# The Factors Influencing Rail Transit Ridership: A Case Study of Klang Valley Malaysia

**Loo Yew Liang, Li Kuo**

**New Era University College, Kajang, Selangor, Malaysia**

**DOI: https://dx.doi.org/10.47772/IJRISS.2025.905000372**

**Received: 14 May 2025; Accepted: 17 May 2025; Published: 17 June 2025**

## ABSTRACT

Klang Valley faces challenges in attracting and retaining rail transit ridership, highlighting a significant gap in existing literature. This study aims to identify and analyze the key factors influencing rail transit ridership, including frequencies of train services, convenience, and ticket price. Adopting a quantitative research design, a sample size of 170 is selected through mixed technique including stratified sampling and random sampling technique, and data is collected using questionnaires sent out through Google form. Diagnostic analysis, inferential analysis (Pearson correlation), and descriptive analysis are conducted to analyze the data. The findings reveal significant insights into the relationships between these factors and rail transit ridership in the Klang Valley. Cronbach's alpha ensures the internal consistency of the measurement scales, while Pearson correlation identifies the impact of frequencies of train services, convenience, and ticket price on ridership. These findings contribute to bridging the existing gap in literature and provide practical implications for transportation authorities and policymakers to enhance ridership and improve public transportation services. In conclusion, a comprehensive understanding of the factors influencing rail transit ridership is essential for optimizing services and meeting the needs of passengers in the Klang Valley.

**Keywords:** Ridership, frequencies of train services, convenience, and ticket price

## BACKGROUND OF THE STUDY

Rail transit systems have emerged as crucial components of urban transportation networks worldwide, offering numerous benefits such as high capacity, comfort, safety, and cost-effectiveness compared to private modes of transport (Litman, 2007). In the context of the Klang Valley in Malaysia, rail transit plays a pivotal role in addressing traffic congestion, reducing travel times, and providing a convenient alternative to private vehicle usage. Despite the advantages of rail transit, achieving high ridership remains a significant challenge in developing countries like Malaysia. Factors such as the growing ownership and usage of private vehicles, including e-hailing services like Grab and Uber, contribute to issues like congestion, accidents, energy consumption, and air pollution (Morikawa et al., 2003). Consequently, there is a pressing need to enhance the utilization of public transportation, particularly rail transit systems.

This research aims to investigate the factors influencing ridership in the Klang Valley rail transit system, focusing on the following independent variables such as frequency of train which refers to the number of train arrivals and departures, plays a vital role in attracting passengers. Research has shown that higher train frequencies provide commuters with greater flexibility and convenience, ultimately increasing ridership (Fillone et al., 2006). Following by the convenience of rail transit encompasses various aspects, including the accessibility of train stations, ease of ticket purchase, and overall comfort during the journey. Previous studies have emphasized that commuters are more likely to choose rail transit when it offers convenient access and user-friendly services (Lau & Chiu, 2004). Ticket price (Cost for the Passenger) is the fare or ticket ticket price for train travel within the Klang Valley is a significant factor influencing ridership. Commuters are sensitive to transportation costs, and affordable fares can attract more passengers to utilize rail transit services (Fillone et al., 2006).

The dependent variable of this research is the number of Rail Transit Ridership taking the train in the Klang Valley. This variable represents the overall volume of individuals utilizing the rail transit services in the region.

Understanding the factors that influence this variable is critical for policymakers and service providers to develop effective strategies to enhance ridership and promote sustainable urban transportation. By examining the relationship between the independent variables (frequency of train, convenience, and ticket price) and the dependent variable (number of riders), this research aims to identify key factors that can increase rail transit usage in the Klang Valley.

The findings provided valuable insights to inform decision-makers about potential areas for improvement, such as increasing train frequencies, enhancing convenience features, and optimizing fare structures. The research is expected to contribute to the existing body of knowledge by shedding light on the specific factors that influence rail transit ridership in the Klang Valley context. The results have practical implications for policymakers, transit authorities, and urban planners, helping them make informed decisions to improve the overall attractiveness and efficiency of the rail transit system. Ultimately, this research aims to contribute to reduced traffic congestion, improved urban mobility, and sustainable transportation in the Klang Valley.

**Problem Statement**

In the Klang Valley, public transportation options including rail, buses, and taxis are available. Rail transit has emerged as the preferred mode of transportation due to its punctuality, affordability, and immunity to traffic congestion. Despite efforts to improve public transportation services by introducing rail transit systems, the modal share of public transportation has declined, primarily due to increased car ownership and deficiencies in bus services. This shift away from public transportation has resulted in traffic congestion and air pollution, with motor vehicles contributing to a significant portion of pollutants in the Klang Valley. The inadequate public transportation facilities in the Klang Valley area have become a pressing issue, exacerbated by the rapid population growth, increasing private vehicle ownership, and expansion of urban areas. The road network is under strain, leading to worsening traffic congestion and road safety concerns. The average speed of public transportation in the Klang Valley is significantly lower than other urban cities, and the region experiences a high number of accident fatalities. To address the issue of inadequate public transportation facilities and attract more passengers, particularly infrequent riders, there is a need to focus on improving the accessibility of rail transit systems. This study aims to investigate the factors influencing rail transit ridership in the Klang Valley, with a specific focus on the accessibility and service quality of the rail transit system. The study aims to explore ways to enhance the access attributes of the Light Rail Transit (LRT) and commuter systems (Keretapi Tanah Melayu, KTM), considering the various access modes used by frequent rail users and private transport users. Additionally, the study considered accessibility for people with disabilities and incorporates service quality elements in its analysis. By identifying influential factors such as travel time, travel cost, reliability, safety, comfort, and convenience, the study aims to propose an integrated model of important rail transit system traits in Klang Valley. However, it is important to acknowledge the limitations and constraints of this study, including the scarcity of related studies on the proposed relationships and the scope of the research.

Despite the importance of accessibility to the success of rail transit systems, it has received less attention compared to efforts focused on improving the rail service itself. Existing research has primarily focused on increasing ridership without adequately addressing the issue of accessibility (Kim et al., 2007; Rietveld et al., 2009). Studies have shown that satisfaction with the level and quality of access to rail services plays a crucial role in travelers' decision-making process. However, there is a gap in research regarding the applicability of findings from urban transportation studies conducted in major European and American cities to Asian cities, considering the differences in city structure and social development (Lau & Chiu, 2004). Moreover, there is a lack of research specifically addressing the issue of poor accessibility to rail services in the Klang Valley. Previous studies conducted in the Klang Valley have primarily focused on factors such as travel time, cost, distance, and fuel ticket prices when examining modal shift between private vehicles, buses, and rail. The importance of accessibility to urban rail transit networks has not been adequately explored in the context of the Klang Valley (Kamba et al., 2007; Almselati et al., 2011). Thus, there is a research gap in understanding the significance of accessibility to rail transit systems in the Klang Valley. To address this research gap, this study proposes a novel framework that examines the causal relationship between service quality, rail users' travel experience, and their satisfaction with the perceived importance of rail transit system traits. While prior research has not explored these relationships comprehensively, the proposed structural model considers new exogenous variables and latent variables measured with multiple indicators.

