



## Mobile Public Transportation Application: Factors Influencing Urban Rail Transit Passengers' Use

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### ABSTRACT

This paper thoroughly explored and discussed the factors that affect Mobile Public Transportation Applications usage among urban rail transit passengers. To do so, a model known as the Unified Theory of Acceptance and Use of Technology (UTAUT) was chosen to determine the significant factors influencing mobile application usage among passengers in Klang Valley, Malaysia. During its primary data collection, an online survey was deployed to 109 passengers using an online survey platform. According to the modal split analysis, most female students and private-sector employees aged 18-29 years use the Mobile Public Transportation Application with route projection during an emergency, depending on the mobile application facilitating conditions. Moreover, based on the factors analysis' result, facilitating conditions are an essential factor compared to the other constructs. However, the study's findings might be biased towards a certain age and gender group due to its respondent reach. Therefore, an equal number of respondents in various age and gender groups is highly recommended for future research to fully grasp the factors that may affect passengers using the Mobile Public Transportation Application in urban mobility.

**Keywords:** mobile public transportation application usage, urban mobility, urban rail transit

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## 1 INTRODUCTION

Mobile Public Transportation Applications have become a popular mobile application among users to plan their trips to their destination on time and manage them cost-effectively (Altay & Okumuş, 2021). The ability of the platform to show the best route in real-time and real situations on users' routes has become the core of future integrated transport mobility development (Matyas, 2020). These mobile applications may also improve passengers' comfort, safety, and awareness while taking public transportation (Bian et al., 2022). A previous report found that 50 per cent of mobile application users claimed that the mobile applications reduced their waiting time in their transits, especially on a mobile application that integrated their systems with mobile payment (Shaheen et al., 2016). These applications have expanded awareness to the government to be integrated with smart mobility planning (Siuhi & Mwakalonge, 2016). Mobile Public Transportation applications are great for urban dwellers to plan their daily trips to get to destinations in time and in a cost-efficient way. Commonly, mobile public transportation apps or platforms have maps that show a better route to commute in real-time and the situation on the actual route, such as Google Maps. Google Maps has a feature to show the directions to any destination, depending on the type of transport the user takes. It is not only for those taking private vehicles but also for those taking public transport, such as urban rail transits. Nine hundred thirty million people worldwide use Moovit (*Moovit Public Transit Index*, n.d.), a mobile app or platform like Google Maps but focus more on public transportation. It demonstrates that roughly 11.93 per cent of the world's population uses Mobile Public Transportation applications (*Moovit Public Transit Index*, n.d.). Mobile Public Transportation Applications is suitable for the Klang Valley Integrated System. With its various transit types, public transportation passengers in Klang Valley can take public transportation efficiently as the system is the most extensive public transportation system in Malaysia. With several types of transport, such as Bus Rapid Transit (BRT), Monorail, Light Rapid Transit (LRT), Mass Rapid Transit (MRT) and the Commuter, the experience can be overwhelming for some public transportation passengers. Therefore, this study believes that using Mobile Public Transportation Applications can help public transport passengers in the Klang Valley.

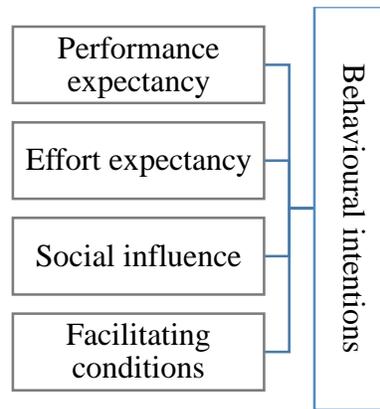
Although Mobile Public Transportation Applications can help urban transportation systems, some public transportation passengers have shown no interest in using Mobile Public Transportation Applications. This problem statement reflects Malaysia's home-developed Mobile Public Transportation Application rating performance on a mobile application store. The home-developed Mobile Public Transportation Application called Pulse by Prasarana was rated 2.3 out of 5 in the iOS App Store (Prasarana, 2020). Passengers expressed their disappointment on the review section of the mobile apps page, as the mobile application was impossible to use for visually impaired users, given that there are no features for disabled users (Prasarana, 2020). Another reviewer also left a disappointed review with the mobile application interface, saying that its user interface is inefficient as it only uploads the public transportation routes to the mobile app in Portable Document Format (PDF) (Prasarana, 2020). Due to this situation, the awareness of journey planning and learning about waiting time, commuting time, numbers of transfers, trip distance, and cost has disintegrated among urban rail passengers. It could also be because there is a lack of

clear frameworks of data gathered through mobile technology users that work for transport sectors (Sun et al., 2021). Previous studies concerning mobile app adaptation in different contexts can affect mobile app users' behaviour (Matyas, 2020; Siuhi & Mwakalonge, 2016). Another previous paper examined the factors influencing e-hailing services in Klang Valley, Malaysia, by learning the relationship between the four factors' constructs and the services offered on the mobile app (Chen & Shafinaz Ahmad Nazar, 2021).

