Sustainability Measurement of Transportation Systems in China: A System-Based Bayesian Network Approach

Wu Jiang1 and Zhou Huan2,3

1School of Statistics, Southwest University of Finance and Economics, Chengdu, China
2School of Public Management, Southwest University of Finance and Economics, Chengdu, China
3Planning and Finance Department, Chengdu Technological University, Chengdu, China

Correspondence should be addressed to Zhou Huan; zhou_8206@163.com

Received 21 November 2021; Revised 28 January 2022; Accepted 11 February 2022; Published 15 March 2022

Academic Editor: Mahmoud Mesbah

Copyright © 2022 Wu Jiang and Zhou Huan. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Sustainability has been a challenging issue in the transportation industry, which necessitates obtaining a better measurement of transport sustainability performance. To appropriately measure performance, this paper presents a hybrid approach based on the hierarchical Bayesian network model (BNM) and Principal Component Analysis (PCA). The proposed BNM encompasses social, economic, environmental, and technological dimensions, where each dimension consists of various subdivisions. The Conditional Probability Table of the model is determined by PCA. Twenty-three sustainable transportation indicators involved in the different stages of traffic management are used to kick off the calculation and probability propagation. The results show that the overall transport sustainability of the selected cities is generally at a medium level, indicating that there is much room for further improvement. The sustainability-economic coupling analysis exhibits the nonlinear relationship between sustainability and economic level, revealing that economic growth does not necessarily lead to the enhancement of the transport sustainability. Additionally, the sensitivity analysis reveals that “Accessibility,” “Serviceability,” “Reliability,” and “Innovation” demonstrate an upward trend, indicating their great effect on transportationsustainability. Last, the policy implications of this study can not only offer a solution for the current needs of transportation systems but also serve as more transparent decision-making to develop a sustainable transportation system in the future.

1. Introduction

Socioeconomic progress, dramatic population growth, and urbanization in recent decades have led to continually growing demand for travel and freight in transportation worldwide, imposing a huge burden and significant challenges on transportation systems [1, 2]. Indeed, increasing transport volumes have resulted in the degradation of both human habitat and the environment; with 103.13 million tons of CO₂ emissions in 2018, China was the largest CO₂ emitter in the world [3], and transportation was responsible for 25% of the total energy-related CO₂ emissions and 65% of the liquid fuel consumption in 2016. The degree of haze pollution suggested to be related to vehicle emissions has been considerably aggravated, especially in the Beijing-Tianjin-Hebei region. Additionally, chronic stresses such as severe congestion and inadequate accessibility critically affect social efficiency and quality of life and ultimately affect the sustainability of our transport systems and society as a whole [4]. In response to these disturbances, the United Nations introduced Sustainable Development Goals [5], and promoting sustainable industrialization was identified as one of the key factors to support economic development and human wellbeing [6]. Achieving sustainability has become a common vision, and traffic policy-makers and practitioners show increasing interest in it and view it as an emerging and essential part of the bigger picture of sustainability.

The sustainability of transportation systems, as a multifaceted concept, is normally perceived as a compound system capability, which is believed to be the ability of
transportation systems to meet society’s transport and mobility needs safely, support a vibrant economy, and establish relationships without sacrificing other essential human or ecological values, today or in the future [7–10]. To reach a sustainable transportation system, policy-makers are required to comprehensively and appropriately measure the current conditions and continuously monitor the sustainability performance of a transportation system [11]. Measuring transport sustainability may contribute to easy-to-understand results, make stakeholders quickly observe and compare the effects of a proposed traffic management strategy, and readily track trends in transportation system performance towards or away from sustainability [12]. Finally, meaningful decision-making and proper action taking can lead to a more sustainable transportation system.

Thus, measuring the sustainability of transportation systems has become an increasingly important topic for traffic policy-makers. However, the measurement of sustainability is a sophisticated and challenging task [13]. A transportation system is highly dynamic, complex, and transdisciplinary in nature [14]. Meanwhile, sustainable transportation is a multiattribute issue in which various indicators from all sustainability dimensions and their subdivisions should be fully taken into account and appropriately chosen [15]. Additionally, the development of sustainable transportation is associated with a great amount of complexity and uncertainty, which makes it more laborious to measure [16]. These eminent challenges lead to an important question: how can suitable quantitative methods be applied to measure the sustainability of a transportation system from a comprehensive point of view?

