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Gendered Travel Mode Choice in Kuantan City: Optimisation on Neural Network Model

Nur Fahriza Mohd Ali[1]*, Anwar P. P. Abdul Majeed[2], Ahmad Farhan Mohd Sadullah[3], Mohd Azraai Mohd Razman[4], Ashiru Sani[5]

[1] *Faculty of Civil Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah, 26300 Kuantan, Pahang, MALAYSIA*
[2] *School of Engineering and Technology, Sunway University, 47500 Bandar Sunway, Selangor, MALAYSIA*
[3] *Faculty of Engineering, Universiti Putra Malaysia, 43400 Serdang, Selangor, MALAYSIA*
[4] *Faculty of Manufacturing and Mechatronics Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah, 26600 Pekan, Pahang, MALAYSIA*
[5] *Department of Civil Engineering, Kano University of Science and Technology, Wudil, NIGERIA*

*Corresponding Author: fahrizaali@umpsa.edu.my
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Abstract

Machine learning techniques are becoming increasingly prominent and extensively utilised in modelling travel mode choice to forecast the mode of transportation made by travellers for destination engagement. A neural network is a powerful algorithm that can learn the complexity of human decision-making; however, the role of the activation function in neural network architecture needs to be investigated to gain an informed understanding of an appropriate activation function to achieve optimal performance of the neural network. This research aims to predict the Kuantan users' travel mode choice based on gender using a neural network model. The data were collected from 386 respondents in Kuantan City. The performance of the Neural Network is being trained with different activation functions, whilst all other parameters have been kept constant. Consequently, it has been observed that the model with the best predictive performance was created using the Rectified Linear Unit (ReLU) for both male and female respondents, with accuracies of 0.731 and 0.735, respectively. Both groups of respondents agreed that waiting time and region are the most crucial features that affect their travel mode choice. In summary, the optimisation of neural networks using the right activation function enhances their efficacy as robust predictive models for travel mode choice analysis, facilitating improvements to current public transportation systems. This process ensures the neural network's capacity for high-performance prediction, contributing to more efficient and informed transportation service planning and decision-making.

1. Introduction

Travelling by public transport is considered a more sustainable mode of travel compared to private vehicles. Travelling using public transportation instead of driving a private vehicle has several advantages, including decreased dependency on fossil fuels, lower carbon emissions, reduced air pollution from traffic, and lower noise pollution [1], [2]. Despite these benefits, travelling by private vehicles is a primary mode of travel in many cities, not only in developed countries [3] but also in developing countries such as Malaysia. In the first half of 2024, Malaysia's total industry volume (TIV), or sales of new cars, increased by 6.6%, or 24,120 units to 390,269 units from 366,176 units in the same period in 2023. According to the most recent data released by the Malaysian Automotive Association (MAA), 356,859 units were passenger vehicles (PVs) and 33,437 units were commercial vehicles (CVs).

The famous subset of artificial intelligence (AI), known as Machine learning (ML), is widely employed in many research fields, including transportation studies. The employment of machine learning techniques has been outlined in the 10-10 Malaysia Science, Technology, Innovation, and Economy (MySTIE) framework, stating that IoT sensor- and camera-equipped streetlights are crucial for achieving smart city and transportation innovation integration. Machine learning is not limited to predictive tasks, such as identifying objects or forecasting traffic patterns in data. It can also be applied to understand and analyse complex human behaviour, typically between genders. Since around 1980, it has been acknowledged that gender plays a significant role in transportation planning, particularly in meeting travellers' requirements for mobility in both urban and rural settings [4]-[7].

Neural networks (NNs) are essential tools for tasks such as forecasting and classification, as their structure resembles statistical approaches like regression analysis and curve fitting. In a neural network, a "neuron" serves as a mathematical unit that processes and organises information according to a specific framework. The network consists of an input layer containing neurons or nodes, followed by one or more hidden layers, often one, two, or three layers and completed with an output layer [8]. Modelled after the human brain and its intricate web of neurons, neural networks facilitate information processing through connections akin to synapses. These layers operate sequentially, with each layer receiving input from the preceding one, refining the data, and passing it forward until the final layer produces the network's output [9].

