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Research article

To pay or not to pay? Understanding public acceptance of congestion pricing: A case study of Nanjing

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Abstract: Congestion pricing has been unquestionably recognized as an efficient strategy for managing traffic demand following the successful introduction of such schemes in a number of cities. However, the lack of political and public acceptance can be blamed for the nonexecution of congestion pricing projects in numerous cities around the world. This paper sheds light on the impacts of congestion pricing and the factors influencing its public acceptance. Our research was aimed to answer the following questions: (i) What are the factors that can influence public acceptance of congestion pricing? (ii) What are the impacts of implementing a congestion pricing scheme? (iii) How can we overcome the barriers that currently stand in the way of public acceptance of congestion pricing? To answer these questions, we developed a case study combining stated preference and revealed preference data collected in Nanjing, China. The study analyzes the acceptance of congestion pricing and the factors influencing it, such as socioeconomics, the perceived impact, fairness and public transit-related factors. We compare logistic regression and artificial neural network models to gain a deeper knowledge of the important factors and investigate the respondents' attitudes. The results revealed that the perceived impacts on congestion, the environment, trips to the city center, revenue allocation, public transportation price satisfaction, annual income, fairness, car ownership and travel frequency, along with the efficiency and capacity of public transport systems, need to be included when evaluating individuals' acceptance of congestion pricing. Among these, the perceived impacts on congestion and the environment, fairness and revenue allocation to public transportation are the most

significant factors. Moreover, we offer further qualitative insight into the individual, economic and social impacts of congestion pricing. This paper provides decision- and policy-makers with important advice on how to promote public acceptance when considering the implementation of a congestion pricing scheme.

Keywords: congestion pricing; public acceptance; machine learning; logistic regression; artificial neural networks; transport policy

1 Introduction

Traffic congestion has been a big issue in many regions around the globe. In addition to increasing travel time and decreasing the effectiveness of transportation systems, it has severe effects on a country's economic growth and environment, thereby limiting the regional sustainable development. In recent years, many analysts and policy-makers have focused their attention on the problem of urban roadway traffic congestion, which is becoming increasingly problematic. As a result of this assessment, congestion pricing has been identified as the most appropriate strategy for ensuring that existing roads are utilized to their full potential.

The concept of congestion pricing was first introduced by Pigou in 1920, but numerous studies have since been conducted to develop and refine it; see, for example, [1–3]. Although the introduction of congestion pricing has been considered and argued numerous times, public acceptance has proven to be the most significant obstacle to its implementation [4]. Congestion pricing has, in theory, two major challenges: political acceptance and public acceptance; these are in contrast to administrative and technological concerns, which many people believe are the fundamental obstacles to congestion pricing implementation. Many democratic countries have found it difficult to implement such programs because of a lack of strong political and public backing, or because of a lack of sufficient political and popular support [5].

Though numerous studies have acknowledged that numerous types of studies acknowledge that congestion pricing is an economically sound strategy for properly managing road traffic congestion, there have been few instances in which such projects have been fully executed beyond the design phase [6]. Thus, understanding road pricing in terms of public acceptance is a key topic, but in order to resolve this contentious subject, a careful analysis must be carried out [7]. Indeed, the absences of interest, familiarity and personal priorities require an immediate understanding of the determinants of the public's attitude (i.e., acceptance or rejection) toward congestion pricing. Recent years have seen a growing interest in the public's acceptance of congestion pricing, as primarily assessed by surveys and interviews; Zhou and Dai [8] investigated the smog awareness effects on the public acceptance of congestion pricing, Jakobsson et al. [9] discussed the factors that influence the acceptance of road charging by private car drivers; Fujii et al. [10], using concepts of fairness and freedom, explored car owners' acceptance of road pricing in Japan and Taiwan; Wang et al. [11] evaluated how public perception of uncertainty over fairness and efficacy influences acceptance of congestion pricing; finally, Li et al. [12] used a multinomial logit model to identify the main sources of the acceptance or rejection of a proposed scheme among business owners and stakeholders in Beijing, China. Therefore, research has tended to focus on particular factors or users, and very few studies were conducted in China.

This research was aimed to investigate, in a holistic way, the relationship between public acceptance and congestion pricing among respondents from different societal backgrounds in Nanjing city. In fact, 94% of the Chinese population resides on less than 43% of the land which has resulted in enormous regional disparities; consequently, the largest cities on the eastern side of China lack space for building and/or extending roads in infrastructure, making them home to the world's most congested roads. Furthermore, Nanjing was ranked among the top 10 most congested cities in China in 2020 [13]; so, congestion pricing could be the best approach in this circumstance. To ensure the success of a future implementation of this strategy in China, and to gain a better knowledge of the public's acceptance of congestion pricing, we evaluated data from Nanjing by using two of the most common and effective data analysis techniques: logistic regression and artificial neural networks.

This work was also aimed to provide a comprehensive analysis, including management strategies, and an interpretation of the impacts on the functional and symbolic levels of individuals and society from a Chinese perspective.

The remainder of this paper is structured as follows. In Section 2, we present a literature review of congestion pricing practices around the world, as well as the determinants of the public acceptance of this strategy. In Section 3, we describe our analysis methods and the datasets we used. In Section 4, we present the results and discuss the findings. In Sections 5 and 6, we discuss the policy implications, as well as the relationship between public acceptance of congestion pricing and its impact, and we compare our findings with those in the literature. In Section 7, we state our conclusions and suggest possible topics for future research.

2 Literature review

2.1 Congestion pricing practices

Congestion pricing is a radical new idea in transportation, but it has already been successfully implemented in cities all over the world. The idea is simple: to reduce city traffic by charging drivers for the privilege of driving during rush hours and on congested roads. The ultimate goal is to achieve healthier and more livable cities.

In London, for instance, the London congestion charge policy was finally adopted in 2003 after 30 years of preliminary feasibility studies. In fact, from 1965, multiple studies concluded that a congestion charging system in Central London would improve traffic and the environment, as well as increase generated revenue [14]. The success of the London scheme demonstrates how environmental objectives can benefit from transport charging as an instrument to discourage private transport. The main lesson learned from the scheme is that political leadership, widespread public support and clear communication are prerequisites for successfully implementing a transport charging scheme.

