Article

The Impact of Traffic Information Provision and Prevailing Policy on the Route Choice Behavior of Motorcycles Based on the Stated Preference Experiment: A Preliminary Study

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Abstract: It is anticipated that the prevalence of motorcycles in Asian countries will continue to increase, causing congestion and network imbalances concerning the nature of motorcycles. Literature demonstrates Variable Message Signs (VMSs) as an effective measure for addressing this issue. Understanding route choice behavior may thus aid in determining the appropriate traffic information to broadcast. This study aims to identify the impact of VMS messages related to traffic conditions and regulations on the route choice of motorcycle riders. In this instance, the core concept of ramp metering is adapted for non-highways to manage the proportion of motorcycles entering the traffic stream of the mainline. Two predetermined routes were offered through a stated preference survey to capture the responses to VMS. A binary logit model was initially introduced, further improved by including the individual characteristics and accommodating the unobserved factors across a series of observations (panel effects) by applying the mixed binary logit. It was revealed that traffic flow conditions significantly affect route preference; therefore, motorcycles tend to choose routes with lower volumes. However, waiting time at a ramp meter has no impact. The present research is a preliminary investigation for further implications in proposing traffic management strategies under mixed traffic situations.

Keywords: route choice behavior; motorcycle riders; traffic information; ramp metering; variable message sign

1. Introduction

One of the most prevalent phenomena in developing countries is the reliance on private modes of transportation, which remains challenging. This occurs not only due to the constraints of facilities and infrastructure but also as a result of the driver's behavior in making transportation decisions, which inevitably leads to traffic congestion. In the majority of Asia countries, notably Thailand, Vietnam, Indonesia, Malaysia, and China, motorcycles are widely popular for daily mobility. More specifically in Indonesia, the share of motorcycles ownership relative to other motorized vehicles is very prominent, reaching 85% in 2020, with an average growth rate of 5.36% during the preceding five [1]; moreover, this number is projected to rise further. This is driven by the benefits of motorcycles over automobiles in terms of flexibility, accessibility, affordability, and maneuverability.

However, the increase in mobilization cannot always be compensated by expanding the network capacity due to space and financial constraints. Instead, using existing infrastructure more efficiently while implementing appropriate traffic management is a crucial key in regulating travel demand, especially in mixed traffic conditions. Chatterjee and McDonald [2] reported that utilizing Variable Message Signs (VMSs) to inform drivers about real-time traffic conditions is an effective strategy for managing the road network's travel demand, along with reducing travel time, enhancing the operational performance of urban transportation systems, and ultimately lowering the environmental impacts. Nonetheless,

as cited by Bierlaire (2006) [3], this important role of real-time traffic information in influencing transportation demand must be backed by comprehensive behavioral models that can explain travel preferences [4–6], one of which is through analyzing route choice decisions. Therefore, the current study focuses on this behavior in response to the provision of traffic information, which in this case, is disseminated through the VMS. It is a media to notify drivers of certain instructions, regulations, warnings, or traffic conditions. As a result, the first factor to be tested here is the degree of traffic flow, as also concluded by Polydoropoulou et al. (1996), who performed a questionnaire survey of commuters in the California Bay Area [7]. Furthermore, other external stimuli believed to affect the route choice decisions of road users include traffic regulations and policies prevailing on the networks since they may alter the trip duration and vehicle speed. An article by van den Berg et al. (2006) [8] cited that the implementation of ramp metering clearly influences the route choices of drivers [9,10]. Thus, this article attempted to evaluate this issue by adopting the core concept of ramp metering for non-freeway roads and predicting the relationship between waiting time on the ramp against route choice. As a matter of maintaining traffic flow and road capacity, it is anticipated that this measure would control the proportion of motorcycles entering a given road from an on-ramp by setting a predetermined time gap between vehicles.

This research considers whether motorcycle riders who travel between identical origin-destination (OD) pairs would pick the same routes depending on the perceived utility stated as a combination of a number of observable and unobservable factors. Motorcycles were selected as the object of analysis due to the scarcity of literature within the scope of this research field [11]. Two alternative routes were introduced, and a Binary Logit model was initially estimated to capture this route propensity. Subsequently, a Mixed Binary Logit model was explored to account for the correlation across observations of the same respondent (panel effect). It should be noted that this article is a preliminary analysis of a study that aims to uncover the relevant factors affecting the route choice behavior of motorcycle riders on a more extensive scale with a greater variety of explanatory variables.

The rest of the paper is organized as follows. The following section contains a review of the literature on route choice behavior, particularly in the traffic information environment. Next, in Section 3, a methodology applied in this work for capturing the route choice behavior of motorcycle riders, in terms of data collection and analysis is elaborated. Section 4 provided the descriptive analysis of the stated preference data. The model estimation in different specifications is elaborated in Section 5, followed by a discussion in Section 6. In the end, some concluding remarks, study implications, and future research directions are described in Section 7.

2. Literature Review

This section describes a concise review of existing studies on route choice analysis, as well as an introduction to the VMS and ramp metering concepts.

2.1. Previous Works

Route choice refers to recurrent route decisions by countless drivers based on personal evaluations of the attributes of the available alternatives. There are a series of applications of route choice analysis, for instance, transportation planning and demand forecasting [12], predicting travelers' preferences within road networks under different hypothetical scenarios [13], as well as identifying the relevance between individual perceptions of route attributes and sociodemographic characteristics [13]. In addition, Prato (2009) concluded that understanding route choice behavior aids in comprehending drivers' reactions to traffic information [12]. Providing road users with traffic information, especially in the form of route guidance, may improve road network efficiency as drivers are more likely to avoid congested areas [14]. Jou et al. (2005) used a stated preference survey method to examine the route switching behavior based on the types of real-time traffic information [15]. They showed that presenting real-time traffic information to drivers might greatly diminish

heavy traffic. Further emphasized by Gao and Zhang (2016), real-time traffic information is able to assist drivers in picking the best route and effectively guide them to use the existing road network more efficiently, thereby minimizing travel time and mitigating severe congestion [16]. In accordance with these wide ranges of implications, the behavioral analysis of route choice has been an essential and favored issue throughout the years. Not only in regard to understanding the decisions of passenger car drivers in choosing routes [17–19], but numerous studies have been performed on the route choice behaviors of cyclists [20,21], and truck drivers as well [22–24]. These studies have a variety of diverse approaches ranging from stated preference (SP) surveys, Global Positioning System (GPS) observations, lab simulations, driving simulator experiments, or a combination of those.

However, unlike automobiles and bicycles, a relatively small amount of research has been undertaken on route choice analysis for motorcycles, with only two studies discovered. First, Turner (2009) identified the presence of a cognitive aspect in the decision to choose routes for motorcycle couriers, who were presumed to be familiar with the road network and capable of mobilizing freely without relying on GPS navigation [25]. The experiment was carried out to assess the effect of angularity on the route taken by 50 couriers in London for a total of 2425 individual motorcycle trips. It was concluded that motorcycle couriers prefer to take a route with the shortest angular distance, although often taking the route with the least block distance. Moreover, the effect of turns on cognitive distance has a substantial influence on their route choices. Second, a study by Schreiner et al. (2007) tried to employ the methodology proposed by Hyodo et al. (2000) [26] for the case of trucks and motorcycles in Ho Chi Minh City, Vietnam [22]. This approach was based on the maximum route overlapping and modified in various network configurations. Among the three factors included in the model, the speed limit variable was the only one shown to influence the behavior of motorcycle route choice, whilst the values of time and payment type were not statistically significant. Overall, it is clear that this present study seeks to fill the gap left by the literature by analyzing the variables that affect the route choice behavior of motorcycle riders in response to external circumstances.