Activation functions play a crucial role in neural networks, enabling the model to capture and interpret complex, nonlinear relationships between inputs and outputs. Over time, advancements in neural network research have contributed to major innovations [10]. Studies suggest that activation functions have a significant impact on a network's overall performance [11]. Their main purpose is to introduce nonlinearity while also regulating neuron values to prevent instability caused by divergence. Previous researches, such as conducted by Adil et al. [8] and Çolak [12], have examined the Rectified Linear Unit (ReLU) activation function and its influence on neuron optimisation. This study will analyse several key activation functions, including Identity, Logistic, Tanh, and ReLU, to evaluate their effectiveness in predicting travellers' mode choices.

The use of public transport might differ between genders, due to perceptions and the impact of the services themselves [13]. To understand the potential for transitioning from driving to public transportation, research by Christensen et al. [14] examines how the public transportation system influences travellers' behaviour. The analysis of data on human travel behaviour makes it possible to identify the aspects of trips and travellers' needs that require particular consideration when considering the pros and cons of using private versus public transportation.

The demographic variables, including gender, age, ethnicity, employment status, and income, are important pieces of information that should be gathered as background for the respondents involved in the survey [15]. Other important variables that represent travellers' mode choice are reasons of travelling, ticket price, and the most unfavoured factor that affected their choice of public transport mode; for example, either walking from home to the nearest bus stop, waiting time, or sitting in the vehicle. However, the most significant variables of concern are the door-to-door variables, which include the time taken to reach the nearest public transport stop, waiting time, in-vehicle time, time taken to reach the destination by walking, and the total travel time [15]. This is crucial for the estimation of travel mode choice models in the future, as well as for determining which problems need to be addressed when aiming to enhance public transportation services and which initiatives can encourage more travellers to use public transport more [16].

In this study, a machine learning technique is employed to generate an automated prediction of the factors influencing travel mode choice between genders, specifically male and female travellers. Specifically, this study develops a predictive model for the choice of transport between genders using a neural network algorithm by varying its activation functions.

2. Methodology

On weekdays, the Revealed/Stated Preference (RP/SP) Survey was used to collect data for this study in Kuantan City Centre [17], [18]. A total of 386 respondents were gathered using a technique known as the random selection method.

