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Demand Modeling for Taxi and Ride-hailing Transport Services (RTS)

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Abstract

The rapid growth of Ride-hailing Transport Services (RTS) demand is found to have caused a fierce market share battle with conventional taxis in previous decades. In selecting a taxi or RTS, understanding the factors affecting passenger's decisions is substantial for better development and more reliable transit service. The aims of this study to evaluate the demand for taxis and RTS in the Jakarta Greater Area, Indonesia, using the demand-supply and dynamic models. It has been conducted by using 519 respondents, with the model inputs consisting of waiting and travel time, trip costs, and the destination of the conventional passengers. Moreover, the choice between taxi and RTS was analyzed based on the stated preferences of respondents. The results showed that the waiting and travel time, as well as costs per trip of RTS, were 1.49 and 2.67 minutes lower and IDR10,902 cheaper than a taxi, respectively. The factors influencing the demand for these transport modes were also the number of trips per-day, mode share, the average vehicle occupancy, operating hours/day, passengers and driver waiting time, as well as travel period. In the dynamic model, the addition of variable service area, peak hour, and average vehicles speed was subsequently observed. Based on the results, the requests for these transport modes in the Greater Area of Jakarta were 64,494 and 55,811 vehicle units for the demand-supply and dynamic models, respectively. This proved that the dynamic model was better than the demand-supply, due to the added parameters representing the area's traffic characteristics. Additionally, subsequent future research are expected to focus on modeling of taxi and RTS demands through the global positioning system data, as well as analysis using machine learning and deep learning.

Keywords: Ride-Hailing Transport Services; Waiting Time; Travel Time; Travel Cost; Dynamic Model; Demand-Supply.

1. Introduction

Nowadays, the emergence of new technological transportation systems has greatly impacted personal mobility not only in developed countries but also in developing countries. This indicates that mobile technologies, in particular smartphones impact are found to impact the needs of travelers [1, 2]. Using an online interface, the application of transportation information and communications technologies facilitates the realistic availability of vehicles for people, which leads to a reduction in private vehicle ownership [3, 4]. The extensive use of smartphones by individuals has also led innovators towards the development of app-based transportation services, broadly known as ride-hailing transport services (RTS), which efficiently link passengers to drivers within minutes. These services have reportedly been operated extensively in more than 600 cities worldwide, such as Gojek, Grab, Uber, which operates

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internationally, Ola in India, Didi Chuxing in China, Go Catch in Australia, and Lyft, which operates in the USA [5]. They also provide methods of sharing mobility, which enable passengers to quickly book a ride directly through smartphone applications [6]. People use smartphone transportation applications to meet their mobility needs [7].

Moreover, a RTS also provides a very personalized mobility experience that offers not only an efficient but also a reliable transportation system. Hence, it has been considered to revolutionize urban mobility through the provision of timely and convenient transportation to anybody, anytime, and anywhere. A RTS is very distinct from traditional personalized mobility options, such as taxis, due to its capability to offer a real-time scanning feature for passengers to find the nearest driver through specific algorithms, which increases functional and financial efficiencies [8]. Unfortunately, such capability means that a RTS fiercely competes with conventional taxis in hard battles for the same market share. Based on this condition, the presence of these services has reportedly been decreasing the number of conventional taxis within global metropolitan areas such as New York, where the values of rides and passengers decreased by 25%/h and 16 million from 2010-2016, respectively [9]. According to Schaller [10], in the United States of America, the number of airport taxi trips has decreased due to a large adjustment to RTS. Another study by Nelson [11] also revealed that the total number of taxi trips in Los Angeles had been reduced by 2.4 million (30%) between 2013-2016. On the other hand, due to being Uber's second-largest market in the world. Brazil has 500,000 Uber-affiliated drivers who serve more than 17 million users, compared, for instance, to Central America, which had an estimated 1.3 million customers in 2018 [12]. A similar situation occurs in San Francisco as well, where conventional taxi ridership decreased by 65% between 2012-2014 due to the growing use of Uber and Lyft [13]. Moreover, in Shenzhen, China, the situation is not far from that in the United States, where the local taxi industry consequently encountered a significant ridership loss from 2013-2015 [14]. Such worldwide disruption for local taxi industries has spread rapidly to Indonesia, in particular to the Jakarta Greater Area, with a reduction of taxi rides of almost 50% from 2015-2020. The above examples show that a study related to factors affecting passenger decisions in selecting a taxi or RTS is crucial not only for better development and more reliable transit service but also to minimize negative impacts on social life.

The decrease in the use of conventional taxis is mainly caused by various factors, such as booking methods, uninformed travel rates before riding, urban area limitations, and undetermined destination routes. While booking is directly carried out online in the RTS system using a mobile application, the riding tariff is determined with an appealing promo as the travel rate and route are known a priori and estimated based on actual and real-time traffic data. Such a huge difference needs a proper modeling of the demands of RTS and taxis to explore the possibility of maintaining proper competition. With the competition between taxis and ride-hailing, the number of fleets must be regulated. Most of the present techniques utilized for these processes are supply-demand models, where taxi demand is defined as a function of passenger travel per-day (or trip per-day), transit access time, population size, median age, educational density percentage, income per capita, number of employment opportunities, and other static parameters [15]. Most of these efforts have focused on taxi trip demand, whereas studies on ride-hailing transport service demand prediction have been relatively limited. That static approach has limitations because the actual supply-demand relationship is a time- and location dependent problem affected by numerous variables. To take into account time and location as model variables, the use of a dynamic model is necessary. By using the Jakarta Greater Area, Indonesia, as an object, we conduct a study on the implementation of such a dynamic model by adding numerous parameters, such as service area, peak hour, and average vehicle speed. The novelty of this study is represented by the development of a demand model for ride-hailing transport services (RTS) and taxis, using a balance between a demand-supply approach and a dynamic model that considers the traffic characteristics of the location, namely the service area (km^2), peak hour factor (%), and average speed of vehicles (km/h). This represents the traffic characteristics and mode choice based on the stated preference survey results.

Finally, we organize this paper as follows, Section 1, this section provides an introduction where our study background and aims are presented. In Section 2, a literature review related to the previous modeling works and factors influencing taxi and RTS demand are explained, with ride-hailing also evaluated. It is then followed by Section 3, where data and methodology are explained, including the description of the study location, data collection, as well as total population and density. This is accompanied by the description of the demand-supply approach and dynamic model in Section 4, where the result presents a brief explanation of the socio-demographic and trip characteristics, origin-destination survey, and discrete choice model. This is accompanied by an evaluation of the waiting and travel times, as well as the average costs of taxi and RTS users in the Jakarta Greater Area, Indonesia. Subsequently, the analysis of the demand-supply and dynamic model-based transit requests is performed. The last section gives the conclusions and future research based on our work here.

2. Literature Review

2.1. Ride-Hailing as a Transport Mode

Most of the present fundamental problems in the transportation system of big cities are often related to traffic jams due to the large volume of private cars. It causes traffic congestion [16], increased air pollution, and travel times, as well as a significant elevation of passengers' stress levels. Therefore, a carpooling system is promising solution to improve such traffic conditions, reduce the number of vehicles on the roads, decrease CO_2 emissions, and reduce fuel consumption per person. For example, traffic was reduced by 59% in Madrid, with people willing to share their homework commute rides with neighbors [17]. In another case, according to Liu et al. [18], the sub-regional structures observed were more easily interpreted for transportation-related issues in Shanghai. This was because the ride-hailing services produced low waiting times, reduced urban traffic congestion [19], as well as decreased commute-related stress [20] and over-crowdedness [21]. With ride-hailing providing economic efficiency in many cases, numerous discrimination and security issues among riders and drivers are reportedly observed [22]. This confirmed that the determination of an appropriate local strategy for a ride-hailing platform and frequent passenger cancellations were very essential [23].