This study aims to understand the factors affecting Mobile Public Transportation applications among urban rail transit users. The objective is to determine the significant factors that influence the usage of Mobile Public Transportation applications among urban rail transit passengers in Klang Valley, Malaysia. A previous study suggested that understanding the factors influencing transport mode choice may make developing effective travel demand management (TDM) plans and policies more manageable and achieve more transportation objectives, such as encouraging road users to shift to public transportation rather than private vehicles (Khoo et al., 2022). Encouraging more passengers to use public transportation is expected to help achieve Sustainable Development Goal (SDG) 11.2 concerning urban transport access (*Goal 11 | Department of Economic and Social Affairs*, n.d.). By determining significant factors using a similar methodology to previous studies, we hope that existing and upcoming Mobile Public Transportation Applications will improve their features to encourage people to use public transportation more.

In this study, we used the Unified Theory of Acceptance and Use of Technology model (Venkatesh et al., 2003) and the Mode Choice model (Ortuzar & Willumsen, 2006) to determine significant factors of Mobile Public Transportation Application usage among urban rail transit passengers. These two models have been used in similar previous studies to determine significant factors of their study variables (Madhuwanthi et al., 2016; Madigan et al., 2017). These two models were the most robust models to investigate the factors of Mobile Public Transportation Application usage among urban rail transit passengers. The models in this study represent information technology and urban mobility, respectively.

This study used the Unified Theory of Acceptance and Use of Technology (UTAUT) model as a research framework to identify factors or behavioural intentions in using technology systems (Venkatesh et al., 2003). The UTAUT model is appropriate for technology acceptance research as it aims to examine users' intentions in using information systems and the like. The UTAUT framework can determine 70 per cent of technology acceptance of users (Venkatesh et al., 2003). A previous study suggested that the model can work in two ways: to determine the behavioural intentions of technology users in terms of mobile applications; and to determine the relations between use behaviour, behaviour intentions, and factors moderated by gender, experience, and age (Santoso & Siregar, 2018). The framework consists of four constructs that explain the users' intentions; (i) performance expectancy, (ii) effort expectancy, (iii) social influences, and (iv) facilitating conditions. Figure 1.0 demonstrates that the four constructs influence the behavioural intentions of technology users.



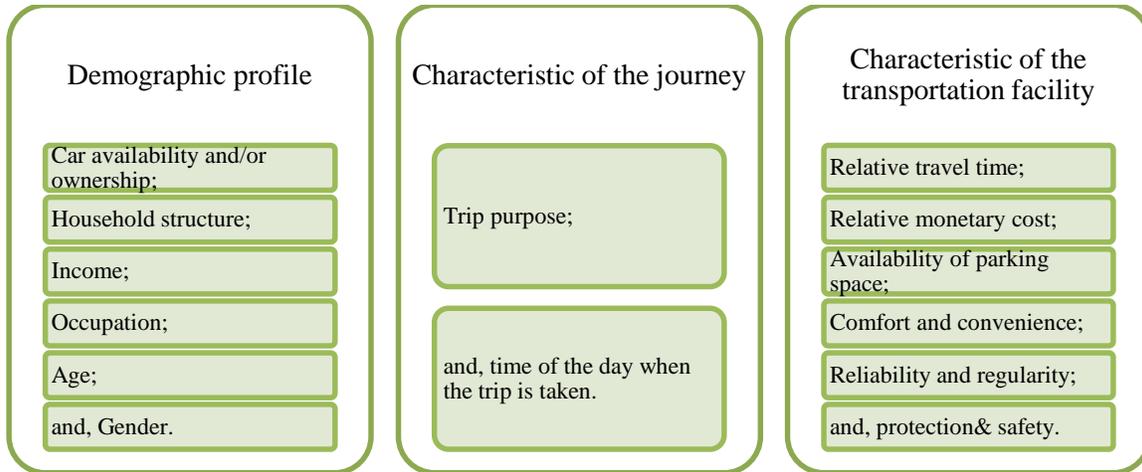
**Figure 1.** Unified Theory of Acceptance and Use of Technology Framework (Venkatesh et al., 2003).

Performance expectancy refers to users' understanding of systems' performance and their performance improvement from time to time. According to Kang (2014), people will likely use technology systems such as mobile apps when it offers efficient responses, convenience, and an easy user interface. Thus, it is an essential determinant for users' attitudes in using various travel apps.

Effort expectancy is a construct that refers to how much an individual's effort is required in using technology systems. Aziz & Rahim (2019) summarised that the high value of effort expectancy factor loadings indicates a positive response influencing users' behavioural intentions to accept and use the technological systems.

The social influence construct measures whether other opinions can affect a person's usage of technology systems. Considering how dependent we are on people's views, it makes sense that social influence is one of the main predictors in the UTAUT framework.

To sustain interest in app usage, facilitating conditions measure the involvement of existing organisations to encourage the use of mobile apps. It suggests that the higher the constructed value, the higher the users' intention (Aziz & Rahim, 2019).



**Figure 2.** Mode Choice Model (Ortuzar & Willumsen, 2006).

We also also used the Mode Choice as a supporting model to the Unified Theory of Acceptance and Use of Technology. A past study explained three categories of Mode Choice factors, as shown in Figure 2 (Ortuzar & Willumsen, 2006). Mode choice is a process where the means of travel is determined based on trip makers' characteristics and desired travel modes (Travel Forecasting, 2022). The mode choice model identifies factors affecting transportation mode selection from the aspects of the trip maker's characteristics and travel-based characteristics for their regular activities (Madhuwanthi et al., 2016). Figure 2 illustrates that mode choice is classified into three characteristics: the demographic profile, journey, and transportation facility.