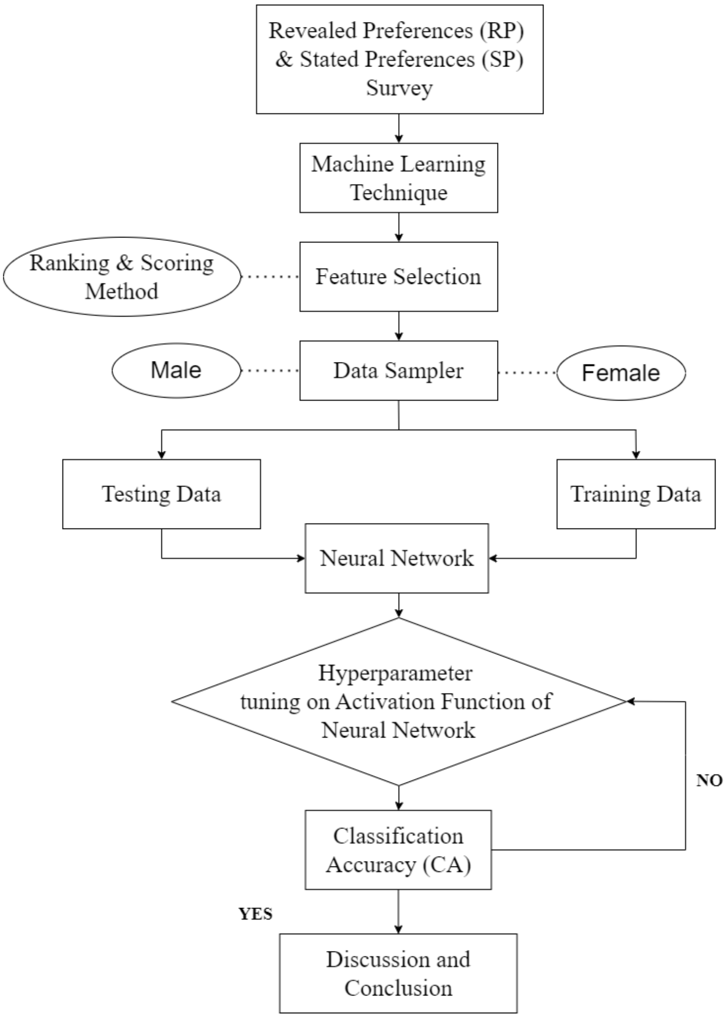

Fig. 1 *Methodology framework for data collection*

2.1 Input Variables

Each respondent was given six public transportation conditions that were presented into two categories: (i) demographic factors, and (ii) the characteristics of travel behaviour. Demographic factors of assorted respondents, including gender, age, ethnicity, nationality, employment status, and personal income, were collected. Respondents' travel behaviour characteristics were explored using travel variables including walking distance from a house to public transport stop (WD1), waiting time at the bus stop (WT), in-vehicle time on the bus (IVT), walking distance from the final stop to desired destination (WD2), total travel time for the whole trip from home to destination (TTT), travel distance (regions), reasons for travelling, ticket price for using public transport as well as dominating factor (DOM) that indicates respondents' reluctance to take public transportation. The results of mode choice were divided into two groups: public transportation (P), which includes buses, and private vehicles (N), which can be used for driving, carpooling, or e-hailing. Therefore, a total of roughly 2316 distinct responses regarding the mode of transportation that travellers choose each day, either private vehicles or public transportation, were gathered.

2.2 Models Implementation

Artificial systems known as neural networks are based on biological brain networks. These systems acquire task-specific knowledge through exposure to diverse data sets and examples. According to the theories, the system may identify characteristics and attributes from input data without being pre-programmed with knowledge of such data sets. The structure of the neural network is shown in Fig. 2.
The explanation of a neural network architecture can be found as follows:

- Input layer: The Input layer uses the input to extract features. It provides the network with data from external sources. No computations are done at the hidden layer; the nodes merely send information (features) to it.

- Hidden layer: This layer is an essential part of the abstraction provided by any neural network. This layer's nodes are hidden from sight. The hidden layer performed computations on the features received from the input layer, and then the weightage was passed to the output layer.
- Output layer: The final layer is known as the output layer, which functions to disseminate the data that the network has gathered to the final prediction.

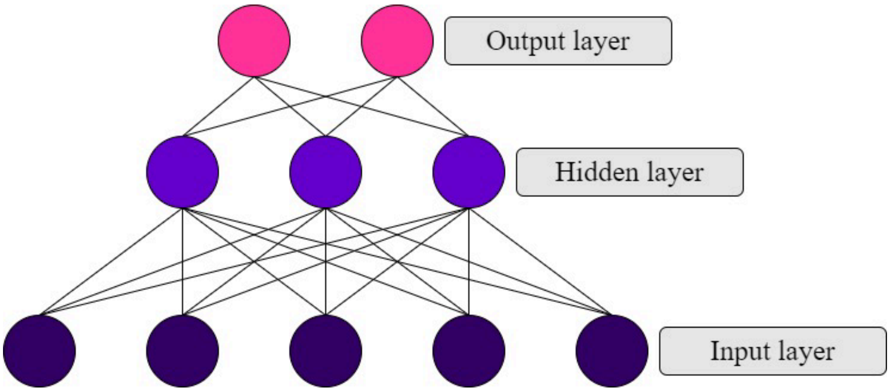

Fig. 2 *Neural network architecture*

As depicted in Fig. 2, a neural network consists of an input layer made up of neurons (also known as nodes or units), one or more hidden layers, and a final output layer [1]. Each connection in the network carries an assigned numerical weight. Generally, a neural network comprises an input layer, one or more hidden layers, and an output layer [19]. The other parameters used in the neural network algorithm are set to their default values. The optimiser is set as Adam with 200 maximum iterations, followed by Replicable training (True) and Alpha (0.0001). The hidden layer, comprising approximately 100 neurons, was utilised to compute the weighted features.

