mass transit was gender, age, average income, auto ownership, total travel cost in private transport, total travel time in public transport and distance range from home to mass transit station. This study identified that age, income, travel time of public transport, the number of car ownership and distance range had an inversely proportional relationship with travelers’ likeliness to use mass transit. On the other hand, gender and travel cost of private transport attributes showed a directly proportional relationship with Thai traveler’s mass transit mode choice.
The binary logit model analysis was used to ascertain the effects of explanatory variables which influenced the likelihood of Thai travelers with respect to four distance ranges to access mass transit stations. For distance range one and two, where the distance to public transport is less than 1 km, five attributes (gender, age, average individual income, household car ownership, total travel time of public transport and the travel cost of private vehicles) had a significance towards the mode choice of Thai travelers. Amongst them, travel cost and travel time variables for the respondents had slightly less impact on the mode choice behavior. This indicated that householders who resided within 1 km distance to the public transport station, when given a choice, were less likely to commute even though the travel cost and time of public transport could be reduced. Results of the next distance categories, i.e., 1–10 km and more than 10 km distance range models, showed that attributes, except the total travel time of public transport, had an impact on Thai travelers’ mode choice. This clarified that respondents who lived far away from public transport stations preferred to use their own vehicles due to lack of accessibility for public transport.

Authors also note that this analysis is based on a few limitations which should be improved through future research. For instance, the results of this study were primarily based on the 4467 respondents of a revealed preference questionnaire survey, which is conducted in two main mass transit user hubs (i.e., Airport Rail Link, and Bangkok Mass Transit System) in Bangkok. Hence, research findings may have a bias issue as the study area limits to two critical locations in Bangkok. Therefore, for a deeper understanding of Thai travel behavior, the study area can be expanded by adding more places that are attracted by Thai road users. Additionally, the number of survey responses can be increased by distributing along a broader region, including other major cities such as Nonthaburi, Nakhon Ratchasima. Authors also highlight the practical difficulties they faced during the data collection, including receiving respondents’ consent on participating in face-to-face interviews during their journey to work. This can be reduced by conducting noncontact, web-based surveys which protect the respondents’ anonymity, and respondents can answer at their convenience. Another limitation is that this study developed binary logit models to analyze mode choice of transport users in Bangkok, Thailand, wherein the transport modes were only categorized into two: private vehicles and mass transit. Expanding the analysis would be interesting to consider respondents’ revealing preferences on their primary specific modes of transport more complex analyzing tools. Additionally, this survey was conducted over a short period of time; hence, it would be worthwhile to validate the findings by reconducting the survey over different time periods.

Finally, exaggeration of positive response can be highlighted as the main practical implication of using the findings that are based on questionnaire surveys. That is, when responding to the survey questions respondents may have anticipated what researchers are trying to conclude from the research and may have answered in the “ideal or the correct” way which is different from their actual opinion. Therefore, the analysis should be completed by examining the change of responses when the respondent is exposed to other mode options and various alternatives to combat the tendency of this exaggeration.
Author Contributions: Conceptualization, P.W. and S.P.; methodology, P.W. and S.P.; software and formal analysis, P.W.; writing—review and editing, P.W., K.S., K.K. and S.H.; supervision, S.P., K.S., K.K. and S.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Khalili, S.; Rantanen, E.; Bogdanov, D.; Breyer, C. Global transportation demand development with impacts on the energy demand and greenhouse gas emissions in a climate-constrained world. *Energies* 2019, 12, 3870. [CrossRef]

2. Santos, G. Road transport and CO₂ emissions: What are the challenges? *Transp. Policy* 2017, 59, 71–74. [CrossRef]

3. Pita, P.; Chunark, P.; Limmeechokchai, B. CO₂ Reduction Perspective in Thailand’s Transport sector towards 2030. *Energy Procedia* 2017, 138, 635–640. [CrossRef]

4. Black, W.R. *Sustainable Transportation: Problems and Solutions*; Guilford Press: New York, NY, USA, 2010.

5. Office of Transport and Traffic Policy and Planning (OTP). Travel Demand Freight Movement Survey For National Transport Planning. Available online: http://www.otp.go.th/uploads/tiny_uploads/ProjectOTP/2560/Project01/2.2-TDS_Exsum_EN_Final_20180515.pdf (accessed on 10 March 2020).

