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Transport Assessment Using Bayesian Method to Determine Ride-Hailing in Kula Lumpur: a Case Study

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ABSTRACT

This research was designed to investigate the factors affecting the frequency of use of ride-hailing in a fast-growing metropolitan region in Southeast Asia, Kuala Lumpur. An intercept survey was used to conduct this study in three potential locations that were acknowledged by one of the most famous ride-hailing companies in Kuala Lumpur. This study used non-parametric and machine learning techniques to analyze the data, including the Pearson chi-square test and Bayesian Network. From 38 statements (input variables), the Pearson chi-square test identified 14 variables as the most important. These variables were used as predictors in developing a BN model that predicts the probability of weekly usage frequency of ride-hailing. According to the final model, the attitude of the commuters towards the speed of ride-hailing over hailing regular taxis was the most important and presented in all probability conditions. Several related studies also identified ride-hailing speed as one of the top reasons for using this travel option. The findings of this study imply that commuters still compare the ride-hailing services with the traditional taxis in Kuala Lumpur, especially in terms of complementarity to other modes, ease of payment, ease of access, and speed. It is critical to have a sustainable strategy for keeping commuters' satisfaction at the highest level because if the ride-hailing services cannot meet the commuters' expectations, they may switch back to conventional transport options.

Keywords: Transport mode, Ride-hailing, Bayesian method, Traditional taxis.

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تقييم أداء شبكة النقل باستخدام طريقة البايزي لسيارات الاجرة المسبقة الطلب في كوالالمبور: حالة دراسة

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الخلاصة

تم تصميم هذا البحث لاستكشاف العوامل التي تؤثر على تكرار استخدام خدمات النقل لسيارات الاجرة المسبقة الطلب في إحدى المناطق الحضرية السريعة النمو في جنوب شرق آسيا، وهي كوالالمبور. تم استخدام المسح الاستبياني لإجراء هذه الدراسة في ثلاثة مواقع معتمدة من قبل إحدى أشهر شركات النقل لسيارات الاجرة المسبقة الطلب في كوالالمبور. حيث تنبأت الدراسة الحالية بالعوامل المؤثرة في طلب الركاب على وتيرة استخدامه و تحقيقا لهذه الغاية تم استخدام الجمع بين نظرية بايز الاحصائية (Bayesian) و إختبار مربع كاي للاستقلالية (Pearson chi-square) في تحقيق التنبؤ الاحتمالي الخاضع للإشراف، من بين 38 عبارة (متغيرات الإدخال)، حدد اختبار كاي–مربع كاي 14 متغيرًا كأكثرها أهمية. تم استخدام هذه المتغيرات كمتنبئات في تطوير نموذج شبكة بايزية يتنبأ بالاحتمالية المتوقعة لتكرار استخدام خدمات حجز الرحلات أسبوعيًا. وفقًا للنموذج النهائي، تشير النتائج تجاه سرعة خدمات النقل لسيارات الاجرة المسبقة الطلب مقارنة بالتاكسيات العادية هو الأكثر أهمية وتم عرضه في جميع الظروف المحتملة. أظهرت العديد من الدراسات المتعلقة بخدمات النقل لسيارات الاجرة بان السرعة في حجز الرحلات هي واحدة من أهم الأسباب لاستخدام هذا الخيار في السفر. تشير نتائج هذه الدراسة إلى أنه من المهم ان تكون هنالك دراسة استراتيجية مستدامة للحفاظ على رضا الركاب على أعلى مستوى لأنه إذا لم تستطع خدمات نقل الركاب تلبية متطلبات الركاب، فقد يعودون إلى خيارات النقل التقليدية.

الكلمات المفتاحية: انظمة النقل ، سيارات الاجرة المسبقة الحجز، طريقة البايزي، سيارات الاجرة التقليدية.

1. INTRODUCTION

The emergence of ride-hailing opens new windows for transporting people across cities. Ride-hailing is a transport service that connects drivers and passengers through smartphones and applications and dynamically matches supply and demand **(Hughes and MacKenzie, 2016; Rayle; Dai et al., 2016)**. Ride-hailing is a segment of “on-demand ride services,” which in itself is a classification of “sharing passenger ride” and “shared mobility” **(Shaheen and Chan, 2016).** Ride-hailing services, also known as Transport Network Companies (TNCs), have grown rapidly worldwide. Some successful TNC companies are Uber and Lyft in the U.S., Didi Express in China, and Grab and MyCar in Malaysia. Ride-hailing has diverse affirmative effects on the accessibility, safety, and economic efficiency of transportation systems **(Ali et al., 2021; Jin et al., 2018).** The advantages of ride-hailing drew the notice of scholars from different areas, such as urban planning, transportation, and economy **(Arteaga-Sánchez et al., 2018; Jiao, 2018; Kima et al., 2018, Wang and Mu, 2018**). However, the research on travel behaviour related to ride-hailing remains in the primary stages.

To date, most research on ride-hailing has focused on the pricing of ride-hailing, and a few studies assessed the passengers' attitudes toward this new model **(Ali et al., 2021; Rayle et al., 2016; Zhanga et al., 2016).** These studies targeted the general population and ride-hailing users to identify their reasons for ride-hailing utilization and the impacts of this kind of transportation on taxicab and public transport usage. Besides, ride-hailing knowledge was mainly from China and the U.S., and very few academic works were conducted in Southeast Asian countries with deficient and unsatisfactory transport systems.
Ride-hailing is one of the most important mobility options in Malaysia. Several ride-hailing companies provide this service to the public (e.g., Grab and MyCar). In this country, an E-Hailing Regulation is available that mandates drivers to get a PSV permit. This license shows that the drivers are assessed regarding their background, health, and cars **(Ali et al., 2020; Grab, 2019a)**. This regulation may be efficient and enhance the ride-hailing service quality in Malaysia. Besides these pragmatic strategies, extensive academic studies may also help ride-hailing firms improve their service quality and use this travel mode for a broad range of commuters. Most ride-hailing investigations were conducted in developed countries like the U.S. and China. To the author's knowledge, very few studies regarding ride-hailing in general and ride-hailing travel behaviour, in particular, were conducted in Malaysia **(Aghaabbasi et al., 2020)**. Therefore, the present investigation strives to determine ride-hailing features that influence the usage frequency of this travel mode in Kuala Lumpur, Malaysia.
The extensive literature on parameters affecting Ride-Hailing influences commuters' mode choice and trip frequency. Some essential factors are sociodemographic, built environment (BE), trip characteristics, travel demand management measures, and psychological and mode-specific factors **(Zhou, 2012)**. While built environment factors received severe attention in academia, transport planning practitioners mainly paid attention to the mode-specific factors, sociodemographic factors, and trip characteristics **(Zhou, 2012; de Azevedo et al., 2021; Svintsov et al., 2020).** Regarding ride-hailing, several studies were conducted that focused on its pricing **(Jiao, 2018; Nourinejad and Ramezani, 2019; Sun et al., 2019; Wang et al., 2016; Zha et al., 2018),** marketability **(Harding et al., 2016, Zha et al., 2016)**, regulating **(Flores and Rayle, 2017, Napalang and Regidor, 2017)**, electrification **(Bauer et al., 2019),** parking provision **(Xu et al., 2017),** and energy implications **(Barreto et al., 2021, Wenzel et al., 2019).**
However, the literature on ride-hailing mode choice and trip frequency is still inadequate because of the recent advancement of this transport mode. Most studies on ride-hailing mode choice investigated the effects of sociodemographic and "BE" factors on ride-hailing adoption by individuals **(Rayle et al., 2016; Dias et al., 2017; Lavieri et al., 2018; Deka and Fei, 2019; Yu and Peng, 2019).** A few studies comprehensively assessed the attitude of commuters toward ride-hailing features, including time-effectiveness, cost-effectiveness, comfort, safety, availability and accessibility, and complementarity to other transport modes **(Rayle et al., 2016; Chen et al., 2018; Irawan et al., 2019; Narayan et al., 2019; Yan et al., 2019)**. A positive or negative attitude towards these features may influence the travel mode choice of individuals. Thus, to encourage more people to use ride-hailing, it is critically important to identify attractive and repulsive features of ride-hailing and improve the unattractive parts.
This present study develops a model for ride-hailing usage frequency prediction. Besides, this research identifies important factors that motivate Kuala Lumpurians to use ride-hailing and assesses the attitudes of Kuala Lumpurians towards ride-hailing features. This