2.3 Evaluation Measurements

Predictions can only be made by neural networks using training and testing data [20]. In order to identify relationships and patterns in the data and create predictions based on those patterns, neural networks, a machine learning model, require a lot of data. A neural network would be unable to learn the relationships in the data without any training data, which would prevent it from producing precise predictions. Similarly, it would be challenging to assess the neural network's prediction accuracy without testing data.

In summary, the refinement and quantity of training and testing data have a significant impact on a neural network's performance; without both, the network cannot produce useful predictions. A machine learning tool, known as the Orange software, which has the ability to create various machine learning models, was used to analyse the data. The data instances are split into 80 (Training Data) and 20 (Testing Data).

3. Results and Discussion

In this paper, the results are presented using two significant ways: (i) the score and ranking of features using the feature importance technique, and (ii) the classification accuracy by varying the activation function of the neural networks.

In this paper, the significant features are depicted by ranking and scoring. These findings suggest that the highest-ranked features have the greatest impact on travel mode choice among travellers. The scores and rankings were derived through feature importance analysis using a Random Forest model. The feature importance indicates the significance of each feature in influencing the travellers' mode of transportation [20]. In society, women and men often do not have equal opportunities for mobility. The importance of gender in transportation planning is increasingly being acknowledged, particularly in addressing the needs of individual mobility in both urban and rural settings.

Fig. 3 depicts the male's scores and ranking features. The most significant features are waiting time, region, and walking distance from the final stop to the desired destination (WD2). The total travel time, reason for travelling, walking distance from a house to the nearest public transport stop (WD1), age, in-vehicle time, ethnicity, and ticket were in the middle ranks. Meanwhile, employment status, dominant factors affecting the journey as suggested by travellers (DOM), and income were the least important features.

Fig. 4 depicts the female's scores and ranking features. The most significant features are region, waiting time, and total travel time. At the middle ranks, the importance of features is followed by in-vehicle time, walking distance from the final stop to the desired destination (WD2), ticket, ethnicity, income, reason of travelling, and dominant factors affecting the journey as suggested by travellers (DOM). The least important features can be depicted as age, walking distance from a house to the nearest public transport stop (WD1), and employment status. Overall, both male and female travellers agreed that region and waiting time are the most significant features that affect the travellers' mode of transport.

