

Article

A Modified Method for Evaluating Sustainable Transport Solutions Based on AHP and Dempster–Shafer Evidence Theory

Luyuan Chen ¹ and Xinyang Deng ^{2,*}

¹ School of Computer, Northwestern Polytechnical University, Xi'an 710072, China; chenluyuan@mail.nwpu.edu.cn

² School of Electronics and Information, Northwestern Polytechnical University, Xi'an 710072, China

* Correspondence: xinyang.deng@nwpu.edu.cn; Tel.: +86-29-8843-1267

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Abstract: With the challenge of transportation environment, a large amount of attention is paid to sustainable mobility worldwide, thus bringing the problem of the evaluation of sustainable transport solutions. In this paper, a modified method based on analytical hierarchy process (AHP) and Dempster–Shafer evidence theory (D-S theory) is proposed for evaluating the impact of transport measures on city sustainability. AHP is adapted to determine the weight of sustainability criteria while D-S theory is used for data fusion of the sustainability assessment. A Transport Sustainability Index (TSI) is presented as a primary measure to determine whether transport solutions have a positive impact on city sustainability. A case study of car-sharing is illustrated to show the efficiency of our proposed method. Our modified method has two desirable properties. One is that the BPA is generated with a new modification framework of evaluation levels, which can flexibly manage uncertain information. The other is that the modified method has excellent performance in sensitivity analysis.

Keywords: sustainability evaluation; analytic hierarchy process; Dempster–Shafer evidence theory; Transport Sustainability Index; car-sharing; sensitivity analysis

1. Introduction

Transport has become the basis for the daily operation of society and economy, yet the reliance on transportation as a daily function is a substantive contributor to numerous problems faced by modern society, such as air pollution, noise, congestion, safety, travel delays, and many more [1,2]. To curb these growing problems, sustainable transport has entered the research field of transportation experts and has gradually gained increasing attention [3–8]. Sustainable transport is defined as “transportation that meets mobility needs while also preserving and enhancing human and ecosystem health, economic progress and social justice now and in the future [9]”. In other words, sustainable transport needs to promote sustainability in terms of society, environment, and economy. Research is under way to develop sustainable transport solutions, aiming to improve urban transport conditions either in terms of the environment, societal benefits, or the economy.

Instead, our attention is shifted to the evaluation of sustainable transport solutions—especially environment-friendly measures—as they influence city sustainability. These transport solutions include mode sharing such as car-sharing, bike-sharing [10], and park-and-ride systems [11]; intelligent transport solutions like electrical vehicles [12] and plug-in electric vehicles (PEVs) [13]; as well as multi-modal transport solutions [14–16], etc. A broad range of methods and techniques have been proposed to assess the impact of transport solutions on city sustainability. Jeon and Amekudzi [17]

developed and determined indicator systems for measuring sustainability in transportation systems. Litman and Burwell [18] addressed the issues related to the definition, evaluation, and implementation of sustainable transportation. Forty-two techniques that could be used to evaluate the sustainability of urban transportation and 20 commentaries on the mentioned techniques were presented by Wellar [19] in the Transport Canada project.

Recently, Anjali Awasthi et al. [20] put forward a hybrid approach based on analytical hierarchy process (AHP) and Dempster–Shafer evidence theory (D-S theory) to evaluate the influence of environment-friendly transport measures on city sustainability. AHP was firstly used to structure and weight the criteria related to sustainability assessment. Then, the data from multiple information sources was combined using D-S theory and the utility estimation could be obtained. Finally, Transportation Sustainability Indexes (TSIs) with respect to the pre-test stage and post-test stage were compared to make a decision regarding whether the transportation measure had a positive impact on city sustainability and thus could be recommended for adoption in the city. The main advantage of this approach lies in the application of D-S theory to deal with uncertain and incomplete information.

However, the most important issue is not well addressed in Anjali Awasthi et al.'s method [20]: the representation of confidence in evaluation levels for utility is not basic probability assignments (BPAs), but only the probability function [21], which does not make full use of the feature of D-S theory. To address this issue, we propose a modified evidential model for evaluating sustainable transport solutions. The modified method can handle the referred issue in a simple but efficient way, which has two desirable properties: one is that the BPA is generated with a new modification framework of evaluation levels and hence it can flexibly manage uncertain information. The other is that the modified method has excellent performance in sensitivity analysis, which is conducted in terms of the conflictive information of the sustainability assessment and the weight changes of different criteria. Two techniques (AHP and D-S theory) are also referred, as AHP is an effective tool to determine the weight of different criteria in a multi-criteria decision-making (MCDM) problem and D-S theory can manage uncertain, ignorant, and missing information well that are very likely to happen in realistic situations [22–29].

The organization of the rest of this paper is as follows. Section 2 starts with a brief presentation of basic concepts. The proposed evidential model based on AHP and D-S theory to evaluate sustainable transport solutions is introduced in Section 3. Section 4 investigates the implementation of car-sharing in our proposed method. A discussion is presented in Section 5. In Section 6, the paper is ended with a brief summary.

2. Preliminaries

2.1. Dempster–Shafer Theory

Information in the real world is affected by a great deal of uncertainty. Many existing theories (e.g., probability theory, fuzzy numbers [30–33], Z-numbers [34–36], D-numbers [37–39], and Dempster–Shafer evidence theory) have been developed to represent various types of uncertainty. Dempster–Shafer evidence theory (D-S theory) can be regarded as a general extension of Bayesian theory. It was first proposed by Dempster in 1967 [40], and was developed to its present form by Glenn Shafer in 1976 [41]. D-S theory can present and handle uncertainty preferably than probability theory [42–44]. Moreover, it provides a combination rule to fuse different data from various information sources. D-S theory is now being studied for use in many fields, such as risk assessment [45,46], decision making [47–49], fault diagnosis [50,51], and others [52–56].