investigation is among those rare studies that examined people's views on ride-hailing in Malaysia.
The research aimed to explore the factors influencing the frequency of ride-hailing usage in Kuala Lumpur, a rapidly growing metropolitan region in Southeast Asia. The study utilized an intercept survey conducted at three locations recognized by a prominent ride-hailing company in Kuala Lumpur. Nonparametric and machine learning techniques were employed to analyze the data, including the Pearson chi-square test and Bayesian Network.
Out of the 38 statements (input variables) considered in the study, the Pearson chi-square test identified 14 variables as the most significant. These variables were then utilized as predictors in developing a Bayesian Network (BN) model, which can estimate the probability of weekly ride-hailing usage frequency. The final BN model revealed that commuters' attitude towards the speed of ride-hailing compared to traditional taxi-hailing was the most crucial variable, consistently appearing across various probability conditions.
This research examined the factors influencing ride-hailing frequency in Kuala Lumpur, Southeast Asia. The study identified the most important variables by employing statistical and machine-learning techniques. It developed a Bayesian Network model to predict the likelihood of weekly ride-hailing usage, with the attitude towards ride-hailing speed being the most influential factor.
Insufficient public transportation systems, such as buses, trains, or subways, cause overcrowding, long waiting times, and inconvenience commuters. This lack of reliable and accessible public transport options can increase reliance on taxis and ride-hailing services. Limited taxi availability in some areas, the number of traditional taxis may be limited, especially during peak hours or in remote locations. This scarcity can make it challenging for people to find a taxi when needed, leading to wait times and frustration longer. High taxi fares taxi fares can be a concern for many passengers, especially if they are not regulated or standardized. Some taxis may charge higher fares during peak hours or take longer routes to increase the fare. This can result in financial burden and dissatisfaction among passengers. Furthermore, safety is a significant issue regarding taxis, especially for solo travellers at night or in unfamiliar areas. Incidents of driver misconduct, theft, or assault can undermine public trust in taxi services and raise concerns about personal security.
Lack of technology integration: traditional taxi services often lag in technology integration compared to ride-hailing platforms. Features like real-time tracking, digital payment options, and driver ratings may be limited or absent, reducing the overall convenience and user experience. Addressing these transport and taxi problems requires a multi-faceted approach involving government regulations, infrastructure development, technology integration, and customer education. Some potential solutions to these challenges include encouraging sustainable public transportation, improving taxi availability, implementing safety regulations, and promoting fair pricing practices. Additionally, incentivizing the adoption of cleaner and greener vehicles in taxi fleets can help mitigate the environmental impact.

2. METHODOLOGIES

The study depends on feature selection techniques and machine learning algorithms used-to predict the probability of the weekly frequency of ride-hailing usage in Kuala Lumpur, Malaysia. Several traditional methods are available to predict travel behaviour and commuters' mode choice, including the multinomial logit (MNL) model, nested logit (NL) model, generalized extreme value (GEV) model, ordered generalized extreme value (OGEV) model, cross-nested logit (CNL) model. According to **(Chang et al., 2019; Chernysheva et al., 2020),** these methods are more suitable for short-term travel behaviour predictions than long-term ones. These methods also assume linear relationships between variables that may not be sufficient for long-term mode choice and usage frequency prediction. Typically, mode choice and frequency data are large and complex, and the assumptions of traditional methods may limit the prediction performance and accuracy of these models **(Washington et al., 1997; Washington and Wolf, 1997; Karlaftis and Golias, 2002; Yan et al., 2010; Aghaabbasi et al., 2020).**

This study uses a Feature Selection (FS) technique, a renowned ML method, to decrease the data dimensionality and improve the BN model performance. In this section, both BN and FS models are described. Besides, the mode-specific factors that are called input variables in this study are explained. The various steps of this study are presented in **Fig 1.**

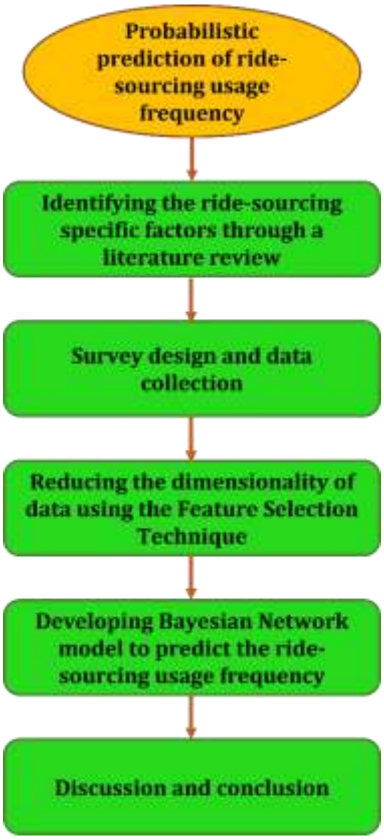

Figure 1. Plan of this work.

Machine Learning (ML) methods can be used as an alternative approach to predict short-term and long-term mode choices. The ML methods have several advantages over traditional statistical methods. These methods relax the assumption of linearity, handle the outliers efficiently, and handle the discrete variables or variables with large categories effectively; and fourth, allow for information extraction from large datasets **(Breiman et al., 1984; Friedman et al., 1997b, Khatami et al., 2017; Ahmad et al., 2018; Utkin et al., 2019)**. Bayesian Network is a well-known ML method that inherits the characteristics of ML and can determine the causal and associative relationships between variables. This method recently drew scholars' notice in transportation **(Prati et al., 2017; Shi and Abdel-Aty,**

2015). Several efficient ML methods, such as Artificial Neural Networks (ANN), were applied to travel survey data **(Ali et al., 2021; Xie et al., 2003)**. However, this method is regarded as a black box with ambiguous relationships between variables. An advantage of the BN method over the ANN and several other ML methods is that this method can reveal the relationships among variables efficiently.

2.1 Mode-Specific Factors

The present study explored existing literature as the initial variable selection and model development source. Thus, six ride-hailing mode-specific factors were identified. These factors included travel time, cost, comfort, safety, accessibility and availability, and complementarity. These ride-hailing features are influenced by other factors explained in the following sub-sections. **Fig. 2** shows the possible influence of these factors and sub-factors on the ride-hailing usage frequency.

