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機車路徑選擇之影響因素：臺北都會區共享機車實證研究

The influential factors on route choices of scooter riders: An empirical study of scooter sharing in Taipei

薛　婕

Chieh Hsueh

指導教授：林楨家　博士

Advisor: Jen-Jia Lin, Ph.D.

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An empirical study of scooter sharing in Taipei

本論文係薛　婕君（B07208011）在國立臺灣大學地理環境資源學系完成之學士班學生論文，於民國 111 年 4 月 8 日承下列考試委員審查通過及口試及格，特此證明。

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摘要

本研究旨在運用共享機車數據資料探討機車騎士路徑選擇偏好，以填補過去文獻在這項議題上的空缺。本研究以臺北共享機車使用者為研究對象，對其全球定位系統記錄進行隨機取樣，並透過 ArcGIS 路網分析依循 K 最短路徑法產生替選路徑，以及運用最大概似法估計二項羅吉特模式，釐清影響機車使用者路徑選擇之因素。實證結果顯示臺北機車使用者願意付出更多旅行距離、時間或金錢以換取更安全及舒適的路徑。其中「安全」為臺北機車使用者的首要考量，例如：在晨峰時段避開十字路口。值得注意的是，本研究分析不同時段的行為，並獲得重要的發現。機車騎士在晨峰時段重視行駛「速度」，在離峰時段在意「順暢」的騎乘經驗，而在深夜則追求騎乘環境的「安全」。另一個值得注意的發現為右轉密度的正向影響，此發現與過去對其他運具研究不同，並顯示機車異於汽車與自行車的獨特性。上述發現不僅可改善現有的機車導航服務，並可提供當地政府設計機車友善環境之參考，更可鼓勵共享機車的使用。同時，本研究結果有助於為未來私有機車研究奠定基礎。

關鍵詞：機車、共享機車、路徑選擇、最短路徑、二項羅吉特

Abstract

The research presented in this manuscript contributes to the insufficiency of route choice studies in the literature by examining the revealed preferences of scooter riders using data on scooter sharing use. This study adopted the Global Positioning System (GPS) records of shared scooters in Taipei as study data and randomly sampled study observations from the collected information. The route choice set was generated using the K-shortest paths method and created by ArcGIS Network Analysis. Binary logit models, whose coefficients were estimated by the maximum likelihood method, were applied to clarify the influential factors on the route choices of scooter riders. Findings suggest that scooter riders in Taipei are willing to use a safe and comfortable route by spending more travel distances, time, or costs. Scooter riders appear to place a relatively high value on "safety," such as avoiding intersections during rush hours and avoiding remote sites at midnight. Notably, this research considered the different periods and obtained exciting findings. Scooter riders value driving "speed" during morning peak hours, sense of "smoothness" during off-peak period, and "security" of circumstance at midnight. A noteworthy discovery is the positive influence of the right turn density on route choice, which is unlike the observations in previous research on other transport modes. Moreover, the discovery reveals the scooter riders' uniqueness from car and bicycle users. These findings can improve the existing scooter navigation services and provide reference for local administrations to design a scooter-friendly environment, even encouraging scooter-sharing usage. Simultaneously, the findings can serve as a foundation for further research progress on private scooters.

Keywords: scooter, scooter sharing, route choice, shortest path, binary logit model

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1. Introduction

Scooters are popular commuting tools in Asia. However, scooters have been largely ignored in traveler behavior discussions and transportation planning. Developments in Google Maps Navigation have steadily replaced traditional navigation instruments and have added convenience to navigation for people. However, Google Maps Navigation was able to provide service for scooter riders starting in 2017. Modak (2018) pointed out that Google Maps Navigation considers riding speed and alleyways. Moreover, the system avoids roads without street signs or has difficulty finding them. Google Maps makes navigation accessible, but the navigation application is not 100 percent accurate. Misguided issues happen regularly as discussed by netizens on various social media platforms. Moreover, navigation information is not adequately localized. The traditional market consisting of many stands, which is a characteristic of Taiwan, is not considered in the route planning. Those stands typically occupy parts of the roads; passing some roads is difficult in the morning, but they are accessible in the afternoon. In fact, scooter riders take detours to avoid the crowd in a traditional market than follow the directions advised by Google Maps Navigation. Hence, a discrepancy exists between the current navigation systems and the actual preference of scooter riders. Clarifying the influential factors on route choices is a critical issue in developing a more practical and localized navigation for scooter riders. In addition, many countries have worked on altering traffic environments by studying route choices to improve transport quality and safety.

Previous studies on route choices have mostly focused on the preferences of cyclists and car drivers. Nevertheless, their findings were not the case for scooter riders' route choices. Moreover, not all influential factors can be alternately applied among different transportation modes. Some differences have been observed in the influential factors on route choices between cyclists and car drivers. Broach and Gliebe (2012) and Fitch and Handy (2020) argued that distances, traffic signals, and bicycle lanes influence cyclists' route choices. Apart from indicating that slopes and intersections affect the route choices of cyclists, Sarjala (2019) mentioned that the age of buildings and land use from the aspect of a built environment are also influential factors. As far back as 2003, Stinson and Bhat (2003) indicated the concepts of link level (including the roadway class, parking lots, bicycle facilities, and bridge types) and route level (including travel time, delay, and intersections) to explain cyclists' choice behaviors. Other than distance and traffic signals mentioned in the study on the route choice of cyclists, the number of turns plays a vital role in explaining the route choice of car drivers (Manley et al., 2015; Ciscal-Terry et al., 2016). Apart from having high mobility such as cars, scooter riders directly expose themselves to traffic environments, similar to what happens with cyclists. Given this characteristic of scooters, the previous studies focusing on car drivers and cyclists cannot be applied directly to scooters. To our knowledge, existing research on route choice behaviors is lacking not only in the understanding of scooter riders but also in the discussion of different periods.

Taiwan is a scooter-island whose density of scooters is number one in the world (Syrbe, 2021) and the second largest scooter-sharing market (Enrico & Alexander, 2021). Hence, Taiwan provides an excellent research environment to investigate the route choice behaviors of scooter riders. To fill the research gap stated above, this research aims to clarify the influential factors on the route choices of scooter riders during different periods to provide reference for the related governmental agencies in designing a scooter-friendly environment based on the local users' preferences. The rest of this manuscript is organized as follows. Section 2 reviews the existing literature and raises a research design concept. Then, Section 3 describes the study areas and observations. Section 4 explains the applied method, study variables, and data sources. Section 5 presents and discusses the results of model estimation. Finally, conclusions are drawn in Section 6, along with recommendations for future research.

2. Literature review

Route choice studies support travelers' behavior analysis and are instrumental in the trip assignment (Prato, 2009; Fitch & Handy, 2020). Stated preference (SP) methods and revealed preference (RP) methods have been used in previous studies, especially RP methods utilizing GPS location data. Using GPS location data can help researchers obtain the implicit preferences in route choice that may not be reflected in questionnaire surveys. The data can provide actual routes and prevent the gap between a respondent's description and his/her reality as mentioned in Fitch and Handy (2020). However, the amount of GPS data is so huge that choosing the sample can be a problem. In one study, Broach and Gliebe (2012) selected specific samples rather than random samples. They opted for respondents who biked regularly and finished the survey regarding demographics; notably, women were oversampled in this study. Manley et al. (2015) picked up 677,411 routes from 300 million routes by a batch-processing algorithm. Then, they used the ten most frequently traveled pairs of postcodes to obtain the appropriate sample size.

