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Use of Structural Equation Modelling and Neural Network to Analyse Shared Parking Choice Behaviour

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ABSTRACT

The shared parking mode represents a feasible solution to the persistent problem of parking scarcity in urban areas. This paper aims to examine the shared parking choice behaviours using a combination of structural equation modelling (SEM) and neural network, taking into account both the parking location characteristics and the travellers' characteristics. Data were collected from a commercial district in Nanjing, China, through an online questionnaire survey covering 11 factors affecting shared parking choice. The method involved two steps: firstly, SEM was applied to examine the influence of these factors on shared parking choice. Following this, the seven factors with the strongest correlation to shared parking choice were used to train a neural network model for shared parking prediction. This SEM-informed model was found to outperform a neural network model trained on all eleven factors across precision, recall, accuracy, F1 and AUC metrics. The research concluded that the selected factors significantly influence shared parking choice, reinforcing the hypothesis regarding the importance of parking location and traveller characteristics. These findings provide valuable insights to support the effective implementation and promotion of shared parking.

KEYWORDS

shared parking; structural equation modelling; neural networks; parking behaviour.

1. INTRODUCTION

UAvailable parking slots within city centre business districts (CBDs) are normally very limited. The growth of vehicle ownership has exacerbated the shortage of parking spots in a specific spatial and temporal environment. Urban parking issues are mainly caused by insufficient parking information and improper dynamic resource allocation, resulting in idle parking resources and unnecessary vehicle cruising [1]. Therefore, finding a suitable parking space in downtown areas (or mixed areas with both residential and business functionalities) often gives a headache to travellers in many large cities. Searching for a parking spot generally takes up a large portion of an individual's travel time. Some scholars have found that about 30 per cent of traffic congestion on roads often takes place when drivers are cruising for vacant parking spaces, and about 8.1 minutes are consumed in the quest to find a parking space (based on the data of several cases) [2, 3]. The frantic struggle to find a parking space can also add to the choking pollution and frequent congestion problem. In Los Angeles alone, about 1.61 million kilometres of low-speed travelling was estimated to waste 95,000 hours annually while consuming more than 45,000 gallons of fuel and releasing over 700 tons of CO2 in the process of finding parking spots [2]. In the context of growing car ownership and shrinking usable land in mega-cities such as London, Hong Kong and Beijing, it is both economically and spatially infeasible to solve the parking problem by resorting to constructing new parking facilities. Instead, many studies have proposed and evaluated a set of strategies such as parking pricing, parking reservation, parking permit systems or mechanisms to effectively manage parking supply and traffic congestion.

As one of the very effective countermeasures, the shared parking mode has also appeared as a new approach to make parking facilities more efficient. Shared parking refers to parking spaces that are shared by multiple users, thereby allowing the usage of parking facilities more efficiently. It is a type of parking management that utilises the fact that a massive number of parking spaces in urban areas are mostly used as part-time parking spots, by a particular driver or group, with patterns of utilisation following a foreseeable daily, weekly and annual pattern, and that a significant portion in many parking facilities often remains unused for the most part [4, 5]. The viability of implementing the shared parking concept in transit-oriented development was analysed, and the management strategy, design approach and mode of operation to apply the shared parking concept were discussed. Some strategies were suggested to promote the applicability and feasibility of shared parking, for instance, by reinforcing the organisation of parking lots, suspending the charge on public parking lots and providing shared parking spaces in new public buildings [4–9]. In other studies, shared parking also has been demonstrated as an effective solution to alleviate parking difficulties according to empirical research [4, 6, 7].

With the advancement in communication and information technology and the recent developments in mobile internet, different applications for private parking sharing are being developed that consider these predictable patterns, thus attempting to match the supply with the demand. It can be found that the intelligent, open residential area and the smartphone have provided a primary environment for shared parking [8, 9]. However, in addition to the underlying technical factors, the factors that influence the choice of parking behaviour more include parking location characteristics, the travellers' characteristics and the trip characteristics. It is very important to understand the effects of introducing or changing parking location characteristics, the travellers' characteristics and the trip characteristics on the parking choice behaviour of users to create appropriate strategies and policies for the successful implementation of this mode of parking.