We found a lack of interest in using the Mobile Public Transportation Application as the basis for inquiry. The application's user interface is quite disappointing and not immensely helpful for planning their trips. Then, it will be combined into the UTAUT model as a mobile application feature to represent mobile public transportation applications, as demonstrated in Figure 4.

## 2 MATERIALS & METHODS

The leading Malaysian transit system, the Klang Valley Integrated System, is in Kuala Lumpur and most parts of Selangor, such as Petaling, Klang, Gombak, Sepang, and Kuala Langat. The system is a primary urban public transportation system in Greater Kuala Lumpur. The public transportation system of the urban rail track's length is around 555.7 km. It currently connects nine urban rail transit routes, as shown in Figure 3. The system is currently expanding to have more coverage zones for rail transits, such as the MRT Putrajaya Line, which will operate in 2023. In addition, the system also caters to bus transits to reach more zones in the Klang Valley. For this reason, we chose the Klang Valley Integrated System as the study area of the research. However, concerning the study's aim, this study only focused on the system's urban rail transits.

The system has served urban dwellers for over a decade, with a daily ridership of more than 671,886 in 2019 (Ministry of Transportation (Malaysia), 2019). The system's extensive coverage serves the main or significant urban areas of the Klang Valley and its outskirts.



**Figure 3.** Greater KL/Klang Valley integrated transit map (Source: <https://www.klia2.info/rail/klang-valley-rail-system/>).

A survey was used to identify factors among urban rail transit users using the Mobile Public Transportation Application as primary data. Meanwhile, secondary data was used in the study through a literature review of past studies on factors influencing mobile app usage and travel mode choice. The literature review acted as a reference to build a list of constructs affecting urban rail transit users to use the mobile application, which was used as a base for the questionnaire form. Once the question material was structured and developed, the material went through a validation process by Dr Safizahanin, who acted as the study's supervisor. Then, the survey was performed using Google Forms and distributed online through social media, private messages, and broadcast messages to academic groups. Unfortunately, there was a restriction due to the Movement Control Order during the survey collection period, which restricted the authors from conducting face-to-face surveys or interviews; therefore, the survey was only conducted online.

The survey was scheduled for only two weeks but was expanded to a month as there were only few respondents who agreed to participate in the first two weeks. At the end of the month, the

survey collected 109 responses, of which 99 respondents claimed to have used similar mobile applications during their rail transit journeys in Klang Valley, Malaysia. However, there was a probability that this survey was biased towards a particular gender or age group, as it was distributed among acquaintances of the authors, the majority of whom were female around 18 - 29 years old.

The survey provided the primary data, targeting any respondents of urban rail transit users of the Klang Valley Integrated System who had used any mobile public transportation application in the urban rail trip. In this sub-section, we will determine the survey's sample size using Slovin's formula – the same formula the previous study used in their sampling (Madhuwanthi et al., 2016). In addition, to have significant research, we used data from the Ministry of Transportation Malaysia for Klang Valley's urban rail ridership count in 2019 as the population size in the formula. In 2019, the Ministry of Transportation reported that more than 671,886 ridership had taken the Klang Valley Integrated System's rail transits (Ministry of Transportation (Malaysia), 2019). However, the report only reported two rail transits' daily ridership counts: Rapid KL and ERL. For this reason, this study only used one rail transit's daily ridership count, with a significant count between the two. Therefore, this study used Rapid KL's daily ridership as the population size, as the rail transit had the highest count, as shown in Table 1. In addition, Rapid KL's zone coverage is quite comprehensive, encompassing Kuala Lumpur and the districts of Selangor. Furthermore, it focuses on serving the main urban areas of Kuala Lumpur and Selangor. Unlike ERL and KTM, which serve as connections from sub-areas to urban areas.

**Table 1.** Daily ridership of urban rail transit in Klang Valley.

Transit Type	Number of Daily Ridership	Remarks
Rapid KL	647,379	Source: (Ministry of Transportation (Malaysia), 2019) – it is assumed that passengers vary from workers to tourists.
KTM	none	
ERL	24,505	

$$n = \frac{N}{(1 + NE^2)} \tag{1}$$

where;

- n = sample size
- N = population size
- E = error tolerance

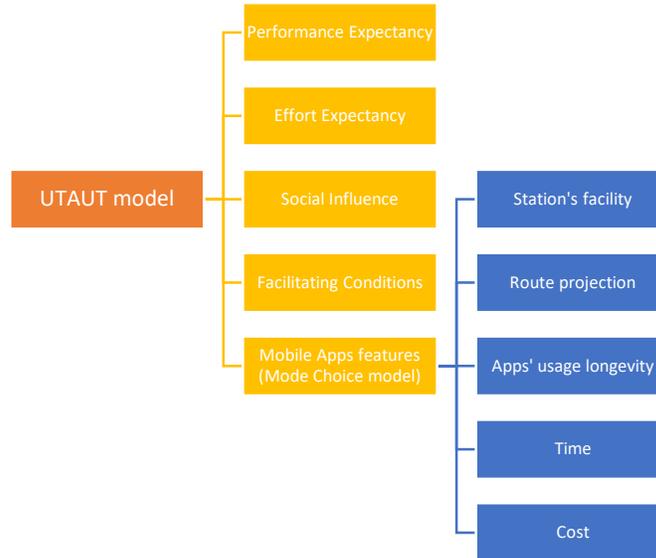
$$n = \frac{647,379}{(1 + (647,379)(0.1)^2)} = 99.98 \text{ (to be rounded up as 100)}$$