Most of the previous studies have adopted logit models, including the binary logit model and the multiple logit model, to analyze cyclists' route choices; moreover, these studies have applied the maximum likelihood method to estimate model coefficients (Prato, 2009). Several advanced logit models have been used for specific considerations. For instance, Broach and Gliebe (2012) took path-size logit to deal with the routeoverlapping issue. In addition, Helbich et al. (2014) took region-wide logit models, autologistic regressions, and geographically weighted logit models to deal with the diversity in various spaces. Meanwhile, studies on the route choice of car drivers have tended to analyze from different aspects, such as Manley et al. (2015), who compared the similarity between the actual route and the simulated route. Furthermore, Ciscal-Terry et al. (2016) used route directness index and geographical route directness index to analyze and compare the paths' characteristics.

The generation of alternative routes may vary according to the different influential factors considered. The methods of K-shortest paths (Van der Zijpp & Catalano, 2005), link elimination (Azevedo et al., 1993), link penalty (De La Barra et al., 1993), and labeling routes (Ben-Akiva et al., 1984) are deterministic approaches to generate route alternatives. The K-shortest paths method aims to minimize the travel distance. The link elimination method sequentially removes links from the network until the new shortest routes are created. By contrast, the link penalty method repeatedly increases the impedance of all links on the shortest path. The labeling route approach utilizes various road segment features, such as travel time or travel cost to generate alternative routes.

Based on the existing literature, travel distance, turn, traffic signal, and travel time are all used as explanatory variables in studying the route choices of cyclists and car drivers. Travel-related factors emphasize the variable related to travel, including travel distance, travel time, and travel cost. Built environment factors also have substantial impacts on the route choices of travelers. The built environment involves all the variables related to how a traveler interacts with the physical world, such as road design and greenness. We categorized built environment factors into two groups, namely, road characteristics and circumstance. Avoiding turns (Broach & Gliebe, 2012; Ciscal-Terry, Dell'Amico, Hadjidimitriou, & Iori, 2016) was the common consideration between cyclists and drivers. The bicycle lane (Broach & Gliebe, 2012; Fitch & Handy, 2020) and the slope (Broach & Gliebe, 2012) were considered in the route choice of cyclists, while the intersection (Manley et al., 2015) was considered in the route choice of car drivers. Along with the increasing health consciousness, air quality became a new consideration of travelers (Hertel et al., 2008). The scenic route for leisure purposes was a popular contemporary choice (Zlot & Schmid, 2005; Gao et al., 2021). Land use attributes were also considered in the route choice of cyclists (Sarjala, 2019).

To sum up, RP and SP have been used in the past research on route choice. However, the SP method based on recall routes or surveys may cause bias wherein a response does not correspond to an actual preference or behavior. By contrast, the RP method reflects the actual behavior, even the implicit preference, which is a reliable method for a prophase study of route choice. Evidently, logit-related models are typical and mature route choice models that can obtain reliable model estimations and have been extensively adopted in the literature (Prato, 2009; Broach et al., 2012; Rossetti & Hurtubia, 2019). Each approach to generate alternative routes has a different consideration. The shortest distance is the main purpose of K-shortest paths, while the labeling route method focuses on less travel time or travel cost. Given the network characteristic, the K-shortest paths method is more suitable for our study. As stated above, the road feature and the built environment are the two most discussed factors in route choice studies, such as those on traffic light density, turn density, and land use. Given the hybrid characteristic of scooters, influential factors on car drivers and cyclists may all be considered in the present study.

3. Context and datasets

3.1. Scooter sharing

Three companies currently offer scooter-sharing services in Taiwan. Table 1 presents the comparison among them. Apart from the difference in the served vehicles, WeMo and iRent use light electric scooters, while GoShare uses Gogoro. The more significant difference among these three companies is that WeMo users can pay their rent at convenience stores. By contrast, users need to pay by credit card to borrow scooters from iRent and GoShare. Given this difference, the customer base of WeMo is broader, which may include students without credit cards. By 2020, GoShare had more users in Taiwan, followed by WeMo and iRent (Li, 2021). Meanwhile, WeMo received the highest satisfaction from the Android App store among the three. Furthermore, WeMo is not only the first scooter sharing operator in Taiwan but also the largest one (Enrico & Alexander, 2021). For the reasons outlined above, this research selected WeMo as the study company, and the study data of GPS records were provided by WeMo.

Table 3-1. The comparison of three companies of scooter sharing service.

Company	WeMo	iRent	GoShare
Vehicle	KYMCO CANDY (light)	New Many 110 EV	Gogoro VIVA, Gogoro 2
Service area	Taipei, New Taipei, Kaohsiung	Taipei, New Taipei, Taoyuan, Taichung, Tainan, Kaohsiung	Taipei, New Taipei, Taoyuan, Yunlin, Tainan
Scooter amount	7,000	5,200	4,200
User amount	300,000	200,000	400,000
Credit card only	X	O	O
App score (1-5)	4.5	2.6	3.7

3.2. Study area

WeMo proclaimed its service areas, including Taipei, New Taipei, and Kaohsiung, on March 17, 2020. The number of scooters in Taipei and New Taipei is up to 5,500, and it also reaches 700 in Kaohsiung. According to the scooter numbers and due to the lack of analysis data in New Taipei, this research narrowed the study area down to Taipei only.

Although the study area was narrowed, WeMo indicated that most of the rental hot spots were in Taipei, thus resulting in the high representation of the city. As of December 31, 2021, Taipei had 0.97 scooter per person, and each individual used this vehicle 2.2 times a day on weekdays on average and 5.7 times a week on average; this rate indicates that nearly everyone has a scooter and uses it frequently in this highest population density capital (Ministry of Transportation and Communication R.O.C. 2022). Notably, according to the Global Moped Sharing Market Report 2021, Taiwan owns the highest scooter sharing service density per inhabitant globally. Moreover, Taipei and New Taipei have the most prominent global scooter sharing fleet. In brief, Taipei serves as a helpful case study for investigating the route choice of scooter riders due to its high ownership per person of scooters and the bullish scooter-sharing market. Although the study area shown in Figure 3-1 only accounts for less than 40% of the area of Taipei, it covers 98% of the population and represents the city.

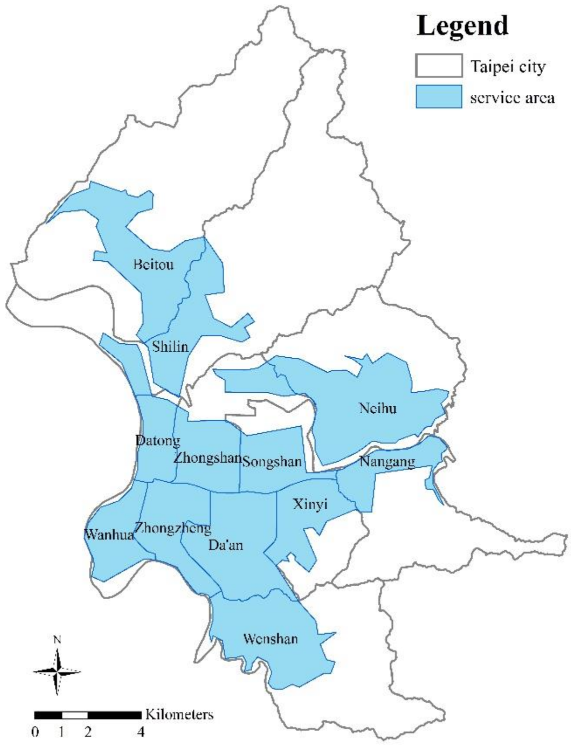

Figure 3-1. The service area of WeMo in Taipei city (the study area).