# LITREATURE REVIEW

## Rail Transit Ridership

Usually, various aspects play a significant role in influencing ridership choices when it comes to selecting public transportation as the preferred mode of travel. Therefore, it is crucial to assess the selection of Light Rail Transit (LRT) as one of the primary transportation options, taking into account the preferences of ridership (Zhou et al.,2014). One of the key considerations for riders when choosing public transport is the factor of time. Travelling time, in particular, heavily impacts passengers' decisions (Meng et al., 2018;Peng & Huang, 2000).Furthermore, saving time while using public transport is a prominent factor that influences the choice of the LRT system (Wang & Liu, 2015). However, according to Haywood et al., (2017), passengers may have limited opportunities to make use of their time during public transport journeys. Apart from time considerations, the cost incurred for each use of public transport is also a concern for passengers (Tirachini & Antoniou, 2020). Ridership generally prefers low and affordable transportation costs, which can be facilitated through subsidies (Zhang & Xu, 2017).Such subsidies not only reduce the overall cost for passengers but also provide them with the flexibility to allocate their saved funds towards other interests. In this context, Zakaria and Anuar, (2017) stated that these cost savings can be redirected to other expenses, enhancing riders' overall experience.

## Frequency of Train Services

The operation of passenger train services relies on the establishment of regular interval or periodic schedules, which is a critical task in railroad operations (Hooghiemstra, 1970). To account for the fluctuating levels of passenger demand, the planning horizon is typically divided into specific operation periods, often on an hourly basis. Understanding the choices made by passengers when boarding trains forms the fundamental basis for effective train service planning, as emphasized by (Chang et al., 2000).Recent research has extensively explored the relationship between train schedules and passenger behavior when selecting which train to board. According to Lam et al., (2002) conducted a user equilibrium analysis that considered the train schedule, while Shi et al., (2009) proposed a method to optimize the schedule based on passenger behavior. Additionally, Bassanini et al., (2002) verified the influence of demand flexibility and ticket ticket prices on train schedules. When scheduling trains, it is essential to consider the interplay between several factors, including train formation length, train frequency, travel service level, passenger demand flexibility, and passenger behavior. However, there remains a lack of comprehensive research on the impact of certain internal factors in train scheduling, such as train formation length and frequency. The current methods used for train scheduling primarily rely on fixed train formations (Chang et al., 2000;Bussieck et al., 1997).This simplifies the problem by merging and integrating costs per train kilometer and per carriage kilometer. However, it does not guarantee the attainment of an optimal train format and frequency during the scheduling process. In practical operations, the formation of trains is closely tied to various factors, including infrastructure characteristics, vehicle utilization, organizational mode, and the railway network. The relationship between these factors and train formation needs to be clearly elucidated. In this context, the present study focuses on analyzing passenger through-trains between two cities. Although the desired departure times of passengers in the railway transport corridor are continuously distributed, the scheduling of trains may require fixed departure times due to the operation's adherence to a specific headway. Based on the previous research discussed, it can be inferred that the number of frequencies of train services have a positive impact on rail transit ridership in the Klang Valley. Therefore, H1 in this study as below:

**H1: The higher number of frequencies of train services is positively influencing rail transit ridership in the Klang Valley.**

## Convenience

The convenience and comfort of passengers are crucial factors that significantly influence their choice to use public transportation (Nikel et al., 2020;Bahreini et al., 2016) Passengers highly value the availability of various services and facilities to enhance their overall comfort during the journey. One important aspect contributing to this comfort is the provision of a dedicated waiting area and comfortable seating (Haywood et al., 2017). Moreover, the condition of toilets plays a significant role in attracting and retaining riders, with cleanliness, suitable equipment, and sufficient units being important considerations (Faisal et al., 2020). The availability of designated prayer areas, particularly for Muslim riders, is also highly valued (Kadir et al., 2020). The design of stairs and the functionality of escalators are additional factors that can influence passengers' intention to continue using public transport services (Chi et al., 2006). The location and design of Light Rail Transit (LRT) stations, as well as the provision of parking lots, are crucial in attracting riders (Lambrinos & Dosis, 2013; Ho et al., 2017).The proximity of parking lots to LRT stations is an important consideration for riders (Hamsa et al., 2014). Similarly, the distance between riders' homes or workplaces and the LRT station plays a significant role in their decision-making process, as shorter distances save travel time (Minn, 2019).Additionally, clear signage information contributes to the ease of using the LRT service (Bai & Kattan, 2014). While good coverage of public transport is generally considered favorable, it may not specifically influence LRT ridership, as suggested by Hensher et al., (2015). Considering this previous research, it can be inferred that improved convenience factors positively impact rail transit ridership in the Klang Valley. Therefore, H2 supports the notion that enhancements in convenience, such as the provision of comfortable waiting areas, clean and well-equipped toilets, designated prayer areas, efficient stair and escalator design, well-located stations and parking lots, shorter distances to stations, and clear signage information, contribute to increased rail transit ridership in the Klang Valley. Based on the previous research discussed, it can be inferred Improved convenience factors have a positive impact on rail transit ridership in the Klang Valley. Therefore, H2 in this study as below:

**H2: The improved convenience is positively influencing rail transit ridership in the Klang Valley.**

### Ticket Price

When examining the relationship between fare integration solutions in urban public transport and the demand for such services, it is crucial to consider factors that drive the need for transportation in cities and the overall demand for transport services. Additionally, established relationships between the ticket price of goods or services and the quantity purchased provide valuable insights. The size of demand, like the amount of goods purchased and services, is influenced not only by ticket price but also by various other factors that may change simultaneously with ticket price adjustments. Therefore, to understand the connections between ticket price and the quantity of goods or services purchased, it is necessary to assume that other factors remain constant. The distribution of demand, represented by the position and shape of the demand curve, serves as a starting point for analyzing the relationship between demand and ticket price. In general, with a few exceptions, both theory and practice demonstrate that when the ticket price of a good or service increases, the demand tends to decrease, resulting in the purchase of fewer goods or services. Conversely, a reduction in ticket price leads to an increase in the quantity demanded by customers. This rule applies to public transport services as well and has been confirmed by numerous studies conducted across different continents and countries over several decades (Bussieck et al., 1997; Litman, 2004). However, the sensitivity to ticket price changes can vary. The quantitative measure that determines how responsive the quantity of purchased goods or services is to ticket price changes is known as the ticket price elasticity of demand. In general, demand is considered inelastic when a ticket price change of, for example, 1% results in a smaller than 1% change in the quantity demanded. Conversely, demand is elastic when a 1% ticket price change leads to a quantity change greater than 1%. When demand is inelastic with respect to ticket price, reducing ticket prices leads to a decrease in income, while increasing ticket prices results in higher income (sales), assuming other factors remain constant (Litman, 2021). Numerous studies have investigated the relationship between public transport demand and fares, providing insights specific to particular modes of transport, cities, geographic areas, markets, and societies (Kholodov et al., 2021;Urbanek, 2002;Dargay & Hanly, 2002). Generally, the ticket price elasticity of public transport demand is relatively low. A meta-analysis conducted by Holmgren (2007), revealed that the coefficient of ticket price elasticity of demand for urban transport can range from -0.009 to -1.32, with an average value around -0.38. Public transport demand and the ticket price sensitivity of demand are influenced by various factors, including demographic factors, trends, economic activity, income levels, built environment, geography and land use patterns, accessible substitutes, and demand management strategies within a specific area (Litman,2021). Moreover, the dynamic development of information and communication technologies (ICTs) has also impacted transport demand, as evidenced during the COVID-19 pandemic. ICTs are predicted to play a key role in limiting or reducing the growth of passenger traffic in cities (Mouratidis & Peters, 2022). Based on the previous research discussed, it can be inferred that lower ticket prices or fares have a positive impact on rail transit ridership in Klang Valley. Therefore, H3 in this study as below:

**H3: Lower ticket price is positively influencing rail transit ridership in the Klang Valley.**

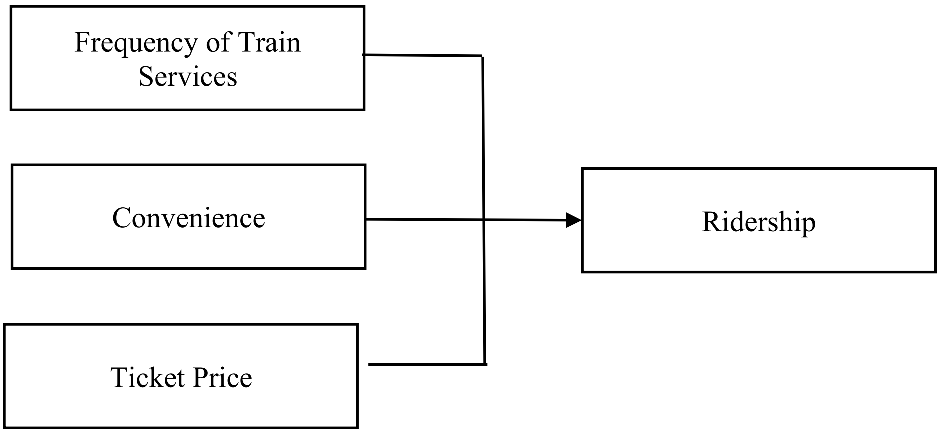


Figure 1: Conceptual Framework

## RESEARCH METHODOLOGY

### Population, Sample Size, Sampling Technique

The population for this study was the passenger of rail transit. The total population of Klang Valley is 1,088,942 individuals. This population can be further categorized into different age groups, 21.26% are between 0 and 14 years old, 71.67% are between 15 and 65 years old, and 7.07% are 65 years and above. The focus of the study was on individuals aged between 15 and 65. To calculate the number of individuals in this age range with multiplying the total population of Klang Valley (1,088,942) by the percentage of individuals aged 15-65 (0.7167) is 780,445 (1,088,942 x 0.7167 = 780,445). In this research, a sampling frame refers to a comprehensive list of all individuals who are part of the population from which the sample is drawn. In the case of this study, the passenger records of rail transits serve as the sampling frame. To determine the appropriate sample size for this study, a sample size calculator was employed, considering a confidence interval of 8.0. From the population of 777,099 individuals, the calculated sample size required for this study is 1,600 respondents.

However, for this research, probability sampling was used. In probability sampling, the elements have some known or nonzero chance of probability of being selected as the subject for this research (Sekaran & Bougie, 2013). Stratified random sampling method was used in the research. The questionnaires were distributed to the passengers of rail transit at Klang valley. The language of the questionnaire was in English since all the passengers could understand the language. According to Krejcie and Morgan (1970), the minimum number of respondents from this research was 80 respondents. Hence, a total of 170 respondents were approached to make sure there would be enough respondents as there is a possibility that some respondents would not return the questionnaires.

### Pilot Test

The pilot test was conducted before the actual research to test the level of validity of the well-structured questionnaires before the full-scale distribution. A pilot test of 30 respondents was conducted to examine the content of validity and reliability of measurement. Cronbach's alpha analysis was conducted to assess the internal consistency of four variables were Ridership ($\alpha = 0.778$, 5 items), Frequency of train ($\alpha = 0.746$, 6 items), Convenience ($\alpha = 0.842$, 6 items), and Ticket price ($\alpha = 0.726$, 7 items). The results indicated moderate to high levels of internal consistency across the variables, suggesting that the items within each variable reliably measure the intended constructs. The pilot test and full-scale study were conducted via the use of SPSS and its new versions have transformed data analysis into various fields. Researchers can leverage advanced statistical techniques offered by SPSS to ensure the accuracy, reliability, and validity of their analyses. These tools enhance researchers' ability to make robust inferences and contribute to the advancement of knowledge in their respective disciplines.

# RESULT AND DISCUSSION

## Cronbach Alpha

Table 1: Cronbach's Alpha Summary

| Variables | Cronbach's Alpha | N of items |
|---|---|---|
| Ridership | 0.778 | 5 |
| Frequency of train | 0.746 | 6 |
| Convenience | 0.842 | 6 |
| Ticket price | 0.726 | 7 |

The Cronbach's alpha analysis was conducted to assess the internal consistency of four variables: Ridership ($\alpha = 0.778$, 5 items), Frequency of train ($\alpha = 0.746$, 6 items), Convenience ($\alpha = 0.842$, 6 items), and Ticket price ($\alpha = 0.726$, 7 items). The results indicate moderate to high levels of internal consistency across the variables, suggesting that the items within each variable reliably measure the intended constructs. Specifically, the variables capture individuals' perceptions of ridership, frequency of train usage, convenience, and pricing aspects. These findings contribute to the overall reliability and validity of the measurement instrument used in assessing these factors in the study.

## Descriptive Analysis

Table 2: Age Data Summary

| **Age** | N | % |
|---|---|---|
| 18-24 years | 9 | 5.3% |
| 25-34 years | 103 | 60.6% |
| 35-44 years | 33 | 19.4% |
| 45-54 years | 9 | 5.3% |
| 55 years or older | 14 | 8.2% |
| Missing System | 2 | 1.2% |

The age distribution analysis of the sample population reveals interesting insights. Among the 170 individuals surveyed, the majority fall within the 25-34 years age group, comprising 60.6% of the sample. The 35-44 years age group follows, accounting for 19.4% of the population. The remaining age groups, including 18-24 years, 45-54 years, and 55 years or older, represent 5.3%, 5.3%, and 8.2% of the sample, respectively. There are also two missing data points, constituting 1.2% of the total sample. These findings provide a snapshot of the age composition within the sample, emphasizing the dominance of the 25-34 years age group.