6. Abu-Lebdeh, G. A108 transport systems and public health: The case of traffic congestion and signal control. *J. Transp. Health* 2015, 2, S61. [CrossRef]

7. Chong, D.K.L. The impact of traffic congestions on tourist behavior: Case study of Chiang Mai, Thailand. In Proceedings of the 14th ApacChrie Conference 2016, Bangkok, Thailand, 11–13 May 2016.

8. Frieden, T.R. A framework for public health action: The health impact pyramid. *Am. J. Public Health* 2010, 100, 590–595. [CrossRef] [PubMed]

9. Albalate, D.; Fageda, X. Congestion, road safety, and the effectiveness of public policies in urban areas. *Sustainability* 2019, 11, 5092. [CrossRef]

10. Abduljabbar, R.; Dia, H.; Liyanage, S.; Bagloee, S.A. Applications of artificial intelligence in transport: An overview. *Sustainability* 2019, 11, 189. [CrossRef]

11. Liyanage, S.; Dia, H. An Agent-Based Simulation Approach for Evaluating the Performance of On-Demand Bus Services. *Sustainability* 2020, 12, 4117. [CrossRef]

12. Liyanage, S.; Dia, H.; Abduljabbar, R.; Bagloee, S.A. Flexible mobility on-demand: An environmental scan. *Sustainability* 2019, 11, 1262. [CrossRef]

13. Luangprasert, M.; Vasithamrong, C.; Pangratananukul, C.; Chantranuwatha, S.; Pumrin, S.; De Silva, I. In-vehicle carbon dioxide concentration in commuting cars in Bangkok, Thailand. *J. Air Waste Manag. Assoc.* 2017, 67, 623–633. [CrossRef]

14. Koppelman, F.S.; Bhat, C. A self instructing course in mode choice modeling: Multinomial and nested logit models. *Elements* 2006, 28, 501–512.

15. Chen, C.; Gong, H.; Paaswell, R. Role of the built environment on mode choice decisions: Additional evidence on the impact of density. *Transportation* 2008, 35, 285–299. [CrossRef]

16. Hurni, A. Transport and Social Disadvantage in Western Sydney: A Partnership Research Project. 2006. Available online: https://researchdirect.westernsydney.edu.au/islandora/object/uws:23088 (accessed on 10 March 2020).

17. Soltanzadeh, H.; Masoumi, H.E. The Determinants of Transportation Mode Choice in the Middle Eastern Cities: The Kerman Case, Iran. *TeMA-J. Land Use Mobil. Environ.* 2014, 7, 199–222.

18. Tyrinopoulos, Y.; Antoniou, C. Factors affecting modal choice in urban mobility. *Eur. Transp. Res. Rev.* 2013, 5, 27–39. [CrossRef]

19. Wójcik, S. The determinants of travel mode choice: The case of Łódź, Poland. *Bull. Geogr. Socio-Econ. Ser.* 2019, 44, 93–101. [CrossRef]

20. Puan, O.; Hassan, Y.; Mashros, N.; Idham, M.; Hassan, N.; Warid, M.; Hainin, M. Transportation mode choice binary logit model: A case study for Johor Bahru city. *IOP Conf. Ser. Mater. Sci. Eng.* 2019, 527, 012066. [CrossRef]
21. Miletić, G.-M.; Gašparović, S.; Carić, T. Analysis of socio-spatial differentiation in transport mode choice preferences. *Promet-Traffic Transp.* 2017, 29, 233–242. [CrossRef]

22. Zhou, Z.; Wang, W.; Hu, Q. An application of hierarchical structure model for trip mode choice forecasting in China. *Math. Probl. Eng.* 2015, 2015, 925963. [CrossRef]

23. Li, J.; Lo, K.; Guo, M. What Influences the Choice Between Private Car and Public Transport for Shopping Trips? Impact of Socio-economic and Built Environment Factors. *J. Asian Energy Stud.* 2018, 2, 28–42. [CrossRef]