3.3. Study observations

WeMo provided half-year de-identification GPS data from May 1, 2019 to November 2, 2019. The research finally selected trips from October 21, 2019 to October 25, 2019 as the study data due to the following considerations. First, we selected one week without precipitation to control the weather conditions. Second, we avoided the consecutive holidays and summer vacation from the end of June to the middle of September to focus on the regular times.

Furthermore, the peak and off-peak periods are based on the 2019 average daily traffic investigation form, which was defined and issued by the Directorate General of Highways, MOTC (2021). The peak periods include the morning peak hours from 7 a.m. to 9 a.m. and the evening peak hours from 5 p.m. to 7 p.m. However, no specific definition has been set for the off-peak period. Considering the time to start work is more consistent among workers than the time to get off, this research selected the morning peak to represent the peak period and defined 2 p.m. to 4 p.m. as the off-peak period. Moreover, with scooter sharing being an alternative to public transport at midnight, we expected different traveler behaviors. Thus, we considered 1 a.m. to 3 a.m. as the midnight period and brought it into the study.

A total of 4,444; 4,191; and 1,110 trips are taken during the morning peak, off-peak, and midnight periods, respectively, in the study data. To reach a sufficient sample size, this research conducted a random sampling process on the study data and collected sufficient observations after checking that the rent time and the return time were entirely within the selected periods. The whole route was entirely within Taipei, and the travel time was more than 2 min. To avoid a round-trip (a trip back to the origin), we set 10 m, considering the location error of GPS, as the threshold. After several screening steps, 446 trips during the morning peak period, 470 trips during the off-peak period, and 392 trips during the midnight period were available for this analysis. The sampling error was controlled under 4%.

4. Method

4.1. Model and variables

Route choice is the decision-making process wherein the user selects a particular route for travel from the origin; it also explores the factors that influence the traveler's route choices (Bapat et al., 2017). Route choice is a tradeoff to maximize travelers' utility. Consequently, generating a choice set of alternative routes and estimating discrete choice models are two essential parts of route choice. The route choice in this research emphasized the selections between the actual used route and the hypothetical alternative route (the shortest route) and discussed the attributes of interest along the route.

The binary logit model was adopted to analyze binary outcomes (whether a route was used or not used). The utility function is specified as follows:

$$U_{ij} \text{ (scooter rider } i's\ utility\ of\ selecting\ route\ j) = \beta_j X_{ij} + \varepsilon_{ij} \qquad (1)$$

where $\beta_j =$ coefficient vector, $X_{ij} = a\ vector\ of\ explanatory\ variables$, and$\varepsilon_{ij} = random\ error$.

We assumed that only two choices were available for scooter riders: the used route (j = 1) and the alternative route (j = 2, the shortest route between the same origin and destination of the used route in this research). In addition, the two routes were independent of each other, this supporting the assumption of the independence of irrelevant alternatives (IIA). The probability of scooter rider i selecting the used route, P_{i1}, is as follows:

$$P_{i1} = P(U_{i1} \geq U_{i2}) = P(\beta_1 X_{i1} - \beta_2 X_{i2} \geq \varepsilon_{i2} - \varepsilon_{i1}) = \frac{EXP(\beta_1 X_{i1})}{EXP(\beta_1 X_{i1}) + EXP(\beta_2 X_{i2})} \qquad (2)$$

Table 4-1 defines the explanatory variables used in the discrete choice model and their hypothetical associations with the route choices. A number of studies indicated that most people opt for the shortest route regardless of whether they are car drivers or cyclists (Aultman-Hall et al., 1997; Howard & Burns, 2001; Prato & Bekhor, 2006; Hood et al., 2011; Sun et al., 2014). Although some research still suggests this hypothesis, other studies have argued that selected/dominant routes are significantly longer than shortest routes (Nielsen et al., 2002; Zhu & Levinson, 2015; Ciscal-Terry et al., 2016; Lu et al., 2018; Sarjala, 2019). Hence, other factors influencing route choices may exist. Ciscal-Terry et al. (2016) demonstrated that car drivers may select longer paths allowing for higher speeds. Their result inferred that route choice may be based on the consideration of speeds. Furthermore, density, institutional land use, slope, and age of buildings may all be associated with the route choices of cyclists (Sarjala, 2019). In another study, Fitch and Handy (2020) pointed out that cyclists preferred bicycling infrastructures. To sum up, car drivers care more about travel volume, while cyclists care more about cycling environments. Despite the existing differences between car drivers and cyclists, these two groups share some similar preferences of route choice, such as the features of distance and traffic lights. Some preferences of route choice are still common among different transportation modes, which implies that the factors included in the abovementioned studies may be considered in the route choice of scooter riders.

Selecting the explanatory variables utilized in the utility function was based on previous empirical findings described in the Literature Review section. It can be categorized into three groups: travel, road, and circumstance. In this research, travel variables denote the attributes of a trip, including travel time, travel distance, and travel cost. Travel time and distance are two acknowledged negative factors affecting route choices. Travelers prefer the lowest cost according to the rationality assumption in neoclassical economics. Scooter sharing users are charged with a flat rate per minute so that users may be more sensitive to travel costs than other private transport mode users. Furthermore, the service has a base charge of $15 TWD within 6 min and $2.5 TWD/min after 6-min use. Notably, the cost changes with time may cause a different influence before and after 6 min.

The road variables include the road features, traffic features, and facilities being supplied along a route, which have been extensively discussed in previous research. Majumdar et al. (2015) indicated that a broad road width is a common concern of travelers. Time-consuming factors are reasonable as significant negative factors in route choice, even though some exceptional situations exist. Making a turn increases the time cost and requires a high cognitive load. The negative preference for turns was proven by Broach et al. (2012). Likewise, although intersections (Buehler & Dill, 2016; Sarjala, 2019) and traffic lights (Broach et al., 2012; Fitch & Handy, 2020) are usually perceived as negative factors, the result of Broach et al. (2012) showed that the influence of traffic lights may be reserved at high-traffic streets. Based on the consideration of safety, cyclists show preference to cycle lanes to avoid high traffic volumes or speeds (Dill & Carr, 2003; Broach & Gliebe, 2012). Howard and Burns (2001) suggested that travelers alter their routes to avoid traffic accidents. In addition, Majumdar et al. (2015) used the word “motorized barriers” to include “presence of motorized vehicles on the road” and “on-street parking.” Moreover, they pointed out the threat to cyclists from motor vehicles faced by scooter riders.

A scooter offers high speed and high mobility, but it is also exposed to high risks. These two aspects show that a scooter combines both the advantages and disadvantages from cars and bicycles on roads. As such, the traffic features mentioned earlier, which are more important to drivers, and the circumstance, which are more important to cyclists, are both considered. The circumstance variables emphasize physically built environment features. Greenness and street trees provide scenic value and play a positive role in the route choice (Buck & Buehler, 2012; Park & Akar, 2019). Krenn et al. (2014) announced that cyclists circumvent stores and commercial land use areas to access an uninterrupted route without many pedestrians. Land use mix is regarded as a friendly environment for travelers (Saelens et al., 2003; Krenn et al., 2014). Prato et al. (2018) argued that highly residential areas imply the perception of longer distances, which may negatively influence route choice. Institutional land uses developed for the community's social, educational, health, cultural, and recreational needs, are the most preferred factors for cyclists in the finding of Sarjala (2019). Apart from land use, traffic jams and crowds related to buses and metros are recognized, thus proving their negative impacts (González et al., 2016).