Let $\Theta = \{\{H_1\}, \{H_2\}, \dots, \{H_n\}\}$ be a finite nonempty set of n elements that are mutually exclusive and exhaustive, 2^Θ is the power set composed of 2^n elements of Θ , and \emptyset denotes the empty

set. In D-S theory, mathematically a basic probability assignment (BPA) is a mapping: $2^\Theta \rightarrow [0, 1]$ that satisfies

$$\sum_{A \subseteq \Theta} m(A) = 1, m(\emptyset) = 0. \tag{1}$$

If $m(A) > 0$, A is called a focal element, and the set of all focal elements is named a body of evidence (BOE). The probability $m(A)$ measures the belief exactly assigned to A and represents how strongly the evidence supports A . The mass of belief in an element of Θ is quite similar to a probability distribution, but differs in the fact that the unit mass is distributed among the elements of 2^Θ , not only on single subsets but on composite hypotheses as well. This is why BPA can better represent the uncertainty of information.

Moreover, a combination tool is offered by D-S theory to fuse multiple belief assignments as follows:

$$m = m_1 \oplus m_2 \oplus m_3 \oplus \dots \oplus m_k, \tag{2}$$

where \oplus represents the operator of combination. For two BOEs, Dempster’s rule of combination is defined as:

$$m_1 \oplus m_2 = m(A) = \frac{\sum_{B \cap C = A} m_1(B)m_2(C)}{1 - K}, \tag{3}$$

where

$$K = \sum_{B \cap C = \emptyset} m_1(B)m_2(C). \tag{4}$$

The denominator, $1 - K$, is a normalization factor. K is called the degree of conflict between BOEs [57,58]. Dempster’s rule strongly implies the agreement between diverse information and ignores the conflict between them. When information sources are in support of a similar proposition, it is able to reduce uncertainty in the combination result.

2.2. Analytic Hierarchy Process

Analytic hierarchy process (AHP), introduced by Thomas Satty (1980) [59], is an effective tool for dealing with complex decision making problem [60–63]. The weight determination process quantifies the subjective assessment of experts, and can check the consistency of decision-makers’ evaluation. Generally, the process of applying AHP can be divided into three steps.

Step 1: Constructing the pair-wise comparison judgement matrix.

Assume that n pieces of decision elements are presented as $(F_1, F_2, F_3, \dots, F_n)$. In order to compute the weight of decision elements, a comparison judgement matrix represented as $M_{n \times n} = [m_{ij}]$ is created:

$$M_{n \times n} = \begin{bmatrix} 1 & m_{12} & \dots & m_{1n} \\ m_{21} & 1 & \dots & m_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n1} & m_{n2} & \dots & 1 \end{bmatrix},$$

which satisfies:

$$m_{ij} = \frac{1}{m_{ji}}. \tag{5}$$

Each entry m_{ij} represents the importance of the i th element on the j th element. If $m_{ij} > 1$, then the i th element is more important than the j th element, while if $m_{ij} < 1$, then the i th element is less important than the j th element. If two elements have the same importance, then the entry m_{ij} is 1. The relative importance between two decision elements is measured according to a numerical scale from 1 to 9, as shown in Table 1.

Table 1. Pair-wise comparison scale for analytical hierarchy process (AHP) preference.

Value of m_{ij}	Interpretation
1	i and j are equally important
3	i is slightly more important than j
5	i is more important than j
7	i is strongly more important than j
9	i is absolutely more important than j
2, 4, 6, 8	intermediate values between the two adjacent judgements

Step 2: Calculating the weight of decision elements.

The eigenvector of $M_{n \times n}$ can be denoted as $\bar{\omega} = (\omega_1, \omega_2, \omega_3, \dots, \omega_n)^T$, which is calculated using:

$$M\bar{\omega} = \lambda_{max}\bar{\omega}, \tag{6}$$

where λ_{max} is the largest eigenvalue of matrix $M_{n \times n}$. The eigenvector corresponding to the largest eigenvalue can be viewed as the final criterion for ranking goals.

Step 3: Checking the consistency index.

A consistency index (CI) is used to measure the consistency within each pair-wise comparison judgement matrix, which is defined as:

$$CI = \frac{\lambda_{max} - n}{n - 1}. \tag{7}$$

Accordingly, the consistency ratio (CR) can be calculated as follows:

$$CR = \frac{CI}{RI}, \tag{8}$$

where RI is the random index. RI and CR are related to the dimension of the matrix, which is listed in Table 2.

Table 2. Values of the random index (RI).

Dimension	2	3	4	5	6	7	8	9	10
RI	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.51

Generally, if $CR > 0.1$, the consistency of the pair-wise comparison matrix M is unacceptable and the elements in the matrix should be revised. Otherwise, M is considered acceptable and the eigenvector ω is treated as the weighing vector after normalization.

There are three main advantages in AHP: simplicity, practicability, and systematicness. Simplicity refers to the fact that the computation to determine the weight of criteria is concise and the result is clear in order to make decision-making convenient. Practicability means that AHP can deal with a wide range of problems compared to traditional optimization methods with the combination of qualitative and quantitative analysis. Systematicness can be understood to describe how AHP comprehensively regards the object as a system and then makes decisions according to the decomposition, comparison, and judgement.

3. The Proposed Method

The Framework of the Proposed Method

The motivation behind the development of the proposed method is to propose a generalized method based on belief functions to evaluate the sustainable transport solutions under consideration. The proposed method addresses both objectives. One is that the flexibility is improved since the method can deal with uncertainty and conflictive information due to D-S theory. The other is that the modified method has good performance in sensitivity analysis. The framework of our proposed method is shown in Figure 1.