A study by Bovy and Stern (1990), who classified four major groupings of factors identified as being associated with route choice behavior [27], supports the significance of broadcasting traffic information to road users when determining their preferred route, including:

- Attributes of the route alternatives (e.g., road properties, traffic situations, environmental issues, etc.);
- Characteristics of the trip (e.g., mode of transportation, trip purpose, etc.);
- Socio-economic characteristics;
- Other external circumstances (e.g., time, weather conditions, and traffic information).

Further stated by Jou et al. (2005), multiple prior works have shown that providing real-time traffic information might alter drivers' route choices [15]. Schofer et al. (1993) reported that road users digest and interpret the information in the VMS based on the nature, substance, and format of the message [28]. In this regard, Xu et al. (2011) assessed the effect of various VMS formats on traffic diversion using real-time traffic data in Shanghai and SP survey data [29]. The probit model estimation revealed the content of information, timeframe, and traffic conditions all had a substantial impact on route choice. Relevant studies have also demonstrated that a warning message significantly influences the route decisions of drivers [30].

A discrete choice model is considered a suitable fit for identifying variables that may contribute to drivers' route choice behavior [31], given that route preferences are determined spontaneously [27]. Numerous research has estimated the magnitude and direction of variables related to route choice behavior by utilizing several model specifications, such as binary logit [11,18,20], multinomial logit [32,33], nested logit [17], link-nested logit [34,35], recursive logit [21,36], and mixed logit [19,37]. In a comparable subject, Vacca et al. [11] used revealed preference in the form of GPS data in Cagliari, Italy, to estimate the route switching behavior pertaining to route features, socio-economic characteristics,

activity-based data, inertial mechanism, and learning effects. By applying the specifications of the Binary and Mixed Binary Logit models, it was discovered that delay, particularly in relation to distance, as well as habits and learnings have a significant role in determining the propensity of route switching. Nevertheless, this research disregarded the impact of external cues on drivers' travel decisions.

2.2. Variable Message Sign (VMS)

A Variable Message Sign (VMS) is a network traffic management scheme that displays real-time traffic information, including advanced warnings about emergencies, incidents, and other occurrences that predictably cause delays [38], as cited by Bature and Georgakis (2016) [39]. This electronic signage board also has a vital role in directing vehicles to alternative routes in an effort to balance network demand. However, up to this point, the utilization of VMS in Indonesia is still limited to the Jakarta Metropolitan Area (known locally as *Jabodetabek*, an acronym for Jakarta-Bogor-Depok-Tangerang-Bekasi), particularly on toll roads and highways.

A large number of existing studies in the broader literature have pointed out the contribution of VMS to the improvement of network performance and service quality [14] by minimizing travel time and traffic delays [40]. A study by Bature and Georgakis (2016) reported that VMS could effectively improve network capacity even without modifying the existing design, as proven by the 38.37% increase in capacity of the Central Business District in Kaduna, Nigeria, hence ultimately solving the perennial congestion [39]. Additionally, in terms of traffic safety, VMS may reduce the risk of traffic collisions [41], as well as direct road users to avoid approaching the affected route in the event of incidents [17]. As a result, the congestion problem, which many cities or countries are still struggling with, can be resolved gradually and consistently [17,39,40]. It is expected that fewer traffic situations would result in lower vehicle emissions and fuel consumption [40]. In the end, these positive impacts of VMS can create a more balanced distribution of traffic flow on the road network [42].

2.3. Ramp Metering

Federal Highway Administration (2020) defines a ramp meter as traffic signals installed on a freeway on-ramp that is set with a substantially shorter cycle time to regulate the frequency of vehicles entering the traffic stream on the mainline by releasing a single vehicle or a very small number of them for each green phase [43]. Implementing this scheme may stabilize and smooth traffic flow by reducing disturbances that generate more prolonged stop-and-go conditions [43]. As a result, the bottlenecks and delays often caused by platoons of vehicles competing over existing gaps may be prevented or, in fact, shifted onto the ramp [44] to accelerate the vehicle flow. The components of ramp metering and the operational diagram of this system are shown in Figure 1.
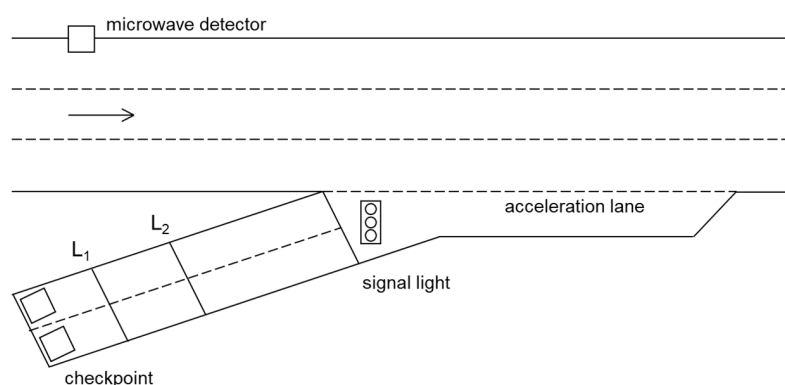

Figure 1. Ramp metering [45].

Ramp metering has proven beneficial for maintaining capacity flow on the mainline, avoiding blockages of upstream ramps, and efficiently decreasing network travel time by half [46]. This notion was further elaborated by the Federal Highway Administration (2020), which highlighted the advantages of implementing ramp metering, including: (1) reducing travel time, delay, and congestion while increasing mobility through the freeway network and traffic throughput; (2) reducing the number of traffic accidents by helping to break up the platoons of vehicles entering the freeway; (3) diminishing the disruption of traffic flow; and (4) lowering vehicle emissions and fuel consumption on the freeway [43].

3. Methodology

This section elaborates on the methodology applied in this paper regarding experimental design, data collection, and development of the discrete choice model.

3.1. Experiment Design

Identifying the factors that might influence the route choice behavior of motorcycle riders was initially analyzed by performing a Stated Preference (SP) survey. A set of hypothetical choice situations were given to capture the behavioral responses of respondents [20,47] by making and comparing trade-offs among available alternatives [48]. This approach was selected considering its time and cost-effectiveness, as well as the predominance of SP experiments that enable the evaluation of rare or nonexistent potential choices that can hardly be revealed [48]. Moreover, its ability to prevent multicollinearity across attributes, and the capacity to pre-define the choice set [49], made the SP survey popular.

The network configuration described in the questionnaire form involved two routes with contrasting levels of road functions. These routes were supposed to be situated in a busy area, generally an office and commercial zone. The choice set generation process, which refers to determining alternative routes between OD pairs, is an essential process in route choice analysis. Respondents were instructed to envision themselves riding a motorcycle from an origin location to a designated destination (see Figure 2). In this event, as motorcycle riders, respondents had to choose one of the predefined route choices (either Route 1 "arterial road" or Route 2 "local road") in accordance with their personal preferences and the given alternative attributes. The underlying assumption in the labeled choice experiment is that Route 1 is primarily an arterial road that traverses the Central Business District (CBD). Typically, this major road has a relatively faster speed (30 to 35 mph), greater capacity with a minimum road width of 8 m, as well as fewer intersections to diminish traffic delay. Arterial roads are designed to deliver traffic between city centers at the highest possible level of service. On the contrary, Route 2 is a local road that connects local secondary roads with arteries through collector roads (speed of 25 mph and a maximum road width of 5 m), accommodating short trips through neighborhoods and serving local access.