4.2. Used and alternative routes

The used and the alternative routes (i.e., routes being not used by riders) were identified on the basis of ArcMap. The observed data were GPS points collected per 30 sec. We employed the GIS tool to create the used routes from these GPS coordinates. In the literature, most of the choice set generation procedures are based on the k-shortest path method. In this research, we set k as one, that is, we identified the shortest distance route as the alternative route for a used route. The shortest routes were generated using the Network Analyst tool included in ArcGIS 10.7. As shown in Fig. 4-1, the origin and destination of the shortest alternative for each used route were the same as the first and last GPS points of a used route. However, the used links and directions of an alternative route and a used route were different.

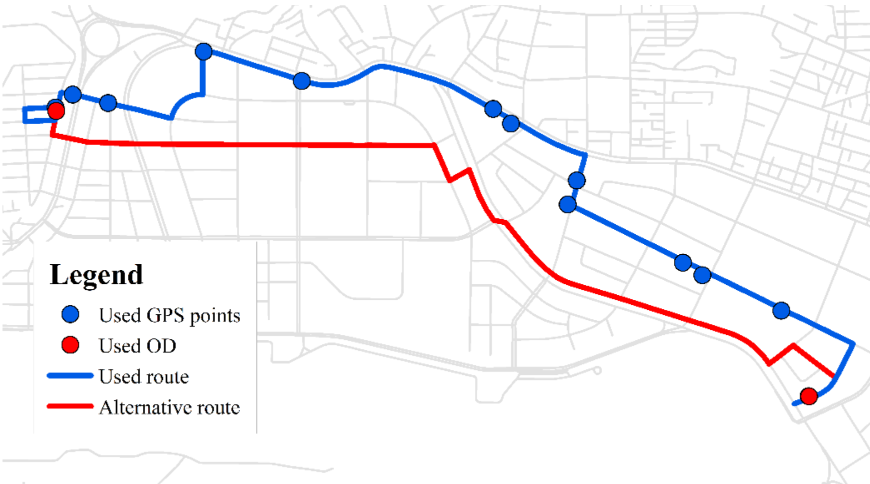

Figure 4-1. The generation of a used route and its alternative.

4.3. Data

A scootering network (Figure 4-2) was created using a geographic information system (GIS) by merging five network datasets from road networks in 2019, which contain provincial highways, city/county roadways, country roadways, town roadways, and alleys. The data were obtained from the Ministry of Transportation and Communications, R.O.C. The travel distances of used routes and alternative routes were measured by ArcMap 10.7. Nevertheless, given the lack of vehicle volume and speed data, we subtracted the end time from the beginning time to determine the travel time of a used route. Then, we estimated the travel velocity to estimate the travel time of an alternative route. The travel costs, based on the announced charge standard, were measured by $15 TWD for 6-min use and $2.5 TWD/min after 6-min use. Regarding the road variables, an average roadway width was calculated by splitting a route into points and averaging the value of all points.

Variable data were prepared via four approaches. First, we used open data to estimate the facility density along routes, such as traffic accident density and traffic light density. Second, we estimated right turn density, left turn density, and intersection density on the bases of the network geometry data. Third, we estimated the coverage ratio of a facility of an entire route and took the scooter priority lane and the scooter exclusive lane as examples. Fourth, we estimated the density or the coverage ratio within a buffer. Although the facility is not on the road, it may still influence travelers' route choices. Each variable was given a specific buffer related to its characteristics. For instance, the Construction and Planning Agency of the Ministry of the Interior (2018) pointed out that a bus station should be 1.5 m apart from a roadway. Therefore, we used a 3-m buffer to estimate the bus station density for each route.

Car parking space and scooter parking space were taken into the parking space density estimation because they are at the roadside and may form a threat to scooter riders. We also categorized the roadways in Fig. 4-2 into arterial roads, collector roads, and local streets. Then, we estimated the proportion of each class of the whole route. As the sum of three is one, which meant strong collinearity among the three, we only put the ratio of the local street into the models. We set a 25-m buffer according to Krenn et al. (2014) to estimate the coverage ratio of greenness and each land use. Greenness included nature reserves, parks, rivers, and so on. The land-use classification was based on the National Land Surveying and Mapping Center, Ministry of the Interior, R.O.C. Instead of drawing a buffer from a route, we measured each route’s proportion within a 500-m service area of the MRT station.

Given that the variables are too numerous to be included in this study, the detailed descriptive statistics of the study variables were provided in the Appendix. The distributions of most variable values displayed reasonable intervals. The strange minimum of the travel time and the travel distance might be due to the existence of round trips (Figure 4-3). The shared scooter should be returned to a legal parking space, which is difficult to find in Taipei. Moreover, users may not park at the same parking space. Consequently, even though we set 10 m as a threshold to avoid the round trip, the round trip with an o-d distance of more than 10 m still existed. In addition, the round-trip travel time must certainly be more than the threshold (2 min).

The values of the average roadway width, maximum roadway width, scooter priority lane, bus route, and MRT service area were in a bell-shaped distribution. Intersection and mixed residential land use were in a bell-shaped distribution during the morning peak and midnight, whereas the scooter exclusive lane was in a bell-shaped distribution during the morning peak and off-peak periods. Traffic light was only in a bell-shaped distribution during the morning peak, whereas traffic accidents was in a bell-shaped distribution during the off-peak period. Except for the aforementioned variables, which indicated a left-skewed distribution, other variables indicated a right-skewed distribution. The coefficients of variation (the ratios of the standard deviation to mean) for most variables were adequate in the analysis, and the variation of the average road width was relatively minimal.

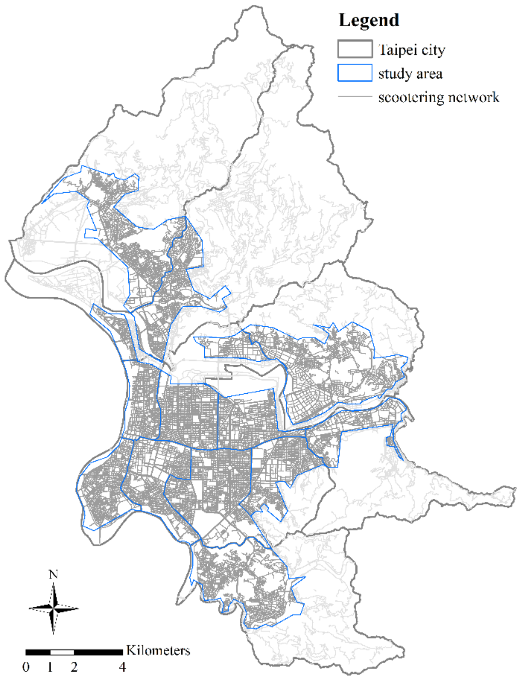

Figure 4-2. Taipei scootering network in 2019 and the study area.

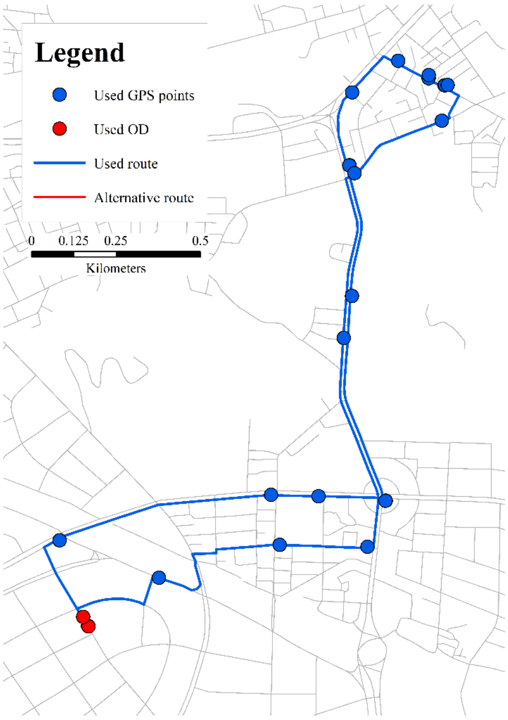

Figure 4-3. An example of a round-trip.