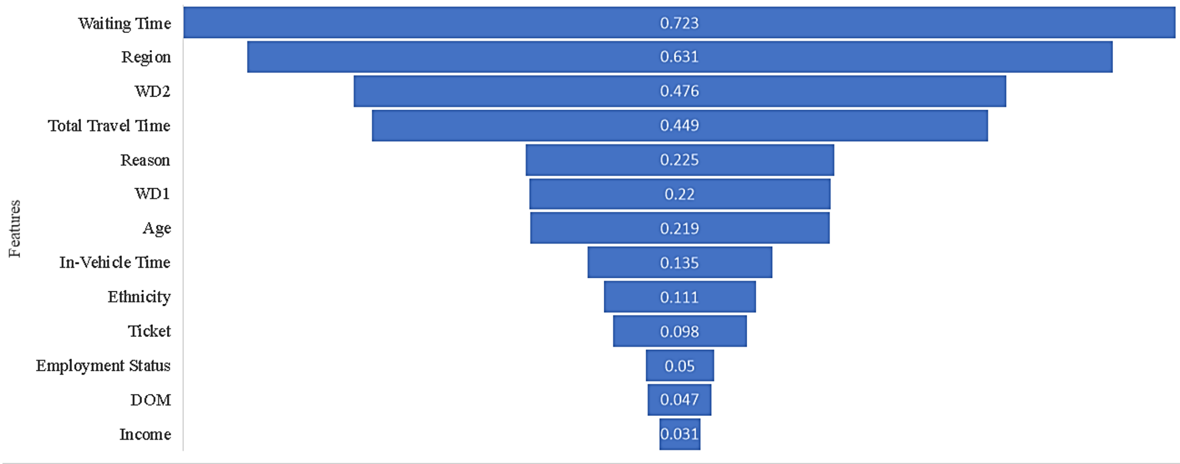

Fig. 3 *Male's scores and ranking features*

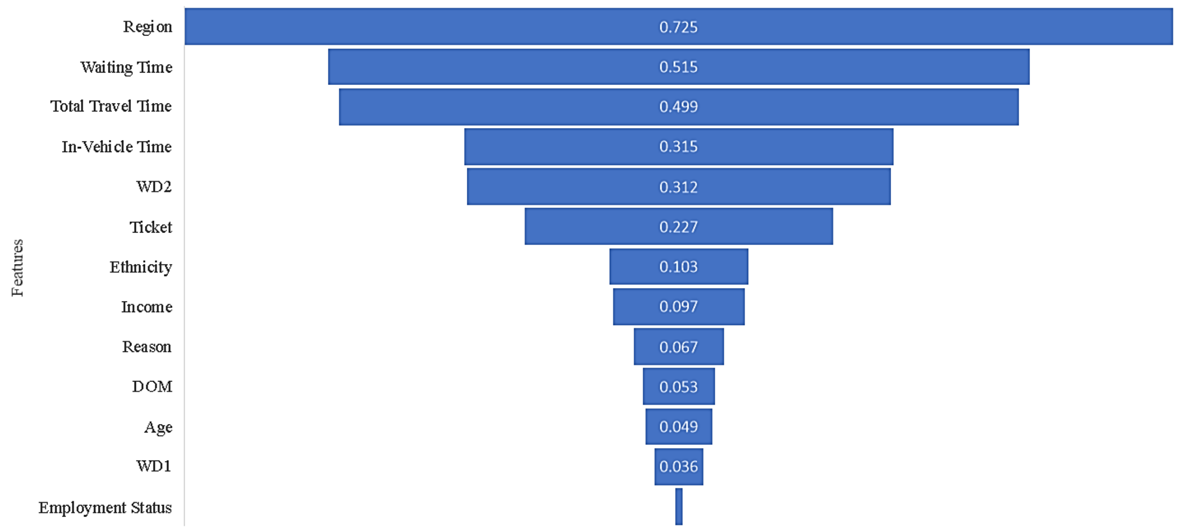

Fig. 4 *Female's scores and ranking features*

The distance between home and the destination might affect the travel mode choice between genders. According to Adlakha et al. [21], even for short journeys, women in middle-to-high income groups prefer to use private vehicles, primarily cars, scooters, and motorbikes. Another study conducted by Anderson et al. [16] found that travellers are more likely to drive alone for shorter distances and have passengers in their cars for longer ones. Additionally, Pourhashem et al. [22], Maas et al. [23], Nam et al. [24], and Dahl et al. [25] have shown that females' travel behaviours are affected by distances, as they are likely to travel shorter distances. As travellers prefer to travel as passengers rather than as drivers for longer trips, this means that travellers are likely to use public transportation as the principal mode for the longest journeys. Mode selections vary greatly depending on the distance, particularly for shorter journeys. The demand for mode shares is clearly steady when examining the selection of travel distances, ranging roughly between 8 and 40 km. More travellers are likely to travel long distances in a companion, as seen by the increase in car passenger shares beyond 40 km [16]. Public transportation can be more comfortable than private vehicles when travelling long distances, as it allows passengers to read, sleep, and take brief breaks.