2.2. Modeling Taxi and RTS Demands

The features significantly associated with carpooling include reservation and travel time, trip length, cost, weather, as well as the reliability of origins and destinations [24]. This shows the occurrence of substantial differences in activity-time use patterns across generations during early adulthood [25]. Furthermore, waiting time is considered the most important factor for frequent users, with the travel period highly valued by almost all customers. This is accompanied by traffic safety [26], accessibility, and comfort [27]. Based on Paronda, for instance, the key performance indicators of RTS in Metro Manila include travel speed, reliability, passenger expense, and service quality [28]. In early 2010, the demand models for taxis and RTS were continuously developed after the operation of RTS in several major cities around the world. In this condition, various determinants of ride-hailing services include socio-economic attributes, the built environment, characteristics of trips [29], attitudinal factors [30], and lifestyle [31]. Age, gender, and educational level were also key socio-demographic characteristics in the modeling of taxi demand [32], with cost effectiveness, trip security, anti-shared mobility, and technology-oriented riders having a significant impact on travel mode choice and the frequency of ride-hailing journeys [33]. To determine the main factor in mode choice, the Analytical Hierarchy Process (AHP) was subsequently used [34]. Moreover, lifestyle is the most important determinant of a non-working trip, where individual patterns have a strong and significant effect [35]. E-hailing is also the process of ordering a car or any transportation mode through virtual devices, such as a computer or mobile device, to help adjust the utilization rate of taxis [14]. These models showed a strong link between the demand for taxis, patterns of land use, and accessibility to other modes. In this condition, mixed land use did not show a strong correlation with taxi demand, whose mode complemented and competed with metro and bus trips, respectively. However, these travel modes were considered for public transit [36].

According to Wang and Mu [29], the spatial heterogeneity for both Uber-X and Uber Black ride-hailing services in Atlanta, USA, was investigated based on the waiting time. It explained why reservation and travel time, cost, length of trip, weather, as well as reliability of origins and destinations were significantly associated with ride-splitting [24]. Another study by Weng et al. [37] also examined people's perceptions and willingness to continuously utilize taxis in Kuala Lumpur, Malaysia, where a dynamic travel network approach was highly volatile for modeling and forecasting the potential ride-sharing utilization over time [38]. Meanwhile, conditional on other covariates, the expected waiting times were longer and shorter in the census block groups (CBGs) with higher average income as well as population and employment densities [39].

In modeling taxi demand, a conceptual framework was also developed using the Structural Equation Modeling (SEM) approach, with income observed as the primary driver of travel mode choice [40], and in SEM with mediation analysis, information and service quality have a significant influence [41]. Moreover, the car-sharing decision parameters were estimated based on the stated choice data using a Bayesian D-efficient optimal design [5]. According to Schreffler [42], the satisfaction level of taxi users and their patterns of selecting transportation modes could be quantified. In this condition, stated surveys and discrete choice models were widely used to analyze commuters' patterns and forecast demand [43]. Using a web-based stated-preference survey, the demand for transit service was also conducted in Chicago [44], where a convolutional neural network model was used to predict ride hailing based on the consideration of temporal and spatial features [45, 46].

At a specific period, the gap analysis between rider demands and driver supply was used to forecast requests, as shown [47]. The fusion convolution long short-term memory network, or FCL-Net, was also used to forecast passenger demand for the ride-hailing services in Hangzhou, through the data provided by DiDi Chuxing. This model was stacked and fused by multiple and standard long- and short-term memories as well as convolutional layers [48]. Based on dynamic pricing, the request for on-demand ride-sharing results in a prediction of shorter subsequent wait times from Uber and Lyft users [49], with the results showing strong support for the consumer welfare gains of these platforms. The surplus was due to shortened waiting times, which relied on better matching technology and the dynamic pricing practice. In another different location, approximately one third of the public transportation trips in Bogota, were potentially shifted to ride-hailing transport. There was an increase in vehicle-kilometers travelled (VKT) the effects of demand reallocation [50]. The list of methods used to model taxi and transit demand is shown in Table 1.

Table 1. Modeling of taxi and transit demand method

No.	Researcher (year)	Method to modeling transit demand
1.	Frei et al. (2017) [44]	Web-based stated-preference survey
2.	Kim et al. (2017) [5]	Stated choice data using a Bayesian D-efficient optimal design
3.	Altshuler et al. (2019) [38]	Dynamic travel network approach
4.	Salanova et al. (2014) [43]	Stated surveys and discrete-choice models
5.	Wang (2017) [47]	Gap analysis between driver supply and rider demands
6.	Ma et al. (2015) [45], Wang et al. (2019) [46]	A convolution neural network (CNN)-based deep learning
7.	Cirillo et al. (2017) [40]	Structural Equation Modelling (SEM)
8.	Ke et al. (2017) [48]	A novel deep learning approach and the Fusion convolutional long short-term memory (LSTM) network
9.	Lam & Liu (2017) [49]	Dynamic pricing predicts shorter subsequent wait time discrete choice demand framework
10.	Schreffler (2018) [42]	Level of satisfaction perceived by taxi users
11.	Do et al. (2019) [51]	Origin-destination data from T-map Taxis, which was analysed via a decision tree
12.	Akbari et al. (2020) [41]	Structural Equation Modelling (SEM) with mediation analysis
13.	Hossain & Habib (2021) [52]	Fusion of trip trajectories, secondary travel surveys, and land use data
14.	Dey et al. (2021) [53]	A multiple discrete-continuous extreme value (MDCEV) model
15.	Shoman & Moreno (2021) [54]	A stated preference survey and multinomial logit model
16.	Wilkes et al. (2021) [55]	A balance of ride-pooling demand and supply

For example, dynamic pricing considering a scenario where an agent (i), who needs to move from origin to destination location at a time (t), demands a ride is studied by Lam & Liu [49]. In this condition given by Lam & Liu [49], users often encountered a set of heterogeneous transportation modes, such as public transit, taxis, and carpooling platforms. This agent evaluated these options by comparing the various attributes affecting their utility, such as trip costs, waiting and travel time, idiosyncratic taste, as well as other observed and unobserved service-specific characteristics. Based on these considerations, the user then selected the transportation mode with the highest utility.

3. Method

3.1. Study Area

The study was done in the Jakarta Greater Area, Indonesia covering 3 provinces namely the Jakarta Special Province, West Java and Banten Province as well as 9 regions namely the Jakarta Special Province (West Jakarta Administrative City, Central Jakarta Administrative City, South Jakarta Administrative City, East Jakarta Administrative City, North Jakarta Administrative City, and *Kepulauan Seribu* Administrative District), the Regency of Bogor West Java, the City of Bogor West Java, the City of Depok West Java, the Regency of Tangerang Banten, the City of Tangerang Banten, the City of South Tangerang Banten, the City of Bekasi West Java, and the Regency of Bekasi West Java is shown in Figure 1. In 2019, the total population of the Greater Jakarta Area and Jakarta Special Province was 31,058,019 and 10,557,810 people, respectively. With a total area of 6,402.38 km^2, the average population density in this region was 8,767 people/km^2. The highest population density was also observed in Jakarta Special Province with 15,900 people/km^2 followed by Tangerang and South Tangerang Cities at 13,552 and 11,875 people/km^2, respectively. Table 2 shows the distribution of population as well as the area and its density in the administrative regions within the study area.

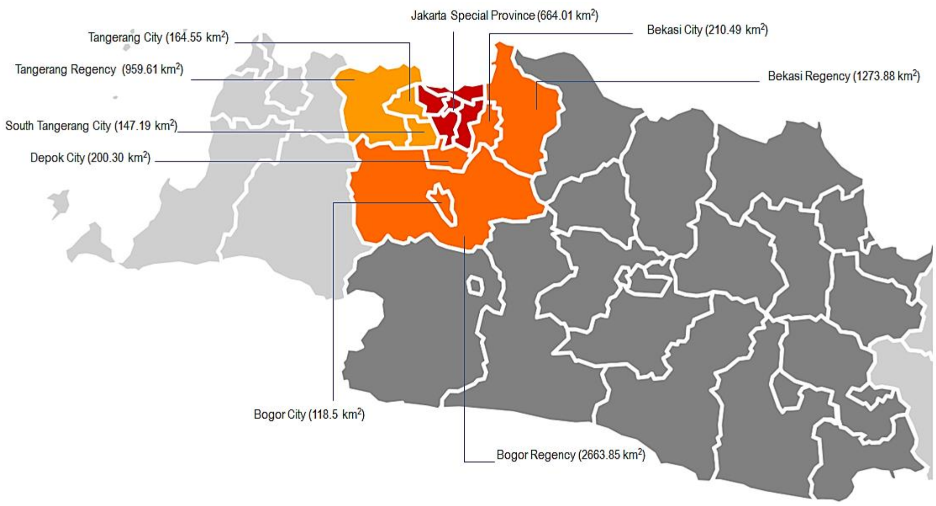

Figure 1. The study area in the Jakarta Greater Area, Indonesia

Table 2. Distribution of population, area and its density in the Jakarta Greater area, Indonesia