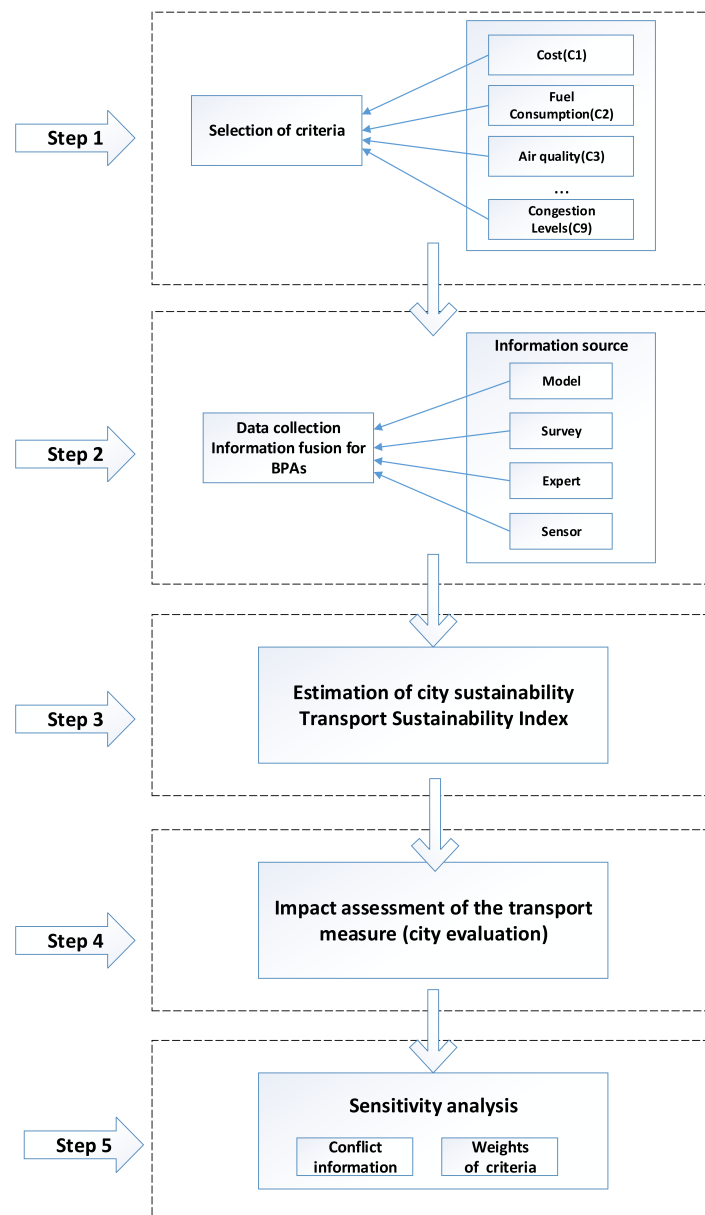


Figure 1. The framework of our proposed method. BPA: basic probability assignment.

Step 1: Selection of criteria.

The elements of sustainability refer to the Brundtland report of 1987 [64], and social, economic, and environmental indicators were concluded by transport researchers. The more detailed elements

on three indicators are based on specific situations. In [20], nine evaluation criteria for sustainability assessment are introduced—namely, cost (C₁), fuel consumption (C₂), air quality (C₃), noise perception (C₄), users numbers (C₅), spatial accessibility (C₆), satisfaction (C₇), security (C₈), and congestion level (C₉), which are shown in Figure 2. AHP is used to determine the weight of different criteria, and detailed steps are represented in Section 2.2.

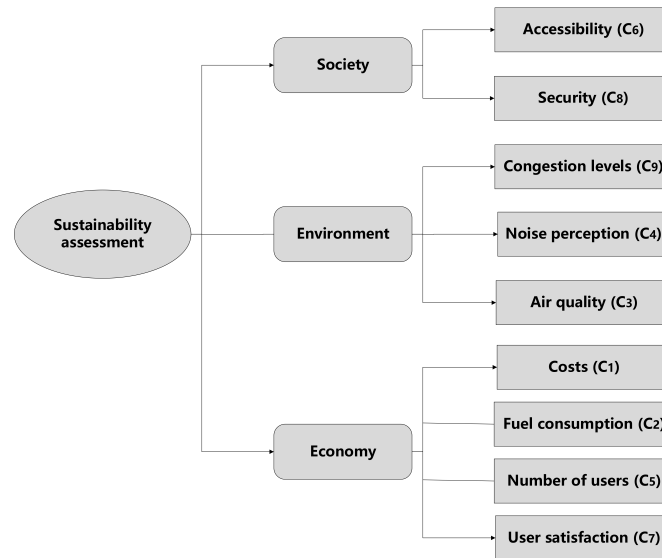


Figure 2. Evaluation criteria for sustainability assessment.

Step 2: Data collection and information fusion for BPAs.

After identifying evaluation criteria, data sets can be collected from various channels during the testing stage of the transportation measure. Anjali Awasthi et al. [20] mention four information sources: “Human experts”, “Sensors”, “Models” and “Survey”. For example, experts usually have professional related experience or knowledge on city transportation to guarantee the reliability of information. Surveys are conducted with city residents and the responses are further aggregated to obtain BPAs. Models can be determined by the type of given data. For example, input data can be the number of votes that support a certain transport solution on different criteria, and thus we can apply a probability model to construct BPAs. Sensors use a measurement technique to allocate BPA values to different criteria for the transportation measure under study. With respect to each criteria, BPAs from different information sources are aggregated using Dempster’s combination rule to generate a single belief function. The following will introduce the construction and representation of BPAs for collected data.

Experts allocate confidence to evaluation levels for each criteria. A new framework of evaluation level is proposed in this article: two evaluation levels, *I* and *D*. *I* means “increase” and *D* means “decrease”. The vector of utility related to evaluation levels is given by $u = \{u(I), u(D), u(I,D)\}$. In other words, there exists a frame of discernment represented as $\Theta = \{I, D\}$, $2^\Theta = \{\{I\}, \{D\}, \{I, D\}\}$, the belief distribution on evaluation levels is represented with a form of mass function (i.e., BPA).

For example, in terms of the criteria “Cost” for car-sharing, a BPA from expert is shown as follows:

$$m\{I\} = 0.25; m\{D\} = 0.25; m\{I, D\} = 0.5.$$

This means that:

- (1) “car-sharing solution will increase utility in terms of cost with the belief degree 0.25”.
- (2) “car-sharing solution will decrease utility in terms of cost with the belief degree 0.25”.
- (3) “the expert does not know whether the utility will increase or decrease with the belief degree 0.5”.