In terms of behaviour studies, researchers in the past have mainly examined the parking choice behaviour of users based on the basic parking data survey examining different factors, such as parking cost, time, walking distance, etc. In this regard, a linear function model was built based on walking distance, travel distance and parking charge [10]. Similarly, another study involved the creation of a linear utility function to assess behaviours in terms of parking choice [11]. Some researchers in their study determined that path selection and the parking experience play crucial roles in parking choice behaviour [12]. Another team studied the choices of urban residents in terms of shared parking spaces by quantitatively analysing the factors that are suspected to influence this choice and built a logit model for discrete choices of shared spaces [13].

Similarly, parking choice behaviour was evaluated for different parking purposes using a binary logit model, which indicated that distance was the most influencing factor for commuters. In contrast, parking price was the most significant factor for non-commuters, impacting the decision among different forms of parking slots [13]. In another study, a disaggregate model was established to investigate how parking information influenced drivers' parking choice behaviours. Some scholars found that parking pricing can serve as a flexible tool to impact parking choice behaviours [14–18]. In a formal study, an analysis of the different kinds of parking slots in Spain revealed that travellers' characteristics such as income, driving experience, age and familiarity with the place played a role in the parking choice behaviour in addition to parking location characteristics, such as walking distance and driving distance [19]. It was concluded that the purposes of travel, the payment of parking fees, and the genders and occupations of people trying to find a parking space had a great effect on the decision-making of parking [13]. In another study, scholars analysed the effect of parking rates, types of parking lots and parking duration on residents' parking choices in detail and built a Bayesian network model [11]. A bi-level programming model was also developed for periodic allocation considering the coordinated utilisation of parking resources and the parking decision-making behaviour of individual drivers [8]. In general, the research on the parking choice behaviour of drivers varies a lot both in methodologies and objectives.

Although a fair amount of research has been conducted, previous studies on parking choice behaviour in general, and shared parking behaviour in particular, lack the assessment of the joint influence of both the parking location characteristics and the travellers' characteristics. Therefore, this paper aims to fill that gap by employing neural networks in combination with structural equation modelling (SEM) to model the simultaneous effect of the parking location characteristics and the travellers' characteristics on shared parking choice behaviour. The study has reached the conclusion that both the parking location characteristics and the travellers' characteristics have significant correlations with the shared parking choice behaviour, as will be explained in the following sections.

2. METHODOLOGY

This research employs a multi-layer feedforward neural network-based model to predict parking choice, using variables from the parking intention survey that significantly impact parking choice. The first step of the proposed methodology is to conduct a structural equation model (SEM) analysis of the parking intention survey data to identify the factors that have the strongest correlation with parking choice. Based on these significant factors, the multi-layer feedforward neural network-based model was developed by training it on the factors determined to have a high correlation from the SEM analysis. This model aims to accurately predict the demand for shared parking slots. The accuracy of the neural network model provides evidence that the selected variables are highly correlated with parking choice.

2.1 Structural equation modelling (SEM)

To identify the effect of each of these factors on parking choice, a structural equation model (SEM) was created by utilising these variables. The SEM is a statistical method that employs multivariate statistical analysis to analyse the structural relationships in a given dataset. It is essentially a combination of factor analysis with multiple regression for analysing the structural relationship among measured variables [20]. In terms of the relationship analysis among variables, the SEM can be used as a replacement for multiple regression, factor analysis, path analysis and covariance analysis as it is capable of analysing the relationship between dependent and independent variables, as well as how the dependent variables are related to each other. The main advantage offered by this method is that a single SEM-based analysis can estimate multiple and interrelated dependencies [21]. The SEM is an extensively employed technique for analysing travel behaviour and constructing parking behaviour-related models.