No.	Administrative Regions	Population (people)	Area (km^2)	Density (people/km^2)
1.	Jakarta Special Province	10,557,810	664.01	15,900
2.	Bogor City West Java	1,048,610	118.50	8,849
3.	Bogor Regency West Java	4,699,282	2,663.85	1,764
4.	Depok City West Java	1,857,734	200.30	9,275
5.	Tangerang City Banten	2,229,901	164,55	13,552
6.	Tangerang Regency Banten	3,800,787	959.61	3,961
7.	South Tangerang City Banten	1,747,906	147.19	11,875
8.	Bekasi City West Java	2,448,830	210.49	11,634
9.	Bekasi Regency West Java	2,667,159	1,273.88	2,094
	Total	**31,058,019**	**6,402.38**	**4,851**

Based on Jabodetabek Urban Transportation Policy Integration (JUTPI) Phase 2 in 2018 [56], the share of private modes increased and presently dominates the mode split of the Jakarta Greater Area, Indonesia, at 90.3%. From the results, the share of public transport was drastically decreasing, with values not more than 10%. The public transport included conventional buses, bus rapid transit (BRT), TransJakarta commuter lines, taxi bikes, taxis, and bajaj. Meanwhile, the private mode was dominated by motorcycles at a share of 75.8% and private cars at 14.5%. For public transport, the modes were also dominated by taxi bikes, conventional buses, BRT TransJakarta, and commuter lines, at 3.1, 2.9, 1.3, and 1.7%, respectively. In 2019, the number of BRT TransJakarta passengers reached 264,032,780 people. This was due to serving 13 corridors with the highest number of passengers, namely Corridor I: Blok M-Kota, which reached 28,703,262 people.

3.2. Research Flow Chart

The stages of the research are divided into four stages, namely as follows: (1) literature review, (2) design of questionnaire, (3) collecting data and survey: household travel survey (socio-demographic and trip characteristics), stated preference survey, service quality of transit (taxi and RTS), demand-supply attribute, dynamic model attribute, and origin-destination survey), (4) analysis data and discussion (household travel survey result, analysis of origin and destination survey (desire-line), service quality of transit: ride-hailing transport service (RTS) and taxi, mode choice model between taxi and RTS, demand-supply forecasting, dynamic model, modeling the demand of taxi and ride-hailing transport service). The stages of the research can be seen in Figure 2.

3.3. Model Input

In the demand-supply model, transit demand (vehicle/day) is defined as a dependent variable, with socio-demographic and trip characteristics being independent variables. This indicates that the socio-demographic data includes the gender of respondents (male or female), respondent age (17–62 years old), educational level, employment status, monthly income (in million IDRs), and respondent's domicile in 9 regions in the Jakarta Greater Area, which were obtained from 519 people through the random sampling technique. Meanwhile, the trip characteristics include travel reasons and utilization frequency of use of transport modes (trips per-week). In this research also included a comparison of the travel or trip cost, taxi and ride-hailing transport services travel and waiting times, as well as the journey's origin and destination. In addition, the mode type involved motorcycles, private vehicles/private cars, taxis, city transport, ride-hailing transport services (Grab, GoCar, Uber, and Maxim), conventional buses, BRT Trans Jakarta, commuter lines, Light Rail Transit (LRT), and Mass Rapid Transit (MRT).

3.3.1. Stated Preference Surveys

A stated-preference (SP) survey has traditionally been considered the go-to method for mode choice model applications in transportation studies. The survey was used to obtain stated-preference data for this report in order to estimate a mode choice model between taxi and ride-hailing services. It was also in line with a utility maximization choice protocol, using a logit binomial model with three parameters and an error-based normal or log-normal distribution. The choice protocol model was specified as a binary logit, which included the travel attributes of waiting times (wait), travel times (time), and travel/trip costs (cost). The utility equations are presented in Equation 1.

$$U_{Taxi} - U_{RTS} = C + (\alpha_1 \times Wait_{Taxi} - Wait_{RTS}) + (\alpha_2 \times Time_{Taxi} - Time_{RTS}) + \left(\alpha_3 \times Cost_{Taxi} - Cost_{RTS}\right) \quad (1)$$

where U_{Taxi} and U_{RTS} are the utility of taxis and the utility of ride-hailing transport services (RTS). C is the coefficient of a constant α_1, α_2, and α_3 are the coefficients of each variable, namely waiting times (wait), travel times (time), and travel costs or trip costs (cost), $wait_{Taxi}$ and $wait_{RTS}$ are the waiting time for taxis, and waiting time for RTS, $time_{Taxi}$ and $time_{RTS}$ are the travel time variables for taxis, travel time for RTS, and $cost_{Taxi}$ and $cost_{RTS}$ are the travel/trip cost for taxis and the travel cost for RTS. Based on this condition, the interview explored the characteristics of the respondents' trips, using taxis and ride-hailing transport services in the Jakarta Greater Area, Indonesia. This included waiting time, travel time, as well as the average cost of performing one trip using both transport modes at the most frequent origins and destinations.

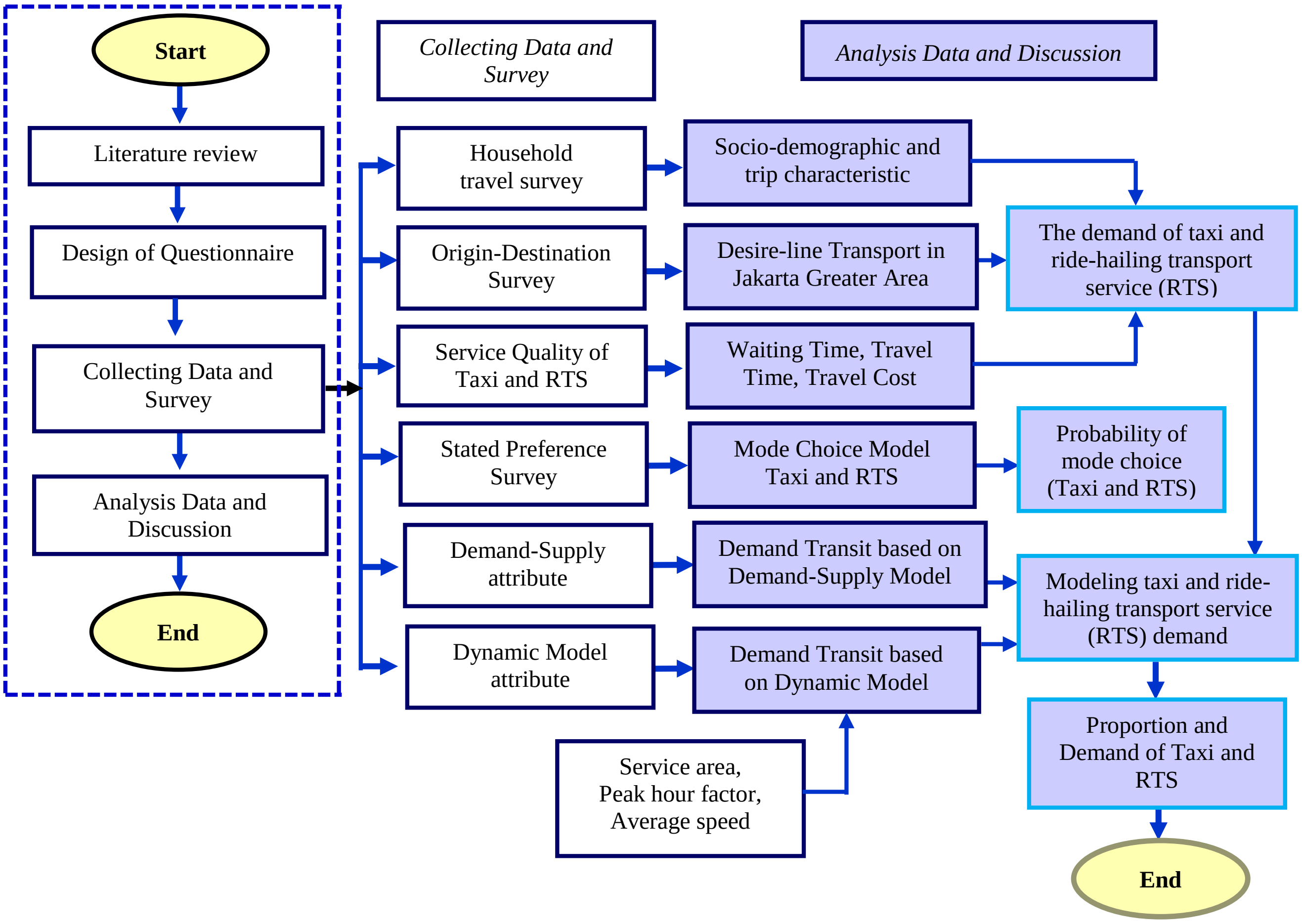

Figure 2. Flow chart of the research

3.3.2. Mode Choice: Binomial Logit Model

For the concept of random utility, the probability of a choice falling on an alternative (i) is observed when $i \geq$ data obtained from C_n (set of alternatives). According to Tamin [57], the alternative probability (i) selected by an individual (n) confronted with many alternatives (C_n) is as follows:

$$P_n(i|c_n) = Prob\,(u_{in} \geq u_{jn}), \forall j c_n \tag{2}$$

Besides the slight goodness of the normal distribution approach, the logistic distribution was also easier to analyze. Assuming that ε_n is logistically distributed, the probability of choice for alternative i is provided as follows:

$$P_n(i) = Prob(u_{in} \geq u_{jn}) = \frac{e^{\propto Bx_{in}}}{e^{\propto Bx_{in}+e^{\propto Bx_{jn}}}} \tag{3}$$