In 2006, the first trial of a congestion pricing scheme was introduced in Stockholm. It aimed to reduce traffic, improve accessibility and enhance environmental quality. The pilot was followed by a citizen referendum in September of the same year, in which 51.3% of Stockholm city residents voted in favor of the policy; the parliament subsequently chose to make the congestion charge system permanent. Six months following the trial, both public and political support had improved, despite the difficulty of convincing vehicle owners of the environmental advantages [15,16].

Singapore is another successful example. Due to its considerably small and limited surface, in the early 1970s, the government had no choice but to introduce an area licensing scheme. This policy led to a 20% increase in bus passengers and a 10% reduction in bus travel time. Tariffs vary during peak hours to increase road users' efficiency and fairness without incurring any additional costs. This was accomplished by implementing variable toll costs based on vehicle classification (vehicle type and the number of axles), the location of the gantry (based on the direction of travel) and the time of day or night [17].

Multiple adjustments were made to the plan's equity and complexity based on public feedback; and, in 1998, the area licensing scheme was superseded by the more sophisticated and adaptive electronic road pricing (ERP) system, in which charges are instantly assigned based on vehicle type, gantry location and time of day [18].

In 2007, the mayor of New York City announced a policy that included a congestion pricing trial [19]; after several revisions to the policy, and public campaigns, the plan was approved by a commission by a vote of 13 to 2. Nonetheless, two rounds afterwards, the state assembly chose not to vote on the proposal due to public and elected official opposition. Since then, researchers have investigated the rejection of this policy and reported that individuals who trusted the stated benefits of the plan, were more aware of it and/or used alternative modes of transportation were more likely to support it [20]. Besides the poor political handling, the absence of a congestion pricing pilot and the inadequacy of the proposed solution to the equity issue, the public and elected officials were primarily responsible for the rejection [21]. However, the state assembly surprisingly passed the congestion pricing law in 2020 when the lengthy path to completing the toll project was shortened by President Biden's approval of an environmental review, making New York City the first city in North America to implement a congestion pricing scheme [22]; it is expected to come into effect by the end of 2023.

Although the primary purpose of Norway's toll cordons was not to reduce traffic congestion, the toll cordons have had that effect. In fact, they have been used as a financial tool for road and infrastructural facility expansion for over eight decades. Toll financing projects were contingent on political agreement after a two-step political procedure consisting of toll finance acceptance and financing scheme approval. The use of road pricing in Norway was also prompted by the country's high gasoline and road maintenance taxes, which involve multiple tax systems and public funding [23].

In 1982, Hong Kong's government implemented the world's first ERP system to control and reduce traffic issues. Hong Kong is an example of a place where a road congestion pricing policy intended to benefit average citizens had to be reevaluated after politicians and decision-makers realized that it was unfeasible due to equity and fairness issues, not to mention its largest obstacle, which was perceived data privacy [24].

In 2008, Milan first implemented a cordon pricing program called "EcoPass", requiring all motorists entering the city center between 7.30 a.m. and 7.30 p.m., Monday through Friday, to pay a pollution tax proportional to their vehicles' emission levels. The program attempted to minimize air pollution and road congestion; as a result, after almost 1 year, traffic dropped by 12.3%, NO_x and CO_2 emissions were lowered by 17 and 14%, respectively, and the number of people using public transportation rose by 9.2% [25]. The plan was later superseded by "Area C" in 2012, which was a "pure" congestion pricing scheme; its impacts on traffic were even greater than those of its predecessor [26].

The Milan congestion charge scheme is a great example of how road pricing can successfully shift from a pollution control scheme to a congestion management scheme, as well as contribute to the whole European experience of pollution charges and road pricing in general.

2.2 Factors influencing congestion pricing acceptance

Based on previous experiences, the public acceptance of congestion pricing was primarily determined, as shown in Table 1, by four factors: privacy, uncertainty, complexity and equity. For each scenario, an additional investigation was conducted to determine the presence of the aforementioned factors, which were then either ignored or considered. Extensive research has demonstrated that problem perception, awareness of choices and alternatives, social norms, efficiency and perceived fairness are crucial acceptance drivers.

Table 1. Factors influencing the public acceptance of congestion pricing.

Factors	Definitions	Cases	References
Equity	The mechanisms for collecting tolls as well as the distribution of tolls among the major sociodemographic groupings.	• Singapore • London • Hong Kong (*) • Edinburgh (*) • New York (*)	[1,20,26,27]
Complexity	To create a tolling system that is, in principle, effective, it is necessary for the general public to have a solid comprehension of the congestion pricing strategy.	• Singapore • New York (*) • Stockholm • Edinburgh	[27–30]
Uncertainty	When users are aware of the current traffic situation, but they are uncertain about the proposed scheme in terms of how it will generate revenue and how it will be distributed.	• Hong Kong (*) • Edinburgh • Stockholm	[4,5,31–33]
Privacy	Drivers are often concerned that the system may record their personal information during transactions, thereby invading their privacy.	• London • Singapore • Hong Kong (*)	[24,30,34,35]
		(*) The case was rejected due to this factor	

To begin with, regarding the privacy concern, in the United Kingdom, the introduction of the London congestion charge sparked a public debate about privacy rights. Public support was threatened by concerns about privacy invasion [29]. Transport for London [30], however, made a statement that it would not store information and that the database would be encrypted and kept in a secure environment. The Singaporean ERP system devised a method of safeguarding the privacy of its users.

Because the ERP system does not retrieve information about specific vehicle occupants, the concern about private information has been alleviated in this case.

Another important factor is equity. The issue of fairness in congestion pricing consists of two components: the tolling tactics and the distribution of tolls across various sociodemographic categories. In fact, there is evidence that, in Hong Kong, New York City and Edinburgh, when proposed congestion pricing schemes were rejected, the question of equity was not addressed properly. In New York City, many revisions were made to the initial policy's complexity and fairness in response to public feedback [31].