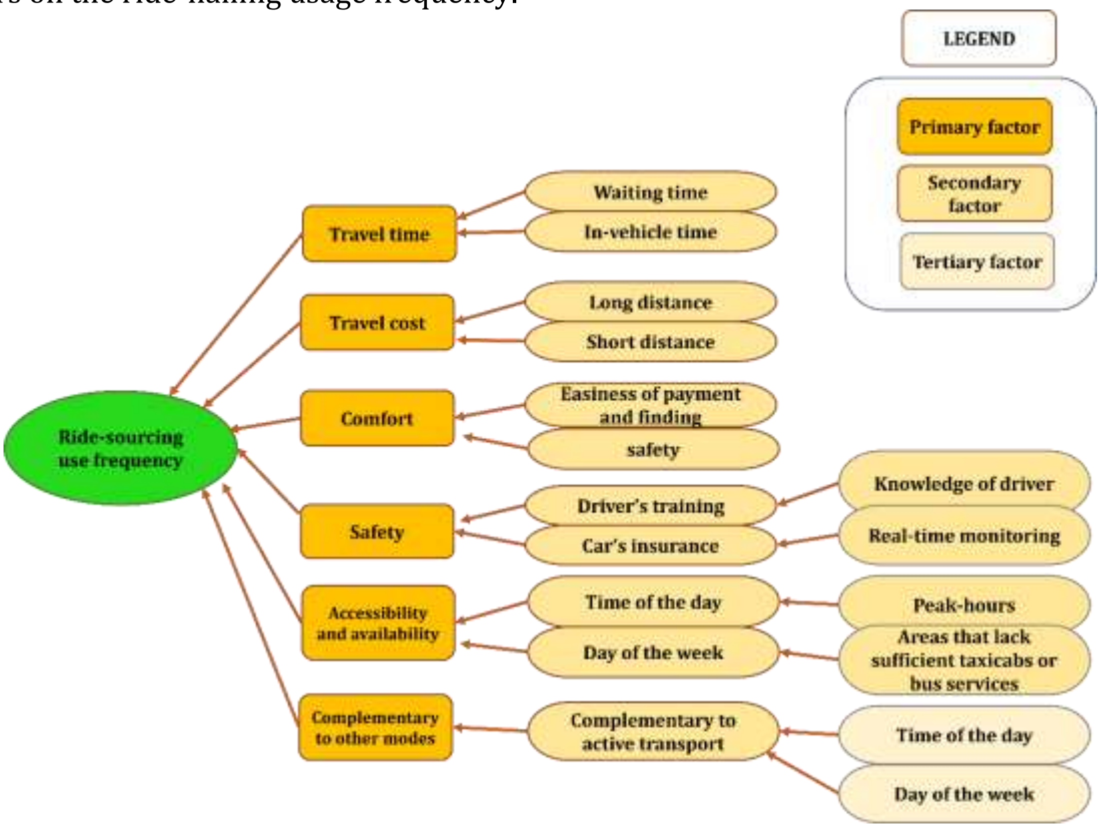

Figure 1. The possible influence of different factors on the ride-hailing usage frequency.

2.1.1 Travel Time of Ride-hailing

Ride-hailing travel time that comprises waiting time and in-vehicle time was used in a study by **(Rayle et al., 2016)** to explore the reasons behind shifting from traditional taxis to ride-hailing in San Francisco. The findings of their investigation implied that the travel time of ride-hailing (waiting time+in-vehicle time) was one of the main reasons commuters shifted from traditional taxis to ride-hailing. Indeed, the waiting time for ride-hailing was shorter than for regular taxis, and most ride-hailing trips had a shorter in-vehicle time than traditional taxis and public transport.

2.1.2 Travel Cost of Ride-hailing

Typically, the travel cost of travel modes varies according to the distance. Ride-hailing companies have different pricing strategies for short and long-distance trips **(Chen et al., 2018).** For example, the DiDi Express discounts short-distance trips in China, while the Hitch discounts long-distance trips. Several investigations indicated that ride-hailing is mainly used for short-distance trips **(Rayle et al., 2016; Irawan et al., 2019; Tarabay and Abou-Zeid, 2019).** The reason for this choice can be found in **(Kumar and Joewono, 2018)** showed that the higher travel charges of ride-hailing increase the tendency of people to use this service for closer locations or shorter travel trips. However, the effects of ride-hailing travel costs on ride-hailing need more investigation. Thus, it is vital to assess ride-hailing's cost-effectiveness concerning short- and long-distance trips.

2.1.3 Comfort of Ride-hailing

Several factors influence ride-hailing comfort. These factors are the ease of payment **(Rayle et al., 2016; Vieira et al., 2018; Tarabay and Abou-Zeid, 2019; Irawan et al., 2019),** accessibility/ease of finding **(Rayle et al., 2016; Tarabay and Abou-Zeid, 2019)**, and safety **(Rayle et al., 2016, Tarabay and Abou-Zeid, 2019)**. Thus, the comfort of ride-hailing should be measured concerning these factors.

2.1.4 Safety of Ride-hailing

Several strategies have been proven to improve the safety perception of commuters towards ride-hailing, including driver training **(Shaheen and Chan, 2016; Jin et al., 2018)**, car insurance **(Watanabe et al., 2016; Henao, 2017; Napalang and Regidor, 2017)**, knowledge of drivers, and real-time monitoring **(Jin et al., 2018)**. Hence, these aspects should be considered during the assessment of ride-hailing safety.

2.1.5 Ride-hailing Accessibility and Availability

Accessibility and availability of ride-hailing may vary depending on the time of the day, day of the week, and peak hours **(Deka and Fei, 2019; Wenzel et al., 2019; Yan et al., 2019)**. Besides, ride-hailing availability in areas lacking sufficient taxicabs or bus services might improve the commuters' perception of ride-hailing accessibility and availability **(Rayle et al., 2016)**. Therefore, the above influencing factors should be considered when assessing people's attitudes regarding ride-hailing availability and accessibility.

2.1.6 Complementary of Ride-hailing to other Modes

Several studies showed that ride-hailing services assist other modes, such as public transport and taxicabs, especially at the weekends and late at night, to transport commuters **(Stiglic et al., 2018; Irawan et al., 2019; Yan et al., 2019)**. In addition, ride-hailing can be a feeder to public transport stops. Ride-hailing can complement active modes, including biking and walking **(Yu and Peng, 2019)**. Thus, the complementarity effects of ride-hailing on other travel options on the usage of ride-hailing should be considered in any analysis.

2.2 Target Variable

This research's target (dependent) variable is the weekly ride-hailing usage frequency. The author considered three ride-hailing commuters, including categories: infrequent, frequent, and regular. The infrequent commuters use ride-hailing once a week; frequent commuters use ride-hailing two to four times per week, and regular commuters use ride-hailing more than five times per week.

2.3 Survey and Data Collection

The present study used an intercept survey to predict the likelihood of ride-hailing utilization frequency in Great Kuala Lumpur. This survey was carried out between May and July 2019. The Great Kula Lumpur is one of the fastest-growing urban areas in Southeast Asia concerning population and economic advancement. The people of this region were 7.80 million in 2019, according to the World Population Review 2019. Three potential locations were identified based on the Grab interactive map **(Grab, 2019b)** and research group observations. The Grab company had determined the data collected from the pick-up/drop-off points within the selected locations. **Fig. 3** shows the position of each ride-hailing location within Great Kuala Lumpur.