When Z is assumed to be a function of the combined costs ($z_i = \alpha_i + \beta C_i$), as well as Ci^1d and Ci^2d in the binomial logit model, the differences obtained were the known parts of the expenses for each mode and origin-destination pair (i, d) [57]. Using regressive linear analysis, the value of α and β was calculated when information was obtained on the selection proportion of each mode for the pair (i, d), P_{idk}. For simplicity, the proportion of P_i per origin-destination pair (i, d) in mode 1 is provided as follows:

$$P_1 = \frac{e^{-(\propto_1+\beta c1)}}{e^{-(\propto_1+\beta c1)}+e^{-(\propto_2+\beta c2)}} = \frac{1}{1+e^{-(\propto+\beta(c2-c1))}} \tag{4}$$

and $P_2 = 1 - P_1$ (5)

where P_1 is the probability of choosing from mode 1 and P_2 is the probability of choosing from mode 2.

3.4. Demand-Supply Model

Based on the concept of shortest-path betweenness centrality measure [58], as well as hub and spoke networks [59, 60] borrowed from the domain of complex analysis, a new traffic assignment model was developed [61]. This indicated that the demand for carpooling systems was expressed as a function of various socio-demographic, land use, and environmental factors [62]. The trip distance, socio-economic features, and land uses were three factors that affected the demand for taxis; furthermore, distance was the most important factor [51]. The approximate pick-up and drop-off locations, trip start times, and land use characteristics around the origins and destinations were used to predict the RTS services [52]. Wilkes et al. use a balance of ride-pooling demand and supply to model the demand for transit [55]. In predicting the demand for taxi and RTS service trips, considerable interest has reportedly been shown in the research community for a few years.

In this study, the demand-supply approach used a calculation variable containing some parameters, namely trips/day, average vehicle occupancy, mode share percentage, operating hours per day, passenger and driver waiting times, as well as travel time periods. These are subsequently described as follows:

1. *Number of trips per day (Σ Trips per-day):*

   This is based on data obtained from the origin-destination survey of national transportation for passengers in Indonesia. It is also used for all transportation modes, such as motorcycles, private cars, buses, taxis, BRT Trans Jakarta, taxi bikes, RTS (Grab, GoCar, Uber, Maxim, etc.), commuter lines, LRT, and MRT.

2. *Percentage of mode share (MS):*

   The value of this parameter is expressed in percent (%).

3. *Average vehicle occupancy (AVO):*

   This is an estimate of the average occupants in a single vehicle in (passengers per vehicle).

4. *Operating hours per day (Σ Operating hours per-day):*

   For taxi and RTS, the values of this parameters based on the field survey.

5. *Waiting time of passengers (WT_{Pass}):*

   This is the time tolerance for awaiting customers of RTS and taxis, through the data obtained from the survey results. The average waiting time of passengers (WT_{Pass}) is calculated based on the comparison of the number of fleets and waiting times for RTS and taxis.

6. *Travel time (TT):*

   The average travel time for using these transport modes is based on the survey results.

7. *Waiting time of driver (WT_{driver}):*

   This is the waiting time for the driver to find a passenger. This is determined based on the results of an interview survey of taxi companies in the Jakarta Greater Area, Indonesia, and ride-hailing transports (GoCar, Grab, Uber, and Maxim). The data obtained is the number of trips per day and operating time.

According to the demand-supply model, the calculation of the taxi and ride-hailing transports service (RTS) demands was carried out using Equation 6.

$$N = \frac{\sum Trips\ per\ day\ x\ MS}{AVO} \times \frac{WT_{pass}\ x\ WT_{driver}\ x\ TT}{\sum Operating\ hours\ per\ day} \tag{6}$$

where N is the demand for transit (ride-hailing transport and taxis) in vehicle units. The sum ($\sum$) of trips per day is the number of trips for passenger travel per-day from the origin-destination survey of national transportation for passengers (trips per-day). MS is the percentage of mode share for the RTS and taxis (%). AVO is the average vehicle occupancy factor for the taxi and RTS (passengers per vehicle). The sum of operating hours per day is the number of operating hours from taxis or RTS per-day (hours). WT_{Pass} is the waiting time of passengers, which is the maximum tolerance of waiting time for the passengers who order the taxi or RTS (hour). WT_{driver} (waiting time of driver) is the waiting time for the taxi driver or RTS to find passengers based on the number of trips per-day and operating time (hour). TT is traveling time based on distance from origin to destination location divided by the speed of the vehicle (in hours).

3.5. Dynamic Model

In the dynamic model, the derived variables were similar to those of the demand-supply approach, although additional parameters were observed, namely service area (km^2), peak hour factor (%), and the average speed of vehicles (km/h). These parameters represented the characteristics of the traffic in the study area. In this model, nine parameters were considered, with the transport demand being calculated using Equation 7 as follows:

$$N = \left\{\left(\frac{A}{V} \times \frac{1}{WT_{pass}}\right) + \left(\frac{\sum Trips\ per\ day\ x\ MS\ x\ PHF}{AVO} \times TT\right)\right\} \times \frac{24}{\sum Operating\ hours\ per\ day} \quad (7)$$

where N is transit demand (RTS and taxis) in vehicle units. The remaining variables are described as follows: A is the total service area (km^2). V is the average speed of vehicles (km/h). WTPass is the passengers waiting time, which is the maximum tolerance of waiting time for passengers who order a taxi or RTS (hour). TT is the distance from origin to destination location divided by the speed of a taxi, or RTS (hours). ∑ trips per day is the number of trips for passenger travel per day from the origin-destination survey for passengers (trips per day). MS is the percentage of mode share for taxis and RTS (%). AVO is the average vehicle occupancy factor for taxis and RTS (passengers per vehicle). PHF is the peak hour factor (%). The sum of operating hours per day is the number of operating hours from taxis or RTS per day (hours).

4. Results and Discussion

4.1. Household Travel Survey Result

Based on the survey of 519 respondents, taxi and RTS users in the Jakarta Greater Area, Indonesia, were generally used by consumers between 37-42 years old (150 people; 28.90%). Due to their working experiences for several years, they had the ability to pay for highly expensive taxis compared to other modes of transportation, such as commuter lines, LRT, BRT Trans Jakarta, and MRT. The male taxi users (53.20%) were also found to be more populated than women (46.80%), with most of the respondents being undergraduates' level (S1) based on their educational level (330 people; 63.71%). This was accompanied by those having diploma qualifications (D1, D2, D3, and D4) as much as 109 people (21.04%), with the average and highest income levels of the respondents at IDR7.7 and IDR7-9 million/month (47.67%), respectively. This result was in line with study by Gehrke et al. [63] the RTS services in the Greater Boston region tended to be relatively younger and more educated passengers than the regional population. Most of them were also found to own private vehicles, motorcycles, and cars, as a total of 5,181 trips were often carried out weekly by all the participants. Furthermore, motorcycles were mostly used as a transportation mode to the origin destination of trips that are most often done (1,664 trips per week of the total trips of all respondents, or 32.12%), accompanied by ride-hailing transport services (Grab Car, GoCar, Uber, Maxim, etc.), private cars or private vehicles, and taxis at 933, 710, and 617 trips per week (18.01%, 13.70%, and 11.91%), respectively. This result was in line with Shaheen et al. [2], multi-modal application users do change their travel behavior who previously used public transportation (City Transport, Trans Jakarta, taxis, or buses) switched to ride-hailing transport services (Grab Car, GoCar, Uber, Maxim, etc.). The socio-demographic and trip characteristics of the sample of 519 people in the Jakarta Greater Area, Indonesia, are shown in Table 3.