(2)

According to the equation performed using Slovin's formula by setting a 10 per cent error tolerance, this survey should obtain a minimum of 100 respondents to reach a significant result. As a result, the survey conducted from 29 April 2021 to 19 May 2021 obtained a total of 109 respondents who have taken two or more journeys with Klang Valley Integrated System's urban rail transits. However, from 109 respondents, only 99 claimed to have used a Mobile Public Transportation Application in their urban rail journeys, which meant the target was not reached. Therefore, given the time limitation of the research, this study continued its analysis with 99 respondents' results.

The survey targeted respondents who had taken two or more journeys using urban rail transits in Klang Valley. The questionnaire form had two parts, three sections for respondents who had used mobile public transportation applications and two sections for respondents who had never used any mobile public transportation applications in their urban rail journeys. Although the survey was open to all respondents, regardless of their use of mobile public transportation applications in their urban rail journeys, this study aimed only to use data collected from respondents who had used these mobile applications as the data collected did not reach the suggested sample size.

The first part of the questionnaire focused on investigating respondents' encounters with mobile applications. The part had three sections; the first section of the survey asked respondents about their experience using Mobile Public Transportation Applications, such as the mobile application's brand, the trip's purpose, and frequency of using the apps in their weekly journey. The second section asked about their preference for the mobile application's features they frequently used. The section also investigated their technology acceptance of mobile public transportation applications based on the diagram illustrated in Figure 4. Figure 4 shows a diagram of the UTAUT model, which was collaborated with the mode choice model. The question material of the section is elaborated in Table 2. Finally, the last section investigated the respondents' demographic profile as a personal characteristic based on the mode choice model.



**Figure 4.** Constructs of factors affecting mobile public transportation application usage.

Meanwhile, the second part of the questionnaire was designated for respondents who have not used any Mobile Public Transportation Applications. The first section of this part asked about their preference for mobile application features and their expectation of mobile application performance. The second section of this part investigated their demographic profile. The purpose of having respondents who have not used any Mobile Public Transportation Applications in the survey is to have another perspective from potential users of mobile public transportation applications. However, the responses did not meet the target sample size. Therefore, this study did not analyse the data collected in part two of the survey.

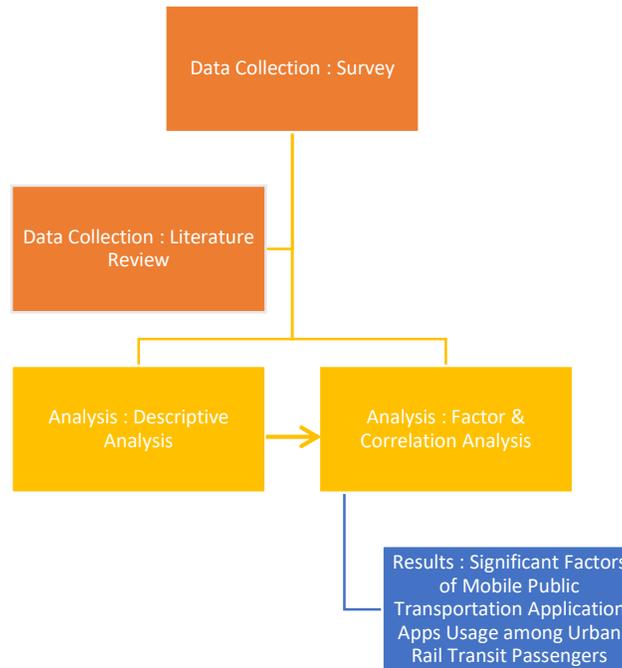
**Table 2.** Questionnaire's question material

Construct	Adapted Item
Performance Expectancy	PE1: Mobile Public Transportation Application is useful PE2: The apps make my travel efficient PE3: The apps save travel time
Effort Expectancy	EE1: The apps' user interface is clear and understandable EE2: The apps are easy to use EE3: It's easy to learn one
Social Influence	SI1: My close circle of friends has recommended I use the apps SI2: Due to my behaviour, people have advised me to use the apps SI3: Officials have advised me to use the apps as part of their new development campaign

Construct	Adapted Item
Facilitating Conditions	FC1: I have the resources to use the apps FC2: I have the knowledge to use the apps FC3: The apps have accurately predicted my transport Mode Choice
Cost	F1: Subscription policy F2: Trip's cost projection
Route projection	F3: Clarity of route projection F4: Clarity of route projection during emergency F5: Clarity of route projection during flood/ heavy rain F6: Alternative route projection if there's technical disruption
Time	F7: Accuracy of time projection for coach train's arrival F8: Accuracy of time projection for travel time
Station's facility	F9: Availability of parking space projection around the station of departure
Apps' usage longevity	F10: Battery efficiency

Before processing the data collected, the data had to go through a cleaning process. First, this study used a Comma-Separated-Value file format containing the participants' responses by downloading it from Google Forms. The purpose of data cleaning is to ensure that there are no missing values in the data. After data cleaning, quantifiable data from the questionnaires were coded to the SPSS package for further analysis. This study used Factor Analysis and Correlation Analysis to determine the study's significant factors, a method used in a past study (Madigan et al., 2017). This study also provided a descriptive analysis to identify respondents' demographic profiles.