Table 3: Occupation Data Summary

| **Occupation** | N | % |
|---|---|---|
| Student | 5 | 2.9% |
| Employed full-time/part-time | 119 | 70.0% |
| Self-employed | 31 | 18.2% |
| Unemployed | 5 | 2.9% |

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue V May 2025

| | | |
|---|---|---|
| Retired | 8 | 4.7% |
| Missing system | 2 | 1.2% |

Among the surveyed individuals, the largest proportion consists of employed individuals, whether full-time or part-time, comprising 70.0% of the sample. Self-employed individuals make up 18.2% of the respondents, followed by retired individuals at 4.7%. Students represent a smaller segment at 2.9%, while both the unemployed and those classified as missing/system account for the same percentage. These findings provide a comprehensive overview of the occupational distribution within the dataset, offering valuable information for further analysis

Table 4: Monthly Income Data Summary

| **Monthly income** | N | % |
|---|---|---|
| Below RM 2,000 | 29 | 17.1% |
| RM 2,000 - RM 4,999 | 39 | 22.9% |
| RM 5,000 - RM 9,999 | 69 | 40.6% |
| RM 10,000 - RM 14,999 | 31 | 18.2% |
| Missing System | 2 | 1.2% |

Among the surveyed individuals, 17.1% reported a monthly income below RM 2,000, while 22.9% fell within the range of RM 2,000 to RM 4,999. The majority, comprising 40.6% of the respondents, reported a monthly income between RM 5,000 and RM 9,999. Additionally, 18.2% fell within the range of RM 10,000 to RM 14,999. The remaining 1.2% of the sample was categorized as missing/system.

Table 5: Gender Data Summary

| **Gender** | N | % |
|---|---|---|
| Male | 67 | 39.4% |
| Female | 101 | 59.4% |
| Missing System | 2 | 1.2% |

Among the respondents, 39.4% identified as male, while 59.4% identified as female. There were also 1.2% of respondents classified as missing/system. These findings provide insights into the gender distribution of the survey participants and serve as a foundation for understanding potential gender-based differences in the factors influencing rail transit ridership.

Table 6: Educational Level Data Summary

| **Education level:** | N | % |
|---|---|---|
| Diploma | 24 | 14.1% |
| Bachelor's degree | 87 | 51.2% |
| Postgraduate | 57 | 33.5% |
| Missing System | 2 | 1.2% |

Among the respondents, 14.1% held a Diploma, while 51.2% possessed a bachelor’s degree. Additionally, 33.5% reported having a Postgraduate degree. There were also 1.2% of respondents classified as missing/system. These findings provide insights into the educational background of the survey participants and establish a foundation for examining the potential relationship between education level and factors influencing rail transit ridership. In conclusion, the descriptive analysis of the collected data provides valuable insights into the various demographic aspects of the surveyed population in relation to the factors influencing ridership for rail transit.

**Inferential Analysis**

Table 7: Mean And Standard Deviation Data Summary

| **Descriptive Statistics** | Mean | Std. Deviation | N |
|---|---|---|---|
| D_MEAN | 2.9893 | .89850 | 168 |
| F_MEAN | 2.9534 | .69235 | 168 |
| C_MEAN | 3.1369 | .84203 | 168 |
| P_MEAN | 3.3818 | .64411 | 168 |

The mean values computed for the variables D_MEAN, F_MEAN, C_MEAN, and P_MEAN is 2.9893, 2.9534, 3.1369, and 3.3818, respectively. These mean values represent the average scores or responses for each variable. Additionally, the corresponding standard deviations of 0.89850, 0.69235, 0.84203, and 0.64411 reveal the variability or dispersion around these mean values. These descriptive statistics aid in understanding the central tendency and spread of the data, allowing for a better interpretation of the regression or multiple regression results. The mean values provide an indication of the typical response level for each variable, while the standard deviations provide insights into the level of variability in the data points. These statistics play a crucial role in analyzing the relationships and effects o

f the independent variables on the dependent variable(s) in the regression model, enabling researchers to draw meaningful conclusions about the findings and implications of the study.

Table 8: Correlation Data Summary

| **Correlations** | | D_MEAN | F_MEAN | C_MEAN | P_MEAN |
|---|---|---|---|---|---|
| D_MEAN | Pearson Correlation | 1 | .495** | .376** | .228** |
| | Sig. (2-tailed) | | .000 | .000 | .003 |
| | Sum of Squares and Cross-products | 134.821 | 51.449 | 47.513 | 22.030 |
| | Covariance | .807 | .308 | .285 | .132 |
| | N | 168 | 168 | 168 | 168 |
| F_MEAN | Pearson Correlation | .495** | 1 | .291** | .343** |
| | Sig. (2-tailed) | .000 | | .000 | .000 |
| | Sum of Squares and Cross-products | 51.449 | 80.051 | 28.322 | 25.538 |
| | Covariance | .308 | .479 | .170 | .153 |
| | N | 168 | 168 | 168 | 168 |
| C_MEAN | Pearson Correlation | .376** | .291** | 1 | .511** |
| | Sig. (2-tailed) | .000 | .000 | | .000 |
| | Sum of Squares and Cross-products | 47.513 | 28.322 | 118.407 | 46.266 |
| | Covariance | .285 | .170 | .709 | .277 |

| | | | | | |
|---|---|---|---|---|---|
| | N | 168 | 168 | 168 | 168 |
| P_MEAN | Pearson Correlation | .228** | .343** | .511** | 1 |
| | Sig. (2-tailed) | .003 | .000 | .000 | |
| | Sum of Squares and Cross-products | 22.030 | 25.538 | 46.266 | 69.286 |
| | Covariance | .132 | .153 | .277 | .415 |
| | N | 168 | 168 | 168 | 168 |

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation table displays the Pearson correlation coefficients between four variables: D_MEAN, F_MEAN, C_MEAN, and P_MEAN. These coefficients measure the strength and direction of the linear relationship between pairs of variables. A correlation coefficient of 1 indicates a perfect positive correlation, while a coefficient of -1 indicates a perfect negative correlation. A coefficient close to 0 suggests a weak or no correlation. The correlation analysis reveals several interesting relationships. Firstly, there is a moderate positive correlation (0.495**) between D_MEAN and F_MEAN. This indicates that as the value of D_MEAN (variable D) increases, there tends to be a corresponding increase in the value of F_MEAN (variable F). Similarly, a moderate positive correlation (0.376**) is observed between D_MEAN and C_MEAN. This suggests that as the value of D_MEAN increases, there is a tendency for C_MEAN (variable C) to increase as well.

Furthermore, a weak positive correlation (0.228**) is found between D_MEAN and P_MEAN. This implies that as D_MEAN increases, there is a slight tendency for P_MEAN (variable P) to increase. Moving on to the correlation between F_MEAN and C_MEAN, a moderate positive correlation (0.291**) is identified. This means that as the value of F_MEAN increases, there is a tendency for C_MEAN to increase as well. Additionally, a moderate positive correlation (0.343**) is observed between F_MEAN and P_MEAN. This suggests that as F_MEAN increases, there tends to be a corresponding increase in P_MEAN.