As a matter of fact, establishing a potential charging scheme that is efficient, transparent, and valuable for motorists and the general public has been shown to be one of the key drivers to the public attitudes towards congestion pricing [27].

Moreover, uncertainty surrounding potential congestion pricing schemes is likely to hinder their future development. To guarantee their successful implementation, trials must therefore provide sufficient knowledge and information to the broader population. In addition, revenue allocation must be set out in detail to ensure public support for any congestion pricing scheme [32].

Several studies have tried to present measurement approaches to congestion pricing, but they have lacked theoretical and practical implementation of the concept [33]. Even though some studies have presented theoretical foundations, relatively few have described any practical implementation of congestion pricing and the primary motivating factors that can impact the public's willingness to accept it. The bulk of studies published on road pricing, such as [34–36], lack guidance toward achieving a comprehensive and well-developed transport policy; they also fail to show a basic economic rationale, something that is quite difficult to manage and implement. The studies lack information on traffic reforms and significant political rationale, because politicians tend to make the issue exceedingly complex and controversial.

3 Study methods

Conventional statistical models, such as logistic regression models, have been widely used in public attitude analyses. Numerous studies have adopted such models to analyze public acceptance and its influencing factors (e.g., [27,37–39]). Although they are accurate for a wide variety of simple datasets and perform well when datasets are linearly separable, these models show their disadvantages in capturing complex relationships.

Artificial neural networks are emerging as a viable alternative to conventional logistic regression, with which they have a large number of similarities [40]. In fact, artificial neural networks show strong ability in classification and, resultingly, high fitting accuracy. For example, to study public acceptance of urban road pricing, Hao et al. [41] used a cluster analysis approach to identify different groups of people. However, because of its relatively low interpretability, this method is still not commonly used in assessing the acceptance of congestion pricing. While the merits of the logistic regression and artificial neural network models are well understood, these models have not been considered in terms of assessing the public acceptance of congestion pricing. In this study, we examined the acceptance level of congestion pricing based on data collected (sample size = 1740) in Nanjing, China; we also considered the factors that influence public acceptance of congestion pricing, including socioeconomic, perceived impact, equity and public transit-related issues. Two models were implemented to meet the analysis requirements and investigate which factors were important for the successful implementation of a congestion pricing scheme.

The questionnaire was divided into two sections. The first section involves revealed preference experiments, which include questions on socioeconomic characteristics (e.g., gender, age, annual income, employment status, car ownership, family structure), travel frequency, level of satisfaction with public transport (e.g., price, service), primary transport mode for traveling to the city center and road condition. The second section involves congestion charges and draws from available literature on stated preference experiments that address specific questions about the most important variables influencing congestion pricing acceptance. The aforementioned variables will serve as independent variables in our models, while the final question of the survey (i.e., to what extent will you support the implementation of a congestion charge scheme in Nanjing?) will be the dependent variable.

3.1 Logistic regression

Logistic regression (alternatively referred to as logit regression) is a statistical model frequently used in supervised learning scenarios to predict the probability of an event based on a known dataset and assess either the likelihood of an event occurring or whether an instance belongs to a specific class. In this way, we can estimate which values of a set of features will produce the most accurate predictions.

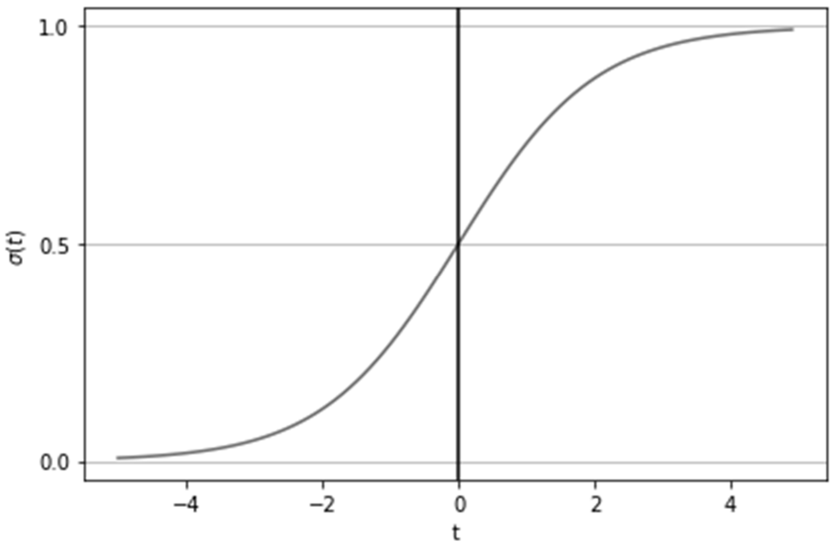


Figure 1. Sigmoid function graph.

The logistic model uses the logistic function, $\sigma(t)$, shown in Eq (1), where $x_1, x_2, \ldots, x_n$ represents the set of predictors, and $\beta_0, \beta_1, \beta_2, \ldots, \beta_n$, the corresponding coefficients. The product of the logistic function is expressed as a function of *t*, which is a linear combination of the predictors and their coefficients. This product forms an S-shaped curve with respect to *t*, ranging between 0 and 1, as shown in Figure 1.

$$\sigma(t)=\frac{e^{\beta_0+\beta_1x_1+\beta_2x_2\dots\beta_nx_n}}{1+e^{\beta_0+\beta_1x_1+\beta_2x_2\dots\beta_nx_n}}=\frac{1}{1+e^{-(\beta_0+\beta_1x_1+\beta_2x_2\dots\beta_nx_n)}}=\frac{1}{1+e^{-t}} \quad (1)$$

where $\sigma(t)$, ranging between 0 and 1, is the probability of the acceptance of a congestion pricing scheme, the set of predictors $x_1, x_2, \dots, x_n$ refers to the explanatory variables (i.e., age, gender, income, travel frequency, satisfaction level of public transport (e.g., price, service), primary transport mode for traveling to the city center, reducing congestion, etc.) , β_0 is the intercept of the model and $\beta_1, \beta_2, \dots, \beta_n$ represent the coefficients of the model for each explanatory variable.