In SEM models, the variables used are of two types: endogenous and exogenous. Endogenous variables can be equated to dependent variables, while exogenous variables can be equated to independent ones. As the data from the survey in this paper have directly provided the parking decision and independent variables, the SEM analysis will only consider endogenous and exogenous variables rather than supplying any latent variables. The SEM model has two primary parts, the structural and the measurement models. The structural model signifies the relationships among different constructs, while the measurement model stipulates how measured variables come together to characterise the theory [22]. The SEM can be expressed as in *Equation 1*

$$\eta = \boldsymbol{B}\eta + \boldsymbol{\Gamma}\xi + \zeta \tag{1}$$

where the endogenous variable is represented by η, the exogenous variable is represented by ξ; the interactions among endogenous variables are represented by $\boldsymbol{B}$. In *Equation 1*, there is also a direct random effect matrix, represented by $\boldsymbol{\Gamma}$, which expresses the impact that exogenous variables tend to have on endogenous variables. However, ζ represents exogenous variables' influence on the endogenous ones that the model is unable to explain. This is also known as the model's residual error. There are classification, continuous and dummy variables in an SEM model. For an SEM model to work properly, the exogenous variables must affect the endogenous variable in a unidirectional manner. However, endogenous variables among themselves can have a one-way or two-way relationship without any issue.

2.2 Artificial neural network-based model

In order to create a model to predict the demand for shared parking slots, a multi-layer feedforward (MLFF) neural network, also termed a multi-layer perceptron (MLP), can be trained on the variables with the most significant influence on parking choice. An MLFF neural network is an interconnectedness of perceptrons in which there is a unidirectional flow of data and calculations from the input side to the output while passing through hidden layers. A number of studies have indicated MLP to be a universal approximator.

Even with a single hidden layer, an MLP has the capability of estimating any finite nonlinear function with a great level of precision. In each layer, some neurons are considered processing elements (PEs) of the MLP network. The basic MLP architecture is presented in *Figure 1*.

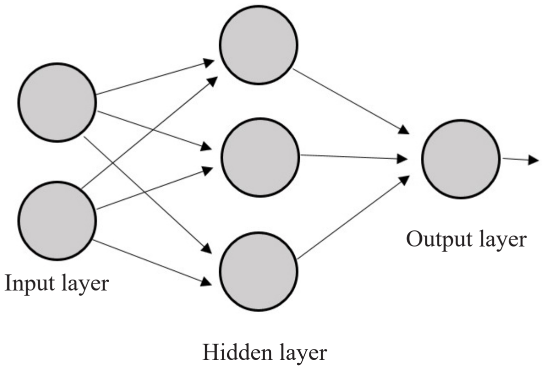

Figure 1 – Basic architecture of a multi-layer perceptron

Each neuron in a layer is linked to the entire number of neurons of the next layer in the network through lines representing the "weight coefficients". The function of the network is altered when these coefficients are subjected to any change. As a matter of fact, the primary goal of training the neural network is to determine the weight coefficients necessary for obtaining the required output. These weight coefficients are continuously adjusted during the learning process based on the learning patterns and methods.

Various activation functions can be used to train an MLP. Our study employed the rectified linear unit (ReLU) activation function for the hidden layer since the data contained no negative values. The ReLU is represented mathematically as $R(z)$=max(0,z), as in *Figure 2*. Regarding usage, the ReLU is the most common activation function in neural networks and is generally preferred as the first choice for many analyses. In ReLU, all positive values are considered linear (identity), while all the negative values are taken as zero. It allows for efficient computation with complicated mathematics being simplified. As a result, the model can be trained and run rather quickly compared to other activation functions. The convergence can also be achieved quickly with no vanishing gradient problem as in other functions such as tanh or sigmoid. Besides, the sigmoid activation function was utilised for the output layer. During the learning or training process, the error between the target output and the network's output is continuously calculated and the feedback is applied to the previous layer to adjust the weight coefficients. This feature of the MLP is known as "error-back-propagation".

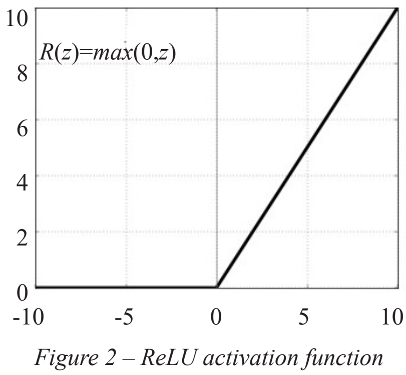

Figure 2 – ReLU activation function

2.3 Data description

The research adopts a subjective approach to analyse the parking choice behaviour and develop a neural network model by selecting the factors, through structural equation modelling, that substantially impact the parking choice. The approach is based on the results obtained from a parking intention survey (SP survey) conducted in a commercial district of Nanjing, China. The objective of this survey was to determine the relationship between the choice of shared parking spaces, the parking location characteristics and the travellers' characteristics. The data were collected through a survey questionnaire with carefully curated questions to determine the influence of parking location characteristics and the travellers' characteristics on the choice of either shared slots or normal parking slots. Previous research determined that the travellers' characteristics were usually composed of factors such as gender, age, income, occupation, etc. [12, 19]. In this survey, participants were asked questions related to the parking duration, walking distance to access the destination, parking