It's important to note that ride-hailing services are subject to local regulations and may have specific operating rules and requirements. Nonetheless, their convenience, affordability, and reliable service have made them a popular transportation choice for many residents and visitors in Kuala Lumpur. Ride-hailing services provide a convenient and hassle-free way to get around the city. With just a few taps on a mobile app, you can book a ride and have a driver pick you up from your location. This eliminates the need to flag down taxis or navigate public transportation systems. Ride-hailing services in Kuala Lumpur are often more affordable than traditional taxis, especially for shorter distances. The transparent pricing model and fare estimates provided by ride-hailing apps help passengers plan their transportation expenses.

Out of the 833 commuters approached, only 371 were eligible to participate in the survey. 371 commuters had used ride-hailing services in the past fourteen days and were willing to share their trip patterns with the survey team.

The research team employed an intercept survey to get data from the selected sites. Thus, the investigation team involved commuters using ride-hailing throughout the past fourteen days. The research team leader trained the survey team to stop every three commuters at the pick-up and drop-off points of the sites. The survey unit asked the commuters if they had used ride-hailing for the past fourteen days. If they answered “no,” they were not qualified to participate in the survey. If their response was “yes,” the survey team requested them to remember their trip pattern. The team approached 833 commuters. However, only 371 commuters were eligible to participate in the survey.

It's important to consider that the comparison between ride-hailing and traditional transportation modes may vary depending on location, cost structure, availability, and individual preferences. Different transportation modes have strengths and limitations, and their choice may depend on specific circumstances and user requirements. The findings from the study reveal that ride-hailing services are competing with and complementing public transit. Still, their roles differ based on the specific purposes and target populations they serve. According to the results, approximately 38% of ride-hailing trips have the potential to be substituted by public transit options when considering the overall travel patterns.

Figure 2. Ride-hailing potential locations within the Great Kuala Lumpur.

However, this proportion increases significantly to 80% when focusing specifically on commuting.On the other hand, for entertainment travel, ride-hailing has emerged as a flexible transportation alternative for low-income families who previously lacked access to private cars, allowing them to enjoy the convenience and benefits that higher-income families traditionally enjoyed.

Regarding commuting, the study reveals that a substantial 80% of ride-hailing trips could be replaced by public transit options, with 41% being suitable for metro and 39% for bus usage. This indicates significant competition between ride-hailing and public transit in commuting. Considering that peak commuting hours often experience high congestion levels in urban transport systems, the potential shift of many ride-hailing trips to public transit could help alleviate traffic congestion and improve overall transportation efficiency.

This research utilized a questionnaire survey, which consisted of three major sections. The first part included 13 sociodemographic questions. The second component contained five questions regarding the usage of the smartphone, the ride-hailing application, and usage frequency. The pilot version of the questionnaire had 32 statements for assessing the attitudes of commuters regarding ride-hailing (part 3). Each respondent was asked to rate their agreement with the statements on a five-point Likert scale ranging from 1 – strongly disagree to 5 – strongly agree.

A panel of experts from transport planning, transport engineering, and urban planning was provided with a list of potential survey items (pilot version) to review. The experts were asked to read each survey item and advise the research team on what important things were missing or unnecessary items should be deleted. Besides, they were asked to indicate whether the questionnaire adequately addressed the issues and features of ride-hailing. The experts accepted the majority of the survey items and statements. Only minor changes took place to clarify the unclear ideas.

Additionally, they added six items that evaluated the respondents' attitudes toward each ride-hailing feature into the third part of the questionnaire (T29, C34, CM41, S46, A52, CO58). Thus, the final version of the questionnaire included 38 statements. The present study also assessed the communicability and practicability of the final version of the questionnaire through a pilot test. 31 individuals were recruited to participate in the pilot survey. Based on their feedback, the research team made minor adjustments, including the response levels of some questions and statements in parts two and three. The final survey statements are shown in **Table 1.**

Table 1. Independent variables were used in the study.

Variable	Variable aim	Related statement
	Time-effectiveness	
T21	To compare the waiting time for ride-hailing and waiting time for bus services	The duration of booking and arrival of a taxi through the mobile application is shorter than the waiting time at the bus stops.
T22	To compare the waiting time of ride-hailing and waiting time of taxicabs	The duration of booking and arrival of a taxi through the mobile application is shorter than waiting time in the street to hail a regular taxi.
T23	To compare the in-vehicle time of ride-hailing and in-vehicle time of bus services	The ride-hailing in-vehicle time is shorter than that of a public bus.
T24	To compare the in-vehicle time of ride-hailing and in-vehicle time of taxicabs	The ride-hailing in-vehicle time is shorter than that of a regular taxi.
T25	To compare travel speed to the destination of ride-hailing and travel speed to the destination of bus services	Using ride-hailing helps to get to their destinations quicker than using bus services.
T26	To compare travel speed to the destination of ride-hailing and travel speed to the destination of Taxicabs	Ride-hailing helps to get to the destinations quicker than a regular taxi.
T27	To compare travel speed to the destination of ride-hailing and travel speed to the destination of private vehicle	Using ride-hailing helps me get to the destinations quicker than using my vehicle (e.g., no need to search for parking).
T28	To compare travel speed to the destination of ride-hailing and travel speed to the destination of walking/biking	Ride-hailing helps me get to the destinations quicker than walking/biking for short trips.
T29	To assess the overall perception towards the efficiency of ride-hailing for decreasing the total travel time	Overall, ride-hailing reduces travel time (waiting time + in-vehicle time). *
	Cost-effectiveness	
C30	To compare the cost of ride-hailing to the cost of taxicabs	It is cheaper to use ride-hailing than to use regular taxis.
C31	To compare the cost of ride-hailing to the cost of bus services	It is cheaper for me to use ride-hailing than using the buses.
C32	To compare the cost-effectiveness of ride-hailing to the cost-effectiveness of taxicabs for short trips	It is cost-effective to use ride-hailing for short trips.
	To compare the cost-effectiveness of ride-hailing to the cost-effectiveness of taxicabs for long trips	It is cost-effective to use ride-hailing for long trips.
C34	To assess the overall perception towards the efficiency of ride-hailing for decreasing the total travel cost	Overall, using ride-hailing is cost-effective. *
	Comfort	
CM35	To compare the ease of fare payment of ride-hailing to the ease of fare payment of taxicabs	It is easier to pay the fare of ride-hailing than a regular taxi. *
CM36	To compare the ease of fare payment of ride-hailing to the ease of fare payment of bus services	It is easier to pay the fare of ride-hailing fare than a bus. *
CM37	To compare the ease of access of ride-hailing to the ease of access of taxicabs near the respondent's house	It is easier to find ride-sourcing than regular taxis near my house. *
CM38	To compare the ease of access to ride-hailing to the ease of access to bus services near the respondent's house	It is easier to find ride-hailing than buses near my house. *
CM39	To compare the safeness of ride-hailing use and bus service use	Using ride-hailing is safer than using bus services.