Lastly, a strong positive correlation (0.511**) is found between C_MEAN and P_MEAN. This indicates that as C_MEAN increases, there is a strong tendency for P_MEAN to increase as well. These correlations, marked as significant at the 0.01 level, provide valuable insights into the relationships between the variables. They suggest that there are meaningful associations among the variables under consideration in the regression or multiple regression analysis. Researchers can further investigate these relationships to better understand the underlying factors influencing the variables and their potential impact on the overall analysis.

Table 9: Model Summary

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | |
|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change |
| 1 | .554[a] | .307 | .294 | .75473 | .307 | 24.228 |

| Model | Change Statistics | | |
|---|---|---|---|
| | df1 | df2 | Sig. F Change |
| 1 | 3 | 164 | .000 |

The Model Summary provides important information about the regression model used to analyze the relationship between the dependent variable (D_MEAN) and the predictors (P_MEAN, F_MEAN, and C_MEAN). The first row of the Model Summary table displays several statistics. The R value represents the correlation coefficient between the predicted values and the actual values of the dependent variable. In this case, the R value is 0.554,

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue V May 2025

indicating a moderate positive correlation between the predicted and actual values of D_MEAN. The R Square value, which is 0.307, represents the proportion of the variance in the dependent variable that can be explained by the predictors. In other words, approximately 30.7% of the variability in D_MEAN can be accounted for by P_MEAN, F_MEAN, and C_MEAN. The Adjusted R Square value, at 0.294, considers the number of predictors and the sample size. It provides a more conservative estimate of the proportion of variance explained by the predictors, accounting for potential overfitting of the model.

The Std. Error of the Estimate is a measure of the average distance between the predicted values and the actual values of the dependent variable. In this case, it is 0.75473, indicating the average amount of error in the prediction of D_MEAN. The Change Statistics table provides information about the improvement in the model fit compared to an intercept-only model. The R Square Change value of 0.307 represents the increase in the proportion of variance explained by adding the predictors to the model. The F Change value of 24.228 indicates that the addition of the predictors significantly improved the model fit.

The second Model Summary table presents the degrees of freedom (df1 and df2) and the significance level (Sig. F Change) associated with the change in the model fit. In this case, the model improvement is statistically significant, with a p-value of 0.000. In summary, the Model Summary provides an evaluation of the regression model's goodness-of-fit. The model, including the predictors P_MEAN, F_MEAN, and C_MEAN, explains a significant portion of the variance in D_MEAN. The improvement in model fit is statistically significant, suggesting that the predictors have a meaningful impact on the dependent variable.

Table 10: ANOVA Data Summary

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 41.403 | 3 | 13.801 | 24.228 | .000[b] |
| | Residual | 93.418 | 164 | .570 | | |
| | Total | 134.821 | 167 | | | |

The ANOVA table provides important information about the analysis of variance for the regression model. It assesses the significance of the regression model in explaining the variability in the dependent variable (D_MEAN) based on the predictors (P_MEAN, F_MEAN, and C_MEAN). The first row of the ANOVA table represents the Regression section. The Sum of Squares value for the regression model is 41.403. This represents the total variability in D_MEAN that is explained by the predictors. The degrees of freedom (df) for the regression model are 3, indicating the number of predictors included in the model. The Mean Square value is calculated by dividing the Sum of Squares by the degrees of freedom. In this case, it is 13. 801.The F-value, calculated by dividing the Mean Square for the regression model by the Mean Square for the residual (error), is 24.228. This F-value assesses the overall significance of the regression model. In this instance, the F-value is statistically significant ($p < 0.001$), indicating that the predictors collectively have a significant impact on explaining the variability in D_MEAN.

The second row of the ANOVA table represents the Residual section. The Sum of Squares for the residual is 93.418, which represents the unexplained variability in D_MEAN after accounting for the predictors. The degrees of freedom for the residual is 164, indicating the number of data points minus the number of predictors. The Mean Square for the residual is 0.570, calculated by dividing the Sum of Squares for the residual by the degrees of freedom. The Total row represents the overall variability in D_MEAN, which is 134.821, with 167 degrees of freedom.

In summary, the ANOVA table demonstrates that the regression model, including the predictors P_MEAN, F_MEAN, and C_MEAN, significantly explains the variability in the dependent variable D_MEAN. The F-test indicates that the model is a good fit for the data, suggesting that the predictors have a meaningful impact on D_MEAN.

Table 4.11: Coefficients data summary

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | .684 | .351 | | 1.947 | .053 |
| | F_MEAN | .565 | .091 | .436 | 6.229 | .000 |
| | C_MEAN | .302 | .082 | .283 | 3.705 | .000 |
| | P_MEAN | -.092 | .109 | -.066 | -1.848 | .008 |

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | (Constant) | | |
| | F_MEAN | .864 | 1.157 |
| | C_MEAN | .724 | 1.381 |
| | P_MEAN | .698 | 1.433 |

The Coefficients table provides information about the unstandardized coefficients, standardized coefficients (Beta), t-values, and significance levels for each predictor variable in the regression model. In this model, the constant term (intercept) has an unstandardized coefficient of 0.684 and a standard error of 0.351. The t-value of 1.947 indicates that the constant term is not statistically significant at the conventional significance level of 0.05 ($p = 0.053$). For the predictor variables, F_MEAN has an unstandardized coefficient of 0.565, indicating that a one-unit increase in F_MEAN corresponds to an expected increase of 0.565 units in the dependent variable (D_MEAN). The standardized coefficient (Beta) of 0.436 suggests that F_MEAN has a moderate positive effect on D_MEAN. The t-value of 6.229 is highly significant ($p < 0.001$), indicating that the effect of F_MEAN on D_MEAN is statistically significant.

Similarly, C_MEAN has an unstandardized coefficient of 0.302, indicating that a one-unit increase in C_MEAN corresponds to an expected increase of 0.302 units in D_MEAN. The standardized coefficient (Beta) of 0.283 suggests that C_MEAN has a moderate positive effect on D_MEAN. The t-value of 3.705 is statistically significant ($p < 0.001$), indicating that the effect of C_MEAN on D_MEAN is significant. On the other hand, P_MEAN has an unstandardized coefficient of -0.092, suggesting that a one-unit increase in P_MEAN corresponds to an expected decrease of 0.092 units in D_MEAN. The standardized coefficient (Beta) of -0.066 indicates that P_MEAN has a small negative effect on D_MEAN. The t-value of -1.848 suggests that the effect of P_MEAN on D_MEAN is marginally significant ($p = 0.008$). Additionally, the Collinearity Statistics table provides information about multicollinearity among the predictor variables. The Tolerance values for F_MEAN, C_MEAN, and P_MEAN are above 0.2, indicating that there is no issue with multicollinearity. The Variance Inflation Factor (VIF) values are all close to 1, further confirming the absence of significant multicollinearity.