Table 4-1 Definitions and hypothesized associations of the explanatory variables with scooter route choice.

Variable	Definition (unit)	Hypothesized association	Reference
Travel			
Travel time	Route travel time (min)	-	Prato et al. (2012); Sun et al., 2014; Majumdar & Mitra (2019)
Travel cost	Route travel cost (TWD)	-	-
Travel distance	Route distance (m)	-	Aultman-Hall et al.(1997); Prato et al. (2012); Sun et al., (2014)
6 min +	Travel cost, if travel time is more than 6 minutes; 0, otherwise	-	
6 min -	Travel cost, if travel time is 6 minutes or less; 0, otherwise	-	
Road			
Average roadway width	Average roadway width along a route (m)	+	Majumdar et al. (2015)
Maximum roadway width	The maximum roadway width along a route (m)	-	
Traffic accident	Number of yearly traffic accidents along a route per km (accident/km)	-	Howard & Burns (2001)
Right turn	Number of right turns along a route per km (right turn/km)	-	Broach et al. (2012)
Left turn	Number of left turns along a route per km (left turn/km)	-	Manley et al. (2015)
Traffic light	Number of traffic lights along a route per km (light/km)	-	Broach et al. (2012); Fitch & Handy (2020)
Intersection	Number of intersections along a route per km (intersection/km)	-	Buehler & Dill (2016); Sarjala (2019)
Parking space	Number of parking spaces along a route per km (parking space/km)	-	Majumdar et al. (2015)
Local street	Distance ratio of local street along a route	-	Winters et al. (2010); Yao et al. (2013)
Scooter priority lane	Distance ratio of scooter priority lane along a route	+	Dill & Carr (2003); Broach & Gliebe(2012)

Table 4-1 (continued).

Variable	Definition (unit)	Hypothesized association	Reference
Scooter exclusive lane	Distance ratio of scooter exclusive lane along a route	+	Dill & Carr (2003); Broach & Gliebe(2012)
Circumstance			
Convenience store	Number of convenience stores along a route per km (store/km)	-	Krenn et al. (2014)
Greenness	Area ratio of green area within 25m buffer along a route	+	Krenn et al. (2014); Park & Akar (2019)
Bus stop	Number of bus stops along a route per km (stop/km)	-	
Bus route	Distance ratio of being overlapped with bus routes along a route	-	González et al. (2016)
MRT service area	Distance ratio of being covered within 500 m buffers of MRT station along a route	-	
Commercial land use	Distance ratio of commercial land use along a route	-	Krenn et al. (2014)
Residential land use	Distance ratio of residential land use along a route	-	Prato et al. (2018); Sarjala (2019)
Mixed residential land use	Distance ratio of mixed residential land use along a route	+	Krenn et al. (2014); Chen et al.(2018)
Government agencies land use	Distance ratio of government agencies land use along a route	+	Sarjala (2019)
School land use	Distance ratio of school land use along a route	+	Sarjala (2019)

Note: MRT means mass rapid transit; + means positive relationship, - means negative relationship.

5. Result and discussion

The present research applied binary logit models and the glm package of R computer language to estimate the relationships between the explanatory variables and binary outcomes. Confidence levels of 99.9%, 99%, or 95% were indicated for every coefficient in the estimation results to represent different significant levels. Tables 5-1 to 5-3 list the estimation results of the binary logit models for the observations during the morning peak period (7 a.m. – 9 a.m.), the off-peak period (2 p.m. – 4 p.m.), and the midnight period (1 a.m. – 3 a.m.), respectively. The models for each period contained five sub-models. Sub-model 1, sub-model 2, and sub-model 3 individually considered the travel distance, cost, and time. Given the different rental fares before and after 6 min, sub-model 4 used a binary variable to present whether the travel time was over 6 min and the interaction with the travel cost. Sub-model 5 ignored any travel-related parameters. Notably, this research did not consider all the distance, cost, and time variables in one model. Although these three variables were three essential factors influencing travelers' behavior based on previous research, significant multicollinearity existed in the data. All VIF (variance inflation factor) values were below 5, which entailed that no significant multicollinearity existed among the explanatory variables. All the estimated models showed acceptable goodness-of-fit, especially during the morning peak. In addition, the coefficient signs for most of the estimated models were consistent with the hypothesized associations in Table 4-1. The results of the chi-square tests were significant, thus revealing that the study attributes significantly contributed to explaining the route choice of scooter riders. The likelihood ratio tests examined the significance levels of the superior goodness-of-fit between different models. The likelihood ratio tests results suggested that Models 1-5, 2-2, and 3-4 had better explanatory power during the three periods, respectively. Given the complexity of comparing and discussing the information in Tables 5-1 to 5-3, we kept all significant variables from three periods and reorganized the associations into Table 5-4 which is discussed in the forthcoming sub-section.

5.1. Travel-related variables

From Table 5.4, we argued that the travel cost, travel time, 6 min -, and 6 min + were significantly and positively related to route choices during the three periods. From this argument, some more crucial factors led scooter riders to take detours instead of taking the shortest route or the quickest route. Travel distance was significantly and positively associated with route choices during the morning peak and off-peak periods but insignificant in explaining route choices at midnight. A smaller traffic volume might have allowed the faster speed at midnight, thus making scooter riders insensitive to travel distances.

Half of the used routes at midnight were less than 10% longer than the shortest paths, while 43% of the used routes during the off-peak period were less than 10% longer than the shortest paths. By contrast, only 7.6% of the used routes during the morning peak were less than 10%

longer than the shortest paths. Furthermore, nearly 90% of used routes at midnight were less than 50% longer than the shortest paths, and so were 84% of used routes during the off-peak period. Meanwhile, only 60% of routes were used during the morning peak. Hence, scooter riders were willing to take lengthy detours during the morning peak to avoid unwanted features and approach preferable services.

The results of off-peak and midnight models approximated the empirical results of cyclists' route choice study from Broach et al. (2012), which indicated that half of all trips were within 10% of the shortest distance, and 95% of trips were less than 50% longer. However, the difference between periods was not considered in previous discussions. This study extracted a dissimilar result from previous studies: scooter riders were willing to take longer detours during the morning peak. In general, most people did not choose the shortest path and took a detour. What factors affect scooter riders taking detours? The answer is discussed in the following two sub-sections.

5.2. Road variables

Without travel-related variables, the density of the intersection negatively impacts riders' choice, primarily extending overwhelming influence during the morning peak. We realized that riders must be more concentrated when they pass the intersection to avoid vehicles from all directions—the same apprehension to the negative impact of a traffic accident during the morning peak. Moreover, the average roadway width is positive during the three periods, whereas the coefficient of maximum road width is negative during morning and off-peak periods. A border road width provides a more prolonged separation between vehicles and scooters to reduce crash frequency. Nevertheless, an overly large separation may cause drivers to feel safer and subsequently accelerate, thus endangering scooter riders (Aarts & Van, 2006). In brief, safety is the most significant factor for scooter riders.