After rearranging Eq (1), the quantity $\frac{p(x)}{1-p(x)}$, which represents the odds, was obtained as in Eq (2).

$$\frac{p(x)}{1-p(x)}=e^{\beta_0+\beta_1x_1+\beta_2x_2\dots\beta_nx_n} \quad (2)$$

The odds $\frac{p(x)}{1-p(x)}$can take any value from 0 to infinity. Values of odds close to 0 and ∞ indicate a significantly low probability of acceptance (strongly disagree) and a high probability of acceptance (strongly agree), respectively.

3.2 Artificial neural network

Artificial neurons implement weightings or multiplication factors to simulate the synaptic junction strength of biological neurons, and summations of signals received from every link model the action of the axon hillock. In 2011, Gyurova and Friedrich [42] described neural networks as being similar to the brain, containing a massively parallel collection of small and straightforward processing units. Models typically comprise numerous non-linear computational elements that operate in parallel and are organized into patterns reminiscent of biological neural nets [43].

For artificial neural network construction, no description of physical relationships nor observational theory is necessary. This aspect has an advantage over regression analysis and is, therefore, suitable for problem modeling when input and output relationships are unclear or significant formulation time is required. Lippman [43] suggested that, beyond optimal linear techniques, artificial neural networks can perform signal filter operations and functional approximations. This is enabled by their non-linear nature: they are capable of executing pattern recognition by defining non-linear regions in the feature space.

However, it has also been noted in most of the literature that artificial neural networks act like a “black box” because the modeling process is relatively complicated to understand, and it is difficult to obtain any physical relationship within the data from the network, resulting in low interpretability [42].

Figure 2 illustrates this concept with a typical artificial neural network structure. The circles (nodes) in Figure 2 represent the neurons (aggregation operations or functions); they constitute the input signal applied to the nodes of the next layer, while the connecting lines are used to represent the weights (coefficients). The output signal set of the output layer of the neural networks represents the response to the activation pattern supplied by the source neurons in the first input layer.

In our study, the nodes of the input layer represent the factors influencing the acceptance of a congestion pricing scheme in our study, i.e., age, gender, income, travel frequency, satisfaction level of public transport (*e.g.*, price, service), primary transport mode for traveling to the city center and likelihood to reduce congestion, whereas the output layer represents the acceptance of the scheme and the connecting lines represent the weight of each variable (the greater the weight, the greater the influence of the variable).

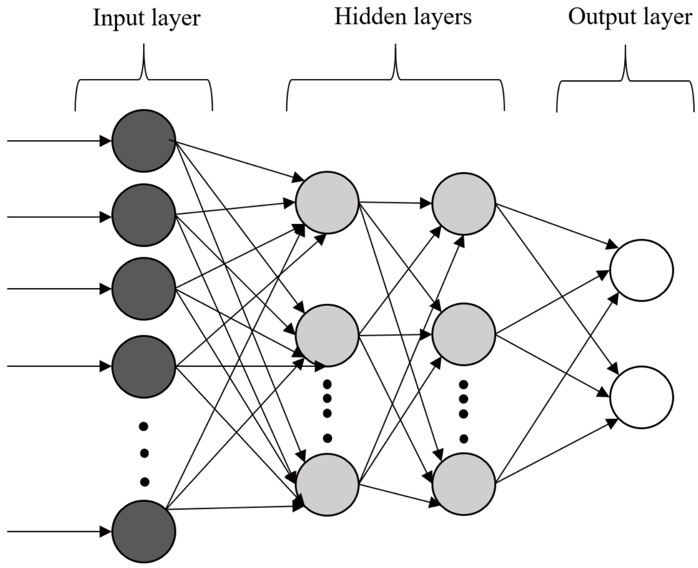
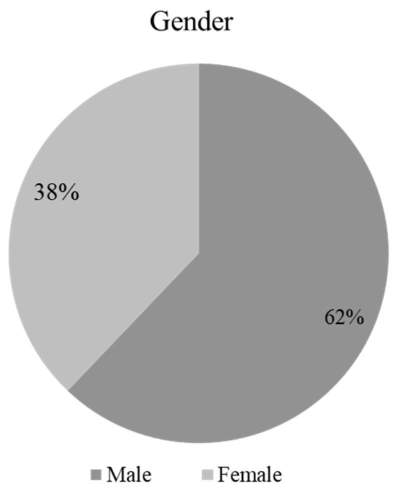


Figure 2. Illustration of neural network architecture.

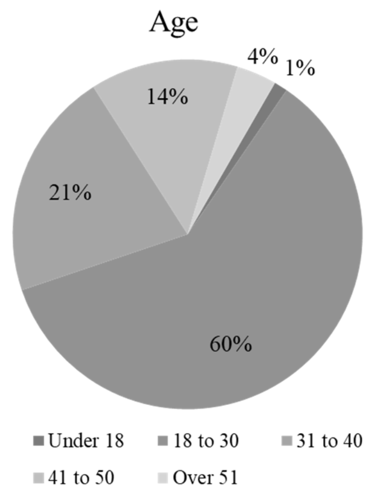
Artificial neural networks learn by minimizing error between predicted and target values through a process called backpropagation [44]; this entails producing a forecast, comparing it to the target value and finally adjusting the coefficients necessary to minimize the error. The first step in making these predictions is usually to set random weights as initialization and then multiply those weights by the nodes in a process called the forward pass.

4 Results and discussion

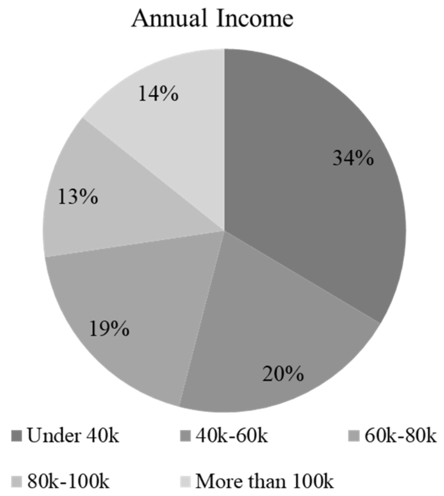
Figure 3 illustrates the percentage distribution of respondents by gender, age, annual income, car ownership and educational background. According to the results, 62% of respondents were men and 38% were women. The majority of respondents were aged 18 to 30 (60%), followed by those aged 31 to 40 (21%) and those aged 41 to 50 (14%). Additionally, 34% of respondents reported an annual income of less than 40,000 Chinese Yuan, while 20 and 19% reported annual incomes of between 40,000 and 60,000 and over 80,000 Chinese Yuan, respectively. Lastly, 48% of respondents claimed to not have access to a vehicle, while the remaining 52% reported having access to at least one vehicle.