Referring to the findings of the study by Long et al. (2021), which revealed that the threshold in the travel time difference for drivers to change routes, given the underlying premise that both inertia and habit are zero, ranges from 0.012 h (7.2 s) to 0.053 h (3 min and 11 s) when real-time travel time is provided [50]. Accordingly, it was assumed that each respondent already had prior knowledge of the average travel time to the destination through Route 1 (8 min) and Route 2 (10 min), as the aforementioned significant difference in travel time. Furthermore, respondents were expected to pay attention to the traffic information broadcast by the VMS, which was strategically located just before the intersection of the two routes (see Figure 2).

The focus of the SP survey was to assess the influence of providing traffic information, in particular by showing the hypothetical real-time traffic conditions and the performance of a traffic management scheme on the route choice behavior of motorcycle riders. This strategy aims to balance the flow of traffic spread across the road network by controlling the proportion of motorcycles on a particular road, which essentially adopts the same principles as ramp metering.
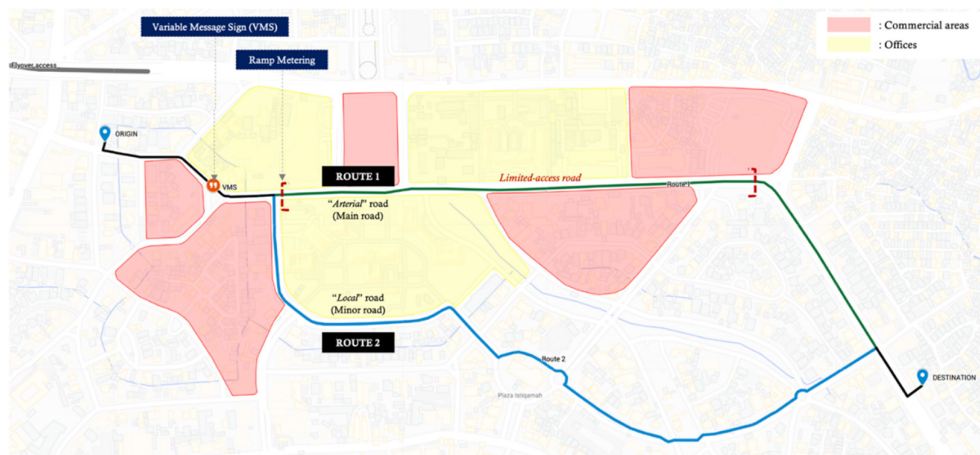
Figure 2. Alternative routes were given in the Stated Preference (SP) survey.

According to Jou et al. (2005), the supply of real-time traffic information should emphasize the quality and accuracy of the contents in order to optimize the system's value [15]. Therefore, all explanatory variables that were accounted for in this research were delivered to the respondents through VMS content, including the traffic flow conditions (light, moderate, and heavy), as well as the estimated waiting time owing to the installation of a ramp meter (0, 3, and 5 min), as listed in Table 1. Referring to Yan and Wu (2014), graphical VMS messages produced a more positive impact compared to the text-only format [51], in line with the results of Choocharukul and Wikijpaisarn (2013) that proved color-coded traffic information can considerably affect drivers' route choice decisions [52]. Moreover, Chatterjee and McDonald (2004) reported that the information presented in graph-only style enables drivers to read and respond more quickly [2]. It is further emphasized by Gan et al. (2006) that the effect of graphical VMS on route choice was discovered to be significant, especially under heavy congestion [53]. In accordance with these findings, the SP survey conducted for the present research provided VMS with color-coded network maps that distinguish traffic flow conditions.

Table 1. The combination of attributes of each alternative was given in the SP survey.

Treatment Combinations	Traffic Flow Conditions		Access Waiting Time with Ramp Metering
	Route 1 "Arterial"	Route 2 "Local"	
1	Moderate	Heavy	3 min
2	Light	Moderate	5 min
3	Heavy	Moderate	0 min
4	Heavy	Heavy	3 min
5	Moderate	Light	0 min

It is understandably not feasible to evaluate all 27 full factorials stated choices for each respondent; thus, a block design consisting of five hypothetical scenarios was established. These treatment combinations were verified to reflect the actual settings adequately. As the road functions were not put into the same categories, it is important to point out that the same level of vehicle flow on Routes 1 and 2 might lead to different performance. Notably, this analysis is a preliminary step toward identifying the key features that influence the route choice of motorcycle riders on a more extensive scope.

3.2. Data Collection

From a total of 160 Indonesians who submitted their responses, only 135 (or 84.4%) claimed to be motorcycle riders. The remaining 15.6% had to be removed from the dataset. It is worth noting that each respondent was given five stated choices, and a dataset of

675 observations was then analyzed to capture the route choice behavior of motorcycle riders. The questionnaire survey of this study mainly included the following four aspects: group classification of motorcycle riders, stated preference choices, along with individual attributes related to socio-economic and driving characteristics.

1. Screening and filtering. This step identified respondents who were motorcyclists and eliminated those who were not in the target population. Furthermore, motorcycle riders were then distinguished into riders who use motorcycles for daily commuting and/or work purposes in terms of service providers, such as motorcycle taxis ('ojek'), delivery couriers, etc.;
2. Stated preference (SP), provided choices towards the attributes of alternatives consisting of the traffic flow conditions and the estimated waiting time on the ramp before entering the mainline;
3. Respondents' driving characteristics, including driver's license ownership, driving age, frequency of driving per day, driving style, regular travel purpose, and current exposure to traffic information;
4. Socio-economic characteristics of respondents, such as gender, age, occupation, education, and income, were collected.

3.3. Model Development

The route choice model that specifies the behavior of motorcycle riders while selecting a route was developed in this study by applying a random utility model. As mentioned in the preceding section, the performed preliminary survey precisely offered respondents with two different route types (Route 1 "arterials" and Route 2 "local road"), which led to the adoption of a logit model with binary specifications to evaluate the impact of some predetermined attributes on their preferred route. Standard binary logit was tested foremost with respect to its simplicity and ease of calculation. However, it was predicted that the IIA (independence of irrelevant alternatives) properties of this model would be irrelevant in the case of route choice, prompting to the estimation in a mixed logit structure capable of capturing the unobserved attributes across individuals, alternatives, or multiple observations in the SP survey.

3.3.1. Binary Logit Model

In accordance with the experimental design, two route alternatives were presented in the SP survey; hence, a discrete choice model with binary specification was introduced to estimate the size and direction of the relationship between dependent and explanatory variables. Equation (1) below illustrates this paradigm.

$$U_{in} = V_{in} + \varepsilon_{in} \tag{1}$$

where U_{in} is the utility function of alternative *i* for individual *n*, V_{in} is the systematic component of the utility of alternative *i* for individual *n*, and ε_{in} is the random utility component that is assumed to be independently and identically distributed (i.i.d.) according to a Gumbel distribution (extreme value type 1). In general, V_{in} can be broken down into the following equations.

$$V_{in} = \beta' X_{in} = \sum_{k=1}^{K} \beta_k \, X_{ink} \tag{2}$$

where β indicates the coefficient of variables (marginal utilities), and X_{ink} is a vector of observable explanatory variables *k* of alternative *i* for individual *n*, which can include attributes of the alternatives and socio-economic characteristics of respondents. Thus, by considering each decision maker *n* and chosen alternative *i*, this systematic utility function is expressed in this study as:

$$V_{in} = ASC + \beta_{Flow} \, TFC_{ink} + \beta_{Ramp} \, RMT_{ink} \tag{3}$$

where TFC_{ink} is the vector of variables related to the traffic flow condition of route i that was displayed in the VMS for motorcycle rider n, and RMT_{ink} is the vector of the variable associated with the waiting time a motorcycle has to wait due to the implemented traffic policy, which works the same way as ramp metering. The ASC represents the alternative specific constant, whereas β_{Flow} and β_{Ramp} are the vectors of parameters to be estimated.