In summary, the Coefficients table provides insight into the magnitude, direction, and significance of the relationships between the predictor variables (F_MEAN, C_MEAN, and P_MEAN) and the dependent variable (D_MEAN). The standardized coefficients (Beta) allow for a comparison of the relative importance of each predictor variable. The absence of multicollinearity among the predictors suggests that their individual effects on the dependent variable can be interpreted independently.

Table 12: Collinearity Diagnostic Data Summary

| Dimension | Eigenvalue | Condition Index | Variance Proportions | | | |
|---|---|---|---|---|---|---|
| | | | (Constant) | F_MEAN | C_MEAN | P_MEAN |
| 1 | 3.912 | 1.000 | .00 | .00 | .00 | .00 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2 | .044 | 9.478 | .03 | .39 | .63 | .00 |
| 3 | .028 | 11.903 | .31 | .59 | .25 | .16 |
| 4 | .016 | 15.465 | .66 | .01 | .11 | .84 |

The Collinearity Diagnostics table provides information about collinearity among the predictor variables in the regression model. It includes the dimension, eigenvalue, condition index, and variance proportions for each dimension. In this model, there are four dimensions represented by the eigenvalues. The first dimension has an eigenvalue of 3.912, indicating that it explains the most variance in the predictor variables. The condition index for this dimension is 1.000, which suggests no collinearity issues.

The second dimension has an eigenvalue of 0.044 and a condition index of 9.478. The variance proportions for this dimension show that F_MEAN contributes the most to this dimension (0.39), followed by C_MEAN (0.63), and P_MEAN (0.00). This suggests a moderate degree of collinearity between F_MEAN and C_MEAN.

The third dimension has an eigenvalue of 0.028 and a condition index of 11.903. The variance proportions indicate that C_MEAN contributes the most to this dimension (0.59), followed by F_MEAN (0.25), and P_MEAN (0.16). This suggests a moderate degree of collinearity between C_MEAN and P_MEAN.

The fourth dimension has an eigenvalue of 0.016 and a condition index of 15.465. The variance proportions show that P_MEAN contributes the most to this dimension (0.84), followed by C_MEAN (0.11), and F_MEAN (0.01). This suggests a moderate degree of collinearity between P_MEAN and C_MEAN.

Overall, the Collinearity Diagnostics table provides insights into the degree of collinearity among the predictor variables. While there is some collinearity between certain variables, it is not severe enough to cause significant issues in the interpretation of the regression results.

Table 13: Residual Statistic Data Summary

| | Minimum | Maximum | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Predicted Value | 1.8705 | 3.9751 | 2.9893 | .49792 | 168 |
| Residual | -1.63569 | 1.59789 | .00000 | .74792 | 168 |
| Std. Predicted Value | -2.247 | 1.980 | .000 | 1.000 | 168 |
| Std. Residual | -2.167 | 2.117 | .000 | .991 | 168 |

The Residuals Statistics table provides information about the residuals (differences between the observed and predicted values) in the regression model. It includes the minimum, maximum, mean, standard deviation, and the number of observations (N) for each type of statistic. For the predicted values, the minimum value is 1.8705, indicating the lowest predicted value, while the maximum value is 3.9751, representing the highest predicted value. The mean predicted value is 2.9893, indicating that, on average, the model predicts a value close to 2.9893. The standard deviation of the predicted values is 0.49792, which measures the dispersion of the predicted values around the mean. These statistics are based on 168 observations.

The residuals, which represent the differences between the observed and predicted values, have a minimum value of -1.63569 and a maximum value of 1.59789. The mean residual is 0.00000, indicating that, on average, the residuals sum up to zero. The standard deviation of the residuals is 0.74792, which measures the dispersion of the residuals around zero. The standardized predicted values (Std. Predicted Value) range from -2.247 to 1.980. The standardized residuals (Std. Residual) range from -2.167 to 2.117. Both standardized values are centered around zero, with a mean of 0.000 and a standard deviation of 1.000 for the standardized predicted values, and a mean of 0.000 and a standard deviation of 0.991 for the standardized residuals.

These statistics provide insights into the distribution and variability of the predicted values, residuals, and their standardized counterparts. They can be used to assess the accuracy and goodness-of-fit of the regression model

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue V May 2025

and identify potential outliers or influential observations.

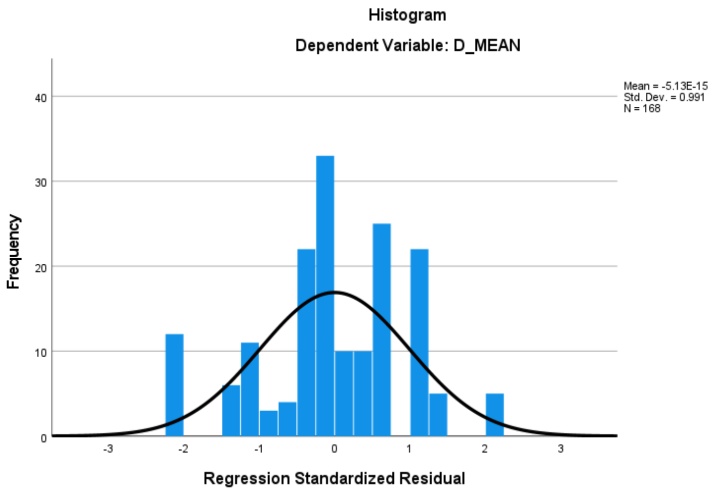


Figure 2: Histogram for ridership regression standard residual

The standardized residuals in regression analysis provide a measure of the deviation of each observation from the predicted values, standardized by the standard deviation of the residuals. Analyzing the standardized residuals helps us assess the model's goodness of fit and identify potential outliers or influential observations.

From the given data, we can observe that the standardized residuals range from -2.167 to 2.117. A standardized residual of 0 represents an observation that perfectly aligns with the predicted values, while positive and negative values indicate overestimation and underestimation, respectively. Positive standardized residuals indicate that the observed values are higher than what the regression model predicts, suggesting potential overestimation. On the other hand, negative standardized residuals indicate that the observed values are lower than the predicted values, suggesting potential underestimation. These deviations are standardized by the standard deviation of the residuals, allowing for a meaningful comparison across different models or datasets. By examining the magnitude and pattern of the standardized residuals, we can identify potential outliers or influential observations. Outliers are observations that deviate significantly from the overall trend of the data, while influential observations have a strong impact on the regression model's parameters. High-magnitude standardized residuals indicate observations that contribute disproportionately to the model's error.

In summary, analyzing the standardized residuals provides valuable insights into the accuracy and reliability of the regression model. It helps identify observations that deviate from the predicted values and allows for a comparison of the magnitude of deviations across different models or datasets.