In addition, scooter riders are only allowed to ride on outside lanes when parking spaces are located at the roadside. Roadside parking spaces cause two severely negative influences on scooter riders. First, when drivers change lanes to park cars, they may obstruct the path of scooter riders. Second, when drivers abruptly open car doors, they may knock scooter riders down. As stated before, parking spaces reveal the negative preference during the morning peak period. Furthermore, scooter riders should follow the two-stage left turn rule in Taiwan. This complex rule makes turning left more time consuming, and the negative impact of the left turn on route choices is certain. By contrast, scooter riders have a significant favorable preference for right turns. Given the advantage of speed and flexibility, scooter riders can easily shuttle between streets to avoid the negative features. Scooter priority lanes and scooter exclusive lanes are predominantly located on busy arterial roads. Therefore, during the morning peak period, scooter lanes may offset the negative influences of the danger caused by the heavy traffic but lead to no residual value of lanes, which is similar to the inference of Broach et al. (2012).

Although scooter lanes provide a separate lane for scooter riders, most scooter lanes can only accommodate one to two scooters in terms of width, which are even narrower than general roads. Thus, scooter riders may take a detour to avoid these lanes during the off-peak period and at midnight.

The significant concern about safety found in this study is consistent with that of the previous studies (Howard & Burns, 2001; Broach et al., 2012; Ciscal-Terry et al., 2016; Buehler & Dill, 2016; Sarjala, 2019). The negative preference for the left turn variable is tantamount to the findings of Broach et al. (2012). However, the positive preference for the right turn variable is unique in the literature, accentuates scooter riders' uniqueness, and needs further exploration in the future.

5.3. Circumstance variables

According to the above discussion, the scooter riders' preference for travel-related variables and road variables does not change over time. Notably, scooter riders' preference for some circumstance variables is opposite during day and night. In the morning, people are used to stopping by convenience stores for shopping on their way to destinations. This practice has contributed to standing vehicles and compelled scooter riders to make a detour to avoid such traffic chaos. It may slow down the travel speed and lead to a negative preference during the morning peak. Conversely, roadways at midnight are desolate, and 24-h convenience stores provide light and security to scooter riders. Therefore, scooter riders prefer roadways with convenience stores at midnight.

In addition, residential areas primarily accommodate housing and residents. During the morning peak, most people flow out from these areas, and the heavy traffic may lead to lower travel speeds. It forces travelers, who are in a rush and value travel speeds, to avoid passing through residential areas. In the afternoon, people's activities in residential areas remain frequent. Scooter riders need to be more careful with crowds and loss travel experiences of smoothness. Consequently, residential land use negatively influences scooter riders' route choices at daytime as suggested in previous research (Prato et al., 2018; Sarjala, 2019). Conversely, at midnight, most people are gathered in residential areas and construct a secure atmosphere called, "ren qi" in Chinese, causing a positive preference. Relatively, the commercial services stop at midnight. Scooter riders are more likely to avoid commercial areas, which are depopulated and without "ren qi."

5.4. Elasticity

Overall, considering the satisfactory goodness-of-fit, sub-model 4 is an appropriate model for discussing the elasticity. The elasticity shown in Table 5-5 demonstrates that the right-turn density dominates the choices of scooter riders during the morning peak. The average roadway width also has a substantial but much smaller impact. By contrast, the average roadway width plays a leading role during the off-peak period. Convenience stores attract scooter riders at midnight. Moreover, scooter riders show a positive preference for the average roadway width and the right turn, whereas they show a negative preference for the left turn. Right-turn density and left-turn density are influential during the three periods and exert opposite effects. Thus, turn density is essential for scooter riders' route choice, especially during the morning peak. The average roadway width, traffic accident density, turn density, and residential land use were more sensitive during the morning peak due to the heavy traffic in the morning. The elasticity of the local street and scooter priority lane is similar between the off-peak period and at midnight.

Table 5-1 Binary logit models for the observations during morning peak period (outcome: used route = 1).

	Model 1-1		Model 1-2		Model 1-3		Model 1-4		Model 1-5	
	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF
Intercept	-6.4170***		-4.8154***		-5.1047***		-5.1058***		9.2596***	
Travel										
Travel distance	0.0006***	0.0001								
Travel cost			0.0587***	1.4993						
Travel time					0.1764***	1.4794				
6 min +							0.1765***	0.0282		
6 min -							0.1767*	0.0895		
Road										
Intersection									-0.4106***	
Average roadway width	0.3419***	1.7617	0.2957***	1.2392	0.2700 **	1.2078	0.2700**	0.0823		
Maximum roadway width	-0.0432*	2.0849								
Traffic accident	-0.0276**	1.4712	-0.0348***	1.4551	-0.0361***	1.4541	-0.0361***	1.2286		
Right turn	1.9030***	1.3022	1.7674***	1.2773	1.8004***	1.2758	1.8004***	1.4591		
Left turn	-0.7904***	1.5116	-0.8991***	1.4985	-0.9031***	1.4941	-0.9031***	1.7367		
Parking space			-0.0042*	1.3215						
Circumstance										
Convenience store	-0.1724*	1.2522	-0.1733**	1.3338	-0.2014**	1.2286	-0.2014**	2.2832		
Street tree	-0.0100*	1.2739	-0.0124***	1.2611	-0.0123**	1.2521	-0.0123**	1.4941		
Residential ratio	-10.1400***	1.7716	-10.2974***	1.7834	-10.9508***	1.7356	-10.9507***	2.0240		
ρ square	0.6384		0.6048		0.6160		0.6160		0.9511	
χ square	790.74***		749.08***		762.98***		762.98***		1178.056***	

Note: Number of observations: 446; *** significant at α=0.001, ** significant at α=0.01, * significant at α=0.05; VIF: variance inflation factor.

Table 5-2 Binary logit models for the observations during off-peak period (outcome: used route = 1).

	Model 2-1		Model 2-2		Model 2-3		Model 2-4		Model 2-5	
	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF
Intercept	-0.3206		-2.0778***		-1.4029*		-1.7254**		-0.2358	
Travel										
Travel distance	0.0002***	1.3335								
Travel cost			0.0525***	1.2014						
Travel time					0.0711***	1.3378				
6 min +							0.0729***	1.8443		
6 min -							0.1489**	1.7451		
Road										
Intersection									-0.0195***	1.4216
Average roadway width			0.1318**	1.7208	0.1432**	1.7650	0.0894*	1.4513	0.1196**	1.4081
Maximum roadway width			-0.0249*	1.7584	-0.0237*	2.0328				
Right turn	0.4351***	1.4123	0.3871***	1.3774	0.4139***	1.3806	0.4257***	1.3911	0.4394***	1.4176
Left turn	-0.1324*	1.3691	-0.1354*	1.3666	-0.1331*	1.3734	-0.1305*	1.3788	-0.1344*	1.4470
Local street	-1.7930***	1.7421	-1.2686**	1.6647	-1.8415***	1.8709	-1.6244***	1.7817	-1.5484***	1.6099
Scooter priority lane	-0.8226*	1.4946	-0.9937**	1.3408	-0.8791*	1.5684	-1.0113**	1.5862	-0.9469**	1.3750
Scooter exclusive lane	-0.6251*	1.6693			-0.6977*	1.6655	-0.6931*	1.6248		
Circumstance										
Greenness	-1.0990***	1.4073	-0.9313***	1.4205	-0.8974**	1.4248	-0.9971***	1.4012	-0.9317 ***	1.4015
Bus stop	0.1509*	1.2735					0.1372*	1.2913		
Residential ratio	-2.3210***	1.0627	-3.0862***	1.0464	-2.5063***	1.0541	-2.4133***	1.0599	-1.7390**	1.0291
ρ square	0.1127		0.1770		0.1309		0.1334		0.1011	
χ square	147.1***		231***		170.8***		174.1***		131.9***	

Note: Number of observations: 470; *** significant at α=0.001, ** significant at α=0.01, * significant at α=0.05; VIF: variance inflation factor.