Numerous studies applied different methods to deal with the transport sustainability. Mahdinia et al. [4] used the Principal Component Analysis method to measure the transport sustainability of fifty states in the USA. De Gruyter et al. [17] used equal weighting method to assess the sustainability of urban public transit systems of several cities in Asia and the Middle East region. Alonso et al. [18] developed a composite index by using equal weighting method to measure the transport sustainability of twenty-three cities in European countries. Stefaniec et al. [19] studied the sustainability of inland transportation in China by applying a triple bottom line-based network DEA approach. Rajak et al. [20] used a fuzzy logic method to evaluate the systems performance of sustainable transportation. Jeon et al. [9] demonstrated an application of Multiple Criteria Decision Making (MCDM) approach for evaluating transportation sustainability at the planning level in the Atlanta region. Baghizadeh et al. [21] developed a G/M/S/M queuing system to optimize transportation system in sustainable logistic for the first time. Ling et al. [22] focused on the sustainability of urban transportation development in China from behavioral perspective. Afrin and Yodo [23] presented a Bayesian network model for probabilistic estimation of traffic congestion. Baghizadeh et al. [24] focused on the resilient route to increase the flexibility of the transportation networks to minimize all costs. Chan et al. [25] focused on the sustainability of public transportation through an examination of user behavior after real-time GPS tracking application.

Many studies developed hybrid methods. Shiau and Liu [26] used Fuzzy Cognitive Map (FCM) and Analytic Hierarchy Process (AHP) to develop the cause-effect relationship for sustainability evaluation of Taipei city. Bray et al. [27] developed a hybrid model with a fuzzy set and DEA to measure the freight transport efficiency. Awasthi and Chauhan [28] presented a hybrid model with AHP and Dempster–Shafer (D–S) theory to evaluate the impact of sustainable transportation on city planning. Staš et al. [29] combined the balanced scorecard (BSC) with Analytical Network Process (ANP) to measure the performance of the green transport initiative in the European automotive industry. Sayyadi and Awasthi [30] presented an integrated approach based on system dynamics and ANP for evaluating sustainable transportation policies.

Prior researches elucidated two limitations. First, a few number of indicators [9, 19, 25] had been used, or sustainability frameworks were mostly confined to few dimensions [4, 22], such as economic, social, and environmental. Second, equal weighting method [17, 18] or AHP method [26, 28] has some limitations in measuring sustainable transport. Equal weighting method assigns equal importance to various indicators; however, this is not the case in reality. AHP based on expert judgment may introduce subjective elements. Therefore, there remains a pressing need for an appropriate method to interpret the complex goal of sustainable transport through using a diverse range of indicators.

Sabet et al. [31] developed a consistent framework to objectively evaluate and compare the travel performance of eleven global cities. Baghizadeh et al. [32] suggested a multiperiod and multiproduct Mixed-Integer Nonlinear Programming (MINLP) model considering transportation discount systems for a sustainable supply chain. Inspired by these ideas, we propose a system-based Bayesian network model for probabilistic measuring multidimensional transport sustainability and comparing cities with a consistent framework. The main contributions of this paper are twofold.

First, this paper proposes a novel approach with more mathematical rigor to practically evaluate the sustainability of a transportation system at the city level. We integrate Bayesian network and Principal Component Analysis (PCA) in this hierarchical model. The Bayesian network is recognized as an excellent tool for tackling probabilistic measurement of multiple variables. PCA is a data-driven statistical method for weighting; their combination can achieve a more powerful effect. This integrated method can appropriately capture complex system’s multidimensional and dynamic attribute in measuring system sustainability and reduce the subjectivity at the same time. In this way, we demonstrate an improved methodology to manage multiattribute decision problem with dynamic characteristics and a great amount of uncertainty. This enriches the decision-making toolkit for transport managers, policy-makers, and other relevant stakeholders.