24. Pitombo, C.S.; Salgueiro, A.R.; da Costa, A.S.G.; Isler, C.A. A two-step method for mode choice estimation with socioeconomic and spatial information. *Spat. Stat.* 2015, 11, 45–64. [CrossRef]

25. Calvo, F.; Eboli, L.; Forciniti, C.; Mazzulla, G. Factors influencing trip generation on metro system in Madrid (Spain). *Transp. Res. Part D Transp. Environ.* 2019, 67, 156–172. [CrossRef]

26. Domarchi, C.; Tudela, A.; González, A. Effect of attitudes, habit and affective appraisal on mode choice: An application to university workers. *Transportation* 2008, 35, 585–599. [CrossRef]

27. Buehler, R. Determinants of transport mode choice: A comparison of Germany and the USA. *J. Transp. Geogr.* 2011, 19, 644–657. [CrossRef]

28. Shen, J.; Sakata, Y.; Hashimoto, Y. A Comparison between Latent Class Model and Mixed Logit Model for Transport Mode Choice: Evidences from Two Datasets of Japan. Available online: http://www2.econ.osaka-u.ac.jp/library/global/dp/0605.pdf (accessed on 10 March 2020).

29. Doori, A.A. Waiting Time Factor In Public Transport By Binary Logistic Regression. *Aust. J. Basic Appl. Sci.* 2017, 11, 72–76.

30. Gadziński, J. Wpływ dostępności transportu publicznego na zachowania transportowe mieszkańców–przykład aglomeracji poznańskiej. *Prace Komisji Geografii Komunikacji PTG* 2016, 19, 31–42. [CrossRef]

31. Chen, J.; Li, S. Mode choice model for public transport with categorized latent variables. *Math. Probl. Eng.* 2017, 2017, 7861945. [CrossRef]

32. Fu, X.; Juan, Z. Exploring the psychosocial factors associated with public transportation usage and examining the “gendered” difference. *Transp. Res. Part A Policy Pract.* 2017, 103, 70–82. [CrossRef]

33. Wang, D.; Zhou, M. The built environment and travel behavior in urban China: A literature review. *Transp. Res. Part D Transp. Environ.* 2017, 52, 574–585. [CrossRef]

34. Limtanakool, N.; Dijst, M.; Schwanen, T. The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium-and longer-distance trips. *J. Transp. Geogr.* 2006, 14, 327–341. [CrossRef]

35. Sanit, P.; Nakamura, F.; Tanaka, S.; Wang, R. Location and mode choice decision mechanism analysis of multi-worker household in Bangkok, Thailand. *J. East. Asia Soc. Transp. Stud.* 2014, 10, 1243–1257.

36. Andong, R.F.; Sajor, E. Urban sprawl, public transport, and increasing CO₂ emissions: The case of Metro Manila, Philippines. *Environ. Dev. Sustain.* 2017, 19, 99–123. [CrossRef]

37. Chalak, A.; Al-Naghi, H.; Irani, A.; Abou-Zeid, M. Commuters’ behavior towards upgraded bus services in Greater Beirut: Implications for greenhouse gas emissions, social welfare and transport policy. *Transp. Res. Part A Policy Pract.* 2016, 88, 265–285. [CrossRef]

38. Chidambaram, B.; Janssen, M.A.; Rommel, J.; Zikos, D. Commuters’ mode choice as a coordination problem: A framed field experiment on traffic policy in Hyderabad, India. *Transp. Res. Part A Policy Pract.* 2014, 65, 9–22. [CrossRef]

39. Hammoudou, H.; Papaix, C. Policy packages for modal shift and CO₂ reduction in Lille, France. *Transp. Res. Part D Transp. Environ.* 2015, 38, 105–116. [CrossRef]

40. Zhong, S.; Zhang, L.; Ge, Y. Optimal Road Pricing for Both Traffic Efficiency and Safety; American Society of Civil Engineers: Reston, VA, USA, 2014.