Waiting time is an unavoidable stage in any public transportation system. Waiting time is like a taboo among those who are travelling by public transport, as waiting time is inherently uncertain in public transport networks, which may lead to an increase in stress levels and anxiety. Among all features, males agreed that waiting time is the most important factor affecting travel mode choice. According to Millonig et al. [26], a study has been conducted by dividing travellers into two clusters: short-time waiting users (waiting less than eight minutes) and long-time waiting users. The findings revealed that most individuals in both duration-related clusters either sit or remain motionless while waiting for public transport to arrive. Only a small percentage of travellers, even those who have been waiting for a long period, appear to try to pass the time by walking around. Particularly in the long-waiting group, travellers who move up and down instead of staying in one spot are typically busy with several other tasks. Reading and conversing with others are common hobbies; most travellers who wait for short periods of time stay standing, while long-term travellers prefer to sit down while reading. In terms of actual wait times, the median waiting time was recorded at 5.7 minutes, with the longest observed wait time up to 32 minutes [26]. A study by Cui et al. [27] indicated that an acceptable waiting period for a bus system falls within the range of 0 to 20 minutes. The implementation of real-time information technology, which displays the remaining minutes before departure, plays a crucial role in helping travellers stay informed about their wait times. This system provides a sense of reassurance, allowing passengers to better plan their journeys before arriving at their destination [2].

The significant feature that affects the travel mode choice suggested by male travellers, after waiting time and region, is the walking distance from the final stop to the destination (WD2). The need to walk from the last stop to the destination somehow brings up an unpleasant mood among male travellers, especially in cases where pedestrian infrastructure is lacking, there are no footpaths, and roads are waterlogged [21]. Prior research has shown that the willingness to walk follows a distance decay pattern, where walking as a preferred mode of transportation significantly declines beyond a distance of 800 to 1000 meters. This means that as the walking distance increases, fewer individuals choose walking as part of their mode of transportation, thus reducing their interest in using the public transportation system [28], [29]. Additionally, environmental factors, particularly hot and humid weather conditions, further discourage walking. This effect is exacerbated by the lack of a well-connected and extensive shaded pedestrian network. In many areas, shaded pathways are available only in certain locations, rather than forming a continuous, integrated network that links different parts of the public transportation system. As a result, pedestrians are often exposed to harsh weather conditions, reducing their motivation to walk for longer distances in order to reach the public transport network [30], [31]. Otherwise, travellers may have the option to continue the journey by taking an Uber or Grab; however, this might add a small extra cost to the travel expenses. The provision of feeder transport is likely to affect the travel behaviour of travellers and their likelihood of travelling by public transport [29]. Ensuring smooth connectivity throughout the door-to-door journey is essential to foster travellers' comfort in utilising public transport.

Meanwhile, the significance factor suggested by female travellers after region and waiting time is followed by total travel time. The travel time of a journey by public transport, starting from home to the destination, involves a couple of stages, or known as a door-to-door journey [15]. As travelling by public transport requires active travel, such as walking from one's home to the closest public transport stop (WD1) and walking from the final stop to the desired destination (WD2), female travellers might be concerned about the safety [21] and the provision of infrastructure, such as a pedestrian walkway. In another study conducted by Mathews et al. [32], the utilisation of public transportation is recognised as a promoter of active travel. However, concerns regarding safety from crime, inconsistent last-mile connectivity, and inadequate access to transit stops, such as bus and train stations, significantly hinder women's use of public transport services in India [21]. Meanwhile, a study by Pourhashem et al. [22] showed that the perception of enjoyable travel time and the perceived mood from the travel experience would enhance the likelihood of ridesharing. Therefore, safe and complete facilities should be provided to increase their confidence in using the public transportation system. The other infrastructure, such as a dedicated lane for public transport, is intended to smooth the journey and be free from congestion.

The variables employed in this study can be concluded as crucial for explaining and predicting travel mode choice among travellers in Kuantan City. Table 1 and Table 2 present the comparison of predictive training and testing results for male and female respondents. Four notable activation functions, namely, Identity, Logistic, Tanh, and ReLU, have been tested to point out the best activation function for prediction.