Step 3: Utilities estimation.

For a certain transport solution, each criteria is either positively or negatively oriented with the utilities. For instance, a higher cost gets a lower utility while a higher air quality gets a higher utility. Complete utility values for nine criteria are shown in Table 3. Note that the number 1 represents the highest utility value, 0 represents the lowest utility value, and 0.3 represents an intermediate value chosen between 0 and 1. The global utility (u_i) for a criteria i can be calculated using the individual utility for evaluation levels $H_k \in \{I, D\}$ and the combined BPA. The formulation is as follows:

$$u_i = \sum_{k=1}^p u(H_k) \times BPA(H_k), \tag{9}$$

where p is equal to 3. $H_k = \{I, D, \{I,D\}\}$, $u(H_k)$ represents the individual utility of evaluation levels as shown in Table 3, and $BPA(H_k)$ is the basic probability assignment related to each evaluation level $u(H_k)$.

Table 3. Utility values for criteria [20].

Evaluation Criteria	Utility Values $u(I), u(D), u(I,D)$
Cost (C_1), Fuel consumption (C_2), Noise perception (C_4), Congestion level (C_9)	(0, 1, 0.3)
Air quality (C_3), Users numbers (C_5), Spatial accessibility (C_6), Satisfaction (C_7), Security (C_8)	(1, 0, 0.3)

Step 4: Estimation of city sustainability.

The global utilities for nine criteria can be used to estimate city sustainability at any given time t by a Transport Sustainability Index (TSI) [20]. Let us denote the global utilities for the criteria $C_1, C_2, C_3, \dots, C_N$ at time t_n by $u_1(t_n), u_2(t_n), u_3(t_n), \dots, u_n(t_n)$. As a result, the transport sustainability index (TSI) at time t_n is given by:

$$TSI(t_n) = u_1(t_n) \times \omega_1 + u_2(t_n) \times \omega_2 + u_3(t_n) \times \omega_3 + \dots + u_n(t_n) \times \omega_n, \tag{10}$$

where ω_i is the weight of criteria obtained from AHP.

Step 5: Impact assessment of the transport measure.

The impact of the transportation measure on city sustainability is assessed by observing the change in TSI with respect to the pre-test and the post-test stages. Let t_{n-1} represents a time instant in the pre-test stage and t_n represent a time instant in the post-test stage, then the change in transport sustainability index over time interval $[t_{n-1}, t_n]$ is given by:

$$\Delta TSI[t_{n-1}, t_n] = TSI(t_n) - TSI(t_{n-1}), \tag{11}$$

If $\Delta TSI > 0$, we can conclude that the impact of the transportation measure on city sustainability is positive and thus the measure can be regarded as sustainable transport. If $\Delta TSI < 0$, the measure will be rejected for recommendation due to unsustainability.

Step 6: Sensitivity analysis.

To check the effectiveness of our proposed method, two experiments of conflictive information and changed weights of criteria will be illustrated in this part to better compare the difference between the method of Anjali Awasthi et al. [20] and ours.

The first experiment is about conflictive information to address the question ‘‘How sensitive is the overall decision to conflictive information during the information fusion process?’’ Conflictive information arises very easily due to man-made error, a fault in the model, or the subjectivity of experts’

opinions. It is necessary to confirm that a method has redundancy to be more flexible and practical so that it has a more extensive application.

The second experiment is about the weight of criteria to address the question "How sensitive is the overall decision to small changes in the individual weight assigned during the pair-wise comparison process?" This question can be answered by slightly varying the values of weight and observing the effects on the decision. Moreover, because the weights of criteria are subjectively determined by experts using AHP, it is useful in situations where uncertainty exists in the definition of the importance of different factors.

4. Car-Sharing Application

Car-sharing means that a car is shared with many people. It is an alternative system of car ownership. In other words, the driver of vehicle only has the use right but no ownership. Car-sharing is similar to chartering a rental car for a short time. Clients reserve the vehicle in advance by telephone or online and then can get access to the vehicle. In general, a company is used to coordinating the vehicle and is responsible for the insurance and parking of vehicles. Car-sharing is a feasible option to reduce vehicle emissions by minimising the number of private vehicle movements inside cities [65–67]. The architecture of a typical car-sharing organization (CSO) is illustrated in Figure 3.

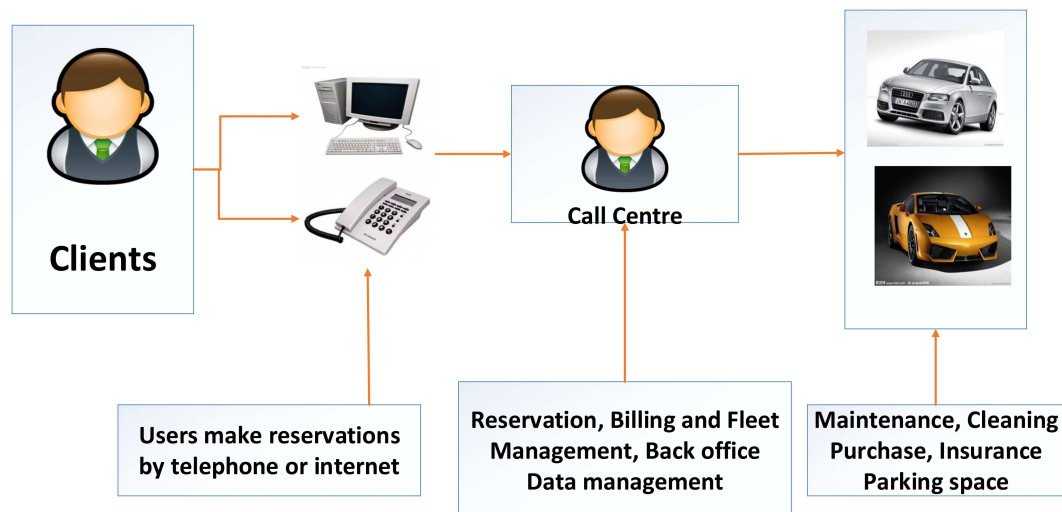


Figure 3. The architecture of a typical car-sharing organization (CSO) [20].