Table 3. Socio-demographic and trip characteristics of the sample in the Jakarta Greater Area, Indonesia

Characteristics	Description of variable	Frequency	Percent (%)
	Socio-demographic characteristics of respondents		
Gender	Male	276	53.20
	Female	243	46.80
Age (years old)	17-22	6	1.16
	22-2`7	26	5.01
	27-32	106	20.42
	32-37	148	28.52
	37-42	150	28.90
	42-47	58	11.18
	47-52	19	3.66
	52-57	3	0.58
	57-62	3	0.50
Educational level	Senior high school	21	4.05
	Diploma program (D1, D2, D3, D4)	109	21.04
	Undergraduate degree (S1)	330	63.71
	Master's and PhD degree (S2, S3)	58	11.20
Employment status	Student/ College student	9	1.74
	Government employees/ Soldier/ Police	52	10.08
	Private employees/ BUMN/ BUMD	252	48.84
	Teachers / Lecturers / Academics	47	9.11
	Housewife	28	5.43
	Others (Doctors, nurses, midwives, pharmacists, etc.)	128	24.81

Monthly income (in million IDRs)	3-5	43	8.33
	5-7	105	20.35
	7-9	246	47.67
	9-12	68	13.18
	12-15	25	4.84
	15-20	6	1.16
	20-25	5	0.97
	25-30	2	0.39
	> 30	16	3.10
Respondent's domicile in the Jakarta Greater Area	The Jakarta Special Province	181	34.87
	Bogor City, West Java Province	16	3.08
	Bogor Regency, West Java Province	71	13.68
	Depok City, West Java Province	51	9.83
	Tangerang City, Banten Province	40	7.71
	Tangerang Regency, Banten Province	53	10.21
	South Tangerang City, Banten Province	37	7.13
	Bekasi City, West Java Province	39	7.51
	Bekasi Regency, West Java Province	31	5.97
Trip characteristics			
Reasons to travel	Be at work	191	36.80
	Study (go to school, campus, or university)	8	1.54
	Business needs	102	19.65
	Tours and traveling	19	3.66
	Shopping or malls	38	7.32
	Family needs	42	8.09
	Others (drugstore, hospital, etc.)	119	22.93
Frequency of use of mode transport (trips/week)	Motorcycles	1664	32.12
	RTS (Grab, GoCar, Uber, Maxim, etc.)	933	18.01
	Private vehicles/ private cars	710	13.70
	Taxis	617	11.91
	City transport and Trans Jakarta	519	10.02
	Commuter lines	370	7.14
	Buses	251	4.84
	Mass Rapid Transit (MRT)	84	1.62
	Light Rail Transit (LRT)	33	0.64

4.2. Origin-Destination (O-D) Survey

In this study, the data consisting of the origin and destination traveled were used to model the trip patterns of people in the Jakarta Greater Area, Indonesia. These were obtained from the present and National Transportation Origin-Destination 2018 Surveys [64]. The origin zone for the travel destination was also based on city districts within the Jakarta Greater Area and its surroundings. The analytical results are shown in Figure 3. The desire line from 15 zones of origin and destinations, namely Central Jakarta, West Jakarta, South Jakarta, East Jakarta, Bogor City, Bogor Regency, Depok City, Tangerang City, Tangerang Regency, South Tangerang City, Bekasi City, Bekasi Regency, Bandung City and its surroundings, Sukabumi and its surroundings, and Serang and its surroundings. The movements in the Jakarta Greater Area were dominant in the Jakarta Special Province. Additionally, the dominant movement is shown in the desire line, as shown in Figure 4.

4.3. Service Quality of Transit

Table 4 shows a comparison of the waiting and travel time (minutes), as well as travel per-trip costs (IDR/trip), for 519 respondents between RTS and taxi passengers. Table 4 indicates that each parameter contains an average or mean, minimum and maximum values, and standard deviation values. In this condition, the average waiting times for taxi and RTS users were 10.56 and 9.07 minutes, respectively [65]. The standard deviation of waiting times for taxi and RTS users was 4.74 and 3.60, respectively. The average travel time for taxi users was 41.55 and 38.88 minutes for RTS. The standard deviation of travel times for taxi and RTS users was 14.99 and 13.78, respectively. The average travel cost for taxi and RTS users was IDR 67,845 per trip and IDR 56,943 per trip, respectively. The standard deviation of travel costs for taxi and RTS users was 34.94 and 28.11, respectively.

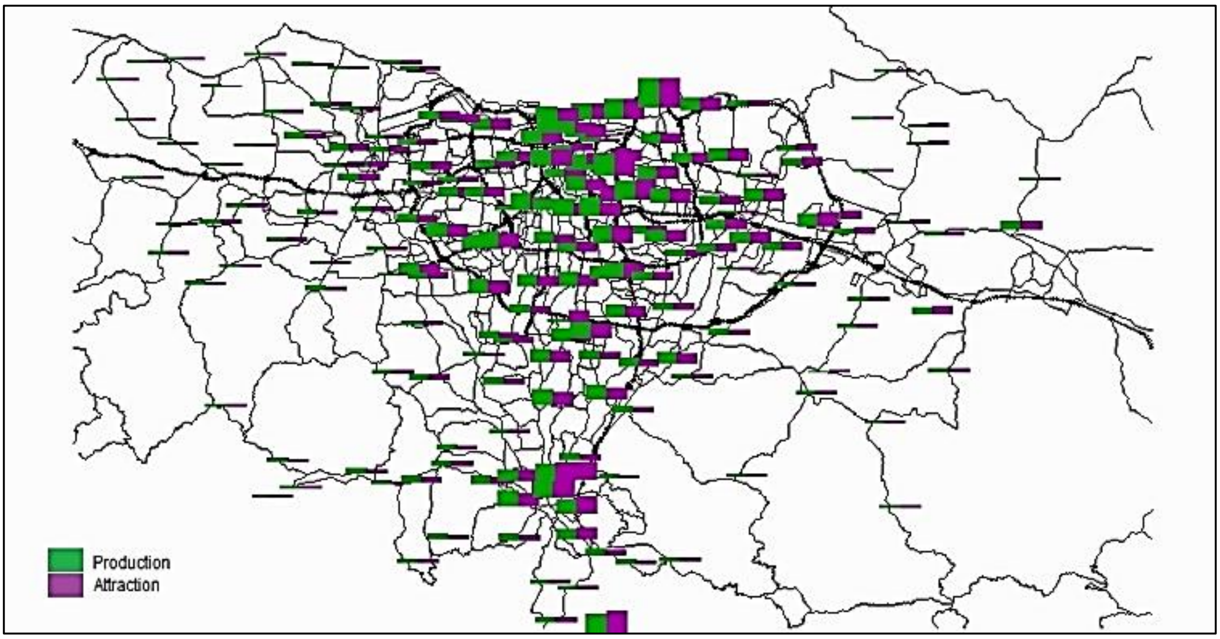

Figure 3. Origin and Destination in the Jakarta Greater Area, Indonesia based on ATTN 2018 [64]

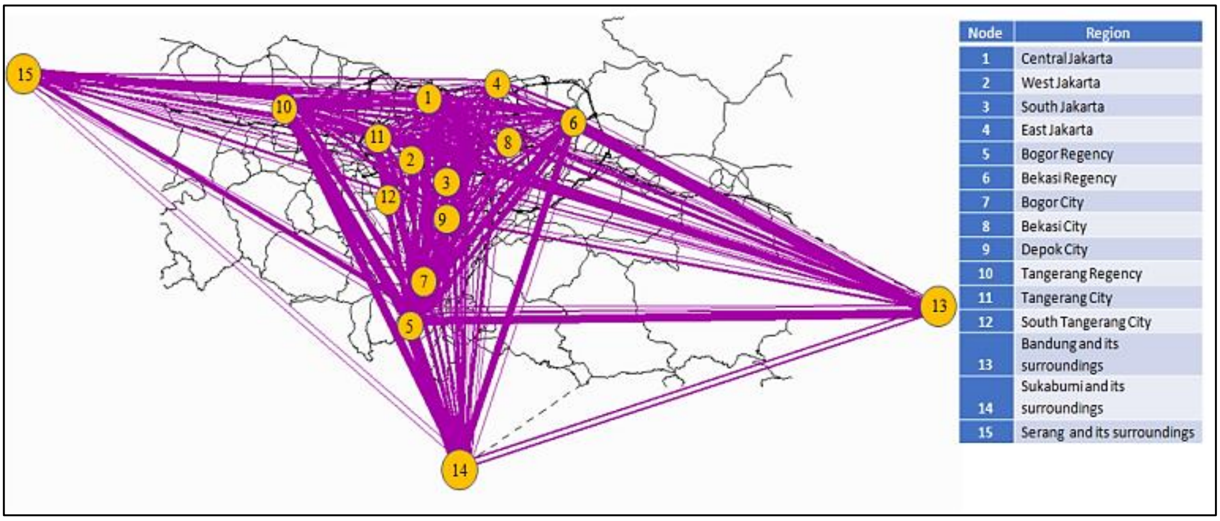

Figure 4. Desire-line in the Jakarta Greater Area based on ATTN 2018

Table 4. Waiting time, travel time, and travel costs for 519 respondents by taxi and RTS in the Jakarta Greater Area