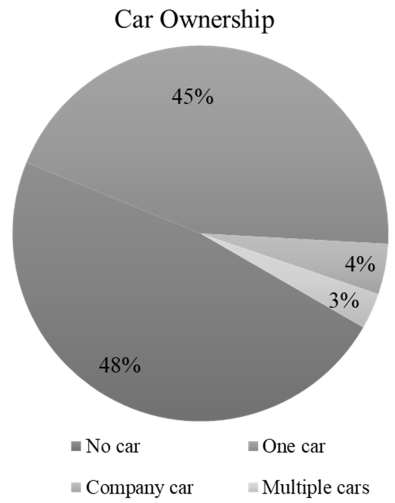
a Gender profile of survey respondents



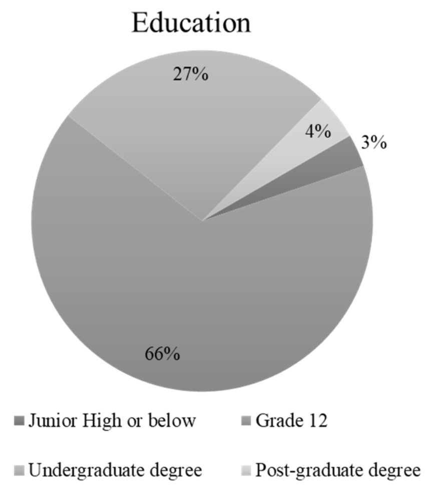
b Age profile of survey respondents



c Respondent annual income



d Respondent car ownership



e Respondent educational background

Figure 3. Respondents sociodemographic characteristics.

Table 2. Logistic regression results.

Pseudo R-squ.:	0.449		Log-Likelihood:			-664.56
Covariance Type:	Non-robust		LLR p-value			5.27E-207
	Coeff	Std err	z	P > |z|	[0.025	0.975]
Gender	0.1808	0.147	1.227	0.22	-0.108	0.47
Age	0.1647	0.151	1.091	0.275	-0.131	0.461
Income	-0.0596	0.082	-0.727	0.467	-0.22	0.101
Education	0.0162	0.152	0.107	0.915	-0.281	0.313
Full-Time Job*	0.6717	0.324	2.074	0.038	0.037	1.306
Part-Time Job	0.8097	0.657	1.233	0.218	-0.478	2.097
Self-Employed	0.5312	0.488	1.088	0.276	-0.425	1.488
Unemployed*	2.7118	1.409	1.925	0.054	-0.05	5.473
Retired*	-1.4182	0.541	-2.622	0.009	-2.478	-0.358
Car Ownership**	-0.544	0.107	-5.098	0.000	-0.753	-0.335
Household Single Person	0.2437	0.316	0.77	0.441	-0.377	0.864
Household Single Parents	0.4454	0.383	1.162	0.245	-0.306	1.197
Household Couple (No Children)	-0.5034	0.37	-1.361	0.173	-1.228	0.221
Household Couple (+ Children)	0.5298	0.31	1.711	0.087	-0.077	1.137
Household with Parents	-0.2489	0.396	-0.628	0.53	-1.025	0.527
Travel Frequency	-0.0734	0.074	-0.985	0.325	-0.219	0.073
Public Transport Efficiency	0.0403	0.125	0.321	0.748	-0.206	0.286
Satisfied with PT Fares*	0.2655	0.125	2.131	0.033	0.021	0.51
Private Car*	-0.7542	0.289	-2.611	0.009	-1.32	-0.188
Public Transport**	-1.1425	0.238	-4.797	0.000	-1.609	-0.676
Bike and Walking*	-1.4982	0.528	-2.838	0.005	-2.533	-0.463
PT Service Satisfaction	-0.2054	0.143	-1.439	0.15	-0.485	0.074
Use Revenue for Transit	-0.0387	0.081	-0.478	0.632	-0.197	0.12
Use Revenue for Environment*	-0.2138	0.099	-2.166	0.03	-0.407	-0.02
Reduce Congestion**	0.8029	0.123	6.541	0.000	0.562	1.044
Reduce Emissions*	0.3623	0.113	3.219	0.001	0.142	0.583
Unfair to Poor*	-0.2603	0.107	-2.434	0.015	-0.47	-0.051
Bad for the Economy	-0.3784	0.11	-3.452	0.001	-0.593	-0.164
PT Sufficiency	0.1588	0.109	1.455	0.146	-0.055	0.373
Use More PT *	0.2707	0.105	2.572	0.01	0.064	0.477
Less Trips to City**	-0.6385	0.115	-5.532	0.000	-0.865	-0.412
Jobs in City Less Appealing*	0.3226	0.126	2.562	0.01	0.076	0.569

*Note: **:P-value ≤ 0.001;* **: P-value ≤ 0.05*

PT: Public Transport *LLR: Log-Likelihood Ratio*

Correlations among variables were tested using the Pearson correlation method. The values that indicate the strength of the correlation range between -1 and 1. Values of 1 and -1 indicate complete correlation, while values closer to 0 suggest weaker correlation; a zero value indicates an independent relationship between two variables. The direction of the relationship is indicated by the sign of the value, where a negative value implies a negative relationship, and vice versa. The results returned values of 1.0 when each independent variable (shown in Table 2) was correlated against itself, while the correlation with other variables ranged mostly between -0.3 and 1, with few values between -0.7 and -0.4.