3.3.2. Mixed Logit Model

Despite the ease of estimation using the Binary Logit model, its inflexibility concerning substitution patterns necessitates using a more flexible model to overcome this issue. According to McFadden and Train (2000), the Mixed Logit model is a very flexible model that is able to approach any random utility model while also avoiding the IIA property of the standard logit model [54]. Further stated by Hess and Polak (2009), this sort of model structure allows for random taste variation across individuals, as well as being able to explicitly explain the serial correlations that arise between repeated choice observations in the case of panel data, which eventually, resulting in a more accurate and reliable behavior than fixed-coefficient models [55]. As a result, a Mixed Binary Logit model was also estimated in this study to consider the correlations across alternatives, which are commonly observed in the context of route choice, as well as among observations of the same motorcycle riders. This model specification in a binary response is in line with the study of Vacca et al. (2017) [11], which will likewise contribute to the expansion of the literature.

To relax the assumption that error term i.i.d. properties are independent across i (alternatives), n (individuals), and t (time), the stochastic component is subsequently split into two additive parts; one is correlated over alternatives and heteroskedastic, and the other one is i.i.d. extreme value over alternatives and individuals, as written in Equation (4). The introduction of α_{in} is intended to capture the unobserved factors that persist throughout time.

$$\varepsilon_{int} = \alpha_{in} + \varepsilon'_{int} \tag{4}$$

where α_{in} is a random term with a zero mean whose distribution over motorcycle riders and route alternatives is generally dependent on underlying parameters and observable data pertaining to rider n and route alternative i, also, ε'_{int} is a random term with zero mean that is independent of underlying parameters or data and identically distributed (i.i.d.) over alternatives.

Therefore, the utility that individual n obtained from alternative i in choice situation t is transformed, as shown in Equation (5). This mixed logit model assumes a general distribution for α (taste of heterogeneity), which may be in the forms of normal, lognormal, or triangular distribution, and an i.i.d. extreme value type 1 distribution for ε' properties [56].

$$U_{int} = V_{int} + \alpha_{in} + \varepsilon'_{int} \quad \forall \, i, t \tag{5}$$

$$V_{int} = \beta' X_{int} \tag{6}$$

Suppose there is an inertia in individual choices that drives them to persist with the previously selected alternative until the other alternative provides a sufficiently greater utility. This behavior was then captured by the following function [57].

$$V_{int} = \alpha Y_{in(t-1)} + \beta X_{int} \tag{7}$$

where Y_{int} equals to 1 if individual n chose alternative i in choice situation t, and 0 otherwise. The negative sign of α reveals that an individual earns higher utility by choosing a different alternative than in the last period. Train (2002) also highlighted the lagged dependent variable $Y_{in(t-1)}$ is uncorrelated with the error term ε_{int} due to the nature of independence over time in the logit model [57].

In addition, the probability of the Mixed Logit model, which is the integration of the standard logit model over a specified distribution of random parameters considered by the model, is expressed as follows [55].

$$(n,\ i) = \int L_i(\beta,\ z_n) f(\beta|\theta) d\beta \tag{8}$$

where z_n is the matrix of the attributes of alternatives encountered by individual n, while $f(\beta|\theta)$ is the density function of β given certain parameters of the distribution θ. Lastly, the function $L_i(\beta,\ z_n)$ portrays the probability of the conditional logit model, as demonstrated by Equation (9) below.

$$L_i(\beta,\ z_n) = \frac{e^{\beta' z_{ni}}}{\sum_{j=1}^{I} e^{\beta' z_{ni}}} \tag{9}$$

4. Sample Characteristics

The detailed proportions of respondents' socio-economic and driving characteristics collected from the online survey are listed in Tables 2 and 3, respectively.

Table 2. Driving characteristics of respondents.

Variable	Category	Total	(%)
Commuter	Yes	123	91.1
	No	12	8.9
Professional rider (service provider)	Yes	51	37.8
	No	84	62.2
Driving license ownership	Have and still valid	117	86.7
	Have but no longer valid	8	5.9
	Do not have	10	7.4
Driving age	<3 years	17	12.6
	3–5 years	12	8.9
	>5 years	106	78.5
Driving frequency	<3 times/day	83	61.5
	3–5 times/day	43	31.9
	>5 times/day	9	6.7
Driving style	Risky	24	17.8
	Steady	76	56.3
	Conservative	35	25.9
Travel purpose	Work	104	36.1
	School	38	13.2
	Recreational/Entertainment	36	12.5
	Social activities	50	17.4
	Shopping/Groceries	57	19.8
	Other	3	1

The outcomes of the online survey show that the majority of the questionnaires were filled out by motorcycle commuters, who accounted for 93.8% of the respondents. Additionally, around 37.8% of respondents also reported riding a motorcycle for professional purposes (service providers, such as motorcycle taxis ('ojek'), delivery couriers, etc.). In terms of respondents' prior knowledge of the primary topic of this research, 52.6% of them had heard about VMSs previously, whereas only 17.8% were aware of ramp metering existence. Among all respondents, about 13.3% still did not possess a valid driving license at the time the survey was administered. Regarding driving experience, over two-thirds of respondents have ridden a motorcycle for more than five years and drive less than three times daily. Overall, more than half of the respondents stated they steadily rode motorcycles, indicating a moderate level of aggressiveness. Additionally, approximately 36.1% of

the respondents ride motorcycles to work, 19.8% for grocery shopping, while only 1% of the respondents use motorcycles merely to wander around the city. In the case of socio-economic characteristics, respondents were dominated by males (68.5%), individuals aged between 17 and 30 years old (86.7%) or had a bachelor's degree (54.1%). In addition, over half of the respondents (54.1%) worked in the private sector, including as entrepreneurs and freelancers, while the other one-fourth of them were public workers, such as civil servants, employees of state-owned enterprises, lecturers, and doctors. Moreover, about 39.3% of respondents are classified as having a middle-low income (IDR 5,000,001 to IDR 10,000,000), while 6.7% had no income.

Table 3. Socio-economic characteristics of respondents.