Parameters	Taxi	RTS
Waiting times (minutes)		
Average	10.56	9.07
Minimum	3	2
Maximum	30	23
Standard deviation (SD)	4.74	3.60
Travel times (minutes)		
Average	41.55	38.88
Minimum	13	10
Maximum	130	120
Standard deviation (SD)	14.99	13.78
Travel costs (IDR/trip)		
Average	67,845	56,943
Minimum	15,000	10,000
Maximum	250,000	225,000
Standard deviation (SD)	34.94	28.11

Based on these results, it is known that to acquire and utilize the RTS, waiting time for users was faster than the taxi, i.e., average waiting time with the RTS was 9.07 minutes compared to the taxi's 10.56 minutes, indicating that it was 1.49 minutes slower than the taxi. The waiting time for the RTS was 14.109% faster than the taxi. For the travel time, utilization of the RTS was faster than that of the taxi; the average travel time of the RTS was 38.88 minutes compared to the taxi's 41.55 minutes. Travel time by RTS was 2.67 minutes lower than by taxi (6.426% faster than by taxi). This result in line with Shaheen et al. [7], the utilization of RTS can save travel times by offering points and discounts, and in line with Pan et al. [66], the RTS services are more equitable than traditional taxi services. For the travel costs, the utilization of RTS was also cheaper (IDR 56,943 per trip), proving that it was IDR 10,902 less expensive than using a taxi (IDR 67,845 per trip). The average travel cost per trip for the RTS is cheaper than a taxi by 16.068%. Therefore, these conditions are often considered when selecting the suitable transportation mode between taxis or RTS. This was in line with Wang and Ross [67], where the relationship between taxis and transit was analyzed in New York City. This verified that transit-extending taxi trips were averagely shorter and significantly larger, based on the travel length and passenger proportions paying with cash, respectively.

In this present work, 15% of the taxi fleet with 2,000 vehicles, each with a capacity of 10, or 3,000 vehicles with a capacity of 4, were highly sufficient to serve 98% of travel demand within a mean waiting time and trip delay of 2.8 and 3.5 minutes, respectively [68]. Despite this, ride-hailing transport services (RTS) were still rapidly growing and becoming one of the most disruptive technologies in the transportation realm. Besides enabling cities to effectively understand people's activity patterns, accurate prediction of trip demand also helped ride-hailing companies and drivers carry out informed decisions to reduce deadheading miles traveled or vehicle-kilometers traveled [69], traffic congestion [21], and energy consumption [46]. The advantages of on-demand, higher-capacity vehicles were based on the significant elevation of service rates as well as the reduction of waiting time and distance traveled. Despite these merits, the estimates did not even consider the cost of other potential negative externalities, such as vehicular emissions (greenhouse gas and particulate matter) [70], travel-time uncertainty [71], and a higher accident propensity [72–74].

4.4. Mode Choice Model

The competitiveness of RTS, e.g., Grab's transport business, was also influenced by the threat of new entry, buyer power, substitution, suppliers, and competitive rivalry [75]. In attribute levels, the experimental design for stated-preference surveys applied the wide-span principles and independent variation [76]. This revealed that the mode choice between taxi or RTS was analyzed regarding the preferences of respondents from the stated-preference survey. In this condition, three slightly sensitive parameters of the model were observed, namely waiting times, travel times, as well as travel/trip costs. Figure 5 shows the preferences of 519 respondents when being interviewed for their preferences in eight different service scenarios.

1. ***Scenario 1:*** In this case, the RTS travel or trip cost, as well as waiting and travel time were 80%, 80%, and 90% of the taxi, respectively.
2. ***Scenario 2:*** In this case, the RTS travel or trip cost, as well as waiting and travel time were 80%, 80%, and 110% of the taxi, respectively.
3. ***Scenario 3:*** In this case, the RTS travel or trip cost, as well as waiting and travel time were 80%, 100%, and 90% of the taxi, respectively.
4. ***Scenario 4:*** In this case, the RTS travel or trip cost, as well as waiting and travel time were 80%, 100%, and 110% of the taxi, respectively.
5. ***Scenario 5:*** In this case, the RTS travel or trip cost, as well as waiting and travel time were 120%, 80%, and 90% of the taxi, respectively.
6. ***Scenario 6:*** In this case, the RTS travel or trip cost, as well as waiting and travel time were 120%, 80%, and 100% of the taxi, respectively.
7. ***Scenario 7:*** In this case, the RTS travel or trip cost, as well as waiting and travel time were 120%, 100%, and 90% of the taxi, respectively.
8. ***Scenario 8:*** In this case, the RTS travel or trip cost, as well as waiting and travel time were 120%, 100%, and 110% of the taxi, respectively.

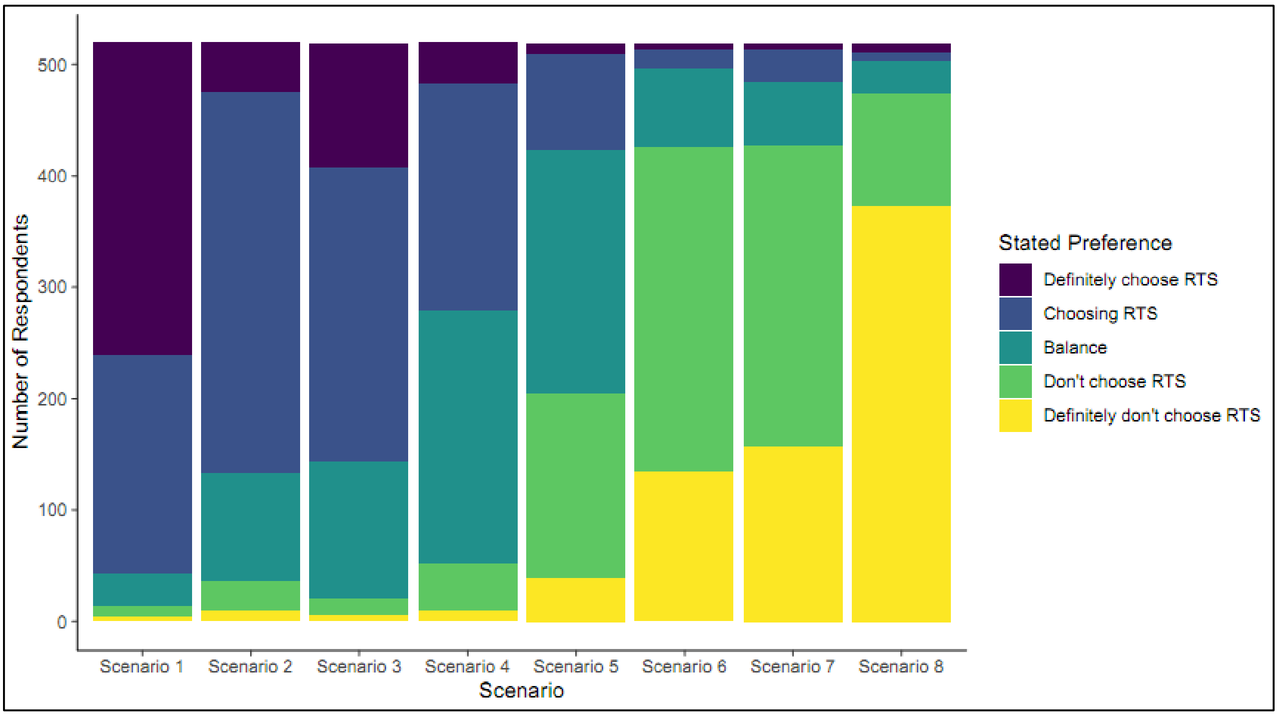

Figure 5. The tendency of choosing ride-hailing transport to taxi

In each scenario, five options are given to choose the type of transportation mode, ride-hailing transport (RTS) or taxi, namely definitely choosing RTS, choosing RTS, balance, not choosing RTS, and definitely not choosing RTS.