CM40	To compare the safeness of ride-hailing use and taxicab use	Using ride-hailing is safer than using regular taxis.
CM41	To assess the overall perception of the comfort level of ride-hailing	Overall, using ride-hailing is convenient. *
Safety concerns		
S42	To assess whether the drivers' training is important for the respondents	Driver training is always important to me when I intend to use ride-hailing.
S43	To assess whether car insurance is important for the respondents	Car insurance is always important to me when I intend to use ride-hailing.
S44	To assess whether the knowledge of drivers increases the trust between passengers and drivers	The knowledge of drivers increases the trust between passengers and drivers. *
S45	To assess whether real-time monitoring increases the trust between passengers and drivers	The awareness that there is a vehicle monitoring system (e.g., real-time location) increases the trust between passengers and drivers.
S46	To assess the overall perception of the safety level of ride-hailing	Overall, using ride-hailing is safe. *
Accessibility and availability		
A47	To assess the access easiness of ride-hailing in the areas that lack sufficient taxicabs	It is easy to find ride-hailing in areas that lack sufficient regular taxis. *
A48	To assess the access easiness of ride-hailing in the areas that lack sufficient bus services	It is easy to find ride-hailing in areas that lack sufficient buses. *
A49	To assess the access easiness of ride-hailing at late nights	It is easy to find ride-hailing at late night. *
A50	To assess the access easiness of ride-hailing at weekends	It is easy to find ride-hailing at weekends. *
A51	To assess the access easiness of ride-hailing at peak hours	It is easy to find ride-hailing at peak hours. *
A52	To assess the overall perception towards the availability and accessibility of ride-hailing	Overall, it is easy to find ride-hailing anytime and anywhere. *
Complementary use to other transport alternatives		
CO53	To assess the complementarity of ride-hailing and bus service	It is easy to complement the use of ride-hailing with the buses. *
CO54	To assess the complementarity of ride-hailing and taxicabs	It is easy to complement the use of ride-hailing with taxis. *
CO55	To assess the complementarity of ride-hailing and walking/biking	It is easy to complement the use of ride-hailing with walking/biking. *
CO56	To assess the complementarity of ride-hailing and bus services at late night or weekends	Complementing ride-hailing with bus services that work nights/weekends is easy. *
CO57	To assess the complementarity of ride-hailing and taxicabs at late night or weekends	Complementing ride-hailing with regular taxis that work nights/weekends is easy. *
CO58	To assess the overall perception towards the complementarity of ride-hailing to other transport alternatives	Overall, it is easy to complement ride-hailing with other transport alternatives. *
Source: **(de Azevedo et al., 2021)**		

2.4 Machine Learning Methods Used in this Study

2.4.1 Feature selection

Feature Selection (FS) is a well-established method to improve the performance and accuracy of ML by decreasing the dimensionality of data. The FS aims to remove irrelevant and/or redundant variables and keep only the relevant ones. While the FS removes the irrelevant variables, the learning performance is unaffected. Several benefits of FS for ML are admitted in other works. For instance, the FS enhances the accuracy of ML prediction, learning efficiency, and effectiveness of data collection **(Liu, 2010)**. The FS assigns a rank to the input variables consistent with the inherent properties of the data and keeps those best

K inputs to determine the most relevant and important input variables. **Table 2** shows the inspection rules and thresholds of FS in this study.
Typically, the FS determines the quality of variables by their correlation with the target variable. The FS then picks those inputs with the greatest associations. The FS uses Pearson chi-square, especially for categorical input and target variables, to test the target's independence.

Table 2. Inspection rules for performing the Feature Selection.

Screening Rule	Cutoff*
Maximum percentage of missing values	70
Maximum percentage of records in a single category	90
Maximum number of categories as a percentage of records	95
The minimum coefficient of variation	0.1
The minimum standard deviation	0.0
The important variables	0.95

2.4.2 Bayesian Network

Bayesian Network (BN) is a form of graphical model that denotes multivariate probability distribution **(Orbanz and Teh, 2010).** The BN typically creates a direct acyclic graph (DAG) presented in **Fig. 4 (McAuley et al., 2010)**. Each node denotes random variables, and each directed arc shows the causal relationship between the variables. To address the interdependencies between variables, the BN employs the Tree Augmented Naive Bayes (TAN) method **Fig. 4 (Friedman et al., 1997a)**. Although several other techniques are available for use by the BN method, the TAN is the most appropriate technique since it relaxes the Bayes variable independence assumption by using a tree structure where each variable only depends on the target variable and one other variable. The development rules of the BN model are given in **Table 3.**

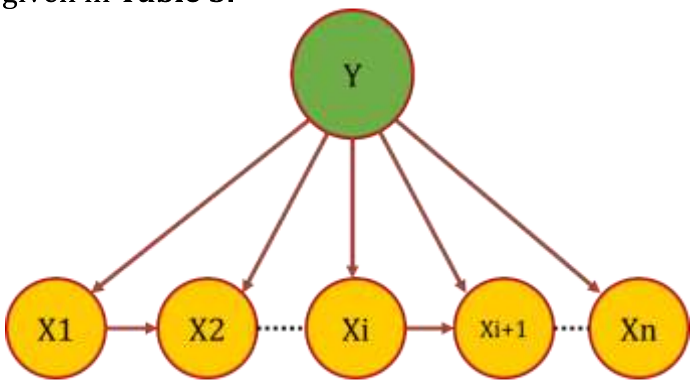

Figure 4. BN model example created using TAN.

Table 3. Rules for developing the BN model.

Model development rules	Cutoff*
Missing values	Only complete records
Independence test	Likelihood ratio
Significance level	0.01
Maximal conditioning set size	5

3. RESULTS AND DISCUSSION

3.1 Variable Selection Utilizing The Feature Selection Procedure

As previously mentioned, this study employed the Pearson chi-square test for feature selection, selecting the most relevant variables for predicting the weekly usage frequency of ride-hailing. This test determined the most 14 important variables out of 38 inputs, shown in **Table 4.** These variables were then used to develop the BN model to forecast the weekly usage frequency of ride-hailing.

Table 4. Important factors identified through the FS.

Rank	Code	Input	Value
1	CM36	It is easier to pay the fare of ride-hailing fare than a bus.	0.999416
2	CO56	Complementing ride-hailing with bus services that work nights/weekends is easy.	0.999023
3	A47	It is easy to find ride-hailing in areas that lack sufficient regular taxis.	0.996623
4	A50	It is easy to find ride-hailing at weekends.	0.99591
5	A51	It is easy to find ride-hailing at peak hours.	0.995342
6	CO58	Overall, it is easy to complement ride-hailing with other transport alternatives.	0.995289
7	T26	Ride-hailing helps to get to the destinations quicker than a regular taxi.	0.994676
8	T27	Using ride-hailing helps me get to my destinations quicker than using my vehicle (e.g., no need to search for parking).	0.989914
9	T25	Using ride-hailing helps to get to their destinations quicker than using bus services.	0.989602
10	S45	The awareness that there is a vehicle monitoring system (e.g., real-time location) increases the trust between passengers and drivers.	0.983537
11	T22	The duration of booking and arrival of a taxi through the mobile application is shorter than waiting time in the street to hail a regular taxi.	0.982739
12	A49	It is easy to find ride-hailing at late night.	0.973565
13	C31	It is cheaper for me to use ride-hailing than using the buses.	0.966994
14	A48	It is easy to find ride-hailing in areas that lack sufficient buses.	0.953876

4.2 Weekly usage frequency of ride-hailing model using the Bayesian Network method

Fig 5 displays the model that the Bayesian Network (BN) created. Tree-augmented naive Bayes (TAN) employs a tree structure, allowing each attribute to depend on the weekly ride-hailing usage frequency and speed compared to hailing normal taxis. The BN model includes eight nodes, seven predictors**,** and one target variable. Besides, Figure 6 shows predictor importance according to the BN model. According to **Figs. 5 and 6**, the BN model identified the speed of ride-hailing compared to hailing normal taxis (T26) as the most important (importance=0.25) factor on the weekly ride-hailing usage frequency of commuters in Kuala Lumpur and speed of ride-hailing compared to private vehicle (T27) as the least important factor (importance=0.02). The other influencing factors included complementarity of ride-hailing to bus services at late night or on weekends (CO56); ease of payment of ride-hailing fare compared to bus services (CM36); ease of access to ride-hailing in the areas that lack sufficient taxicabs (A47); ease of access of ride-hailing at weekends (A50); ease of access of ride-hailing at peak-hours (A51).