4.1 Logistic regression results

The results of the logistic regression model analysis are shown in Table 2. It can be seen that respondents who reported a high level of acceptance are likely to believe that congestion pricing will help reduce congestion (coefficient = 0.80, $p < 0.001$) and car emissions (coefficient = 0.3623, $p < 0.001$). On the other hand, the belief that congestion pricing revenue will be used to improve the environment unexpectedly showed a negative correlation with congestion pricing acceptance (coefficient = -0.21, $p < 0.05$). Additionally, respondents who were satisfied with public transportation prices (coefficient = 0.26, $p < 0.05$) and believed that a congestion pricing scheme would not only increase people's reliance on public transportation for downtown travel (coefficient = 0.27, $p < 0.05$), but would also result in a lack of interest in city-based jobs (coefficient = 0.32, $p < 0.05$), had a higher acceptance rate. In contrast, strong respondent opposition to this proposal was based on the notion that a congestion charge would discourage people from visiting the city for shopping or entertainment (coefficient = -0.63, $p < 0.05$). Additionally, individuals who owned at least one car (coefficient = -0.54, $p < 0.001$) or believed that the scheme was unfair to car users and low-income groups (coefficient = -0.26, $p < 0.05$) were more likely to express significant opposition to this approach. Congestion pricing acceptance appeared to be unaffected by other factors such as age (coefficient = 0.16, $p = 0.27$), gender (coefficient = 0.18, $p = 0.21$), education (coefficient = 0.01, $p = 0.91$), income (coefficient = -0.05, $p = 0.46$) and travel frequency (coefficient = -0.07, $p = 0.32$).

The logistic regression results have merit in that the direction and intensity with respect to each input variable and its statistical significance are explicitly given, allowing for direct quantification of the expected impact of a change of a specific predictor in the planning stage. However, the assumed linear relationship (i.e., the input t is a linear function of the predictors and their coefficients) can be overly modeled, and the basic assumption of (nearly complete) independence among the predictors might cause biased or over-/underrated results if some of the results are correlated. The observed, counterintuitive results may be due to limitations of the logistic modeling method.

4.2 Artificial neural network model results

The neural networks were built using Scikit-Learn, and a multilayer perceptron (MLP) architecture was adopted for the model.

A grid search algorithm was used to optimize model performance by traversing given combinations of parameters. In grid search cross-validation, the algorithm optimizes the model performance according to the results of cross-validation. Cross-validation on a fundamental level is referred to as k-fold cross-validation [45]. The training set was divided into k subsets. The following procedure was followed for each of the k "folds":

• A model was trained using k-1 of the folds as training data;

• The resulting model was validated on the remaining part of the data.

The k-fold cross-validation performance measure is therefore the average of the values obtained in the loop. While this strategy is computationally intensive, it avoids excessive data waste, which is critical for issues such as inverse inference, which requires a minimal number of samples.

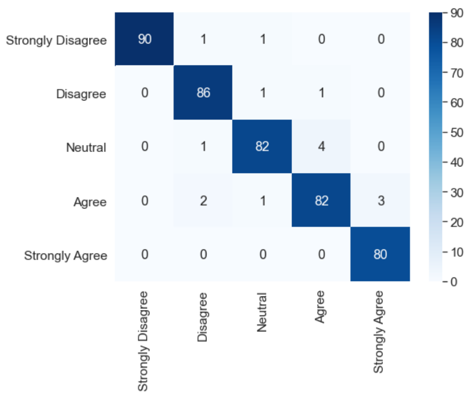
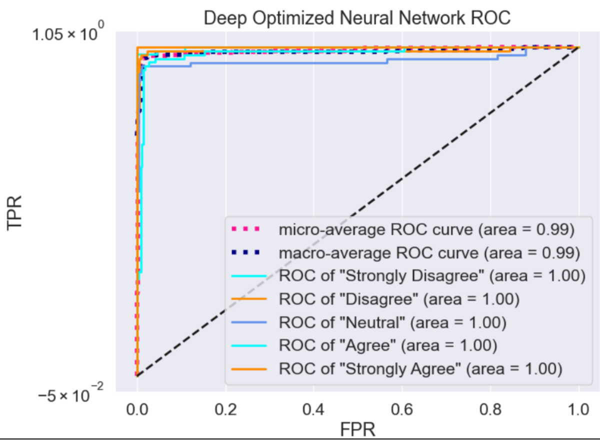
Grid search cross-validation was used to build an optimized MLP classifier; the tested parameters were as follows:

- Single hidden layer with 25, 50, 75 and 100 nodes
- Two hidden layers with corresponding numbers of nodes of (25, 25), (50, 50), (75, 75) and (100, 100)
- Activation functions tested were logistic, tanh and ReLU

Twenty-two total combinations were tested; and, the result of the optimized architecture with the highest accuracy came from the tanh activation function with a (100, 100) hidden layer size.

Table 3 shows an overview of the optimized neural network MLP classifier (100, 100) model results. The receiver operator characteristic (ROC) curve is commonly used to illustrate the compromise between sensitivity (or the true positive rate (TPR)) and specificity (1 – false positive rate (FPR)). A random classifier is expected to generate points along the diagonal (FPR = TPR) as a baseline. The less accurate the test, the closer the curve is to the 45° diagonal of the ROC space, while classifiers that generate curves closer to the upper-left corner perform better. The ROC curve and the confusion matrix of the model indicate that the optimized neural network MLP classifier gives clearly better results than the precedent model; it also has a reasonably extensive convergence, because the predicted outputs matched the actual targets at a rate of 96%.

Table 3. Artificial neural network confusion matrix and ROC curve.

<table>
<tr><th></th><th>Confusion matrix</th><th>ROC curve</th></tr>
<tr><td>Optimized neural network MLP classifier</td><td>
</td><td>
</td></tr>
</table>

	Precision	Recall	F1-score	Support
Accuracy	0.965517	0.965517	0.965517	0.965517

To assess the factors that highly influence congestion pricing acceptance according to the optimized neural network model, the weights of the features were set as listed in descending order of strength in Table 4.

Table 4. Weights of features in optimized neural network MLP classifier.