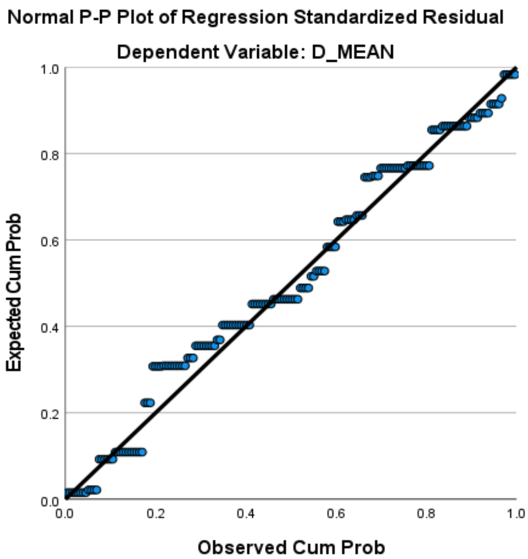


Figure 3: Normal P-plot of regression standardize residual

The normal probability plot of regression standardized residuals for the dependent variable D_MEAN is a graphical tool that assesses the normality assumption of the residuals in the regression model. It helps determine if the residuals follow a normal distribution, which is a key assumption for many statistical analyses. In the normal probability plot, the observed standardized residuals are plotted against the expected standardized residuals under the assumption of normality. If the observed residuals closely follow a straight line, it indicates that the residuals are normally distributed. Deviations from the straight line suggest departures from normality.

Interpreting the normal probability plot involves examining the pattern of the plotted points. If the points closely follow a straight line without significant deviations, it suggests that the residuals are approximately normally distributed. This indicates that the assumption of normality for the residuals is reasonable, which is desirable for conducting valid statistical inference.

However, if the points in the plot deviate from the straight line, it suggests departures from normality. For example, if the points exhibit a pronounced curvature or display an S-shape pattern, it indicates non-normality in the distribution of the residuals. This could be due to outliers, skewness, heavy tails, or other deviations from normality assumptions.

In the specific case of the dependent variable D_MEAN, analyzing the normal probability plot of regression standardized residuals can help assess the adequacy of the normality assumption for the residuals associated with this variable. If the plot shows a linear pattern with points closely following the straight line, it suggests that the residuals for D_MEAN are normally distributed. However, if there are significant deviations or patterns in the plot, it indicates potential departures from normality, requiring further investigation and potential consideration of alternative modeling approaches or transformations.

In summary, the normal probability plot of regression standardized residuals for the dependent variable D_MEAN provides a visual assessment of the normality assumption. It helps determine if the residuals are normally distributed or if there are departures from normality that may impact the validity of statistical analyses.

## DISCUSSION & CONCLUSION

Each factor plays a significant role in attracting passengers and enhancing their overall experience with public transportation. The first hypothesis (H1) suggests that a higher number of frequencies of train services positively influence rail transit ridership in the Klang Valley. The study's result supports this hypothesis, indicating that an increase in the number of train frequencies can attract more passengers and contribute to higher ridership. Passengers prefer a higher number of frequencies as it allows them to align their travel schedules more effectively. Therefore, transportation authorities should prioritize providing frequent train services to meet the demand and attract more riders.

The second hypothesis (H2) proposes that improved convenience factors positively influence rail transit ridership in the Klang Valley. The study's result confirms this hypothesis, suggesting that factors such as comfortable waiting areas, clean and well-equipped toilets, designated prayer areas, efficient stair and escalator design, well-located stations and parking lots, shorter distances to stations, and clear signage information contribute to increased rail transit ridership. By focusing on enhancing these convenience factors, transportation authorities can create a more pleasant and convenient experience for passengers, thereby attracting more riders.

The third factor examined is ticket price (H3) stated that lower ticket price positively affects rail transit ridership in the Klang Valley. The study's result aligns with this hypothesis, indicating that lower fares have a positive impact on rail transit ridership. Passengers generally prefer affordable transportation costs, and lower fares make rail transit more accessible and appealing. By offering lower ticket prices, transportation authorities can attract a broader range of passengers and increase ridership.

It is important to note that these factors are interconnected and can influence ridership choices in combination. Passengers consider various aspects when selecting public transportation, including travel time, cost, convenience, and service frequency. Therefore, a holistic approach is required to optimize rail transit ridership in the Klang Valley. By addressing the frequency of train services, convenience factors, and ticket prices simultaneously, transportation authorities can create an attractive and efficient rail transit system that meets passengers' preferences and needs. By understanding and addressing these factors, transportation authorities can attract more passengers and provide them with a satisfying and efficient public transportation experience. However, it is essential to consider the interdependencies among these factors and adapt strategies accordingly to optimize ridership in the region. Further research and analysis are recommended to gain a more comprehensive understanding of these factors and their specific impacts on rail transit ridership in the Klang Valley.

The purpose of this study was to analyze the factors influencing rail transit ridership in Klang Valley and provide recommendations for optimizing ridership. The findings indicated that the frequency of train services, convenience factors, and ticket prices or fares play significant roles in passengers' choices when selecting public transportation. In conclusion, a holistic approach that considers the frequency of train services, convenience factors, and ticket prices or fares is recommended to optimize rail transit ridership in the Klang Valley. By implementing the recommendations outlined in this chapter, transportation authorities can attract more riders, provide them with a convenient and efficient rail transit system, and contribute to sustainable urban mobility in the region. Further research and analysis are encouraged to explore additional factors and their impacts on rail transit ridership in the Klang Valley. This will contribute to a deeper understanding of the dynamics involved and support the ongoing improvement of the rail transit system in the region.

## REFERENCES

1. Almselati, A. S. I., Rahmat, R. A. O. K., & Jaafar, O. (2011). An overview of urban transport in Malaysia. In Social Sciences (Vol. 6, Issue 1, pp. 24–33). https://doi.org/10.3923/sscience.2011.24.33
2. Bahreini, A., Mirzan, H., Moeinaddini, M., Asadi-Shekari, Z., Shah, M. Z., & Sultan, Z. (2016). Evaluating Significant Factors That Influence Public Transport Usage in Kerman, Iran. Planning Malaysia, 4.
3. Bai, Y., & Kattan, L. (2014). Modeling riders' behavioral responses to real-time information at light rail transit stations. Transportation Research Record, 2412(1), 82–92.
4. Bassanini, A., La Bella, A., & Nastasi, A. (2002). Allocation of railroad capacity under competition: a game theoretic approach to track time pricing. Transportation and Network Analysis: Current Trends: Miscellanea in Honor of Michael Florian, 1–17.
5. Bussieck, M. R., Winter, T., & Zimmermann, U. T. (1997). Discrete optimization in public rail transport. Mathematical Programming, 79, 415–444.
6. Chang, Y.-H., Yeh, C.-H., & Shen, C.-C. (2000). A multiobjective model for passenger train services planning: application to Taiwan's high-speed rail line. Transportation Research Part B: Methodological, 34(2), 91–106.
7. Chi, C.-F., Chang, T.-C., & Tsou, C.-L. (2006). In-depth investigation of escalator riding accidents in heavy capacity MRT stations. Accident Analysis & Prevention, 38(4), 662–670.
8. Dargay, J. M., & Hanly, M. (2002). The demand for local bus services in England. Journal of Transport Economics and Policy (JTEP), 36(1), 73–91.
9. FAISAL, A. F. B. I. N. A., SABIRIN, S. B., & FAISAL, M. A. I. B. I. N. M. (2020). CUSTOMER SATISFACTION TOWARDS QUALITY SERVICES AT LRT STATION MASJID JAMEK, KUALA LUMPUR.
10. Fillone, A. M., Chalermpong, S., Kagaya, S., Wibowo, S., & Vitug, E. (2006). Application of Discrete Choice Modeling to Access Modes of the LRT Systems.
11. Hamsa, A. A. K., Adnan, S., & Khalid, U. A. (2014). Analysis of parking usage at the park and ride facility in Klang Valley, Malaysia. Urban Transport XX, 138, 179.
12. Haywood, L., Koning, M., & Monchambert, G. (2017). Crowding in public transport: Who cares and why? Transportation Research Part A: Policy and Practice, 100, 215–227.
13. Hensher, D. A., Ho, C., & Mulley, C. (2015). Identifying preferences for public transport investments under a constrained budget. Transportation Research Part A: Policy and Practice, 72, 27–46.
14. Ho, P. W., Ghadiri, S. M., & Rajagopal, P. (2017). Future Parking Demand at Rail Stations in Klang Valley. MATEC Web of Conferences, 103, 9001.