Table 5-3 Binary logit models for the observations during midnight period (outcome: used route = 1).

	Model 3-1		Model 3-2		Model 3-3		Model 3-4		Model 3-5	
	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF
Intercept	-0.9937		-0.6485		-0.6594		-0.6341		-0.1919	
Travel										
Travel distance	0.0001 *	1.3660								
Travel cost			0.0159 *	1.2168						
Travel time					0.0413 *	1.2657				
6 min +							0.0410 *	1.3090		
6 min -										
Road										
Intersection	-0.0778 ***	1.4762	-0.0803 ***	1.4539	-0.0800 ***	1.2657	-0.0794 ***	1.4507	-0.0862 ***	1.409
Average roadway width	0.2160 *	1.5188	0.2048 *	1.5554	0.2004 *	1.2657	0.1958 *	1.5573	0.2441 **	1.505
Right turn	0.4098 **	2.3542	0.3899 **	2.2986	0.3887 **	1.2657	0.3915 **	2.3147	0.4065 **	2.223
Left turn	-0.3415 *	2.2919	-0.3461 *	2.2471	-0.3402 *	1.2657	-0.3337 *	2.2724	-0.3815 **	2.179
Local street	-4.9060 ***	2.2321	-5.0024 ***	2.2134	-4.9859 ***	2.2134	-4.9538 ***	2.1997	-5.2129 ***	2.206
Scooter exclusive lane	-3.0950 ***	1.3517	-3.0613 ***	1.3599	-3.0495 ***	1.3606	-3.0438 ***	1.3559	-3.1906 ***	1.357
Circumstance										
Convenience store	0.7556 ***	1.8195	0.7491 ***	1.8085	0.7506 ***	1.8088	0.7566 ***	1.8171	0.7521 ***	1.834
Commercial land use	-19.0900 ***	1.5215	-19.3796 ***	1.5235	-19.3189 ***	1.5209	-19.5097 ***	1.5206	-19.3409 ***	1.533
Residential land use	13.9400 ***	2.5155	13.7633 ***	2.4881	13.9153 ***	2.4924	13.9759 ***	2.4936	13.7590 ***	2.483
ρ square	0.6129		0.6119		0.6125		0.6137		0.6076	
χ square	665.68 ***		664.56 ***		665.19 ***		666.55 ***		659.88 ***	

Note: Number of observations: 393; *** significant at α=0.001, ** significant at α=0.01, * significant at α=0.05 ; VIF: variance inflation factor.

Table 5-4 Empirical effects of variables on route choice during different periods.

Variable	Morning peak	Off-peak	Midnight
Travel			
Travel distance	+	+	+
Travel cost	+	+	+
Travel time	+	+	+
6 min +	+	+	+
6 min -	+	+	△
Road			
Intersection	△/△/△/△/-	△/△/△/△/-	-/-/-/-/-
Average roadway width	+/+/+/+/△	△/+/+/+/+	+/+/+/+/+
Maximum roadway width	-/△/△/△/△	△/-/-/△/△	
Traffic accident	-/-/-/-/△		
Right turn	+/+/+/+/△	+/+/+/+/+	+/+/+/+/+
Left turn	-/-/-/-/△	-/-/-/-/-	-/-/-/-/-
Parking space	△/-/△/△/△		
Local street		-/-/-/-/-	-/-/-/-/-
Scooter priority lane		-/-/-/-/-	
Scooter exclusive lane		-/△/-/-/△	-/-/-/-/-
Circumstance			
Convenience store	-/-/-/-/△		+/+/+/+/+
Greenness		-/-/-/-/-	X
Bus stop		+/△/△/+/△	X
Bus route			X
MRT service area			X
Commercial land use			-/-/-/-/-
Residential land use	-/-/-/-/△	-/-/-/-/-	+/+/+/+/+

Note: The results are synthesized from Tables 5-1 to 5-3 and presented as: sub-model 1/sub-model 2/sub-model 3/sub-model 4/sub-model 5; +: significantly positive effect, -: significantly negative effect, △: a significance worse than α = 0.05, □ : significances of the 5 sub-models are all worse than α = 0.05, X: no hypothesized association.

Table 5-5 Elasticity of variables explaining route choice during different periods.

Variable	Morning peak Model 1-4	Off-peak Model 2-4	Midnight Model 3-4
Travel			
6 min +	0.4150	0.4682	0.0023
6 min -	0.0530	0.1093	-
Road			
Average roadway width	0.7202	0.6022	0.0109
Traffic accident	-0.3863	-	-
Right turn	1.4883	0.5235	0.0035
Left turn	-0.3371	-0.1335	-0.0028
Local street	-	-0.2051	-0.0048
Scooter priority lane	-	-0.2197	-
Scooter exclusive lane	-	-0.1728	-0.0073
Circumstance			
Convenience store	-0.1727	-	0.0304
Greenness	-	-0.1807	X
Bus stop	-	0.1264	X
Commercial land use	-	-	-0.0068
Residential land use	-0.2329	-0.1402	0.0049

Note: -: significances are all worse than α = 0.05, X: no hypothesized association.

6. Conclusion

The phenomenon of taking a detour in Taipei shows that scooter riders are willing to spend more distance, time, or costs to avoid risky facilities or pursue positive factors. First, the evidence that safety matters for scooter riders is overwhelming, including observations where riders avoid intersections and accidents during the morning peak. Second, turn density is also critical during the three periods. Scooter riders are willing to take a right turn to seek a favorable route but abhor the time-consuming and dangerous left turns. Although detour behavior and some critical factors manifest regardless of period, some influential factors vary over time. As pointed out in the Result and discussion sections, we suggest that "safety" is the critical factor in scooter riders' route choice no matter when. Except for this common point, scooter riders have different considerations over three periods. During the morning peak, scooter riders value travel "speed" and tend to avoid areas with the crowd. Among the study observations in this research, the average travel speed in the morning is obviously faster than the other periods, which may be a result of valuing speed. During the off-peak period, scooter riders prefer driving "smoothness" along their trips. It leads scooter riders to avoid local streets and narrow scooter lanes. At midnight, "security" is the most essential consideration for scooter riders. They are more sensitive to the security of circumstances.

In conclusion, this research reveals some opportunities for future studies related to scooter riders' route choices and takes the first step to fill the knowledge gap regarding these riders' route choice behaviors. The empirical findings may contribute to mature and practical navigation. Moreover, altering road environments to improve safety for scooter riders can decrease the mileage and carbon emissions by decreasing scooter riders' detours. Determining the preferences for scooter-sharing users may increase the usage rate of the scooter-sharing service and achieve the vision of a circular economy.

6.1. Limitations and future works

For further clarification on the route choice of scooter riders, future studies should examine five issues that reflect the limitations of this study. The first issue is owing to measurement limitations. The findings in this research are based on a sample made up of riders of shared scooter. To increase reliability and validity significantly, riders of private scooter should be considered. In addition, owing to the de-identification data, individual variables were not excluded in this research. The data limitations also forced this research to relinquish testing further road characteristics, such as the lack of real-time traffic information, which can be included in future works. Owing to this limitation, this study did some subjective explanations and required more convincing evidence in the future.

The second issue relates to the initial data extraction. Owing to the lack of individual information, this research could not completely remove round trips and multi-purpose trips from the study observations. Based on the characteristic of a flat rate, this research inferred that these ineffective observations are uncommon in shared-scooter uses. However, they may persist and influence the research findings. Better initial data extraction processes to clear round trips should be considered in future studies.