Second, this paper develops a robust four-layer hierarchical Bayesian network model (BNM) to interpret transport sustainability from a broader and exhaustive perspective.
The proposed model encompasses three dimensions, namely, economic, social, and environmental, and adds the fourth technological dimension as an important pillar. Furthermore, we consider various multidimensional indicators involved in different stages of design, construction, operation, management, and innovation. This best utilizes available potentially rich sources of statistical data to identify abstract-related sustainability.

The rest of this paper is organized as follows. Section 2 introduces the methodology, including the fundamental theory of the Bayesian network, constructing the structure of the Bayesian network model, and the procedure of setting the Conditional Probability Table of the Bayesian network model based on Principal Component Analysis. Section 3 and Section 4 elaborate upon case studies and empirical findings from the model inference, which lead to managerial and practical implications. Finally, Section 5 provides conclusions of the study, implications, limitations, and guidance for future research.

### 2. Methodology

#### 2.1. Theory of Bayesian Network

A Bayesian network model (BNM), also called a Belief network model, is a combination of graph theory and probability theory [33]. It is composed of a directed acyclic graph (DAG) and a joint probability distribution (JPD) [34]. DAG, also known as the structure of the BNM, consists of nodes and arcs between nodes. Nodes represent different random variables, and arcs represent the association relationship within the variables [35, 36]. The relations represented by DAG allow JPD to be specified by the Conditional Probability Table (CPT) of each node [37]. The essence of BNM is to compute the posterior probability distribution of target variables conditioned on input variables [38–40].

For the purpose of mathematically representing BNM, we let $V = \{X_1, X_2, \ldots, X_n\}$ be the set of variables in a given BNM, and the conditional dependence among variables is represented by the topology of the network. As shown in Figure 1, an outgoing arc from $X_i$ to $X_j$ indicates that $X_i$ is the parent node of $X_j$, and $X_j$ is the child node of $X_i$. In general, there are three kinds of nodes in BNM: (1) root nodes are those nodes without parent nodes, (2) leaf nodes are those nodes without child nodes, and (3) intermediate nodes are those nodes with both parent and child nodes [35]. For example, in Figure 1, the root nodes are $X_1$, $X_2$, and $X_3$, the leaf node is $X_6$, and the intermediate nodes are $X_4$, $X_5$, $X_6$, and $X_7$.

The association relationships among variables in BNM can be measured by their CPTs [37]. The general expression for full JPD of BNM can be written as follows:

$$P(B_1, B_2 \ldots B_n) = \prod_{i=1}^{n} P(B_i | \text{Parents}(B_i)).$$  \hspace{1cm} (1)

The design of a BNM involves two steps: determining the structure and setting the CPT for the nodes. Generally, the available methods of designing a BNM can be classified into three categories [41]. The first method is to learn the structure and the CPT entirely on training data. As a data-driven approach, the prominent advantage of this method is rigorosity and objectivity. Nevertheless, it has demanding requirements on both the quantity and quality of the training data. The second method depends entirely on expert prior knowledge for both structure and the CPT. Obviously, the outcome of this method may have discrepancies with the real status due to the limitation in knowledge acquisition [37]. The third method is a combination of the first two methods as a compromise.

In this paper, we consider the third method. In fact, a large strand of literature has accumulated on this theme, which can serve as effective prior knowledge for structure learning of a BNM. Moreover, PCA can be applied to determine the CPT of the proposed model. PCA is a multivariate statistical method and is commonly recognized as one of the most useful tools in sustainability studies [42]. The principles of PCA are to construct weights in the indices based on the correlation between the indicators. Owing to its data-driven nature, the subjectivity problem of weighting can be solved [15]. This hybrid method can combine the advantages of BNM and PCA to achieve a more powerful effect. In this way, the proposed BNM can increase the adaptability of the outcome while reducing the subjectivity of the BNM design as much as possible.