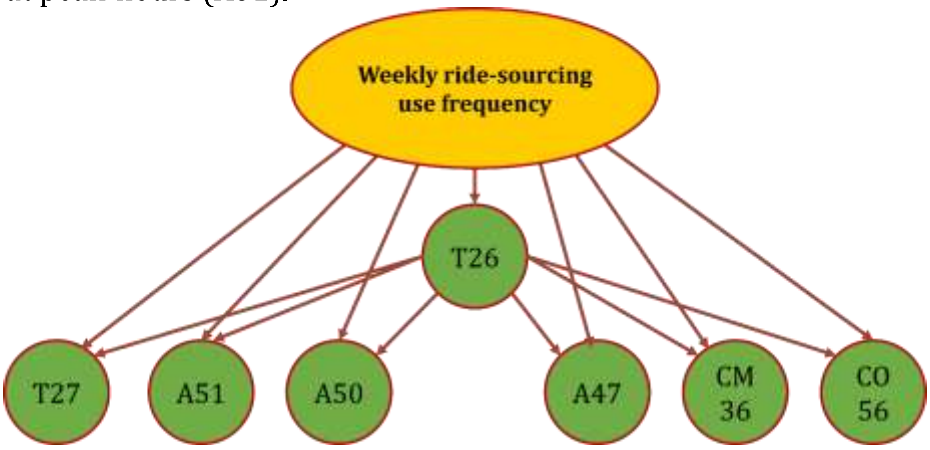

Figure 3. BN model of ride-hailing usage frequency.

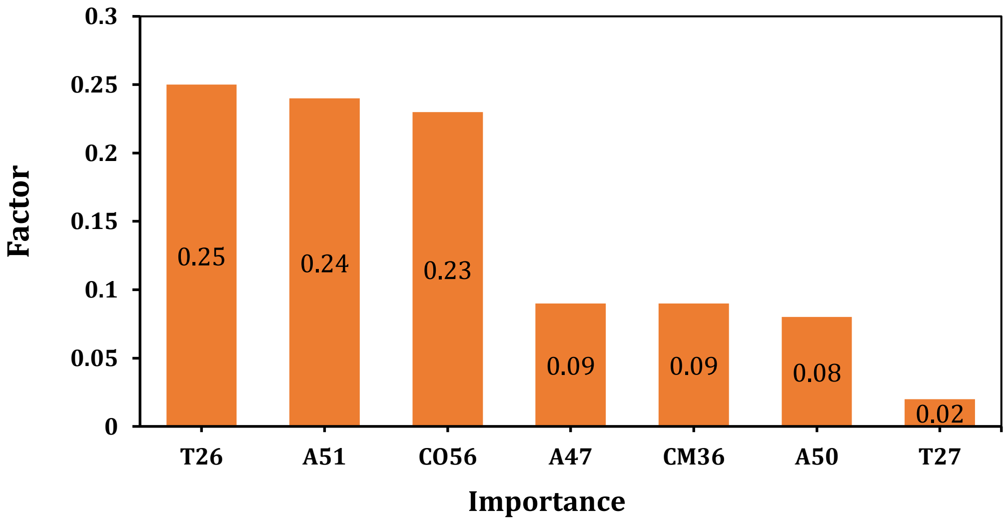

Figure 4. Importance of variables based on the BN model.

Tables 5 to 10 show the conditional probabilities that BN identified. The probability of one (1.00) is considered perfect. **Table 5** summarizes the conditional probability for each value of "complementarity of ride-hailing to bus services at late night or weekends" (CO56) across all combinations of values of ride-hailing usage frequency and "speed of ride-hailing compared to hailing normal taxis" (T26). The probability of the infrequent use of ride-hailing is perfect (1.00) when the views on the complementarity of ride-hailing to bus services at late night or weekends and speed of ride-hailing compared to taxicabs are negative. If opinions on (1) the complementarity of ride-hailing to bus services at late night or on weekends are positive, and (2) attitudes on the speed of ride-hailing compared to taxicabs is negative, then the BN predicts that the greatest probability of frequent and regular usage of ride-hailing occurs.
Table 6 displays the conditional probabilities of "ease of payment of ride-hailing fare

compared to bus services" (CM36), taking into consideration the influence of "speed of ride-hailing compared to hailing normal taxis" (T26). The probability of infrequent ride-hailing usage is perfect (1.00) when the attitudes towards ease of payment of ride-hailing fare compared to bus services and speed of ride-hailing compared to taxicabs are negative.

Table 5. T26/CO56 conditional probabilities.

RUF	T24	CO56 Probability				
		1	2	3	4	5
Infrequent	1	1.00	0	0	0	0
Infrequent	2	0	0	0.83	0.17	0
Infrequent	3	0	0.05	0.58	0.37	0
Infrequent	4	0	0	0.48	0.43	0.09
Infrequent	5	0	0.09	0.09	0.73	0.09
Frequent	1	0	0	0	1.00	0
Frequent	2	0.14	0.14	0.14	0.43	0.14
Frequent	3	0	0.06	0.47	0.41	0.06
Frequent	4	0	0.03	0.46	0.43	0.09
Frequent	5	0	0.05	0.2	0.25	0.5
Regular	1	0	0	0	0	1.00
Regular	2	0	0	0.33	0.33	0.33
Regular	3	0	0.17	0.83	0	0
Regular	4	0	0.1	0.3	0.6	0
Regular	5	0.15	0	0.23	0.54	0.08
Ride-hailing usage frequency=RUF; Using application-based taxi service helps to get to the destinations quicker than using hailing normal taxi=T26; It is easy to complement the use of application-based taxi services with public transport that operates at late night or weekends=CO56						

If (1) the attitudes on ease of payment of ride-hailing fare compared to bus services are neutral and (2) attitudes on the speed of ride-hailing compared to taxicabs are negative, the BN predicts that the occurrence probability of frequent ride-hailing is perfect. The probability of the infrequent use of ride-hailing is perfect (1.00) if (1) the attitudes on the ease of payment of ride-hailing fare compared to bus services are positive and (2) attitudes on the speed of ride-hailing compared to taxicabs is negative.