The aim of this part is to evaluate the influence of car-sharing on city sustainability and provide valuable suggestions for the city transportation authority to determine whether car-sharing can be implemented in the city.

4.1. Selection of Criteria

In the car-sharing system, nine criteria as mentioned previously are identified for sustainable evaluation: criteria cost (C_1), fuel consumption (C_2), air quality (C_3), noise perception (C_4), users numbers (C_5), spatial accessibility (C_6), satisfaction (C_7), security (C_8), and congestion level (C_9).

4.2. Data Collection and Information Fusion for BPAs

The data of BPAs on two evaluation levels (increase (I), decrease (D)) for nine criteria were collected from four information sources: expert, model, survey, and sensors/actual measurement. In order to provide convenience for calculation and comparison, note that the data at pre-test stage and post-test stage was from [20], yet there is a change in the framework of evaluation levels, and corresponding BPAs are shown respectively in Tables 4 and 5. In [20], three evaluation levels were

introduced: I (increase), N (no change), D (decrease). In our article, only levels I and D are considered, and the original data corresponding to level N is mapped to the set {I,D}, in which BPA representation is formed.

Table 4. Data collection of BPAs at the pre-test stage [20].

Evaluation Criteria	Expert			Model			Survey			Sensors		
	I	D	Θ	I	D	Θ	I	D	Θ	I	D	Θ
<i>cost</i> (C ₁)	0.25	0.25	0.5	0.6	0.2	0.2	0.5	0.2	0.3	0.5	0.15	0.35
<i>fuel consumption</i> (C ₂)	0.3	0.3	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.2	0.5	0.3
<i>air quality</i> (C ₃)	0.65	0.15	0.2	0.7	0.2	0.1	0.6	0.2	0.2	0.8	0.1	0.1
<i>noise perception</i> (C ₄)	0.25	0.65	0.1	0.8	0.1	0.1	0.5	0.2	0.3	0.1	0.8	0.1
<i>users numbers</i> (C ₅)	0.7	0.2	0.1	0.2	0.1	0.7	0.8	0.1	0.1	0.6	0.1	0.3
<i>spatial accessibility</i> (C ₆)	0.5	0.3	0.2	0.6	0.1	0.3	0.5	0.2	0.3	0.7	0.1	0.2
<i>satisfaction</i> (C ₇)	0.6	0.1	0.3	0.7	0.1	0.2	0.6	0.1	0.3	0.8	0.1	0.1
<i>security</i> (C ₈)	0.4	0.3	0.3	0.4	0.2	0.4	0.4	0.2	0.4	0.5	0.3	0.2
<i>congestion level</i> (C ₉)	0.4	0.4	0.2	0.1	0.5	0.4	0.2	0.5	0.3	0.2	0.6	0.2

Table 5. Data collection of BPAs at the post-test stage [20].

Evaluation Criteria	Expert			Model			Survey			Sensors		
	I	D	Θ	I	D	Θ	I	D	Θ	I	D	Θ
<i>cost</i> (C ₁)	0.3	0.2	0.5	0.4	0.2	0.4	0.2	0.1	0.7	0.1	0.3	0.6
<i>fuel consumption</i> (C ₂)	0.2	0.5	0.3	0.1	0.5	0.4	0.2	0.3	0.5	0.2	0.4	0.4
<i>air quality</i> (C ₃)	0.6	0.1	0.3	0.7	0.1	0.2	0.6	0.2	0.2	0.7	0.2	0.1
<i>noise perception</i> (C ₄)	0.1	0.6	0.3	0.1	0.8	0.1	0.2	0.7	0.1	0.2	0.6	0.2
<i>users numbers</i> (C ₅)	0.8	0.1	0.1	0.7	0.1	0.2	0.6	0.3	0.1	0.8	0.1	0.1
<i>spatial accessibility</i> (C ₆)	0.6	0.1	0.3	0.8	0.1	0.1	0.6	0.3	0.1	0.7	0.1	0.2
<i>satisfaction</i> (C ₇)	0.7	0.1	0.2	0.8	0.1	0.1	0.6	0.2	0.2	0.6	0.1	0.3
<i>security</i> (C ₈)	0.25	0.4	0.35	0.3	0.3	0.4	0.2	0.3	0.5	0.2	0.4	0.4
<i>congestion level</i> (C ₉)	0.2	0.5	0.3	0.1	0.7	0.2	0.2	0.6	0.2	0.2	0.4	0.4

According to Equations (2)–(4), a comprehensive evaluation for each criterion can be calculated by Dempster’s combination rule. Consider the criterion “Cost” in Table 5; let us denote the BPA from Expert by m_1^1 , from Model by m_2^1 , from Survey by m_3^1 , and from Sensors by m_4^1 . The detailed procedure for data combination can be shown as follows:

1. Original BPAs from Table 5 is:

$$\begin{aligned}
 m_1^1(I) &= 0.3, m_1^1(D) = 0.2, m_1^1(\Theta) = 0.5, \\
 m_2^1(I) &= 0.4, m_2^1(D) = 0.2, m_2^1(\Theta) = 0.4, \\
 m_3^1(I) &= 0.2, m_3^1(D) = 0.1, m_3^1(\Theta) = 0.7, \\
 m_4^1(I) &= 0.1, m_4^1(D) = 0.3, m_4^1(\Theta) = 0.6.
 \end{aligned}$$

2. Data information: Using Equations (2)–(4), we have $m_1^1 \oplus m_2^1 \oplus m_3^1 \oplus m_4^1 =$

$$\begin{aligned}
 m_1(I) &= 0.5645, \\
 m_1(D) &= 0.3226, \\
 m_1(\Theta) &= 0.1129.
 \end{aligned}$$

From the above analysis, a comprehensive BPA is obtained for the criteria “Cost” from four information sources. Likewise, the remaining BPAs for eight criteria can be computed. The aggregated BPA results for nine criteria at the pre-test and post-stage stages of car-sharing are represented in Table 6.