41. Washbrook, K.; Haider, W.; Jaccard, M. Estimating commuter mode choice: A discrete choice analysis of the impact of road pricing and parking charges. *Transportation* 2006, 33, 621–639. [CrossRef]

42. Jain, D.; Tiwari, G. How the present would have looked like? Impact of non-motorized transport and public transport infrastructure on travel behavior, energy consumption and CO₂ emissions–Delhi, Pune and Patna. *Sustain. Cities Soc.* 2016, 22, 1–10. [CrossRef]
43. Hasnine, M.S.; Aboudina, A.; Abdulhai, B.; Habib, K.N. Mode shift impacts of optimal time-dependent congestion pricing in large networks: A simulation-based case study in the greater toronto area. *Case Stud. Transp. Policy* 2019, 8, 542–552. [CrossRef]

44. Irfan, M.; Khurshid, A.N.; Khurshid, M.B.; Ali, Y.; Khattak, A. Policy implications of work-trip mode choice using econometric modeling. *J. Transp. Eng. Part A Syst.* 2018, 144, 04018035. [CrossRef]

45. Collins, C.M.; Chambers, S.M. Psychological and situational influences on commuter-transport-mode choice. *Environ. Behav.* 2005, 37, 640–661. [CrossRef]

46. Eboli, L.; Forciniti, C.; Mazzulla, G. Spatial variation of the perceived transit service quality at rail stations. *Transp. Res. Part A Policy Pract.* 2018, 114, 67–83. [CrossRef]

47. de Oña, J.; de Oña, R.; Eboli, L.; Forciniti, C.; Mazzulla, G. Transit passengers’ behavioural intentions: The influence of service quality and customer satisfaction. *Transp. A Transp. Sci.* 2016, 12, 385–412. [CrossRef]

48. Department of Provincial Administration. Thailand Population: Official Statistics Registration Systems. Available online: https://stat.bora.dopa.go.th/new_stat/webPage/statByYear.php (accessed on 2 November 2020).

49. Gebeyehu, M.; Takano, S.-E. Modeling the Relationship between Travelers’ Level of Satisfaction and their Mode Choice Behavior Using Ordinal Models. Available online: https://pdfs.semanticscholar.org/7ceb/97ecde3f2f876a6d1b1345d0d2d10ad2e5e2.pdf (accessed on 2 November 2020).

50. Khan, O.A. Modelling Passenger Mode Choice Behaviour Using Computer Aided Stated Preference Data. Available online: https://core.ac.uk/download/pdf/10885199.pdf (accessed on 2 November 2020).

51. Ben-Akiva, M.; Lerman, S.R. Transportation Studies. In *Discrete Choice Analysis: Theory and Application to Travel Demand*; MIT Press: Cambridge, MA, USA, 2018.

52. Ben-Akiva, M.E.; Lerman, S.R.; Lerman, S.R. *Discrete Choice Analysis: Theory and Application to Travel Demand*; MIT Press: Cambridge, MA, USA, 1985; Volume 9.

53. Mackett, R.L.; Ahern, A. *Potential for Mode Transfer of Short Trips: Report on the Analysis of the Survey Results*; University College London: London, UK, 2000.

54. Ashiabor, S.; Trani, A.; Baik, H.; Hinze, N. Development of a Intercity Mode Choice Models for New Aviation Technologies. In *Aviation: A World of Growth, 29th International Air Transport Conference*; ASCE: Reston, VA, USA, 2007; pp. 61–77.

55. Miskeen, M.A.A.B.; Alhodairi, A.M.; Rahmat, R.A.A.B.O. Modeling of Intercity Travel Mode Choice Behavior for Non-Business Trips within Libya. *Res. J. Appl. Sci. Eng. Technol.* 2014, 7, 442–453. [CrossRef]

56. Anwar, A.M.; Yang, J. Examining the effects of transport policy on modal shift from private car to public bus. *Procedia Eng.* 2017, 180, 1413–1422. [CrossRef]

57. Charoentrakulpree, W.; Sajor, E.; Zimmermann, W. Middle-class travel patterns, predispositions and attitudes, and present-day transport policy in Bangkok, Thailand. *Transp. Rev.* 2006, 26, 693–712. [CrossRef]

**Publisher’s Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).