#### 2.2. Constructing the Structure of the Model

For the structure of the BNM, we design a four-layer hierarchical topology. The top layer is the ultimate goal layer; achieving sustainability is the ultimate goal that the transportation system pursues as mentioned before. The second layer includes the four sustainability dimensions. The third layer is the attribute layer consisting of twelve system attributes related to the four dimensions, and the fourth layer is the indicator layer consisting of multiple indicators. In this proposed BNM, sustainability can be set as a “leaf node,” whose quantitative assessment can be achieved from probabilistic inference from the “root node.” The indicators act as elements of root nodes to kick off the calculation and probability propagation in the BNM (Figure 2).
2.2.1. Dimension Layer. The purpose of the dimension layer is to establish the macrolevel dimension that directly contributes to the overall system sustainability. At this level, the reasoning process is based on established frameworks and commonly agreed-on definitions proposed in the sustainability engineering field.

Many studies have proposed a sustainability framework that includes three main pillars: society, economy, and environment [43–46]. It is noteworthy that the technological dimension is added as the fourth basic dimension in this study based on the powerful momentum presented in transportation development [47, 48]. In other words, the four essential dimensions, including social, economic, environmental, and technological dimensions, outline the four essential abilities of being sustainable (Figure 3). They are generally applied in transportation systems and interpreted as follows:

Social dimension: urban transportation is a public product that should satisfy the basic interests of residents in a manner that is consistent with safety and human health [2, 19]. Moreover, it should be equally beneficial for all residents at various socioeconomic levels, especially for the elderly and the disabled.

Economic dimension: this dimension indicates that urban transport operates efficiently and supports a vibrant economy [43, 46]. Economic vitality is important to transport systems. The former can nurture the latter. Conversely, sustainable transportation plays a significant role in improving productivity and work opportunities, reducing economic operating costs, facilitating economic development, and finally promoting the sustainable development of the overall economy.

Environmental dimension: this dimension indicates that sustainable transportation should be environmentally friendly [43, 44]. Traffic-related emissions and energy consumption should be reduced within the scope of resources and ecological carrying capacity. The negative externalities or threats to the ecological environment should be controlled as much as possible.

Scientific and Technological Dimension: the aim of this dimension is to emphasize the powerful momentum of science and technology present in the sustainable development of transport system. In particular, the application of cutting-edge technology in the transportation sector is showing a booming trend [47, 48], and technology-related issues seem to be promising ways to reach a sustainable transportation system.

2.2.2. Attribute Layer. Twelve fundamental system attributes were introduced to form the attribute layer in the proposed BNM, including “Safety,” “Accessibility,” “Reliability,” “Serviceability,” “Equity,” “Repairability,” “Low-carbon,” “Land-use resilience,” “Economic efficiency,” “Financial affordability,” “Innovation,” and “Intelligence” (Figure 4). These attributes are the subdivisions of the aforementioned four dimensions and have significant contributions to general transportation system sustainability.

The five attributes of “Safety,” “Accessibility,” “Reliability,” “Serviceability,” and “Equity” are crucial to the social dimension. Traffic accidents cause unacceptable damage to residents’ lives and properties, leading to social and economic losses. “Accessibility” refers to the ability to reach the destination quickly and easily by various transport services, providing a user-friendly system with lower travel impedance [49]. “Reliability” and “Serviceability” are believed to be the most significant factors of sustainable transport, which meet the basic transportation needs of residents and can bring convenience and improvement of transportation service quality for residents [50]. “Equity” directly and heavily affects social welfare and the public’s sense of gain. Indeed, life is more pleasant when mobility is efficient, accessible, and cheaper. All five attributes inevitably affect the overall quality of life.

The three attributes of “Repairability,” “Low-carbon,” and “Land-use resilience” are designed to capture environmental sustainability. As a scarce resource for cities, the use of land can contribute to transportation sustainability. “Repairability” and “Low-carbon” are related to energy preservation, noise pollution prevention, toxic air...
contaminants, and greenhouse effect prevention, which are associated with urban livability and ecosystem health. All three attributes focus on maintaining the social-environmental balance.

The essential economic dimension for sustainability includes “Economic efficiency” and “Financial supportability.” Any sustainable system must be efficient and productive to operate with minimum expense [46]. Public finance, which is directly related to the budget of the city, can nurture urban transportation and ultimately contribute to the safety, accessibility, and innovation of the transportation system.