Figure 5 shows the flowchart of the research methodology. The first stage was to perform a descriptive analysis that identified respondents' demographic profiles, such as age, gender, and experience, as independent variables of the study. Secondly, this study performed factor analysis using varimax rotation extraction and maximum likelihood to determine factor loadings for each adapted component, the same methodology used in the previous study (Madigan et al., 2017). In addition, data had to pass KMO (Kaiser-Meyer-Olkin) and Bartlett's test to determine its significance in the first round of analysis. Finally, this study performed correlation analysis with hierarchical multiple regression to examine the relationship between two variables or more and the strength of its relationship to each variable and model the independent variables influencing passengers' behavioural intentions in using mobile public transportation applications (Madigan et al., 2017).

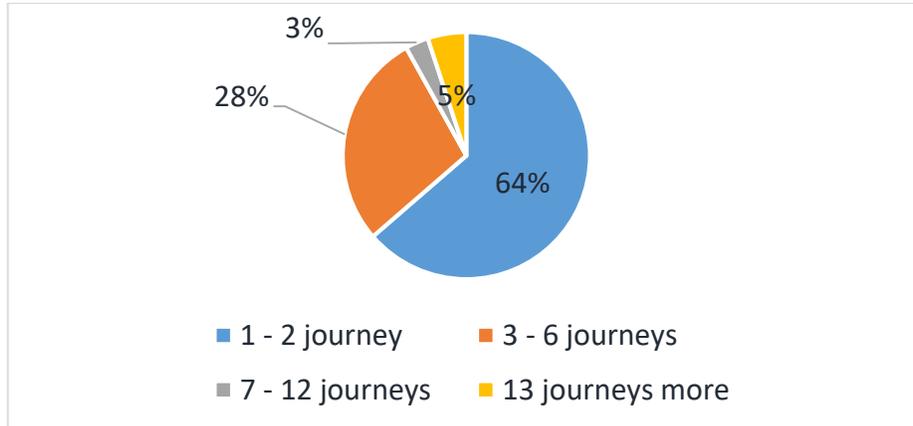


**Figure 5.** Flow chart of research methodology.

To determine viability of factors investigated, this study used mobile application features as the dependent variable, representing the study's primary variable. Effort expectancy, performance expectancy, facilitating condition, social influence, experience, age, and occupation as predictors, were categorised as independent variables. We proceeded to determine the significant values of each variable in the next stages of analysis.

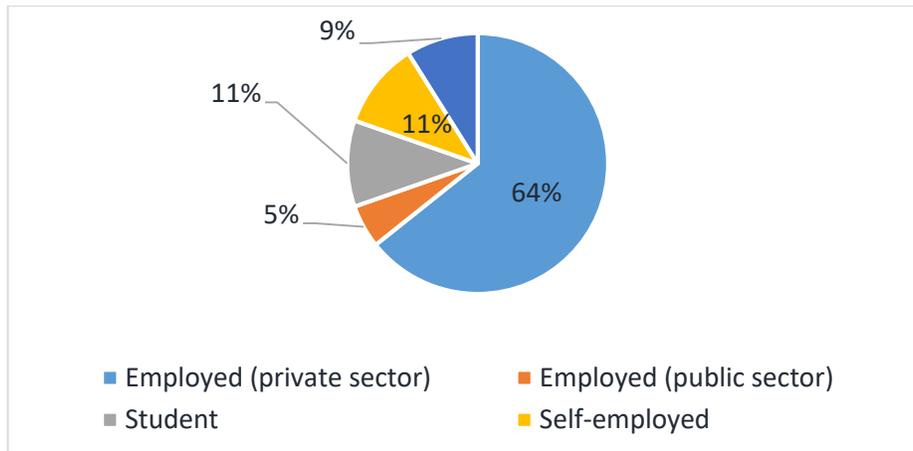
### 3 RESULTS AND DISCUSSION

Ninety-one per cent (90.8%) of 109 passengers had used a Mobile Public Transportation Application. Passengers used Google Maps (82%) and Moovit (11%) more frequently than Pulse by Prasarana in their daily trip planning. The results demonstrate that most of the respondents (64 per cent) only use Mobile Public Transportation Applications for 1-2 journeys per week. Furthermore, most respondents used Mobile Public Transportation Applications for planning their leisure or tourism trips (Figure 6). The results also show that passengers used Mobile Public Transportation Application for infrequent trips rather than daily trips.