Variable	Category	Total	(%)
Gender	Male	89	65.9
	Female	46	34.1
Age	17–30 years old	117	86.7
	31–40 years old	13	9.6
	41–60 years old	4	3
	>60 years old	1	0.7
Occupation	Student	19	14.1
	Public servant	37	27.4
	Private sector	73	54.1
	Unemployed	6	4.4
Education level	Middle high school	2	1.5
	High school	13	9.6
	Undergraduate	75	55.6
	Graduate	45	33.3
Personal income	No income	9	6.7
	≤IDR 5,000,000	41	30.4
	IDR 5,000,001–IDR 10,000,000	53	39.3
	IDR 10,000,001–IDR 15,000,000	22	16.3
	>1DR 15,000,000	10	7.4

Along with individual characteristics, the questionnaire survey was also circulated to identify the attitudes of motorcycle riders in planning and undertaking their mobilization in terms of route choice decisions, as well as the utilization of traffic information sources, as illustrated in Figure 3. It was found that about 3% of all respondents stated they never arrange a route before departure, whereas the other 40.7% and 39.3% very frequently or even always plan their trips in advance, respectively. Approximately two-thirds of motorcycle riders often adjust routes in response to traffic circumstances, while 2.2% of respondents stated the opposite. Concerning the employment of traffic guidance, slightly more people access particular sources before beginning a motorcycle ride than during the trip. These results are consistent with the premise behind this study, which argues that motorcycle riders often observe some sources of information about traffic conditions prior to or while riding a motorcycle.

Figure 4 depicts the extent to which motorcycle riders utilize different traffic information sources in determining their routes. It was discovered that mobile phone applications, such as Google Maps, are the most preferred media for monitoring real-time traffic, either before departure (52%) or while riding a motorcycle (39%). Nearly one-third of all respondents regularly choose travel routes based on direct observations made along the way, followed by the proportion of those who rely on street signs in route choice. The remaining 0.44% of respondents occasionally talk to acquaintances to inquire about the potential routes before a trip.
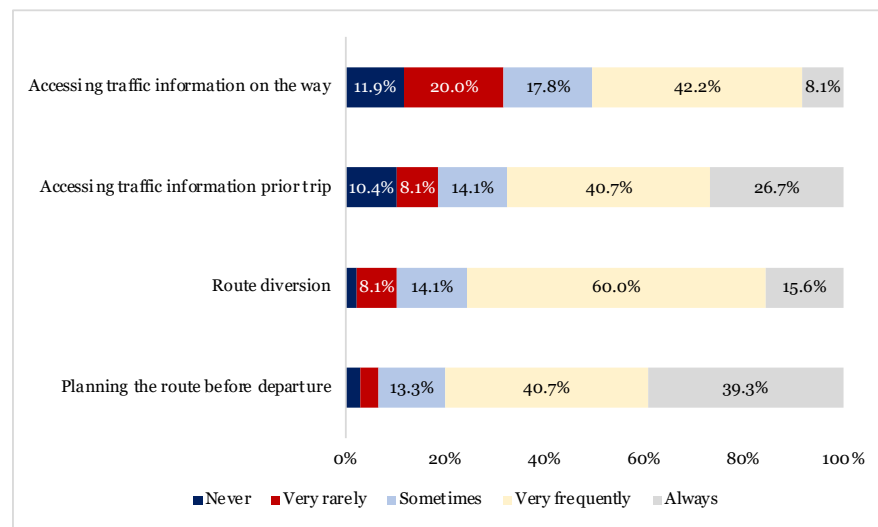
Figure 3. The SP survey results on the attitude of motorcycle riders towards route choice.
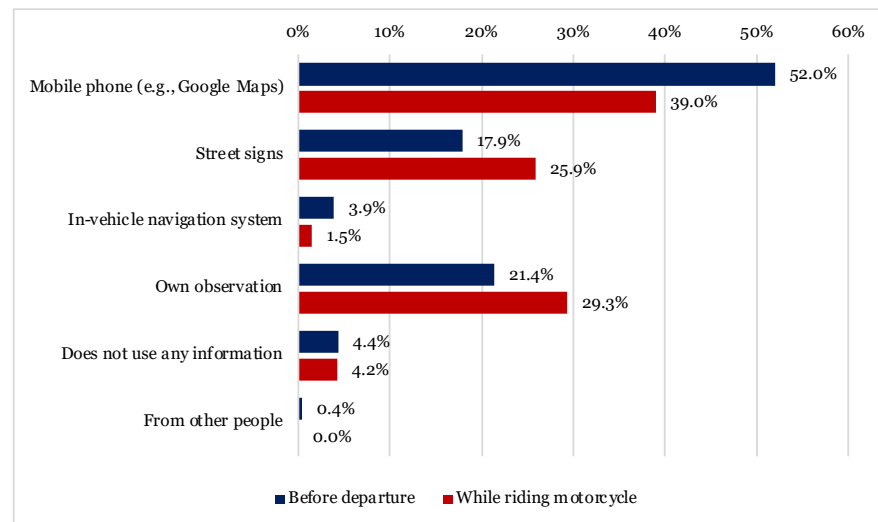

Figure 4. The SP survey results on sources of information about traffic conditions.

5. Route Choice Model

The current research analyzed the route choice behavior of motorcycle riders by employing a discrete choice model, more precisely, a logit model. In this instance, as cited by Kasraian et al. (2021) [58], the decision maker determines the choice from a number of mutually exclusive and collectively exhaustive alternatives [57]. The following section investigates the statistical findings and the links between a set of explanatory variables to routing decisions.

5.1. Model Estimation

The parameters that specify the route choice behavior of motorcycle riders were estimated using the freely accessible discrete choice analysis software, BIOGEME [59]. Of the 135 respondents assigned five different hypothetical situations in the SP survey, a total of 675 observations were aggregated into one dataset. A variety of model specifications were assessed in this study, as summarized in Table 4.

The first model contains generic attributes that fundamentally do not distinguish distinctive features among alternatives (hereinafter referred to as Model 1). This Binary Logit model disregards the correlation between observations of the same road users. As a result, the estimation of Model 1 revealed the significant effect of traffic flow situations on

the decisions of motorcycle riders in choosing the route to be taken (see Table 4). The inverse relationship between these two variables shows a greater disutility toward denser traffic flows, indicating that motorcycle riders less prefer routes with higher traffic volumes. This tendency conforms to the initial expectations of the relevance between variables. Similarly, the positive sign of the alternative specific constant (ASC) implies that Route 1 was often selected more frequently than Route 2 to reach the destination. In contrast, when the ramp metering system on Route 1 is implemented and activated, the model estimation results demonstrate that the waiting time a motorcycle rider must endure to be able to access this route was found to be negligible since it does not have a significant influence on route choice; therefore, this variable was excluded from the models. This finding may have been encouraged by the fact that only 17.8% of respondents had previously heard of ramp metering and motorcycle riders are less likely to feel bothered by a 5 min wait on a ramp. Nonetheless, more studies are required to evaluate this attribute category on a larger scale.

Table 4. Comparison of the estimation results with different model specifications.