“Innovation” and “Intelligence” are designed to capture the scientific and technological dimension. The former is an inexhaustible driving force for national and social development, and the latter can make cities smarter. Rail transit systems and new energy vehicles can be regarded as the application of innovation and intelligence in the transportation system, which will continue to be an essential part of the urban mobility system in the foreseeable future. New energy vehicles, such as hybrid vehicles, and cleaner diesel vehicles can reduce carbon and toxic gas emissions; others such as tram, subways, and other rail transit systems can greatly increase transportation capacity and efficiency.

2.2.3. Indicator Layer. The indicator layer acts as a micro-level bottom in the proposed BNM, which enables the application of the attribute layer. Indicators are bits of information that reflect the status of a large system from different perspectives. Although many studies have been dedicated to defining an appropriate indicator set, it remains an intangible term with great fuzziness, without any universal rule for its choice. Based on available data and research purposes, a set of indicators, including the level of municipal facilities, peak congestion coefficient, average commute speed, air pollutant emissions, traffic power consumption, and new energy vehicles, are deliberately chosen as root nodes in the BNM. During the selection, these indicators are involved in the different stages of traffic management such as design, construction, operation, maintenance, and innovation to ensure its comprehensiveness and universality. Table 1 illustrates a summary of the nodes in all three layers.

2.3. Determining the CPT of BNM Based on PCA. PCA is used to determine the CPT of the proposed BNM. For the sake of clarity, the process of determining the CPT is divided into four steps as follows.

2.3.1. Normalization of Indicators. The raw data must go through normalization because they have different units, which may cause inconsistency [51]. In this study, the indicators are normalized by using the truncated normal distribution method (TNORM). This method treats the raw data as random variables and models a truncated normal distribution by calculating the mean ($\mu$), standard deviation (STD), upper bound (UB), and lower bound (LB) of the variables (Figure 5). For instance, the $\mu$ of a certain variable is $a$, the STD is $b$, UB is determined as the maximum value, LB is the minimum value, and “1” expresses the cumulative probability of the variable. Then, the TNORM is used for modeling:

$$TNORM \sim (\mu = a, STD = b, UB = \max(x), LB = \min(x), 1). \quad (2)$$
In a BNM, the node variables are Boolean variables with two states of positive and negative. If an indicator is a positive-effect indicator, then its normalized value is calculated as the integral of the probability density of \( TNORM \) to \([LB, X]\). If an indicator is a negative-effect indicator, its normalized value is calculated as the integral of the probability density of \( TNORM \) to \([X, UB]\). Raw data are normalized to a range between 0 and 1 by implementing this method.

### 2.3.2 Calculation of Subdivision Weights

The calculation of subdivision weights is demonstrated in the second step. In this step, the latent factors \( j \) of indicators \( k \) corresponding to each subdivision \( s \) and dimension \( d \) are extracted by applying PCA. \( NI_{kjsd} \) stands for the normalized indicator value. Then, the indicators corresponding to each latent factor \( j \) are weighted by equation (3) and aggregated by equation (4).

#### Table 1: Summary of all the nodes in the proposed BNM.

| Dimension layer | Indicator layer | Unit |
|-----------------|-----------------|------|
| \( D_1: \) social | \( S_1: \) ratio of fatalities on traffic accidents | N/A |
| \( D_2: \) environmental | \( A_1: \) area of paved roads | 10000 Sq.m |
| \( D_3: \) economical | \( A_2: \) length of paved roads | km |
| \( D_4: \) scientific and technologic | \( A_3: \) per capita area of paved roads | Sq.m |
| Attributes layer | \( A_4: \) per vehicle area of paved roads | Sq.m |
| \( AT_1: \) safety | \( R_1: \) congestion index | N/A |
| \( AT_2: \) accessibility | \( R_2: \) average commute speed | km/h |
| \( AT_3: \) reliability | \( SE_1: \) number of public transport operating vehicles | 10000 vehicles |
| \( AT_4: \) serviceability | \( SE_2: \) length of public transport line | km |
| \( AT_5: \) equity | \( SE_3: \) number of vehicles | Vehicle |
| \( AT_6: \) low-carbon | \( E_1: \) per capita households expenditure on transportation | Yuan |
| \( AT_7: \) land-use resilience | \( E_2: \) ratio of per capita households expenditure on transportation | N/A |
| \( AT_8: \) economic efficiency | \( R_1: \) toxic air contaminants emission by transportation | \( \mu g/m^3 \) |
| \( AT_9: \) financial affordability | \( R_2: \) greenhouse gases emission by transportation | \( \mu g/m^3 \) |
| \( AT_{10}: \) innovation | \( R_3: \) noise pollution | Decibel |
| \( AT_{11}: \) intelligence | \( L_1: \) electricity consumption by transportation | 10000 kwh |
| Attributes layer | \( LA_1: \) area of land consumed by transportation infrastructure | Sq.km |
| | \( EC_1: \) GDP of the transportation industry | 100 million Yuan |
| | \( F_1: \) fiscal expenditures on transportation | 100 million Yuan |
| | \( F_2: \) fixed asset investment on transportation | 100 million Yuan |
| | \( I_1: \) length of rail transit lines | km |
| | \( I_2: \) number of new-energy vehicles | Vehicle |