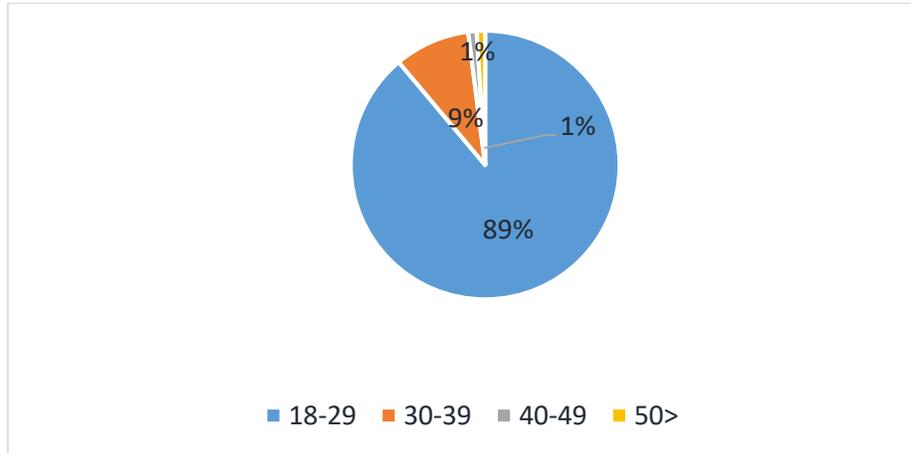
**Figure 6.** Mobile public transportation application's usage per week.

We found that most Mobile Public Transportation Application users are workers in the private sector (64%), followed by students (11%) (Figure 7). This result indicated that most users were from various working environments utilising Mobile Public Transportation Applications.



**Figure 7.** Mobile public transportation application users' employment status.

Most Mobile Public Transportation Application users were from the active working group and young adults (Figure 8). Most of the users were 18-29 years old (89 per cent), followed by the age group of 30-39 years old (9 per cent).



**Figure 8.** Mobile public transportation application users' age group.

The study analysed factors most likely to influence urban rail transit passengers to use mobile public transportation applications in the Klang Valley. Data was assembled in a Comma-Separated-Value file format and coded into SPSS before tests are run.

**Table 3.** KMO (Kaiser-Meyer-Olkin) and Bartlett's test

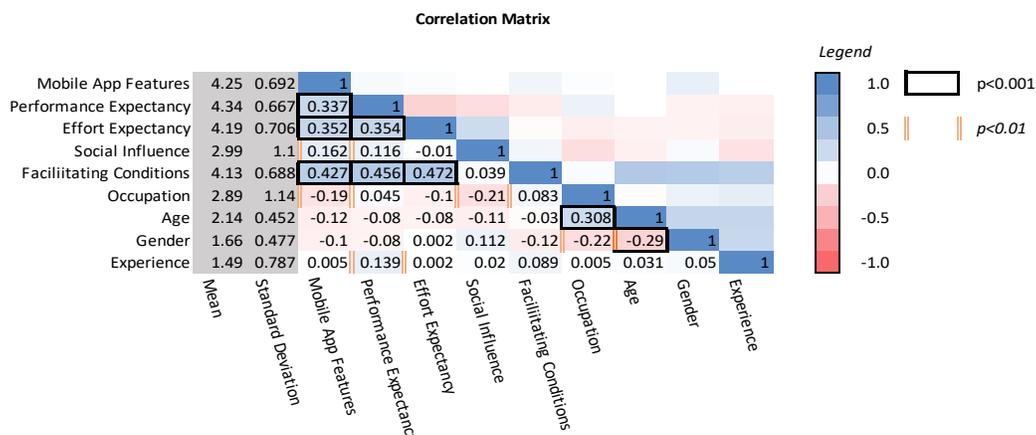
Kaiser-Meyer-Olkin Measure of Sampling	.781
Bartlett's Test of Approx. Chi-Square	789.050
Sphericity Df	105
Sig.	.000

We performed a four-factor analysis to test if the data was significant. The fourth attempt at the analysis resulted in a significant analysis. The KMO (Kaiser-Meyer-Olkin) value was above 0.70, which was 0.781. Bartlett's test of Sphericity tested the adequacy of the correlation matrix and yielded a value of 789.050 and an associated level of significantly smaller than 0.001. Thus, the correlation matrix has significant correlations among at least some variables, as shown in Table 3. This analysis generated five factors, each of its factors resulting in three adapted items, as shown in Table 4. With eigenvalues of 0.00, Table 4 depicts the final constructed construct of factors affecting Mobile Public Transportation Application characteristics (Watkins, 2018). The results also show that four factors of the generated factors are items of the UTAUT model. Furthermore, the fourth factor of the generated factors is mobile application features, of which its adapted items are leaning towards alternating routes during technical disruption, natural disasters, and emergencies.

**Table 4.** Factor analysis output.

Construct	Adapted Items	Factor Loadings
Effort Expectancy	EE2: The apps are easy to use	.943
	EE3: It's easy to learn one	.769
	EE1: The apps' user interface is clear and understandable	.688
Social Influence	SI3: Officials have recommended I use the apps as part of their new development campaign	.863
	SI2: Due to my behaviour, people have advised me to use the apps	.838
	SI1: My close circle of friends have recommended I use the apps	.815
Performance Expectancy	PE2: The apps make my travel efficient	.824
	PE1: Mobile Public Transportation Application is useful	.739
	PE3: The apps save travel time	.723
Mobile apps features	F6: Alternative route projection if there's technical disruption	.791
	F5: Clarity of route projection during flood/ heavy rain	.723
	F4: Clarity of route projection during emergency	.709
Facilitating Conditions	FC1: I have the resources to use the apps	.736
	FC2: I have the knowledge to use the apps	.679
	FC3: The apps have accurately predicted my transport Mode Choice	.666

The second analysis in the study is Correlation test using hierarchical multiple regression. The purpose of the Correlation analysis is to examine multicollinearity among the factors. Figure 9 demonstrates the results of the correlation analysis. The figure shows no multicollinearity in the data, as the correlation values were less than 0.70. In addition, each predictor's Variance Inflation Factor value was less than 0.10, indicating no correlations in the data (Crowson, 2020).