Parameters	MODEL 1 (Binary Logit with Generic Attributes)			MODEL 2 (Mixed Logit with Panel Effect)			MODEL 3 (Mixed Logit with Panel Effect—Error Component)		
	Est.	*t*-Test	Sig.	Est.	*t*-Test	Sig.	Est.	*t*-Test	Sig.
Estimated parameters									
Constant	1.11 *	1.95	0.05	1.29 **	2.21	0.03	1.11 **	2.21	0.03
Traffic flow	−1.06 **	−4.08	5.0×10^{-5}	−1.25 **	−4.29	1.8×10^{-5}	−1.06**	−4.31	1.6×10^{-5}
Waiting time on the ramp	−0.24	−0.77	0.44	−0.27	−0.85	0.40	−0.02	−0.87	0.38
Road (standard deviation)	-	-	-	-	-	-	-5.5×10^{-17} **	−6.61	3.8×10^{-11}
Panel effect—Route 1	-	-	-	0.76 **	2.05	0.04	-5.6×10^{-11} **	−3.48	5.0×10^{-4}
Panel effect—Route 2	-	-	-	−0.71 **	−2.03	0.04	6.7×10^{-12} **	3.51	4.4×10^{-4}
Model fit statistics									
Final log-likelihood	−397.014			−385.103			−397.014		
Init log-likelihood	−467.874			−467.874			−467.874		
Likelihood ratio test	141.722			165.543			141.722		
Rho-square (ρ^2)	0.151			0.177			0.151		
Rho-square-bar (Adj. ρ^2)	0.145			0.166			0.139		
Akaike Information Criterion	800.027			780.205			806.027		
Bayesian Information Criterion	813.571			794.732			823.459		
Number of parameters	3			5			6		
Number of draws	-			1000			1000		
Sample									
Number of respondents	135			135			135		
Number of observations	675			675			675		

** Significant at 5%, *p*-value (0.01–0.05); * Significant at 10%, *p*-value (0.05–0.10).

Overall, Model 1 generates an adequately acceptable pseudo-R-squared value of 0.151, which reflects how well the model can predict the result and how much it outperforms the null model with a single intercept. The hypothesis testing by applying the likelihood ratio test led to the conclusion that Model 1 is statistically better fitted compared to the model with a single ASC (−2LL = 141.722; chi-square $\chi^2_{95\%, 2}$ = 5.99). It can thus be argued that the explanatory variables included in this model can improve the quality of the predicted output. However, the Binary Logit model is constrained by the nature of independence of irrelevant alternatives (IIA). Adopting the Mixed Logit model by adding error terms that permit correlation between choices predictably may solve this problem [60]. As only two alternatives are offered, the mixture model here fundamentally refers to the Mixed Binary Logit model.

Multiple observations of hypothetical route choice settings acquired by presenting the same respondent with numerous stated choices in the questionnaire survey led to the emergence of a serial correlation. This correlation reveals the error terms associated with observations from the same individual that may share some unobserved factors. Subsequently, this phenomenon compelled the development of a model capable of addressing a series of observed choices and the intrinsic correlation between them. In addition, the

assumption of observation independence in the standard logit model is then violated by these correlated responses across observations [56], leading to the utilization of Mixed Logit models to relax the IIA property. Since the integral configuration of the Mixed Logit choice models does not generally have a closed-form solution, a simulation using Monte Carlo integration at a given number of draws was necessary. A total of 2000 Halton draws [61] was used for the parameter estimation in BIOGEME. This approach is deemed sufficient for this analysis, concerning the number of random parameters and the correlation between attributes and alternatives.

According to the results listed in Table 4, the agent effect included in Model 2 (Mixed Binary Logit model) is significant for both alternatives (Route 1 "arterial road" and Route 2 "local road"). This scheme illustrates that this model can capture intrinsic correlations between observations from the same respondent. As expected, motorcycle riders prefer to travel from origin to destination (see the map in Figure 2) through an arterial route rather than a local one. This might be owing to the common belief that major roads often have more capacity and fewer traffic flow interruptions. Nevertheless, when a specific traffic policy to smooth the traffic streams is implemented, the estimated waiting time on the ramp that a motorcycle rider is required to undergo to reach Route 1 was found to be insignificant, which is similar to the situation of Model 1. This conveys that respondents did not consider the waiting time on the ramp as a relevant attribute when selecting a route to a specific destination. As a consequence, this variable was also omitted from the model. In addition, the ASC interacted with the first alternative, and produced statistically significant parameters with a positive coefficient. Hess and Polak (2009) demonstrated that, in the case of SP data being employed, the ASCs capture at least two effects: one is substantive effects related to actual preferences, and the other one is effects related to the design of the SP survey [60]. To summarize, the statistical parameters estimated by Model 2 in the mixed binary logit indicate that it outperforms the standard logit, as shown by the better-fitted values of log-likelihood, pseudo-R-squared (ρ^2), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). This conclusion is further supported by the output of hypothesis testing, which pointed out that the restricted model can be rejected since the likelihood ratio exceeds the chi-square ($-2LL = 23.822$; $\chi^2_{95\%, \, 2} = 5.99$).

Furthermore, it was assumed that an unobserved effect is also correlated across alternatives in the stated choices provided. Therefore, Model 3 describes a Mixed Logit model that incorporates both the panel effect and the error component in an effort to capture the correlation between the two alternative routes. In this analysis, the unobserved attribute that may be shared amongst alternatives is represented by the variable "*ROAD_random*", which is assumed to be normally distributed as follows: *ROAD_random* ~ N (*ROAD_mean*, *ROAD_std*^{2}), while the parameter *ROAD_mean* is fixed to zero. Referring to the estimation outputs in Table 3, the variable *ROAD_std* is significant at the 95% confidence level, where the square of this parameter is the variance of the random term that captures unobserved shared attributes between Route 1 and Route 2. Hence, in this instance, the sign of the *ROAD_std* is irrelevant and can be disregarded. In summary, this model structure has significantly captured the intrinsic correlations between observations of the same individual as a result of the stated preference survey design.

5.2. Model Estimation with Individual Characteristics

Unlike the attributes of alternatives that have been described previously, the characteristics of the decision-maker do not vary across alternatives. Therefore, in this case, all these covariates were introduced in the model by incorporating them as the main effect to the utility function of the second alternative route (local road) to further capture the heterogeneity of preferences. Table 5 shows model specifications with the inclusion of individual characteristics in conjunction with the variables of traffic conditions and waiting time due to the ramp metering. As in line with the findings of Dia and Panwai (2006), it was determined that income had no impact on the decisions towards route choice [18]. This might be due to the wide diversity of the economic statuses among motorcycle riders.

Table 5. Comparison of the estimation with individual characteristics and different specifications.