Table 1 – Variable statistics summary

Category	Variable	Level	Count	Percentage
Traveller characteristics	Gender	Male	124	50.00%
		Female	124	50.00%
	Income	>10,000 yuan	36	14.52%
		8,000–10,000 yuan	59	23.79%
		5,000–8,000 yuan	84	33.87%
		2,000–5,000 yuan	49	19.76%
		<2,000 yuan	20	8.06%
	Driving experience	1–5 years	156	62.90%
		5–10 years	69	27.82%
		>10 years	23	9.27%
	Travel purpose via private car	Working	125	50.40%
		Shopping	34	13.71%
		Sightseeing	54	21.77%
		Picking up friends and relatives	28	11.29%
		Others	7	2.82%
	Acceptable parking fee	15–20 yuan/hour	9	3.63%
		10–15 yuan/hour	44	17.74%
		5–10 yuan/hour	86	34.68%
		2–5 yuan/hour	78	31.45%
		<2 yuan/hour	31	12.50%
	Maximum walking distance	0–5 min	60	24.19%
		5–10 min	142	57.26%
		15–20 min	35	14.11%
		>20 min	11	4.44%
	Normal parking duration	>6 hours	54	21.77%
		4–6 hours	40	16.13%
		2–4 hours	81	32.66%
		0.5–2 hours	64	25.81%
		<0.5 hours	9	3.63%
Parking location characteristics	Limited parking time	No effect	7	2.82%
		General effect	64	25.81%
		Main influence	126	50.81%
		Important influence	51	20.56%
	Information limited	No effect	7	2.82%
		General effect	64	25.81%
		Main influence	82	33.06%
		Important influence	95	38.31%
	Vehicle safety	No effect	16	6.45%
		General effect	73	29.44%
		Main influence	85	34.27%
		Important influence	74	29.84%
	Others	No effect	48	19.35%
		General effect	145	58.47%
		Main influence	43	17.34%
		Important influence	12	4.84%

fee, parking location, etc. Regarding the parking location characteristics, it measured the influence of different variables related to parking location using a four-point Likert scale ranging from 1 (No effect) to 4 (Important influence). In addition, the survey also collected socioeconomic and travel information from the travellers. Finally, participants' subjective evaluations of the preference between normal and shared parking were also recorded in the survey. In short, the parking intention survey analysed a total of 12 factors from 248 respondents to find out their influence on parking choice behaviour. The variables used in the study and their basic statistics are shown in *Table 1* and *Figure 3*, respectively.