Table 6. The aggregated BPA results for nine criteria.

Evaluation Criteria	Pre-Test Stage			Post-Test Stage		
	I	D	Θ	I	D	Θ
cost (C ₁)	0.8413	0.1365	0.0222	0.5645	0.3226	0.1129
fuel consumption (C ₂)	0.5039	0.4488	0.0472	0.1234	0.8225	0.0541
air quality (C ₃)	0.9831	0.0161	0.0008	0.9796	0.0189	0.0015
noise perception (C ₄)	0.4260	0.5714	0.0026	0.0088	0.9908	0.0004
users numbers (C ₅)	0.9680	0.0285	0.0035	0.9861	0.0132	0.0008
spatial accessibility (C ₆)	0.9375	0.0550	0.0075	0.9907	0.0089	0.0004
satisfaction (C ₇)	0.9855	0.0117	0.0027	0.9891	0.0098	0.0010
security (C ₈)	0.7379	0.2388	0.0233	0.3566	0.5778	0.0657
congestion level (C ₉)	0.1377	0.8503	0.0120	0.0343	0.9598	0.0060

4.3. Utilities of Estimation

After BPAs for nine criteria are obtained, global utility of each criteria on car-sharing can be calculated using individual utility values from Table 3. For example, the global utility for criteria “Cost(C₁)” and criteria “Air quality(C₃)” are computed using Equation (11):

$$\begin{aligned}
 u_1 &= u(I) * BPA(I) + u(D) * BPA(D) + u(\Theta) * BPA(\Theta) \\
 &= 0 * 0.5645 + 1 * 0.3226 + 0.3 * 0.1129 \\
 &= 0.3565
 \end{aligned}$$

$$\begin{aligned}
 u_3 &= u(I) * BPA(I) + u(D) * BPA(D) + u(\Theta) * BPA(\Theta) \\
 &= 1 * 0.9796 + 0 * 0.0189 + 0.3 * 0.0015 \\
 &= 0.9800
 \end{aligned}$$

Similarly, global utilities of the remaining seven criteria can be computed. The results are shown in Table 7.

Table 7. Global utilities for nine criteria.

Evaluation Criteria	At the Pre-Test Stage	At the Post-Test Stage
cost (C ₁)	0.1432	0.3565
fuel consumption (C ₂)	0.4630	0.8387
air quality (C ₃)	0.9834	0.9800
noise perception (C ₄)	0.5722	0.9909
users numbers (C ₅)	0.9691	0.9863
spatial accessibility (C ₆)	0.9398	0.9908
satisfaction (C ₇)	0.9864	0.9894
security (C ₈)	0.7449	0.3763
congestion level (C ₉)	0.8539	0.9615

4.4. Estimation of City Sustainability

As mentioned before, a Transport Sustainability Index (TSI) can be used to measure city sustainability at any given time with global utilities. The Transport Sustainability Indexes of car-sharing at pre-test and post-test stages are denoted by TSI(*t_{before}*) and TSI(*t_{after}*), respectively. Assuming an equal weight of 0.111 for all criteria, using global utilities (Table 7) and criteria weight, we have:

$$\begin{aligned}
 TSI(t_{before}) &= 0.1432 * 0.111 + 0.4630 * 0.111 + 0.9834 * 0.111 \\
 &+ 0.5722 * 0.111 + 0.9691 * 0.111 + 0.9398 * 0.111 \\
 &+ 0.9864 * 0.111 + 0.7449 * 0.111 + 0.8539 * 0.111 \\
 &= 0.7388
 \end{aligned}$$

$$\begin{aligned}
 TSI(t_{after}) &= 0.3565 * 0.111 + 0.8387 * 0.111 + 0.9800 * 0.111 \\
 &+ 0.9909 * 0.111 + 0.9863 * 0.111 + 0.9908 * 0.111 \\
 &+ 0.9894 * 0.111 + 0.3763 * 0.111 + 0.9615 * 0.111 \\
 &= 0.8292
 \end{aligned}$$

4.5. Impact Assessment of the Transport Measure (Transport Solution Evaluation)

From the above, we can obtain the TSI values for car-sharing at pre-test and post-test stages and easily find that $TSI(t_{after}) > TSI(t_{before})$, $0.8292 > 0.7388$. Therefore, a conclusion is drawn that the change brought by the transportation measure “car-sharing” is positive and thus car-sharing is suggested for adoption in the city.

4.6. Sensitivity Analysis

4.6.1. Experiment 1

From Tables 4 and 5, we can find that most BPAs have a similar trend to support the same evaluation level. For example, in Table 5 for the criteria “Air quality (C_3)”, most BPAs from four information sources have the most confidence in supporting the evaluation level “I”; for the criteria “Congestion levels (C_9)”, the collected data show that there is strong confidence with the evaluation level “D”. However, in real life, it is noteworthy that incorrect data is possibly derived from human error, fault in the model, or the subjectivity of experts’ opinion. Regardless, conflictive data may occur. Experiments were performed to determine the sensitivity of the final decision with respect to conflictive BPAs, and a comparison between Anjali Awasthi et al.’s method [20] and our proposed method is given.

From Table 5, for the criteria “Number of users”, the model and sensor respectively provide a BPA: $m(I) = 0.7, m(D) = 0.1, m(\Theta) = 0.2$; $m(I) = 0.8, m(D) = 0.1, m(\Theta) = 0.1$. In this experiment, two new BPAs are substituted: $m(I) = 0, m(D) = 0.1, m(\Theta) = 0.9$; $m(I) = 0.9, m(D) = 0.1, m(\Theta) = 0$. The other two information sources “Expert” and “Survey” support the evaluation level “I” with a strong confidence $m_5^1 = 0.8, m_5^3 = 0.6$, while the new BPA from the model has the most confidence in supporting the set “ Θ ”. Generally, it is called a piece of conflict evidence. Global utilities for nine criteria at the post-test stage with two methods are shown in Tables 8 and 9.