The results indicate that ReLU is the most effective activation function in predicting travel mode choice for both male and female travellers, with training results of approximately 0.731 and 0.735, respectively. The difference between the training and testing prediction results of the machine learning model is relatively small and within an acceptable range, with a variance of just 0.041 for both male and female predictions. This minimal discrepancy indicates that the model generalises well to new data and does not suffer from significant overfitting or underfitting. Furthermore, these results underscore the significant role of activation functions in determining the overall performance of a neural network. Since activation functions influence how the network processes and learns from data, their selection directly impacts the model's accuracy and effectiveness, as supported by Sharma et al. [11]. This research work discusses the role of the ReLU activation function to gain insight into its effect on the performance of the neural network. Due to its popularity in recent research, Nair et al. [33] proposed the use of ReLU, citing its primary advantage: it is a non-saturated function that accelerates optimisation convergence. Furthermore, investigations by Adil et al. [8] and Çolak [12] highlighted the influence of the ReLU activation function on neuron optimisation within a neural network model. Their findings suggest that ReLU plays a significant role in enhancing the efficiency of neurons by improving the learning process and reducing computational complexity. Due to its ability to introduce non-linearity while maintaining simplicity, ReLU helps prevent issues such as vanishing gradients, making it a widely used activation function in deep learning applications.

Table 1 *Comparison of training and testing results for male respondents*

Activation function	Training	Testing
Identity	0.691	0.719
Logistic	0.706	0.690
Tanh	0.712	0.713
ReLU	0.731	0.690

Table 2 *Comparison of training and testing results for male respondents*

Activation function	Training	Testing
Identity	0.713	0.731
Logistic	0.719	0.717
Tanh	0.718	0.717
ReLU	0.735	0.694

The ReLU function is experimentally known to increase prediction accuracy [23], [25] and is effective in the process of optimisation [24]. Therefore, the results of this study demonstrate the effectiveness of ReLU in predicting travellers' mode choice by gender, compared to other activation functions. This paper presents an individual-level mode choice behaviour model using a neural network architecture, prompting us to consider the intrinsic properties of choice models, such as the fact that each person makes unique choices. Therefore, the operators of the public transportation system are recommended to adopt the findings of this research to improve the existing public transportation system.

4. Conclusions

The use of public transport might differ between genders, due to perceptions and the impact of the services themselves. This research examines how the public transportation system influences travellers' behaviour to understand the potential for switching from private to public transportation. When comparing private and public transportation, it is feasible to identify which aspects of travellers and their trips deserve particular attention using data on human travel behaviour. To effectively enhance conditions for public transport users, it is crucial to gather detailed data on relevant issues. This information is essential for estimating travel mode choice models and identifying initiatives that could incentivise greater public transportation usage. In this study, a machine learning technique is employed to generate an automated prediction of the factors influencing travel mode choice between genders, specifically male and female travellers. This work specifically develops a model for the travel mode choice problem using a neural network structure. Overall, the major finding of this research is that both male and female travellers agreed that region and waiting time are the most significant factors resulting in different preferences for mode of transport. Meanwhile, ReLU is depicted as the best activation function in predicting travel mode choice for both male and female travellers, with training results of approximately 0.731 and 0.735, respectively. The role of the ReLU activation function has been extensively discussed to gain insight into its effect towards the performance of the neural network.

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Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***Study conception and design:*** *Nur Fahriza Mohd Ali, Ahmad Farhan Mohd Sadullah;* ***Data collection:*** *Nur Fahriza Mohd Ali, Mohd Azraai Mohd Razman;* ***Analysis and interpretation of results:*** *Nur Fahriza Mohd Ali, Anwar P. P. Abdul Majeed, Author Z;* ***Draft manuscript preparation:*** *Nur Fahriza Mohd Ali, Ashiru Sani. All authors reviewed the results and approved the final version of the manuscript.*

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