Feature	Weight
Reducing Congestion	0.2017 ± 0.0242
Public Transport	0.0714 ± 0.0047
Reduce Emissions	0.0638 ± 0.0129
PT Efficiency	0.0613 ± 0.0078
Unfair to Poor	0.0552 ± 0.0105
Car Ownership	0.0527 ± 0.0068
Income	0.0440 ± 0.0085
Use More Public Transport	0.0359 ± 0.0049
Private Car	0.0352 ± 0.0054
Less Trips to City	0.0333 ± 0.0028
Satisfied with PT Fares	0.0319 ± 0.0023
PT Service Satisfaction	0.0282 ± 0.0109
Use Revenues for Transit	0.0277 ± 0.0053
Travel Frequency	0.0268 ± 0.0042
Self-Employed	0.0231 ± 0.0039
Household Single parents	0.0207 ± 0.0048
Gender	0.0192 ± 0.0066
Use Revenue for Environment	0.0161 ± 0.0035
Bike and Walking	0.0159 ± 0.0026
Household Single person	0.0149 ± 0.0025
PT Sufficiency	0.0123 ± 0.0043
Household Couple (No Children)	0.0118 ± 0.0023
Bad for the Economy	0.0097 ± 0.0028
Age	0.0078 ± 0.0037
Retired	0.0058 ± 0.0044
Jobs in City Less Appealing	0.0057 ± 0.0042
Household Couple (+ Children)	0.0055 ± 0.0037
Education	0.0043 ± 0.0039
Full-Time Job	0.0028 ± 0.0008
Part-Time Job	0.0025 ± 0.0011
Household with Parents	0.0021 ± 0.0006
Unemployed	0.0020 ± 0.0016

Consistent with the logit model, the artificial neural network results show that the primary elements that influence public acceptance of congestion pricing include the presumption that a pricing scheme would help reduce traffic congestion and vehicle pollutants, along with fairness to the lower-income class and car drivers; the effect of fairness is perhaps somewhat counterintuitive given that one might naturally think that people would be more willing to pay in order to get what they perceive as a valued service. Under certain assumptions, this can be construed as implying that perceived inequity will generate resentment, which ultimately may provoke counterproductive reactions by drivers who perceive themselves as having been forced to pay rather than voluntarily paying the fee.

Moreover, other factors that are mainly related to public transport were interestingly shown to be more influential in the current model outputs than in the logistic regression model, such as comments on bus efficiency, public transport price and service and the use of revenue to improve public transportation systems. In other words, the accuracy of predicting public acceptance of congestion pricing was increased by public transportation system improvements and bus efficiency including pricing and service. As such, it can be useful both for planners and policy-makers to understand how they can improve the conditions of the public transport systems to increase public acceptability of congestion pricing, hence ultimately increasing its chance of implementation.

Besides this, the results show that people who travel frequently by using public transport had a higher acceptance rate for congestion pricing, which may also reflect, on the other side, that respondents who own at least one car will strongly oppose charging schemes; thus, car ownership and income do influence congestion pricing acceptance.

The pattern of results suggests that income helps predict willingness to pay for road use. Given that the model indicated that there is in fact a relationship between income and support for congestion charging, we believe that lower-income groups may be more skeptical about this policy. This result also suggests that low-income people may have less flexibility in their travel options and higher levels of dependence on public transport. These findings may shed light on how certain individuals perceive similar policies differently depending on their social class and level of social mobility.

Additionally, contrary to expectations, this study did not find a significant association between willingness to pay and any of the following variables in either the linear regression or neural networks models: education, household structure, age, gender and occupation.

Finally, the analysis of the dataset using the aforesaid models shows that the main factors that can influence congestion pricing acceptance are as follows: ability to reduce road congestion and car emissions, car ownership, comments on public transportation systems fees, the use of a private car/public transport as primary transportation mode, fairness of the scheme, traveling less to city center for entertainment and switching to multimodal transport. However, what is surprising is that some factors, which we believe to be very important according to the literature in Section 2, were not included in the panel of the most influencing factors in the logistic regression model, e.g., income, travel frequency and using congestion pricing revenue to improve public transportation systems. On this basis, various hypotheses arise to account for these observations, such as those regarding the accuracy of the model or the possibility of a strong correlation between two variables.

The present findings confirm that logistic regression is a simpler and more straightforward technique to implement and use to analyze results. It can indicate not only the relevance of a predictor (coefficient), but also the direction of the relationship between the dependent and the independent variables (positive or negative). In spite of this, the primary constraint for logit models is the linear association between the variables, which can make it difficult to capture complex relationships. This approach is readily outperformed by more powerful and compact algorithms, such as neural networks.

5 Public acceptance and impacts of congestion pricing

Our results cast a new light on the importance of understanding the relationship between the public's willingness to support congestion pricing and the policy effects, many of which are centered on the economic, social and individual aspects. Table 5 shows the functional (i.e., What does it do for you/ for society/ for the economy?) and symbolic dimensions (i.e., What does it represent?) of each of the aforementioned aspects.

Table 5. Functional and symbolic dimensions of congestion pricing impacts.

	Functional Dimension	Symbolic Dimension
Social Impacts	• Reduces pollution and emissions • Reduces congestion • Generates revenue • Reduces accidents	• Healthier environment • Improves travel time and speed • Improves public transportation • Benefits users • Increases safety
Individual Impacts	• Time gaining • Modal switch (more walking, biking and carpooling)	• Reduces delays and stress • Better health • More savings
Economic Impacts	• Guarantees free flow of traffic • Generates revenue • Increases trip time predictability	• Ensures reliability • Keeps business and goods costs low • Allows more deliveries per hour

Our findings are directly in line with previous findings, such as those of Bhatt et al. [46], who stated that allocating revenues to the most favored purposes is essential for public support. According to the literature, revenue dedicated to public transportation and/or infrastructure improvements may generate support in some regions, but may also compete with other inclinations, such as potential tax cuts, in others. Moreover, equity among income groups exposed to pricing frequently causes experts in the field of road pricing to discuss fairness. However, studies suggest that congestion pricing acceptance may not differ significantly across income levels, and that a broader definition of equity may predominate and require more consideration. Specifically, the following equity perspectives may be pertinent: fairness of outcome, i.e., assurance that some are not evading the pricing area; procedural fairness, i.e., allowing the public to contribute to the plan's development; and fairness to special groups, such as persons with disabilities and reduced mobility and emergency workers.