Parameters	MODEL 4 (Binary Logit)			MODEL 5 (Mixed Binary Logit)			MODEL 6 (Mixed Binary Logit)		
	Est.	*t*-Test	Sig.	Est.	*t*-Test	Sig.	Est.	*t*-Test	Sig.
Estimated parameters									
Constant	−0.62	−0.99	0.32	−0.70	−1.08	0.28	−0.80	−1.16	0.24
Traffic flow	−1.15 **	−4.09	4.3×10^{-5}	−1.26 **	−4.27	1.9×10^{-5}	−1.26	−4.27	1.9×10^{-5}
Waiting time on the ramp	−0.26	−0.77	0.44	−0.27	−0.85	0.40	−0.27	−0.85	−0.39
Socio-economic characteristics									
Gender	−0.46 **	−2.34	0.02	−0.55 **	−2.12	0.034	−0.57 **	−2.20	0.03
Age group (17–30 years old)	−0.63 **	−2.27	0.02	−0.44	−0.56	0.574	−0.21	−0.25	0.81
Age group (31–40 years old)	−0.72 **	−1.98	0.05	−0.52	−0.59	0.559	−0.47	−0.50	0.62
Age group (>60 years old)	2.26 **	2.66	0.01	2.68 **	3.18	0.001	2.50 **	2.93	0.01
Occupation (public servant)	−0.46 **	−2.04	0.04	−0.62	−1.39	0.164	−0.61	−1.37	0.17
Occupation (unemployed)	1.20 **	3.29	0.01	1.32 **	4.16	3.2×10^{-5}	1.21 **	2.50	0.01
Education (middle high or less)	−1.54	−1.21	0.23	−1.69 **	−1.99	0.05	−0.89 *	0.45	0.06
Education (senior high school)	−0.71 *	−1.94	0.05	−0.82	−1.60	0.11	−0.78	−1.52	0.13
Driving characteristics									
Motorcycles for the service provider	−0.35 *	−1.82	0.07	−0.41 *	−1.79	0.07	−0.48 *	−1.78	0.07
Driving license ownership	−0.72 **	−2.50	0.01	−0.59	−1.53	0.13	−0.39	−1.52	0.13
Driving frequency	0.35 **	2.40	0.02	0.39 **	2.15	0.03	0.38 **	2.09	0.04
Travel purpose (work)	−0.42 *	−1.83	0.07	−0.58 *	−1.85	0.06	−0.67 **	−2.13	0.03
Driving style (conservative)	−0.60 **	−2.64	0.01	−0.68 **	−2.24	0.03	−0.69 **	−2.28	0.02
Error terms									
Error component–Road (std)	-	-	-	-	-	-	2.4×10^{-17} *	1.83	0.07
Panel effect—Route 1	-	-	-	−0.54 **	−2.15	0.03	−0.66 **	−3.53	4.1×10^{-4}
Panel effect—Route 2	-	-	-	0.57 **	2.28	0.02	−0.74	−2.54	0.01
Model fit statistics									
Final log-likelihood	−369.287			−365.586			−365.852		
Init log-likelihood	−467.874			−467.874			−467.874		
Rho-square	0.211			0.219			0.218		
Rho-square-bar	0.174			0.178			0.175		
Akaike Information Criterion	772.574			769.172			771.704		
Bayesian Information Criterion	849.325			824.372			829.809		
Number of parameters	17			19			20		
Number of draws	-			1000			1000		
Sample									
Number of respondents	135			135			135		
Number of observations	675			675			675		

** Significant at 5%, *p*-value (0.01–0.05); * Significant at 10%, *p*-value (0.05–0.10).

The first model presented in Table 5 for describing the route choice behavior of motorcycle riders is the binary logit model, which does not consider the error terms correlated across observations generated by the conducted SP survey, as well as the shared unobserved factors between the two route alternatives. Similar to the case of Model 1, the length of time that motorcycle riders had to wait because of the ramp metering restriction did not significantly influence their route preferences. Finally, the model demonstrates disutility related to the relevance of traffic flow situations to the route choice decisions of motorcycle riders. Overall, this model was adequately acceptable and has been able to enhance statistical parameters referring to pseudo-R-squared (ρ^2) by 0.211, AIC by 772.574, and BIC by 849.325, compared to the model that did not account for individual characteristics. Moreover, with a value of −369.287, the log-likelihood was determined to be more fitted, as numerically evidenced by the likelihood ratio test between Model 1 (restricted) and Model 4 (unrestricted) that could reject the null hypothesis (−2LL = 55.454; $\chi^2_{95\%, 14}$ = 23.68). It was indicated that adding individual characteristics to the list of explanatory variables may improve the binary logit specifications with generic attributes.

The Mixed Binary Logit model was estimated by taking both driving and socio-economic characteristics into consideration. As expected, there were unobserved factors generated by reoccurring observations simultaneously on a single motorcycle rider. These

error terms were captured by the panel effects and calculated using 2000 Halton draws in BIOGEME. Even though some individual characteristics were later discovered to have no impact on route decisions for this group of motorcycle riders, the resulting Model 5 turned out to be statistically better than the earlier specifications, as indicated by the likelihood ratio test ($-2LL = 7.402$; $\chi^2_{95\%,\ 2} = 5.99$). Attempts were also made to identify correlation across alternatives, as Route 1 and Route 2 might share unobserved factors represented by the error component with zero mean and a variance equal to the square of "*ROAD_std*". This specification of the Mixed Binary Logit model (see Model 6) is stated to have stronger statistical parameters than standard logit, referring to the enhanced adjusted pseudo-R-squared, AIC, BIC, and log-likelihood values. As predicted, the sign of the traffic flow conditions' coefficient indicates an inverse relationship against route preferences. In addition, the statistically significant parameters of the *ROAD_std* variable show that the error terms of the first and second route alternatives are correlated, therefore, the null hypothesis that the true value is zero can be rejected. Further detailed elaboration of the estimated parameters will be discussed in the next section.

6. Discussion

Prior studies have recognized that the series of questions in the stated preference survey administered to the same respondent may yield the presence of unobserved factors that are shared across observations. The standard logit model, however, is incapable of reflecting this correlation. Therefore, this study explored the features of the Mixed Logit model, in the binary choice, to account for the error terms that might exist in explaining the behavior of motorcycle riders when selecting a route to be taken. As noted in the previous section, the additional agent effects for this specification effectively improve the model in a statistical manner. Furthermore, the inclusion of individual characteristics was seen to enhance the model's fit even more ($-2LL_{\text{Model 2–Model 5}} = 39.034$; chi-square $\chi^2_{95\%,14} = 23.68$). The Mixed Binary Logit model (Model 5) has increased the log-likelihood to -365.586 and the adjusted rho-square to 0.178, as well as minimizing the Akaike Information Criterion (AIC) parameter by 11.033 in order to reduce the chance that the model would be overfitting. However, it was found that the null hypothesis that the addition of the correlation between alternatives (an error component) may be statistically better than Model 5 must be rejected with the parameters $-2LL = 0.532$ and chi-square $\chi^2_{90\%,\ 1} = 2.71$.

It should be noted that alternative-specific variance models have been evaluated in the normal distribution, but this model specification yields an insignificant variance of alternatives. It can be concluded that the null hypothesis suggesting that the variance of unobserved components differs over alternatives cannot be rejected, and the constants of each alternative are not distributed randomly across alternatives. Furthermore, efforts were also made to permit the inclusion of random coefficients to identify the taste variation across individuals. The degree of traffic flow conditions variable is considered to have a normal or lognormal distribution throughout the population. Despite the fact that it was discovered that normal distribution produces a model with a better fit in terms of statistical parameters, the results indicated that there were 19.23% of respondents preferred routes with heavy traffic flow, which pointed out the incorrect estimation. In comparison, when this variable is lognormally distributed, it was determined that this model specification was not significant, although the non-positive coefficient is fundamentally consistent with the a priori belief that people tend to choose routes with light traffic flow over heavier ones (severely congested). In summary, it was revealed that none of the utilized specifications resulted in statistically significant estimates for either the random coefficients or alternative-specific variances, nor did they improve the model fit of motorcycle route choice behavior.

6.1. Attributes of Alternatives

Two attributes describing alternatives were evaluated to identify their contribution to influencing the route decisions of motorcycle riders. These were accounted for as traffic information in the form of Variable Message Signs (VMSs). First, according to model

estimates in the Binary Logit and Mixed Binary Logit specifications (see *B_FLOW*), the depiction of traffic flow conditions in the VMS significantly impacted respondents' route preferences. The greater the number of automobiles on a route, the less favorable it is for motorcycles to take that road. Second, this research tried to adopt the basic concept of traffic regulations regularly applied on the highway: ramp metering. By shifting the delay and queue to the ramp, ramp metering is supposed to generate a smoother traffic stream in the mainline, particularly on major roads that should have a less disturbed flow and limited access, by shifting the delay on the ramp. Nonetheless, referring to Table 6, the model estimation resulted in an insignificant variable of waiting time on the ramp in relation to the route preference of motorcycle riders. This indicates that the amount of time motorcycles had to wait on the ramp to reach Route 1 in the hypothetical scenario provided did not affect their route choice judgments. It may be related to the fact that the highest tested duration of a motorcycle being held on the ramp is 5 min, which is predictably regarded differently for a short trip.