Table 7 shows the conditional probabilities of attitudes towards "ease of access of ride-hailing in the areas that lack sufficient taxicabs" (A47), considering the influence of "speed of ride-hailing compared to hailing normal taxis" (T26). If (1) the attitudes towards ease of access of ride-hailing in the areas that lack sufficient taxicabs and (2) attitudes regarding the speed of ride-hailing compared to taxicabs are negative, the BN forecasts that the occurrence probability of infrequent ride-hailing is the greatest. The probability of ~~the~~ infrequent usage of ride-hailing is perfect when (1) the attitudes towards ease of access of ride-hailing in the areas that lack sufficient taxicabs are positive and (2) attitudes on the speed of ride-hailing compared to taxicabs are negative. If (1) the attitude on ease of access of ride-hailing in the areas that lack sufficient taxicabs is positive and (2) the attitude towards the speed of ride-hailing compared to taxicabs is negative, the BN forecasts that the occurrence probability of regular ride-hailing is perfect.

Table 6. T26/CM36 conditional probabilities.

RUF	T24	CM36 Probability				
		1	2	3	4	5
Infrequent	1	1.00	0	0	0	0
Infrequent	2	0	0	0.5	0.33	0.17
Infrequent	3	0	0.02	0.56	0.37	0.05
Infrequent	4	0	0	0.41	0.57	0.02
Infrequent	5	0	0.09	0.36	0.45	0.09
Frequent	1	0	0	1.00	0	0
Frequent	2	0	0.14	0.14	0.29	0.43
Frequent	3	0	0.18	0.44	0.29	0.09
Frequent	4	0.03	0.03	0.46	0.43	0.06
Frequent	5	0	0.05	0.35	0.5	0.1
Regular	1	0	0	0	1.00	0
Regular	2	0.33	0.33	0	0.33	0
Regular	3	0	0	0.67	0.33	0
Regular	4	0	0.1	0.5	0.3	0.1
Regular	5	0.23	0	0.38	0.31	0.08
Ride-hailing usage frequency=RUF; Using application-based taxi service helps to get to the destinations quicker than using hailing normal taxi=T26; It is easier to pay ride-hailing fare than to pay the bus fare=CM36						

Table 8 indicates the conditional probability for every value of "attitudes towards ease of access of ride-hailing at weekends" (A50) across all combinations of values of ride-hailing usage frequency and "speed of ride-hailing compared to hailing normal taxis" (T26). The probability of the infrequent, frequent, and regular use of ride-hailing is perfect (1.00) when (1) the attitudes concerning the speed of ride-hailing compared to taxicabs is negative and (2) attitudes towards ease of access of ride-hailing at weekends are negative, neutral, and positive, respectively.

Table 7. T26/A47 conditional probabilities.

RUF	T24	A47 Probability				
		1	2	3	4	5
Infrequent	1	0	1.00	0	0	0
Infrequent	2	0	0	0.5	0.33	0.17
Infrequent	3	0.02	0.02	0.6	0.3	0.05
Infrequent	4	0	0.02	0.52	0.41	0.05
Infrequent	5	0	0	0.18	0.36	0.45
Frequent	1	0	0	0	1.00	0
Frequent	2	0.14	0.43	0.29	0.14	0
Frequent	3	0	0.06	0.41	0.5	0.03
Frequent	4	0	0	0.31	0.54	0.14
Frequent	5	0	0.1	0.3	0.3	0.3
Regular	1	0	0	0	1.00	0
Regular	2	0	0	0	0	1.00
Regular	3	0	0	0.67	0.33	0
Regular	4	0	0	0.2	0.8	0
Regular	5	0.23	0	0.31	0.38	0.08
Ride-hailing usage frequency=RUF; Using application-based taxi service helps to get to the destinations quicker than using hailing normal taxi=T26; It is easy to find ride-hailing in the areas that lack sufficient normal taxi services=A47						

Table 8. T26/A50 conditional probabilities.

RUF	T24	A50 Probability				
		1	2	3	4	5
Infrequent	1	0	1.00	0	0	0
Infrequent	2	0	0	0.33	0.67	0
Infrequent	3	0.02	0.09	0.37	0.49	0.02
Infrequent	4	0.02	0.1	0.36	0.48	0.03
Infrequent	5	0	0	0.36	0.45	0.18
Frequent	1	0	0	1.00	0	0
Frequent	2	0	0.43	0.14	0.29	0.14
Frequent	3	0	0.03	0.32	0.5	0.15
Frequent	4	0	0	0.4	0.49	0.11
Frequent	5	0	0.05	0.25	0.5	0.2
Regular	1	0	0	0	1.00	0
Regular	2	0.33	0	0	0.33	0.33
Regular	3	0	0	0.67	0.33	0
Regular	4	0	0	0.3	0.6	0.1
Regular	5	0.15	0	0.23	0.31	0.31
Ride-hailing usage frequency=RUF; Using application-based taxi service helps to get to the destinations quicker than using hailing normal taxi=T26; It is easy to find ride-hailing at weekends =A50						

Table 9 exhibits the conditional probabilities of "attitude towards ease of access of ride-hailing at peak-hours" (A51), taking into consideration the influence of "speed of ride-hailing compared to hailing normal taxis" (T26). If (1) the attitude towards ease of access of ride-hailing at peak hours is neutral and (2) the attitude on the speed of ride-hailing compared to taxicabs is negative, the BN expects the occurrence probability of infrequent ride-hailing is perfect. The probability of the frequent use of ride-hailing is perfect when (1) the attitude towards ease of access of ride-hailing at peak hours is positive and (2) the attitude on the speed of ride-hailing compared to taxicabs is negative. If (1) the attitudes towards ease of access of ride-hailing at peak hours are neutral to positive and (2) attitudes on the speed of ride-hailing compared to taxicabs is negative to neutral, the BN forecasts that the occurrence probability of regular ride-hailing is the greatest.

Table 9. T26/A51 conditional probabilities.

RUF	T24	A51 Probability				
		1	2	3	4	5
Infrequent	1	0	0	1.00	0	0
Infrequent	2	0.33	0.17	0.33	0.17	0
Infrequent	3	0.02	0.09	0.53	0.3	0.05
Infrequent	4	0	0.09	0.48	0.33	0.1
Infrequent	5	0	0.18	0.18	0.36	0.27
Frequent	1	0	0	0	0	1.00
Frequent	2	0	0.29	0.43	0.14	0.14
Frequent	3	0	0	0.41	0.47	0.12
Frequent	4	0	0.09	0.4	0.34	0.17
Frequent	5	0	0	0.35	0.45	0.2
Regular	1	0	0	0	1.00	0
Regular	2	0.67	0	0.33	0	0
Regular	3	0	0	1.00	0	0
Regular	4	0	0	0.5	0.4	0.1
Regular	5	0.15	0	0.31	0.38	0.15
Ride-hailing usage frequency=RUF; Using application-based taxi service helps to get to the destinations quicker than using hailing normal taxi=T26; It is easy to find ride-hailing at peak-hours =A51						

Table 10 shows the conditional probabilities of "attitudes on the speed of ride-hailing compared to private vehicle" (T27), considering the influence of "speed of ride-hailing compared to hailing normal taxis" (T26). The probability of the infrequent, frequent, and regular use of ride-hailing is perfect (1.00) when (1) the attitudes concerning the speed of ride-hailing compared to taxicabs are negative and (2) attitudes towards the speed of ride-hailing compared to the private vehicle are negative, neutral, and positive, respectively.