With those of options, we try to show that the mode choice model between these transport taxi and ride-hailing transport services is an option to know the patterns where the government is provided to formulate policies related to the taxis and RTS sectors. Three parameters that were considered sensitive to the mode choice between taxi and RTS, namely waiting times, travel times, and travel costs. Regarding the survey conducted, the formulation of mode choice was obtained as follows:

$$U_{Taxi} - U_{RTS} = 0.4642 - 0.048 \times \Delta_{Travel_{cost}} - 0.0342 \times \Delta_{Waiting_{time}} - 0.0346 \times \Delta_{Travel_{time}} \tag{8}$$

where U_{Taxi} - U_{RTS} is utility differences (utility taxi - utility RTS). Δ_{Travel_cost} is a travel $cost_{taxi}$ - travel $cost_{RTS}$ (IDR/trip). $\Delta_{Waiting\_time}$ is waiting $time_{taxi}$ - waiting $time_{RTS}$ in minutes. Similarly, Δ_{Travel_time} is the difference between travel time for taxi and travel time of RTS in minutes.

Figure 6 shows the probability curve for mode choice based on the utilization of taxis or RTS in the Jakarta Greater Area, Indonesia. This explained that the probability of selecting a taxi was in line with the RTS when the utility difference between both modes was 0. When this difference in utility value of taxis and RTS (U_{Taxi} - U_{RTS}) = -4, the probabilities of selecting a taxi and RTS were 1.80 and 98.20%, respectively. Meanwhile, the probabilities of selecting a taxi and RTS were 98.201 and 1.799% when the utility difference (U_{Taxi} - U_{RTS}) = 4, respectively. Based on Figure 6, business-related trips were observed as the most frequent mode of travel with a tight schedule. This confirmed that the travel time was used to select the transportation mode to be used. These results were in line with some previous studies where this variable was used in the calculation of passenger transportation needs. Besides the travel time, another variable that contributed to the mode choice was trip costs. This was because various travel destinations provided different perceptions of fares; e.g., respondents were less and more sensitive to costs and trip time, respectively. These were subsequently in line with family visitations, where costs became more important than the travel time, which was relatively more relaxed.

According to the results obtained in Figure 6, the input variables to be able to be applied in the mode selection model and analysis are shown in Table 5. Using the existing variables (travel cost, waiting time, and travel time), with the present service, the respondents selected ride-hailing transport services and taxis by 73.306% and 26.694%, respectively. This result is in line with Pan et al. [66], the equity of RTS in New York City was higher than that of traditional taxis. In another study by Shoman and Moreno [54], travel time, travel cost, and the value of time were used as measures for the mode choice between ride-hailing and metro in the city of Munich, Germany. Ride-hailing services' popularity among those aged 18–39 years old, larger households, and households with fewer autos [54]. In Munich, Germany, the mode share of ride-hailing was between 7.6% and 16.8% [55].

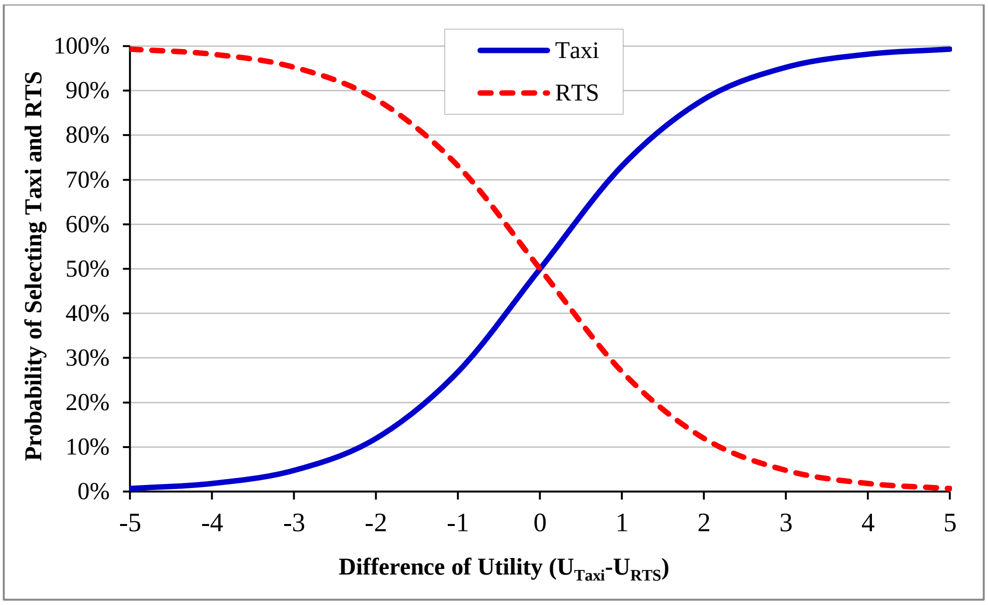

Figure 6. Probability curve for mode choice between taxi and RTS in the Jakarta Greater Area, Indonesia

Table 5. Probability of mode choice between taxi and RTS in the Jakarta Greater Area, Indonesia

Parameters	Travel cost (IDR/trip)	Waiting time (minutes)	Travel time (minutes)
Taxi	67,845	10.56	41.55
Ride-hailing transport services (RTS)	56,943	9.07	38.88
Application of preferred mode choice equations			
Percent comparison attribute value between RTS and taxi	16.07%	14.08%	6.41%
U_{Taxi}-U_{RTS}		-1.010	
Probability of RTS (P_{RTS})		73.306%	
Probability of Taxi (P_{Taxi})		26.694%	

4.5. Modeling the Demand of Taxi and RTS

4.5.1. Demand-Supply Model

In this model, seven parameters were used to determine the demand for taxi and ride-hailing transport services (RTS) using Equation 6. Based on the results, the values of travel time, passenger and driver waiting time, as well as vehicle occupancy rates in the Jakarta Greater Area, are as follows:

1. *Number of trips per day (∑ Trips per-day)*

   The number of trips per day for passengers in the Jakarta Greater Area, Indonesia, obtained from the origin and destinations survey in 2018 was 62,397,792 trips per day [64]. Using the assumption of a growth rate of 5% per year, it is estimated that the amount of trips/day in 2020 will be 68,793,566 trips per day. The number of trips was for all transportation modes like motorcycles, private cars, buses, taxis, RTS, commuter lines, Light Rail Transit (LRT), and Mass Rapid Transit (MRT).

2. *Percentage of mode share (MS)*

   The percentage of mode share for taxis and RTS in the Jakarta Greater Area based on data obtained from the Greater Jakarta Transport Authority, Ministry of Transportation of the Republic of Indonesia in 2020 was 1.50%.

3. *Average vehicle occupancy (AVO)*

   The AVO factors for taxis and RTS in the Jakarta Greater Area, based on data obtained from the Greater Jakarta Transport Authority and Jabodetabek Urban Transportation Policy Integration (JUTPI) Phase-2 in 2018 [56], are to be filled with 2 passengers per vehicle.

4. *Number of operating hours per day (∑ Operating hours per-day)*

   Based on the survey, the operating hours per day for RTS and taxis vary from 12 to 24 hours. In this case, taking into account the traffic safety and physical condition of the driver, the operating hours were 16 hours with 2 drivers (each driver works 8 hours per-day) [65].

5. *The waiting time of passengers (WT_{Pass})*

The waiting time of passengers was the time tolerance for customer waiting using data from the survey results (Table 4), which show that the average user getting a taxi was 10.56 minutes and the RTS was 9.07 minutes [65]. The number of taxis in the Jakarta Greater Area in July 2020 was 17,268 units, and the number of RTS was 33,133 units. The average waiting time of passengers was calculated based on the comparison of the fleets and waiting times obtained 9.591 minutes (0.1598 hours).

6. *Travel time (TT)*

The average travel time for using these transport modes (taxis and RTS) based on the survey results and shown in Table 4 was 38.88 minutes (0.648 hours) for RTS and 41.55 minutes (0.6925) for taxis. The average travel time for taxi and RTS users was calculated based on the comparison: the number of taxis was 17,268 units, and the number of RTS units was 33,133 units, resulting in 39.785 minutes (0.6631 hour).