The third issue is associated with the model set. Although this research took the morning peak instead of the evening peak to represent rush hours, the model of evening peak may be different from that of morning peak and should be considered in the future. Furthermore, this research noticed that a longer detour usually accompanied a longer trip. Consequently, future studies can consider distinguishing models by travel distances.

The fourth issue concerns the generation of alternatives. In this study, the K-shortest path method was applied to generate alternatives. However, the K-shortest path method may generate a circuitous alternative or an unattractive alternative (Prato, 2009). Future studies may attempt other adequate approaches for generating alternatives, such as labeling routes (Ben-Akiva et al., 1984) or Google Maps Route Planner.

Finally, the fifth issue is according to the IIA assumption. This research assumed the existence of IIA among the study observations. However, a used route and its alternative may overlap in the real world. Hence, future researchers can apply Path Size Logit (PSL) models to adjust the utilities partially for link-overlap (Frejinger & Bierlaire, 2007; Broach et al., 2012; Khatri et al., 2016).

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Appendix

Table A-1. Descriptive statistics of the explanatory variables for the observations of morning peak model.

Variable	Minimum	Maximum	Median	Mean	Coefficient of Variation
Travel					
Travel time (min)	0.8787	42.0000	9.0000	10.6353	0.6205
Travel cost (TWD)	15.0000	105.0000	22.5000	27.8182	0.5495
Travel distance (m)	165.8046	18453.6110	3311.9012	4178.2997	0.7256
Road					
Average roadway width (m)	5.1635	23.0192	10.6588	10.7002	0.1595
Maximum roadway width (m)	7.0000	48.0000	23.0000	25.1861	0.3776
Traffic accident (accidents/km)	0.0000	158.5600	41.3796	42.9192	0.4299
Right turn (right turns/km)	0.3004	15.5709	3.0115	3.3159	0.6065
Left turn (left turns/km)	0.0000	10.2925	1.2555	1.4971	0.7416
Traffic light (traffic lights/km)	0.0000	7.6403	2.2638	2.5070	0.5598
Intersection (intersections/km)	0.5049	94.7581	20.3738	29.4556	0.8135
Parking space (parking spaces/km)	0.0000	533.9456	89.5675	107.4032	0.7254
Local street	0.0000	1.0000	0.1457	0.2167	0.9851
Scooter priority lane	0.0000	0.9943	0.2505	0.2924	0.7553
Scooter exclusive lane	0.0000	1.000	0.2898	0.3385	0.7156
Circumstance					
Convenience store (stores/km)	0.0000	14.5139	2.9442	3.4393	0.6583
Greenness	0.0000	0.5512	0.0395	0.0636	1.0756
Bus stop (stops/km)	0.0000	6.1023	1.0922	1.2597	0.8054
Bus route	0.0000	1.0071	0.2950	0.3182	0.5841
MRT service area	0.0000	1.0000	0.6792	0.6226	0.4842
Commercial land use	0.0000	0.4033	0.0767	0.0869	0.6848
Residential land use	0.0000	0.4830	0.0635	0.0853	0.8827
Mixed residential land use	0.0000	0.5080	0.1363	0.1483	0.5588
Government agencies land use	0.0000	0.1365	0.0081	0.0154	1.3071
School land use	0.0000	0.3670	0.0247	0.0352	1.1330

Table A-2. Descriptive statistics of the explanatory variables for the observations of the off-peak model.

Variable	Minimum	Maximum	Median	Mean	Coefficient of Variation
Travel					
Travel time (min)	0.0320	59.0000	9.7733	11.7032	0.7060
Travel cost (TWD)	15.0000	147.5000	20.0000	28.2050	0.6872
Travel distance (m)	3.1605	20728.8296	2309.0595	3071.1098	0.8518
Road					
Average road width (m)	3.0000	18.9838	10.9500	11.0152	0.1812
Maximum road width (m)	3.0000	44.0000	23.0000	24.3649	0.3956
Traffic accident (accidents/km)	0.0000	253.4884	50.6540	53.4498	0.4627
Right turn (right turns/km)	0.0000	11.7637	1.6874	2.0107	0.7265
Left turn (left turns/km)	0.0000	23.5274	1.2978	1.6732	0.9604
Traffic light (traffic lights/km)	0.0000	15.2163	2.7038	2.9497	0.6116
Intersection (intersections/km)	0.0000	175.8393	51.4253	52.6110	0.3071
Parking space (parking spaces/km)	0.0000	808.5758	99.7251	125.0845	0.8304
Local street (-)	0.0000	1.0000	0.1314	0.2065	1.0999
Scooter priority lane (-)	0.0000	1.0000	0.3176	0.3553	0.7222
Scooter exclusive lane (-)	0.0000	1.0000	0.3664	0.4076	0.6997
Circumstance					
Convenience store (stores/km)	0.0000	20.4184	3.6539	4.1476	0.7179
Greenness	0.0000	1.0000	0.1678	0.2963	1.1169
Bus stops (stops/km)	0.0000	10.1976	1.3035	1.5064	0.8803
Bus route overlapped (-)	0.0000	1.0000	0.3244	0.3457	0.6314
MRT service area overlapped (-)	0.0000	1.0000	0.8125	0.7059	0.4354
Commercial ratio (-)	0.0000	0.9425	0.0778	0.1327	1.1359
Residential ratio (-)	0.0000	0.8372	0.0549	0.0950	1.2360
Mixed residential ratio (-)	0.0000	0.9971	0.1344	0.2060	0.9529
Government agencies ratio (-)	0.0000	0.7773	0.0073	0.0302	1.9863
School ratio (-)	0.0000	0.8252	0.0222	0.0499	1.6511

Table A-3. Descriptive statistics of the explanatory variables for the observations of midnight model.

Variable	Minimum	Maximum	Median	Mean	Coefficient of Variation
Travel					
Travel time (min)	0.0512	59.0000	9.9965	11.4379	0.6487
Travel cost (TWD)	15.0000	147.5000	24.9912	29.7794	0.5829
Travel distance (m)	2.3519	23244.5247	3284.0146	3957.2629	0.7472
Road					
Average road width (m)	5.3571	18.9369	10.6975	10.8115	0.1564
Maximum road width (m)	7.0000	46.0000	25.0000	25.8788	0.3735
Traffic accident (accidents/km)	0.0000	155.3243	49.0891	51.0474	0.3876
Right turn (right turns/km)	0.0000	15.7856	1.4100	1.7486	0.8202
Left turn (left turns/km)	0.0000	17.7588	1.2082	1.6197	0.9937
Traffic light (traffic lights/km)	0.0000	10.4957	2.5821	2.8712	0.5857
Intersection (intersections/km)	0.0000	134.1527	50.8283	52.2129	0.2494
Parking space (parking spaces/km)	0.0000	2976.2829	89.3649	121.2842	1.1554
Local street (-)	0.0000	1.0000	0.1230	0.1897	1.0418
Scooter priority lane (-)	0.0000	1.0000	0.3651	0.4142	0.6471
Scooter exclusive lane (-)	0.0000	1.0000	0.3342	0.4667	2.0691
Circumstance					
Convenience store (stores/km)	0.0000	425.1833	5.1526	7.8216	2.0573
Commercial ratio (-)	0.0000	0.3908	0.0679	0.0735	0.5804
Residential ratio (-)	0.0000	0.6208	0.0476	0.0686	1.0878
Mixed residential ratio (-)	0.0000	0.5625	0.1380	0.1522	0.5350
Government agencies ratio (-)	0.0000	0.3476	0.0066	0.0138	1.7226
School ratio (-)	0.0000	0.5629	0.0192	0.0308	1.6158