Table 6. The final model estimates the route choice behavior of motorcycle riders.

Parameters	Final Model		
	Est.	*t*-Test	Sig.
Estimated parameters			
Constant	−0.28	−0.55	0.580
Traffic flow	−1.05	−7.33	0.000
Socio-economic characteristics			
Gender	−0.52	−1.92	0.055
Occupation (unemployed)	1.53	5.17	0.000
Education (middle-high school)	−1.45	−1.97	0.049
Motorcycles for the service provider	−0.5	−1.86	0.062
Driving frequency	0.36	1.99	0.046
Travel purpose (work)	−0.53	−1.66	0.097
Driving style (conservative)	−0.83	−2.67	0.008
Error terms			
Panel effect—Route 1	0.68	3.83	0.000
Panel effect—Route 2	−0.4	−0.45	0.041
Model fit statistics			
LL (β)			−370.921
LL (ASC)			−467.874
ρ^2			0.207
Adjusted ρ^2			0.182
AIC			765.841
BIC			800.704
Number of parameters			11
Number of draws			2000
Number of respondents			135
Number of observations			675

6.2. Individual Characteristics

In this study, individual characteristics data acquired can be divided into factors about driving properties and socio-economic characteristics. As stated earlier, these kinds of variables can only be estimated in the model as a main effect or interaction term against an explanatory variable, which in this instance were treated as main effects only on route alternative 2 since they did not vary between alternatives.

First, the tested driving characteristics of motorcycle riders were related to driving frequency, years of driving experience, driving style, license ownership, as well as regular travel purpose. According to the Binary Logit and Mixed Binary Logit model estimation

results, it was found that the average number of times a respondent rides a motorcycle daily has a significant influence on their route choice behavior, as also observed by Choocharukul and Wikijpaisarn (2013) in a slightly different circumstance [52]. Respondents who ride motorcycles more often each day are more likely to prefer the local road (Route 2) over the arterial road (Route 1). This is expected given that around 67% of respondents who ride motorcycles more than five times per day very frequently utilize traffic information sources. Consequently, they may be greatly exposed to VMS information that specifies how long motorcycles must wait on a particular on-ramp. Concerning driving style, respondents who were conservative in riding motorcycles were discovered to have a substantial influence on route choice. This group of riders favored Route 1 with arterial roads, as indicated by the negative sign of the estimated parameter. This conclusion is in accordance with the principle that conservative drivers are more cautious while mobilizing; hence they choose less hazardous traffic conditions. It is supported by the fact that only 5.71% of respondents with a conservative style of motorcycle riding always divert routes and that 62.86% usually plan a route before embarking on a trip. This relationship is further proven by the chi-square test, which confirms the existence of a connection between driving style and route choice. In general, the purpose of using a motorcycle has little bearing on route choice, unless it is intended for commuting to work, in which case the preferred route is the first alternative. Route 1 is an arterial road with a wider width, fewer delays at intersections, and less interrupted flows; thus, it should have a faster speed and smoother traffic stream to prevent them from being late for work. Similarly, respondents who need a motorcycle for their profession as a service provider (e.g., motorcycle taxi or delivery courier) also tend to take Route 1 in order to gain higher mobility. However, with 13.3% of respondents not holding a valid license at the time, it was revealed that the ownership status of a motorcycle rider's license did not impact their route preferences.

Second, regarding socio-economic characteristics, the model estimate results discovered that gender, age, occupation, and education were all significant in the binary logit specification. However, when random terms capturing either panel effect or error component interacted with the model, older and male motorcycle riders showed a tendency to take Route 2 rather than Route 1, which is consistent with the findings of existing studies [15,18,33,51]. However, the dummy variable representing groups of respondents over the age of 60 years old was subsequently removed from the model due to the inequalities of proportion in the dataset. In addition, the model estimation results, while accounting for the correlation between stated choice observations, reported that the occupations of motorcycle riders (i.e., students, private sector employees, or public officers) had no effect on the route choice decisions. In contrast, the responder group of motorcycle riders who did not possess any job yet at the time of the survey pointed out a strong preference for local roads, which is consistent with preceding findings about driving characteristics.

6.3. Final Model

After testing several combinations of independent variables, coefficients with statistical significance of 0.10 or higher were excluded from the final model (it is assumed that the model satisfies a 90% confidence interval). As a result, taking into account other statistical parameters, the final model regarding the route choice behavior of motorcycle riders is presented in Table 6.

7. Conclusions

The current study investigated the factors that influence the decisions in selecting the route, specifically in the form of Variable Message Sign (VMS) content relating to traffic flow conditions and waiting times at a ramp meter. The preferences of respondents were gathered with a stated preference (SP) survey technique by presenting them with a variety of hypothetical situations. Subsequently, the compilation of 675 observational data was estimated based on the discrete choice in the specification of both the Binary Logit and Mixed Binary Logit models.

A major contribution of this research is that, in contrast to the existing literature, which primarily focuses on passenger cars and bicycles in the specified subject, it concentrates on the analysis of route choice behavior among motorcycle riders, who predominate in most Asian countries. The standard logit model was initially introduced to identify the route preferences. However, it then revealed the presence of significant correlations as a consequence of multiple observations on a single respondent at the same time. The inclusion of these random terms relevant to panel effects, for all considered datasets, was such that the utilization of the Mixed Binary Logit model produced a better fit over the Binary Logit model. It was found that the degree of a traffic flow variable, with a negative sign, greatly affected the route choice behavior of motorcycle riders and showed their preferences for avoiding denser roads. Nonetheless, the estimated parameter of waiting time on the ramp with the implementation of the ramp metering regulation was discovered to have had no impact. Furthermore, it was also highlighted that several individual parameters significantly contribute to the route decisions of motorcycle riders. These include daily frequency of riding, the purpose of using motorcycles to commute to work and service providers, a conservative riding style, as well as gender, unemployment status, and education level of middle high school or less.

Two study limitations should be noted. First, the alternative routes provided to respondents remain limited and do not accurately represent the network topology in developing countries where motorcycles are popular, which often consist of multiple narrower roads that motorcycles may cross easily. Second, the tested explanatory variables were still limited and led to the necessity for further exploration of varying aspects to describe the behavior of motorcycle riders in choosing routes. In addition, it was challenging to determine whether respondents could visualize the case study based on their personal perceptions and preferences in real scenarios. Despite the limitations, the findings are valuable in light of several implications, especially related to the proposed traffic management strategies to regulate motorcycles in mixed-traffic situations by interpreting how motorcycle riders make trade-offs while selecting routes.

A key step for future research is, therefore, in terms of performing SP surveys, to develop a hypothetical network structure and stated choices that predictably will generate more representative behavior. Hence, the number of alternative routes will rise and their road characteristics may not be homogeneous along the route, allowing for better capture of route preferences. In addition to the necessity for more diversified attributes of alternatives, further studies should highlight the unique properties of motorcycles compared to automobiles, as well as the distinctive spatial networks in developing countries, which are comprised of varying road levels. Furthermore, a larger sample size must also be concerned to cover diversity in perceived utility. Regarding the analytical methods, a dynamic discrete choice model should be tested to extend the explanations of the repeated route decisions made by road users along the trip based on the traffic circumstances.

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