**Figure 9.** Correlation matrix of variables.

Another step in this analysis is to perform hierarchical multiple regression. This study performed three regression attempts, as the results were not statistically significant. Finally, the result was statistically significant in the third attempt, as shown in Table 5. The goal of this study's hierarchical multiple regression is to find the significant factor with the most significant factor loadings influencing the use of the Mobile Public Transportation Application. Overall, 22.9 per cent of mobile application features were used differently in this study. Two statistically significant factors influencing passengers' use of the mobile public transportation application were: facilitating conditions ( $\beta = 0.301$ ,  $p < 0.010$ ) and occupation ( $\beta = -0.228$ ,  $p < 0.10$ ). The occupation was shown to be the most critical factor in explaining the user profile of mobile public transportation application users, as shown in Table 5.: facilitating conditions ( $\beta = 0.301$ ,  $p < 0.010$ ) and occupation ( $\beta = -0.228$ ,  $p < 0.10$ ). Occupation was shown to be the most critical factor in explaining the user profile of mobile public transportation application users, as shown in Table 5.

**Table 5.** Correlation values of the factors

Model		$\beta$	Sig.	$R^2$	$\Delta R^2$
1	Performance expectancy	.156	.126	.229	.229
	Effort expectancy	.132	.204		
	Facilitating conditions	.301	.006**		
2	Occupation	-.228	.014*	.279	.051
	Gender	-.096	.295		

*Dependent variable: mobile app features*

\* $p < 0.01$ , \*\* $p < 0.001$

#### 4 CONCLUSION

Mobile Public Transportation Applications have become popular among users who want to organise their travels to arrive on time and save money (Altay & Okumuş, 2021). With the current technology trends, incorporating ICT (Information and Communication Technology) and transportation systems to develop Smart Mobility is expected to have a more efficient workflow, particularly in urban rail transits. However, despite the flexibility and benefits that Mobile Public Transportation Applications offer, there is still a lack of interest in utilising them while taking public transportation in Klang Valley. Reviewers of Malaysia's mobile public transportation application in a mobile phone application store mentioned that certain factors stopped them from using the mobile application, such as the mobile application's user interface, which they considered inefficient.

By seeing this opportunity, this study investigates the factors affecting the usage of Mobile Public Transportation applications among urban rail transit passengers in Klang Valley, Malaysia. The study's objective is to determine the significant factors affecting the usage of mobile applications.

The significance of this study is to help existing and upcoming mobile public transportation applications to improve their performance and features that could attract and demonstrates efficient and effective travel by using public transportation, especially urban rail transits.

There are two types of data in this study, which are primary and secondary. The primary data was a survey distributed online as a movement restriction was placed during the data collection period. The survey was conducted for a month and obtained 109 respondents, of whom 99 claimed to have used mobile public transportation. Unfortunately, the responses did not reach the sample size's target, but the analysis proceeded as there were time limitations for this study. Meanwhile, secondary data was a literature review of the study, which supported the primary data in developing its question materials.

The methodology of this study on data analysis referred to a past study where there were two analyses: factor analysis and correlation analysis with hierarchical multiple regression (Madigan et al., 2017). Unfortunately, both analyses were not significant in the first attempt. Therefore, factor analysis had four attempts which resulted in five factors, which are the main four factors of the UTAUT model and the mobile application features. In addition, the mobile application features had three adapted items leaning toward public transportation's alternative routes during an emergency, natural disasters, and technical disruptions. Then, correlation factors were analysed, which found no multicollinearity in the data as the correlation values were less than 0.70. Finally, the last step of this analysis was to perform hierarchical multiple regression to find the significant factor with the most significant factor loadings influencing the use of Mobile Public Transportation Application. The results showed that the facilitating conditions ( $\beta = 0.301$ ,  $p < 0.010$ ) were statistically significant factors affecting urban rail passengers using Mobile Public Transportation Applications ( $\beta = -0.228$ ,  $p < 0.10$ ) was also one of the most significant factors in explaining the user profile in using Mobile Public Transportation Applications.

In conclusion, most female students and private-sector professionals aged 18 to 29 use Mobile Public Transportation Applications with route projection in an emergency traffic situation, depending on the mobile application's supporting conditions. However, this study's results can be biased toward a particular gender and age group as most of the survey respondents were friends of the main author, most of whom were women and aged around 18 - 29 years old. Therefore, an equal number of respondents and responses that reach the sample size's target are highly recommended for future research.

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## REFERENCES

Altay, B. C., & Okumuş, A. (2021). User adoption of integrated mobility technologies: The case of multimodal trip-planning apps in Turkey. *Research in Transportation Business & Management*, 43, 100706. <https://doi.org/10.1016/j.rtbm.2021.100706>

Aziz, R. C., & Rahim, M. A. (2019). *Behavioural Intention to Use Travel Mobile*. February 2020, 9–16.