15. Holmgren, J. (2007). Meta-analysis of public transport demand. Transportation Research Part A: Policy and Practice, 41(10), 1021–1035.
16. Hooghiemstra, J. S. (1970). Design of regular interval timetables for strategic and tactical railway planning. WIT Transactions on The Built Environment, 20.
17. Kadir, N. A. A., Mohamad, M. R., Olabayonle, O. A., Zahari, M. Z. M., Bachok, S., & Osman, M. M. (2020). TRAVELLERS'PERCEPTION OF WORSHIP FACILITIES FOR MULTIMODAL USERS OF MRT SBK LINE. PLANNING MALAYSIA, 18.
18. Kamba, A. N., Rahmat, R. A. O. K., & Ismail, A. (2007). Why Do People Use Their Cars: A Case Study In Malaysia. Journal of Social Sciences, 3(3), 117–122. https://doi.org/10.3844/jssp.2007.117.122
19. Kholodov, Y., Jenelius, E., Cats, O., van Oort, N., Mouter, N., Cebecauer, M., & Vermeulen, A. (2021). Public transport fare elasticities from smartcard data: Evidence from a natural experiment. Transport Policy, 105, 35–43.
20. Kim, S., Ulfarsson, G. F., & Todd Hennessy, J. (2007). Analysis of light rail rider travel behavior: Impacts of individual, built environment, and crime characteristics on transit access. Transportation Research Part A: Policy and Practice, 41(6), 511–522. https://doi.org/https://doi.org/10.1016/j.tra.2006.11.001
21. Lam, W. H. K., Zhou, J., & Sheng, Z. (2002). A capacity restraint transit assignment with elastic line frequency. Transportation Research Part B: Methodological, 36(10), 919–938.
22. Lambrinos, L., & Dosis, A. (2013). DisAssist: An internet of things and mobile communications platform for disabled parking space management. 2013 IEEE Global Communications Conference (GLOBECOM), 2810–2815.
23. Lau, J. C. Y., & Chiu, C. C. H. (2004). Accessibility of workers in a compact city:: the case of Hong Kong. Habitat International, 28(1), 89–102. https://doi.org/https://doi.org/10.1016/S0197-3975(03)00015-8
24. Litman, T. (2004). Transit ticket price elasticities and cross-elasticities. Journal of Public Transportation, 7(2), 37–58.
25. Litman, T. (2007). Evaluating rail transit benefits: A comment. Transport Policy, 14(1), 94–97. https://doi.org/10.1016/j.tranpol.2006.09.003
26. Litman, T. A. (2021). Understanding Transport Demands and Elasticities-How Ticket prices and Other Factors Affect Travel Behavior.
27. Meng, M., Rau, A., & Mahardhika, H. (2018). Public transport travel time perception: Effects of socioeconomic characteristics, trip characteristics and facility usage. Transportation Research Part A: Policy and Practice, 114, 24–37.
28. Minn, M. (2019). Contested power: American long-distance passenger rail and the ambiguities of energy intensity analysis. Sustainability, 11(4), 1200.
29. Morikawa, T., Yamamoto, T., Dissanayake, D., Sanko, N., Kurauchi, S., Maesoba, H., Ohashi, S., Tiglao, N., Rubite, C., & Rivera, M. (2003). Travel behavior analysis and its implication to urban transport planning for Asian cities: Case Studies of Bangkok, Kuala Lumpur, Manila, and Nagoya. ICRA Project Report, Graduate School of Environmental Studies, Nagoya University, Nagoya.
30. Mouratidis, K., & Peters, S. (2022). COVID-19 impact on teleactivities: Role of built environment and implications for mobility. Transportation Research Part A: Policy and Practice, 158, 251–270.
31. Nikel, C., Eldeeb, G., & Mohamed, M. (2020). Perceived quality of bus transit services: a route-level analysis. Transportation Research Record, 2674(2), 79–91.
32. Peng, Z.-R., & Huang, R. (2000). Design and development of interactive trip planning for web-based transit information systems. Transportation Research Part C: Emerging Technologies, 8(1–6), 409–425.
33. Rietveld, P., Brons, M., & Givoni, M. (2009). Access to railway stations and its potential in increasing rail use. Transportation Research Part A: Policy and Practice, 43, 136–149. https://doi.org/10.1016/j.tra.2008.08.002
34. Shi, F., Luo, D. G., Wang, Y. Z., & Tan, G. J. (2009). Optimization of operating frequency and ticket ticket price of intercity bus with elastic demand. J Jilin Univ Engng, 39(6), 1475–1479.
35. Tirachini, A., & Antoniou, C. (2020). The economics of automated public transport: Effects on operator cost, travel time, fare and subsidy. Economics of Transportation, 21, 100151.

36. Urbanek, A. (2002). Potential of modal shift from private cars to public transport: A survey on the commuters' attitudes and willingness to switch–A case study of Silesia Province, Poland. Research in Transportation Economics, 85, 101008.
37. Wang, D., & Liu, Y. (2015). Factors influencing public transport use: a study of university commuters' travel and mode choice behaviours.
38. Zakaria, M. A., & Anuar, H. S. (2017). Light Rail Transit (LRT) survey implementation in one of the university in northern Malaysia.
39. Zhang, M., & Xu, T. (2017). Uncovering the potential for value capture from rail transit services. Journal of Urban Planning and Development, 143(3), 4017006.
40. Zhou, F., Huang, J., & Xu, R. (2014). Study on Influencing Factors of Public Transport Attractiveness Based on the Binary Logit Model. In CICTP 2014: Safe, Smart, and Sustainable Multimodal Transportation Systems (pp. 1412–1420).