3.2 Discussion

Now, ride-hailing is viewed as an effective travel mode across the globe. However, people's attitudes towards this transport mode's features are not well-studied. The present study predicted the influential factors of ride-hailing on its usage frequency. To this end, a well-known supervised machine learning method, the Bayesian Network, was combined with a feature selection technique, Pearson chi-square. The Feature Selection method lessened the input variables from 38 to 14. The picked variables were then employed to fit the Bayesian Network model. The findings show that the higher speed of ride-hailing compared to hailing normal taxis was the most important factor for the weekly frequency of ride-hailing usage.

Table 10. T26/T27 conditional probabilities.

RUF	T24	T27 Probability				
		1	2	3	4	5
Infrequent	1	0	1.00	0	0	0
Infrequent	2	0	0.5	0.33	0.17	0
Infrequent	3	0	0.07	0.53	0.37	0.02
Infrequent	4	0	0.1	0.38	0.41	0.1
Infrequent	5	0	0	0.27	0.27	0.45
Frequent	1	0	0	1.00	0	0
Frequent	2	0	0.43	0.14	0.14	0.29
Frequent	3	0	0.03	0.41	0.53	0.03
Frequent	4	0.03	0.03	0.43	0.46	0.06
Frequent	5	0.1	0.05	0.15	0.3	0.4
Regular	1	0	0	0	1.00	0
Regular	2	0	0.33	0.33	0	0.33
Regular	3	0.17	0	0.67	0.17	0
Regular	4	0	0.2	0.2	0.4	0.2
Regular	5	0	0.31	0.15	0.15	0.38
Ride-hailing usage frequency=RUF; Using application-based taxi service helps to get to the destinations quicker than using hailing normal taxi=T26; Using application-based taxi service helps to get to the destinations faster than using my vehicle (e.g., due to parking availability) =T27						

Alternatively, the fastness of ride-hailing compared to private vehicles was the least important factor. Other influencing factors on weekly ride-hailing are the complementarity of ride-hailing to bus services at late night or on weekends, convenient payment of ride-hailing fare compared to bus services, ease of access to ride-hailing in the areas that lack sufficient taxicabs, convenient access to ride-hailing at weekends, and access easiness of ride-hailing at peak-hours. The ride-hailing firms can use the study findings to enhance service quality and encourage people to use ride-hailing more frequently.

Across all conditional probabilities, the infrequent commuters had negative attitudes towards the speed of ride-hailing compared to hailing normal taxis (T26). Besides, their attitudes towards the other factors, including complementarity of ride-hailing to bus services late at night or on weekends (CO56), ease of payment of ride-hailing fare compared to bus services (CM36), ease of access of ride-hailing in the areas that lack sufficient taxicabs (A47), ease of access of ride-hailing at weekends (A50), and speed of ride-hailing compared to private vehicle (T27) were negative. These imply that having negative attitudes towards two or more ride-hailing features caused less use of this travel mode.

Concerning the frequent ride-hailing users, the commuters again exhibited negative attitudes towards the speed of ride-hailing compared to hailing normal taxis (T26). On the other hand, they almost had positive attitudes towards other factors. The perfect probability (1.00) was achieved for these commuters when they maintained neutral to positive perceptions towards other factors. It can be said that although the frequent ride-hailing users had negative attitudes towards the speed of ride-hailing compared to hailing regular taxis, this did not stop them from using ride-hailing as they showed favourable attitudes towards other ride-hailing features (e.g., payment method). Just like the infrequent and frequent users, regular ride-hailing commuters mostly had negative attitudes towards the speed of ride-hailing compared to hailing traditional taxis (T26). However, most perfect probabilities were achieved when the users exhibited merely positive attitudes towards the other ride-hailing factors (e.g., no need for parking).

Regardless of their ride-hailing usage frequency, most ride-hailing users maintained a negative attitude towards the speed of ride-souring compared to normal taxis. This can be explained by the fact that both normal taxis and ride-hailing use the same routes to pick up and drop off commuters; thus, the in-vehicle time is almost the same. However, several studies demonstrated that the waiting time for ride-hailing is shorter than for public transportation and even hailing taxis **(Henao, 2017; Irawan, Belgiawan et al., 2019; Napalang and Regidor, 2017; Rayle et al., 2016)**. The respondents may only have considered the in-vehicle time when responding to the survey conveyed for this study.

From an engineering perspective, ride-hailing services offer promising solutions to tackle critical challenges in transportation, particularly congestion, emissions, and accidents. Engineers are crucial in developing innovative strategies and technologies to address these issues and create a more efficient and sustainable ride-hailing ecosystem. Reduced Congestion and Emissions: Ride-hailing services can reduce traffic congestion and emissions by optimizing routes and minimizing idle time. Multiple passengers sharing rides further reduces traffic volume and environmental impact. Ride-hailing offers convenience, accessibility, time-saving, cost-effectiveness, safety, flexibility, and environmental benefits. These factors have contributed to the growing popularity and widespread adoption of ride-hailing services as a preferred mode of transportation for many people worldwide.

4. CONCLUSIONS

For regular ride-hailing users, several important factors contribute to their satisfaction. These factors were ease of payment, access easiness, and speed of ride-hailing compared to private vehicles. For these users, important factors were the ease of access to ride-hailing in areas lacking sufficient taxicabs and at weekends and peak hours. This sounds intelligible because taxis and buses are usually stuck in peak Kuala Lumpur traffic. Commuters may have to substitute these modes with other options, including ride-hailing or underground transport. However, the author suspects that the in-vehicle time of ride-hailing at peak hours is lower than public buses or regular taxis. In Kuala Lumpur, normal taxis are relatively scarce at weekends; thus, it can be explained why the accessibility of ride-hailing at weekends is important to commuters. In addition to the metered taxis, several radio taxis operate in Kuala Lumpur. However, the suburb of Kuala Lumpur is not well-covered by metered and radio taxis. Thus, this increases the importance of ride-hailing availability in ~~the~~ areas that lack sufficient services. Regular ride-hailing users also had another concern: ride-hailing speed compared to a private vehicle. The total travel time of cars comprises (1) in-vehicle travel time, (2) parking searching time at the destination, and (3) walking time from the car to the destination. The field observation of the investigation group shows that the search period to find parking is relatively high, specifically in the city center of Kuala Lumpur and at peak hours or weekends. In contrast, the ride-hailing travel time only comprises (1) the waiting time and (2) in-vehicle time and is not associated with parking searching time. Thus, it can be explained why people have a positive mindset about ride-hailing speed compared to private vehicles.

Ride-hailing companies in Kuala Lumpur can use the findings of this study to improve their service quality and encourage people to use this service more. First, companies must consider areas lacking taxicabs, buses, or underground transport. The suburbs should be at the center of attention. Second, different types of incentives should be given to the people to encourage them to use ride-hailing at weekends or peak hours. In addition, the companies should ensure that a sufficient number of drivers are available at the weekends and peak hours. This can be achieved by providing drivers with additional incentives. Ride-hailing companies should develop third, different payment methods to make payment easier, especially for disabled and senior commuters. Finally, ride-hailing companies should obligate the drivers to use navigation applications to find the shortest path with the lowest traffic congestion to the destination and consequently minimize travel time.

Finally, this study assessed the attitudes of commuters on ride-hailing features. Future studies can add to these attitudes with trip observations. Finally, this survey was carried out among people in a developing country where the vehicle ownership rate is high, and the overall condition of infrastructures that support active transport is not desirable. Therefore, a cautious approach should be taken toward transferring the results to developing countries.

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