Bian, J., Li, W., Zhong, S., Lee, C., Foster, M., & Ye, X. (2022). The end-user benefits of smartphone transit apps: a systematic literature review. *Transport Reviews*, 42(1), 82–101. <https://doi.org/10.1080/01441647.2021.1950864>

Chen, O. B., & Shafinaz Ahmad Nazar. (2021). Exploring Factors Influencing E-Hailing Services in Klang Valley, Malaysia. *International Journal of Business and Economy*, 3, 32–46.

Crowson, M. (2020). *Hierarchical multiple regression using SPSS (February 2020)*. Retrieved from [https://www.youtube.com/watch?v=RyDteu6E7HY&ab\\_channel=MikeCrowson](https://www.youtube.com/watch?v=RyDteu6E7HY&ab_channel=MikeCrowson)

*Goal 11 | Department of Economic and Social Affairs*. (n.d.). United Nations. Retrieved June 13, 2021, from <https://sdgs.un.org/goals/goal11>

Kang, S. (2014). Factors influencing intention of mobile application use. *International Journal of Mobile Communications*, 12(4), 360-379. <https://doi.org/10.1504/IJMC.2014.063653>

Khoo, H. L., Low, Y. C., & Lee, A. S. H. (2022). User Mode Choice Behavior in Public Transportation: A Systematic Literature Review. *Journal of Engineering*, 34(1), 11–28. [https://doi.org/10.17576/jkukm-2022-34\(1\)-02](https://doi.org/10.17576/jkukm-2022-34(1)-02)

Madhuwanthi, R. A. M., Marasinghe, A., Rajapakse, R. P. C. J., Dharmawansa, A. D., & Nomura, S. (2016). Factors Influencing to Travel Behavior on Transport Mode Choice. *International Journal of Affective Engineering*, 15(2), 63-72. <https://doi.org/10.5057/ijae.ijae-d-15-00044>

Madigan, R., Louw, T., Wilbrink, M., Schieben, A., & Merat, N. (2017). What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of

automated road transport systems. *Transportation Research Part F: Traffic Psychology and Behaviour*, 50, 55-64. <https://doi.org/10.1016/j.trf.2017.07.007>

Matyas, M. (2020). Opportunities and barriers to multimodal cities: lessons learned from in-depth interviews about attitudes towards mobility as a service. *European Transport Research Review*, 12(1), 7. <https://doi.org/10.1186/s12544-020-0395-z>

Ministry of Transportation (Malaysia). (2019). Bilangan penumpang bagi perkhidmatan pengangkutan Rel, 2019 [Number of passengers for rail transport services, 2019]. In *Statistik Rel 2019*. [https://www.mot.gov.my/en/Statistik Rel/2019 4 - SUKU IV 2019/Jadual 2.9 Q4 2019.pdf](https://www.mot.gov.my/en/Statistik%20Rel/2019%204%20-%20SUKU%20IV%202019/Jadual%202.9%20Q4%202019.pdf)

*Moovit Public Transit Index*. (n.d.). Moovit Insights. Retrieved June 13, 2021, from [https://moovitapp.com/insights/en/Moovit\\_Insights\\_Public\\_Transit\\_Index-countries](https://moovitapp.com/insights/en/Moovit_Insights_Public_Transit_Index-countries)

Ortuzar, J. de D., & Willumsen, L. G. (2006). *Modelling Transport* (Third). John Wiley & Sons, LTD.

Prasarana. (2020). *Pulse by Prasarana*. IOS App Store. Retrieved from <https://apps.apple.com/my/app/pulse-by-prasarana/id1545938705#see-all/reviews>

Santoso, B. S., & Siregar, S. L. (2018). Factors affecting use behavior to use transportation services applications using Unified Theory of Acceptance and Use of Technology (UTAUT) 2 model. *Jurnal Ilmiah Informatika Komputer*, 23(2), 80–94. <https://doi.org/10.35760/ik.2018.v23i2.2350>

Shaheen, S., Martin, E., Cohen, A., Musunuri, A., & Bhattacharyya, A. (2016). *Mobile Apps and Transportation: A Review of Smartphone Apps and A Study of User Response to Multimodal Traveler Information*. Retrieved from <https://escholarship.org/uc/item/6m332192>

Siuhi, S., & Mwakalonge, J. (2016). Opportunities and challenges of smart mobile applications in transportation. *Journal of Traffic and Transportation Engineering (English Edition)*, 3(6), 582–592. <https://doi.org/10.1016/j.jtte.2016.11.001>

Sun, Y., Liu, C., & Zhang, C. (2021). Mobile technology and studies on transport behavior: A literature analysis, integrated research model, and future research agenda. *Mobile Information Systems*, 2021, 1–24. <https://doi.org/10.1155/2021/9309904>

Travel Forecasting. (2022). *Mode Choice*. Travel Behaviour. Retrieved from [https://tfresource.org/topics/Mode\\_choice.html](https://tfresource.org/topics/Mode_choice.html)

Venkatesh, Morris, Davis, & Davis. (2003). User acceptance of information technology: toward a unified view. *MIS Quarterly*, 27(3), 425. <https://doi.org/10.2307/30036540>

Watkins, M. W. (2018). Exploratory factor analysis: A guide to best practice. *Journal of Black Psychology*, 44(3), 219–246. <https://doi.org/10.1177/0095798418771807>