In addition to this, our results show that the general public appears to be more receptive to congestion pricing if it is believed that the revenue from the scheme will be distributed to help improve the environment and that the system will help reduce congestion and emissions. In fact, the cases of London and Stockholm were successful for these reasons, as there have been reports of better air quality within and in the areas surrounding congestion-charging zones. Some of these reductions are due to decreased traffic volumes, but the majority are attributable to the growth of public transit, as made possible by the revenue generated from congestion pricing, which has the potential to decrease pollution and sustain reductions over time [46]. Specifically, in Stockholm, congestion charging resulted in an up to 14% reduction in emissions [47].

Our analysis also demonstrates that people's perceptions of fairness have a substantial impact on their perception of congestion pricing; hence, the equity implications of the policy are crucial in determining whether or not it will be supported by the general public. This is determined by comparing the amount charged to the average income of the population, the availability of other modes of transportation and the effectiveness of all systems; most important, however, are the impacts of congestion pricing on traffic and the environment.

6 Policy implications

There are different criteria for implementing schemes in different cities, such as private car ownership and the flexibility of the public transportation system. Furthermore, there are some important points to be accepted by both sides of the debate. First, congestion charging cannot always solve all traffic congestion and space utilization issues. Second, the scheme can only play an important role in improving transportation efficiency if it is designed within a comprehensive transport planning approach. Third, it will be necessary to put in place measures to complement and reinforce any congestion charging scheme, such as the investment of public funds in public transport infrastructure. For example, in China, the government has made significant investments in new bus lines and metro lines, which will be helpful in reducing the number of private cars using road space and increasing public acceptance of any eventual congestion pricing scheme in cities like Shanghai, Beijing, Guangzhou or Nanjing.

Our investigation in Nanjing revealed a strong association between the public acceptance of congestion pricing and satisfaction with the quality of transit and related services. Therefore, congestion pricing must be included in any comprehensive package of transportation measures. When London first implemented congestion pricing, 33 complementary measures were also implemented to improve public transit services, provide alternative options and optimize signal timing. In addition, it is worth noting that China's transportation system has dramatically improved over the last few years. Nanjing, for example, has expanded its subway network from 2005 to the present with 11 lines and 191 stations, and it has over 10 new lines and extensions under construction that are expected to be completed by 2026 [48], making it an ideal location for the implementation of a congestion pricing scheme.

Before adopting such schemes, many publicity campaigns must be carried out through both print and online media to increase market development. In addition, the local government of Nanjing should initially implement a trial plan and use the generated revenue to upgrade transit systems, offer discounts to public transportation passengers and reduce peak-hour transit fares. Parking management is an additional complementary strategy, especially in the Xinjiekou area and across the central business district. This strategy can strongly influence demand. Nevertheless, it has been underutilized by several authorities. It can help lower demand for automotive travel and, as a result, address location- and time-based traffic congestion.

Furthermore, transparency in toll fees collected and how they are spent can make congestion pricing more acceptable to the public. The public is often conscious of fees paid through congestion pricing policies, and hence is keen to ensure that revenue is not wasted or lost. Therefore, it is extremely important that the process be transparent, and that information on revenue generated and how it is spent to benefit the public must be clearly communicated.

Finally, there should be some sort of compensation mechanism in place for disadvantaged groups and businesses that are affected. Most importantly, though, it is critical to maintain a cost-effective user charge and improve the performance of the plan through the employment of an affordable and adaptable pricing system.

7 Conclusions

Among the ideas to alleviate traffic congestion, constructing new infrastructure and improving available alternatives are abstract concepts; the possibility of congestion charging, however, is concrete. In many instances, low public acceptance prior to the implementation is the major impediment to congestion pricing schemes. Thus, this paper investigates several factors that influence public support for congestion pricing before and during its implementation by government.

Based on the survey analysis results of three different methods, we derived the general facts that the perceived impacts on congestion and the environment, trips to the city center, revenue allocation, public transportation price satisfaction, annual income, fairness, car ownership and travel frequency, along with the efficiency and capacity of public transport systems, need to be included when evaluating individuals' acceptance of congestion pricing. Among these factors, the perceived impacts on congestion and the environment, fairness and revenue allocation to public transportation are the most significant features. Additionally, respondents who support the ideas that congestion pricing can help protect the environment by reducing vehicle emissions, and that its revenue can be used to improve the environment, are likely to strongly support the congestion pricing policy. In contrast, the belief that congestion charging will discourage people from visiting the city center for shopping or entertainment is the primary reason that some respondents oppose the policy. Additionally, individuals who own at least one car are more likely to express significant opposition to this approach. Accordingly, the key to increasing public acceptance is to improve public transportation, raise public awareness about policy and revenue redistribution strategies and alter individual expectations regarding congestion charging impacts.

Unsurprisingly, as with any other innovation, the system has a number of inherent limits that, when considered, may result in its installation being rejected. Given these points, our study offers further insight into the individual, economic and social impacts of congestion pricing. Additionally, we provide decision- and policy-makers with important advice on how to promote the public approval of a congestion pricing scheme. To increase public trust and confidence, it is necessary to educate the general public vigorously about the complexity, privacy and fairness of the scheme. The government should safeguard the confidentiality of the personal information of all parties concerned. To achieve the overall goals, a forecasting model should be established to predict possible changes that will arise from implementation of the plan.

The findings of this research can provide knowledge for policy-makers as they consider the implementation of congestion pricing policies and attempt to enhance public acceptance. However, more improvements may be made in future research; for example, we plan to incorporate more features into the models, such as pricing and time options. These elements will provide decision- and policy-makers with more adaptable insight, assisting them in increasing congestion pricing acceptance.

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Conflict of interest

The authors declare no conflict of interest.

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