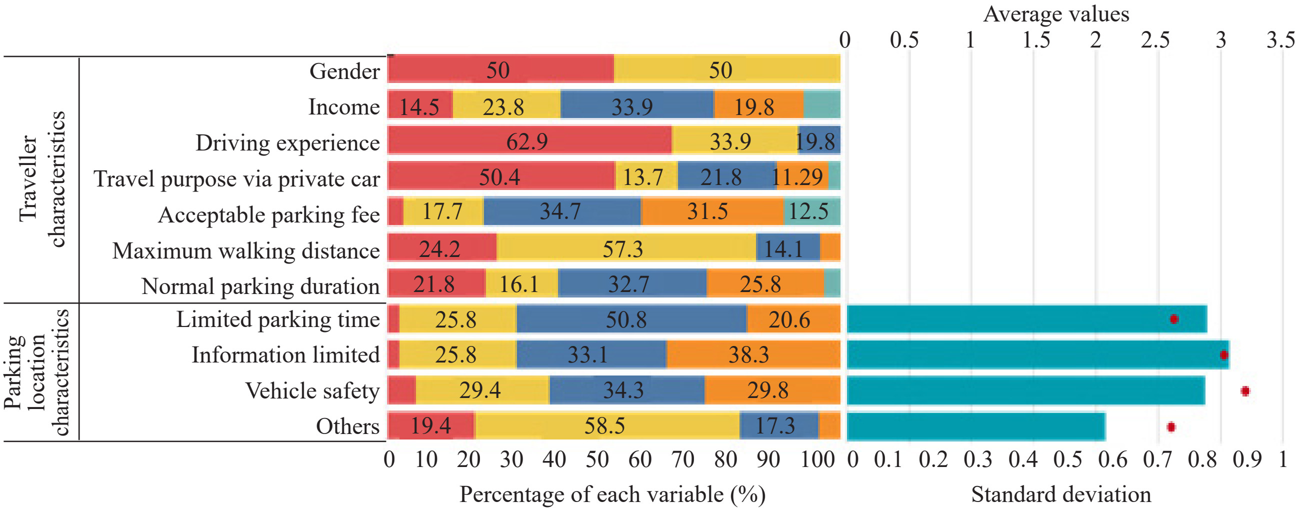

Figure 3 – Descriptive analysis of each variable

3. RESULTS

3.1 Selecting factors selected by SEM

The SEM for this study was created with SPSS Amos. The model's path diagram represents the relationships between exogenous and endogenous variables. A conceptual framework of the SEM established for this study is shown in *Figure 4*.

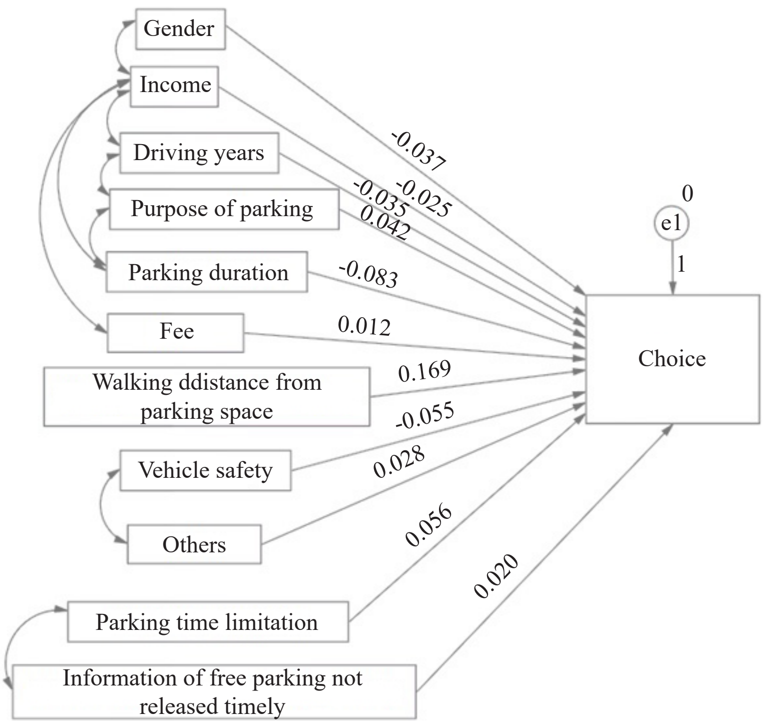

Figure 4 – Standardised regression weights of SEM model

-From the path diagram in *Figure 4*, it is clear that parking choice is the endogenous variable, whereas all the other eleven factors are exogenous variables. After creating the path diagram and assignment of the data labels, the SEM was employed with the maximum likelihood method. *Table 2* outlines some key goodness-of-fit parameters, which show that the model has achieved a good fit.

Table 2 – Goodness-of-fit statistics for SEM analysis

Goodness-of-fit statistic	Critical value	Model value
Root mean square error of approximation (RMSEA)	<0.05	0.019
Comparative fit index (CFI)	>0.9	0.966
Relative chi-square (CMIN/DF)	<2	1.094
Incremental fit index (IFI)	>0.9	0.971

In SEM, the acceptability of the overall model is established with the help of the fit indices. The different goodness-of-fit statistics values for the model fall within the acceptable range, which means that the constructed model is acceptable. Hence, the factors which have the most significant correlation with parking choice can be reasonably determined. For this purpose, the standardised regression weights yielded by the model were employed.