Table 8. The testing BPA fusion results.

Evaluation Criteria	Anjali Awasthi et al.’s Method			Our Proposed Method		
	I	D	Θ	I	D	Θ
cost (C_1)	0.0274	0.9589	0.0137	0.2258	0.5053	0.2689
fuel consumption (C_2)	0.0146	0.4380	0.5474	0.2296	0.3596	0.4108
air quality (C_3)	0.9910	0.0067	0.0022	0.5893	0.2087	0.2018
noise perception (C_4)	0.0020	0.0030	0.9951	0.2026	0.2399	0.5574
users numbers (C_5)	0	0	1.0000	0.6913	0.1894	0.1932
spatial accessibility (C_6)	0.9956	0.0030	0.0015	0.5946	0.2373	0.1681
satisfaction (C_7)	0.9931	0.0059	0.0010	0.5771	0.2566	0.1661
security (C_8)	0.0661	0.6167	0.3172	0.2529	0.3743	0.3727
congestion level (C_9)	0.0089	0.0536	0.9375	0.2290	0.3350	0.4359

Table 9. Global utilities of testing for nine criteria with two methods.

Evaluation Criteria	Anjali Awasthi et al.’s Method	Our Proposed Method
cost (C_1)	0.1432	0.3565
fuel consumption (C_2)	0.4630	0.8387
air quality (C_3)	0.9834	0.9800
noise perception (C_4)	0.5722	0.9909
users numbers (C_5)	0	0.9846
spatial accessibility (C_6)	0.9398	0.9908
satisfaction (C_7)	0.9864	0.9894
security (C_8)	0.7449	0.3763
congestion level (C_9)	0.8539	0.9615

From Table 10 and Figure 4, it can be easily seen that before modifying the data, a positive impact on urban transportation can be obtained by testing the transportation solution, while a negative impact

is found after the emergence of conflictive evidence in Anjali Awasthi et al.’s method [20]. However, in our proposed method, we can come to the same conclusion that the influence brought by car-sharing in the city is positive and therefore car-sharing is recommended for adoption, which demonstrates that the proposed method can handle conflictive data well.

The Transport Sustainability Index (TSI) at the post-test stage for the two methods and the comparison of the two methods are shown in Table 10.

Table 10. Comparison of the two methods.

	Anjali Awasthi et al.’s Method	Our Proposed Method
$TSI(t_{before})$	0.7033	0.7388
$TSI(t_{after})$	0.6843	0.8190
ΔTSI	$TSI(t_{before}) > TSI(t_{after})$	$TSI(t_{before}) < TSI(t_{after})$
Transport solution evaluation	Negative	Positive
Transport solution evaluation (without conflict)	Positive	Positive

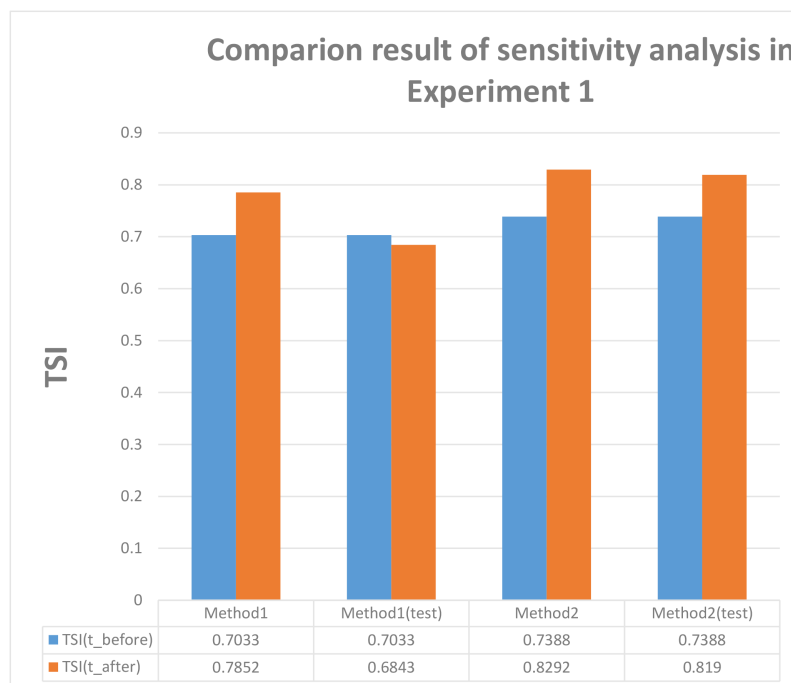


Figure 4. The first comparison in the sensitivity analysis of two methods. Method 1: Anjali Awasthi et al.’s method. Method 2: Our proposed method.

4.6.2. Experiment 2

In this article, equal weight for different criteria is assumed to calculate the TSI at pre-test and post-test stages for simplicity. Experiments were conducted to determine the sensitivity of the final decision with respect to weight changes of different criteria. These experiments are represented in Table 11.

Table 11. Different weight for nine criteria [20].

Experiment 2	Weights of Criteria								
	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈	C ₉
1	1	0	0	0	0	0	0	0	0
2	0	1	0	0	0	0	0	0	0
3	0	0	1	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0
5	0	0	0	0	1	0	0	0	0
6	0	0	0	0	0	1	0	0	0
7	0	0	0	0	0	0	1	0	0
8	0	0	0	0	0	0	0	1	0
9	0	0	0	0	0	0	0	0	1
10	0	0	0.2	0	0.2	0.2	0.2	0.2	0
11	0.1	0.1	0.2	0.2	0.05	0.1	0.05	0.1	0.1
12	0.25	0.25	0	0.25	0	0	0	0	0.25
13	0.125	0.125	0.1	0.125	0.1	0.1	0.1	0.1	0.125
14	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.111
15	0.5	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625
16	0.0625	0.5	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625
17	0.0625	0.0625	0.5	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625
18	0.0625	0.0625	0.0625	0.5	0.0625	0.0625	0.0625	0.0625	0.0625
19	0.0625	0.0625	0.0625	0.0625	0.5	0.0625	0.0625	0.0625	0.0625
20	0.0625	0.0625	0.0625	0.0625	0.0625	0.5	0.0625	0.0625	0.0625
21	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.5	0.0625	0.0625
22	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.5	0.0625
23	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.5