7. *The waiting time of driver (WT_{driver})*

The waiting time of the driver, which is the time it takes to get passengers from the driver's side, was determined based on the results of an interview survey on taxi companies operating in the Jakarta Greater Area, Indonesia, and RTS (Grab, GoCar, Maxim, etc.). The number of trips per day based on the results of an interview survey varies, with a range of 7-8 trips per-day. In this study, the number of operating hours per-day for RTS and taxis is 16 hours, and the number of trips per-day is 8 trips. The average waiting time for passengers is 9.591 minutes (0.1598 hours), and the average travel time for taxi and RTS users is 39.785 minutes (0.6631 hours). Based on the data, the waiting time for the driver to find a passenger was 70.623 minutes (1.1770 hours).

Table 6 shows the calculation of ride-hailing transport services and taxi demands based on the demand-supply approach. Regarding the value of each parameter, 64,494 vehicle units were obtained in the Jakarta Greater Area, Indonesia. In this condition, the significant variables were the operating hours/day, trips/day, as well as waiting and travel time. Using the stated-preference technique, the proportion of taxis and RTS was also analyzed based on the mode choice model. This indicated that the respondents selected the RTS and taxi modes by 73.31% and 26.69%, respectively, using Equation (8) with the existing input variables and the present service. Therefore, the values of taxi and RTS demands were 17,216 and 47,278 vehicle units, respectively.

Table 6. Taxi and RTS demand based on demand-supply model

No.	Parameter (unit)	Value
1.	Number of trips per day (trips per-day)	68,793,566
2.	Percentage of mode share (%)	1.5
3.	Average vehicle occupancy factor (passengers per-vehicle)	2
4.	WT_{pass} (hours)	0.1598
5.	WT_{driver} (hours)	1.177
6.	TT or travel time (hours)	0.6631
7.	Operating hours per day (hours)	16
8.	Transit demand (vehicle units)	64,494
9.	Probability of taxi: 26.694%	17,216
10.	Probability of RTS: 73.306%	47,278

4.5.2. Dynamic Model

In this model, a total of nine parameters were used to determine the demands for taxis and RTS using Equation (7). In this condition, three variables were subsequently added to represent the traffic characteristics in the location, namely service area (km^2), peak hour factor (%), and average vehicle speed (km/h). Using the dynamic model, the input variables involved in calculating the number of taxis and RTS are as follows:

1. *Service area (A)*

The total service area from the 9 regions within the Jakarta Greater Area, Indonesia (Table 2) was 6,402.38 km^2.

2. *Average vehicle speed (V)*

The average vehicle speed in the Jakarta Greater Area based on data obtained from Greater Jakarta Transport Authority in 2020 was 20 km/h.

3. *Waiting time of passengers (WT_{Pass})*

The average waiting time for taxi and RTS passengers in the Jakarta Greater Area for dynamic model same with demand-supply approach was 9.591 minutes (0.1598 hour).

4. *Travel time (TT)*

   The average travel time for taxi and RTS users in the Jakarta Greater Area for dynamic model same with demand-supply approach was 39.785 minutes (0.6631 hour).

5. *Number of trips per day (∑ trips per-day)*

   The number of daily trips was estimated at 68,793,566 trips per-day in 2020.

6. *Percentage of mode share (MS)*

   The mode share percentage for these transportation mode (taxis and RTS) in the Jakarta Greater Area, Indonesia based on data obtained from Greater Jakarta Transport Authority was 1.5%.

7. *Average vehicle occupancy (AVO)*

   AVO for taxis and RTS based on data obtained from Greater Jakarta Transport Authority and Jabodetabek Urban Transportation Policy Integration (JUTPI) Phase-2 in 2018 [56] to be filled with 2 passengers per-vehicle.

8. *Peak hour factor (PHF)*

   The daily demands for these transportation modes (taxis and RTS) were calculated during peak hours to obtain knowledge of the number of transits that needed to be operated. This approach is the same as that of Dey et al. [53] the data for the analysis was drawn during weekday morning peak hours. During peak hours, a surge in service demand was observed at approximately 10.29% of total trips per day, according to the operator's data. This was quite relevant to road traffic conditions, where 10% of the total daily vehicles were loaded at peak hours.

9. *Number of operating hours per day (∑ Operating hours per-day)*

   The operating hours were 16 hours with 2 drivers, which maximally work for 8 hours daily based on traffic safety.

By substituting each variable value into Equation 7, the calculation of this vehicular demand in the Jakarta Greater Area was 55,811 vehicle units using the dynamic model. This indicated that the mode choice probabilities for ride-hailing transport services and taxis were 73.31% and 26.69%, respectively. Therefore, the number of taxi and RTS demands was 14,898 and 40,913 vehicle units, respectively. Demand for ride-hailing systems was expressed as a function of a variety of demographic, land use, and environmental factors [77]. Several determinants of ride-hailing transport services exist, including the built environment, the attributes of socio-economic status [65], the characteristics of trips [29], attitudinal factors [30], and lifestyle [31]. Gender, age, and level of education are the key socio-demographic characteristics in modeling taxi demand in China [32].

In a previous study, six factors determined the number of taxi pickups and drop-offs: transit access time, population size, median age, percent of the population educated beyond a bachelor's degree, income per capita, and number of employment opportunities [15]. The other method that can be used to predict taxi demand distributions is clustering algorithms [78]. Moreira-Matias et al. [79] applied time series techniques to forecast taxi passenger demand. This study is represented by the development of a demand model for ride-hailing transport services (RTS) and taxis, using a balance between a demand-supply approach and a dynamic model that considers the traffic characteristics of the location, namely the service area (km^2), peak hour factor (%), and average speed of vehicles (km/h). The results of this study, based on comparative analysis, showed that the calculation of these vehicular demands was 64,494 and 55,811 vehicle units, respectively, regarding the utilization of the demand-supply and dynamic models. The transit demand (taxi and RTS) is lower than previous studies; the forecasting demand of taxi and ride-hailing in the Jakarta Greater Area using the demand-supply model in 2020 is 71,660 vehicles [65]. One of the reasons is that the percentage of mode share for taxi and ride-hailing in the Jakarta Greater Area is 1.75% in Sugiyanto et al. [65], while in this study it is 1.50%. In the Jakarta Greater Area, the numbers of taxis and ride-hailing transport services were 17,268 and 33,133 units in July 2020, respectively. Based on both transportation modes, the total value obtained was 50,401 vehicle units. In the dynamic model, the rate of demands also led to the number of taxis and RTS being lower and closer to the values of operational transportation modes in the field. This proved that the dynamic model was better than the demand-supply approach due to the additional parameters representing the traffic characteristics and service area in the study area.

5. Conclusion

The three parameters considered in this study for the mode choice between taxi and ride-hailing transport services (RTS) were waiting times, travel times, and travel costs. The RTS service was better than the taxi based on the following: the RTS was 1.49 minutes lower (14.109% faster) than the taxi (10.56 minutes), due to the waiting time being 9.07 minutes; the RTS was 2.67 minutes lower (6.426% faster) than the taxi (41.55 minutes), with the travel time value at 38.88 minutes; and the RTS was IDR10,902 cheaper (16.068% cheaper) than the taxi (IDR67,845 per-trip), based on the travel costs being IDR56,943 per-trip.

The factors influencing taxi and RTS demands were the daily trip values, average vehicle occupancy, mode share percentage, operating hours per day, passenger and driver waiting time, as well as travel time. Moreover, the variables obtained by the dynamic model were similar to those obtained by the supply-demand approach, although three parameters were subsequently added as the traffic characteristics of the location, namely service area (km^2), peak hour factor (%), and average vehicle speed (km/h). The mode choice probabilities of RTS and taxis were 73.306 and 26.694%, respectively. Based on the demand-supply and dynamic models, the taxi and RTS demand in the Jakarta Greater Area were 64,494 and 55,811 vehicle units, respectively. This proved that the dynamic model was better than the demand-supply model due to the added parameters representing the area's traffic characteristics.

Based on these results, the next research is expected to be conducted on the modeling of taxi and RTS demands using global positioning system (GPS) data and schedule transit information, as well as analysis using machine learning and deep learning. A comparative analysis is also expected to be performed with the demand-supply and dynamic models.

6. Declarations

6.1. Author Contributions

Conceptualization, G.S., A.W., and T.T.; methodology, G.S., Y.Y., A.W., and T.T.; formal analysis, G.S., A.W., and T.T.; investigation, G.S. and T.D.; resources, G.S., A.W., and T.T.; data curation, G.S. and A.W.; writing original draft preparation, G.S. and Y.Y.; writing-review and editing, G.S. and Y.Y.; visualization, T.D. and Y.Y.; supervision, G.S., Y.Y. and A.W.; funding acquisition, G.S., A.W., and T.D. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

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6.4. Acknowledgements

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6.5. Conflicts of Interest

The authors declare no conflict of interest.

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