Figure 4 also represents the influence of different variables on the choice variables. Based on the standardised estimates, it can be seen that some variables are positively correlated with the choice, while others have a negative correlation. Based on the absolute estimates of these variables, the following top seven variables have been selected and ranked in order of their estimates from highest to lowest in *Table 3*. These selected factors, which are walking distance from parking space, parking duration, parking time limitation, vehicle safety, purpose of parking, driving experience and gender, have higher correlations with the parking choice.

Table 3 – Standardised regression weights

Variable	Estimate	Correlation	Variable	Estimate	Correlation
Walking distance from parking space	0.169	positive	Driving experience (years)	-0.035	negative
Parking duration	-0.083	negative	Others	0.028	positive
Parking time limitation	0.056	positive	Income	-0.025	negative
Vehicle safety	-0.055	negative	Information about free parking was not released timely	0.02	positive
Purpose of parking	0.042	positive	Fee	0.012	positive
Gender	-0.037	negative			

3.2 Training a neural network with the factors selected by SEM

Since the number of samples that have chosen shared parking slots in the dataset is much larger than those choosing normal parking slots, the positive and negative samples have been balanced by the synthetic minority oversampling technique (SMOTE) algorithm. SMOTE is a comprehensive sampling synthetic data algorithm for solving an imbalanced class problem. The general idea of this method is to artificially generate new examples of the minority class using the nearest neighbours of these cases. Furthermore, the examples of the majority class are also under-sampled, leading to a more balanced dataset.

Based on the results of SEM, it is evident that seven factors have a high degree of influence on shared parking behaviour. These seven factors are selected as the inputs to train a neural network to predict the shared parking choice of car users. A multi-layer feedforward neural network was created using the scikit-learn library in Python. The network consisted of one input layer with seven neurons corresponding to seven factors, one hidden layer with eleven neurons and an output layer with one neuron.

For comparison, we have also used all 11 variables to train another neural network to predict the behaviour of drivers' shared parking choices. Five measurement metrics, namely, accuracy, precision, recall, F1 and the area under the curve (AUC) were used to evaluate the two models' performance. *Table 4* summarises the comparison results of the two neural networks. It is easy to find that the neural network trained by seven selected factors from SEM performed better on shared parking choice prediction in terms of all the measurements, i.e. accuracy, precision, recall, F1 and AUC.

Table 4 – Summary of classification results

	Accuracy	Precision	Recall	F1	AUC
Neural Network 1	0.859	0.818	0.915	0.864	0.94
Neural Network 2	0.810	0.810	0.823	0.816	0.90

In addition, a receiver operating characteristic (ROC) curve is also used to visualise model performance (*Figure 5*). The ROC curve in red is for a neural network trained with seven factors and the yellow one is for a neural network trained with 11 factors, respectively. *Figure 5* shows that using the selected factors by SEM to train a neural network yields better results. It predicts the drivers' shared parking behaviour closer to their actual parking choice.

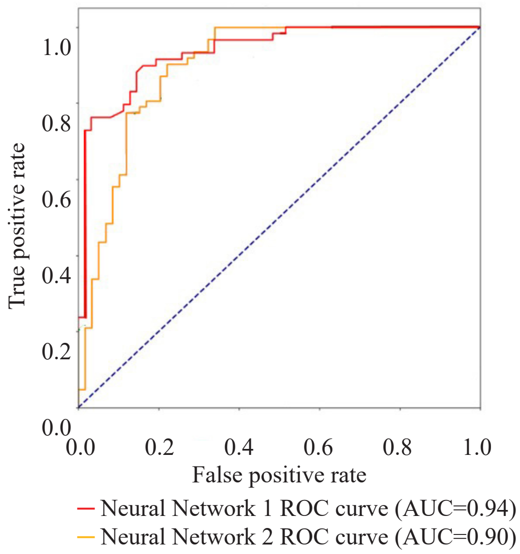

Figure 5 – Comparison of ROC curve between two NNs

4. DISCUSSION

Among the eleven attributes surveyed, seven were found to be the most relevant ones to parking choice based on the structural equation model. Among these seven attributes, parking location characteristics are the walking distance, vehicle safety aspect and parking time limitation. In contrast, gender, driving years, the purpose of parking and parking duration are the characteristics related to travellers. Using these seven factors to train neural networks for predicting drivers' shared parking choice behaviour produces better performance in terms of accuracy, precision, recall, F1 and AUC. The reasonable accuracy of the neural network model further verifies the influence of these attributes, thereby supporting the original hypothesis that the parking location characteristics and the traveller characteristics correlate with the shared parking choice behaviour, which can be used in the effective implementation and promotion of the shared mode of parking. The study also confirms the results of previous research on the topic by verifying that walking distance from the intended location to the parking spot substantially influences parking choice.