From Table 11, we can find that:

- (1) Experiments 1–9 consider one criterion at a time with a maximum weight = 1 and allocate weight = 0 to the remaining eight criteria.
- (2) Experiment 10 provides equal weight = 0.2 to the criteria with the high utility values for increase (I) for post-test stage (i.e., C₃, C₅, C₆, C₇, C₈). The weight of the remaining criteria is equal to 0.
- (3) Experiment 11 gives a random allocation of weight to different criteria.
- (4) Experiment 12 provides equal weight = 0.25 to the criteria with low utility values for increase (I) for the post-test stage (i.e., C₁, C₂, C₄, C₉).
- (5) Experiment 13 distributes equal weight = 0.1 to criteria with high utility values for increase (I) for the post-test stage (i.e., C₃, C₅, C₆, C₇, C₈). Equal value = 0.125 is given to criteria with low utility values for increase (I) for post-test stage (i.e., C₁, C₂, C₄, C₉).
- (6) Experiment 14 sets 0.111 as the weight of all criteria.
- (7) Experiments 15–23 provide weight = 0.25 over one criteria and distribute the remaining 0.5 weight over eight criteria, making their criteria weight = 0.0625.

The results are presented in Figure 5.

From Figure 5, we can find that most experiments support the conclusion that the Transportation Sustainability Index (TSI) at the post-test stage is higher than the pre-test stage regardless of the changes in criteria weight, which shows the robustness of our proposed method. As a result, we can draw the conclusion that car-sharing has a positive impact on improving transport conditions inside the city. Car-sharing is recommended for adoption.

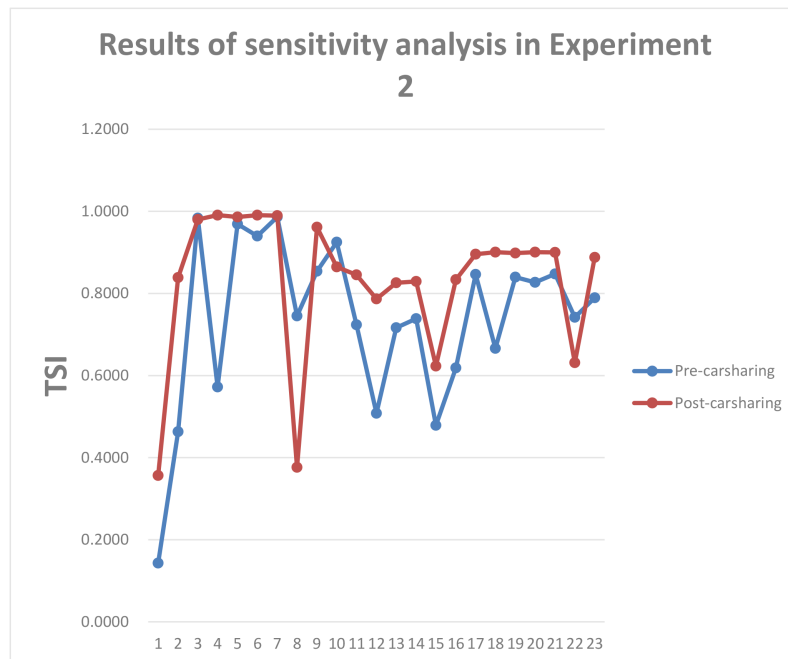


Figure 5. Results of sensitivity analysis in Experiment 2.

5. Discussion

In our proposed model, analytic hierarchy process (AHP) and Dempster–Shafer evidence theory (D-S theory) are combined to evaluate the impact of transport measures on city sustainability. The desirable properties of the model are stated as follows:

Basic probability assignment (BPA) rather than probability function is used to represent the confidence of evaluation levels for all criteria. In Anjali Awasthi et al.'s method [20], three evaluation levels {I, N, D} are mentioned which satisfies the equation $p(I) + p(N) + p(D) = 1$; while in our method, $m(I) + m(D) + m(\Theta) = 1$, which means that the unit mass is distributed among the singletons in Θ and composite hypotheses as well. Through a modification, the probability function was transformed to BPA in D-S theory to better express the uncertainty. D-S theory has a strong function to manage uncertain information from various sources to make a decision. Furthermore, conflictive information can be handled well in our proposed method. As can be seen in Experiment 1, when conflictive data occur, two very different results are obtained in Anjali Awasthi et al.'s method [20], instead of the consistent result obtained in our proposed method.

Furthermore, in this article we come to the conclusion that car-sharing has a positive effect on city sustainability, which can be explained as follows: by reducing trips in private vehicle movements in the city, car-sharing can reduce vehicle emissions, as well as the occurrence of accidents and traffic congestion in the urban network to some extent. Moreover, car-sharing provides alternatives for humans' travel and thus can bring convenience. In a word, car-sharing can promote city sustainability through the improvement of urban conditions in terms of social and environmental aspects.

6. Conclusions

In this article, a modified method for evaluating sustainable transport solutions combining AHP and Dempster–Shafer evidence theory is proposed. AHP is adopted to determine the weight of sustainability criteria while D-S theory is used for data fusion of sustainability assessment. A Transport Sustainability Index (TSI) is presented as a primary measure to determine whether transport solutions have a positive impact on city sustainability. Finally, a case study of car-sharing is illustrated to show the efficiency of our proposed method. Compared with existing methods, two advantages can be listed: one is that the BPA is generated with a new modification framework of evaluation

levels, which can flexibly address uncertain information. The other is that the modified method has excellent performance in sensitivity analysis. The model can be widely used in evaluating the impact of environment-friendly transport measures on city sustainability.

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