Based on the findings of this study, the following suggestions are provided for the implementation and advancement of the shared mode of parking:

– Regarding the selection of the site of parking slots, the walking distance from the intended destination to the parking slot needs to be minimised as much as possible to make the shared mode of parking more convenient for users. In addition, the parking process should be made more simplified to curb the needless parking time of the driver.
– The factor of vehicle security also holds great importance in the choice between different parking spots. The majority of the survey respondents were middle-aged people, who normally pay great attention to the

safety of their vehicles. Therefore, measures and procedures need to be implemented to improve the safety of shared parking lots to promote this mode of parking.

- The survey also found a correlation between the travellers' characteristics and the service level of the parking-sharing platform. Therefore, shared parking mode can be more attractive if the parking platform improves its level of service, makes the shared parking apps more user-friendly, and reinforces the interconnectivity between online parking lot reservations and the parking service on the ground level. The travellers' characteristics can also be considered to provide a much more personalised parking service.
- To promote and encourage shared parking, the parking platforms can create different promotion offers by categorising the users into different target groups based on the attributes analysed in this study.

5. CONCLUSION

The outstanding contributions of this paper are as follows. First, the current study has examined the different factors affecting the choice of the traveller for the shared mode of parking, where the factors have been grouped into two categories: parking location characteristics and traveller characteristics. A parking intention survey for the eleven different attributes was conducted, and structural equation modelling (SEM) was applied to identify the attributes with the most substantial impact on shared parking choice. This can help the factor choice be more considerable and make the model more accurate. Second, based on the results, a neural network model was developed to predict travellers' shared parking behaviour choice, and the performance improvement supports the attribute selection process by SEM. Finally, the research has revealed the main factors that impact travellers' decisions regarding shared parking mode, providing a foundation for decision-making regarding the implementation and promotion of shared parking. Therefore, the government and e-parking platforms can yield informed decisions about shared parking location, quantity and service level allocation. In addition, understanding shared parking choice behaviour can ensure that e-parking platforms recommend optimised parking spots to users, reducing the time and effort required for parking search and evaluation. This can lead to improved traffic conditions on roads.

It is important to note the limitations of this study. Among the 11 attributes, seven were found to be highly correlated with shared parking choice. However, the ignored attributes are not useless and their significance may vary with demographic variation. The sample size of 248 respondents may not represent all demographics and regions, and the study could be extended to include an even larger sample size. Furthermore, this study only analysed the parking choice intention from the user's perspective and further research is needed to examine the parking sharing intention from the supplier's perspective as well. Despite these limitations, shared parking can be a cost-effective solution to accommodate urban areas' growing population and vehicle numbers. As predictive models become more extensive and accurate, shared parking will likely become even more effective in the near future.

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朱翊，陈淑燕，吴颖，乔凤祥，马永锋

基于组合结构方程模型和神经网络的共享停车行为选择分析

摘要

共享停车模式是解决城市停车位稀缺问题的可行方案。 本文旨在结合结构方程模型（SEM）和神经网络来研究共享停车选择行为，同时考虑停车位置特征和出行者特征。 数据来自中国南京的一个商业区，通过在线问卷调查收集了影响共享停车选择的 11 个因素。 该方法包括两个步骤：首先，应用SEM来检验这些因素对共享停车选择的影响。 接下来，使用与共享停车选择相关性最强的七个因素来训练共享停车预测的神经网络模型。 研究发现，这种基于 SEM 的模型优于在精确度、召回率、准确度、F1 和 AUC 指标等所有 11 个因素上训练的神经网络模型。 研究得出的结论是，所选因素显着影响共享停车选择，强化了有关停车位置和旅行者特征重要性的假设。 这些发现为支持共享停车的有效实施和推广提供了宝贵的见解。

关键词

共享停车，结构方程模型， 神经网络，停车行为。