#### Figure 5: An illustrative example of a truncated normal distribution.

In a BNM, the node variables are Boolean variables with two states of positive and negative. If an indicator is a positive-effect indicator, then its normalized value is calculated as the integral of the probability density of \( TNORM \) to \([LB, X]\). If an indicator is a negative-effect indicator, its normalized value is calculated as the integral of the probability density of \( TNORM \) to \([X, UB]\). Raw data are normalized to a range between 0 and 1 by implementing this method.

\[
W_{kjsd} = \frac{\left(\text{FactorLoading}_{kjsd}\right)^2}{\text{Eigenvalue}_{jsd}}, \quad k \in K_s, j \in J_s, s \in S_d, d \in D, \tag{3}
\]

\[
\text{CFI}_{jsd} = \sum_k W_{kjsd} NI_{kjsd}, \quad k \in K_s, j \in J_s, s \in S_d, d \in D. \tag{4}
\]
After calculating the composite factor indices \((\text{CFI}_{jd})\) by equation (4), the weights of subdivision can be calculated by equation (5). Then, composite subdivision indices \((\text{CSI}_{sl})\) can be aggregated by using equation (6).

\[
\begin{align*}
a_{jd} &= \frac{\text{Eigenvalue}_{jd}}{\sum_{jd} \text{Eigenvalue}_{jd}}, \quad j \in J, s \in S_d, d \in D, \\
\text{CSI}_{sl} &= \sum_{jd} a_{jd} \text{CFI}_{jd}, \quad j \in J, s \in S_d, d \in D.
\end{align*}
\]

### 2.3.3. Calculation of Dimension Weights

The analysis process of the third step is somehow similar to that of the second step. However, the output of this step will be dimension weights. In this step, \(j'\) is the latent factor of each dimension \((d)\). The weights of latent factors can be calculated by equation (7), and then composite factor indices \((\text{CFI}_{j'd})\) can be aggregated by equation (8). Then, the weights of the dimensions can be calculated by equation (9).

\[
\begin{align*}
W_{sf'd} &= \frac{(\text{Factor Loading}_{sf'd})^2}{\text{Eigenvalue}_{j'd}}, \quad j' \in J_d, s \in S_d, d \in D, \\
\text{CFI}_{j'd} &= \sum_{s} W_{sf'd} \text{CSI}_{sl'}, \quad j' \in J_d, s \in S_d, d \in D, \\
a_{j'd} &= \frac{\text{Eigenvalue}_{j'd}}{\sum_{j'd} \text{Eigenvalue}_{j'd}}, \quad j' \in J_d, d \in D, \\
\text{CD}_{ld} &= \sum_{j'} a_{j'd} \text{CFI}_{j'd}, \quad j' \in J_d, d \in D.
\end{align*}
\]

### 2.3.4. Determining the CPT of BNM Based on the Weight System

The weights of each subdivision and each dimension were calculated by PCA in the former steps. Finally, in this step, the weight system will be applied to determine the CPT of BNM. The derivation of the equivalence relationship is as follows: taking indicators \(E_1\) and \(E_2\) aggregated into subdivision \(AT_3\) as an example, the relationship is

\[\text{AT}_3 = E_1 \times \beta_{E_1} + E_2 \times \beta_{E_2} \quad \beta_{E_1} + \beta_{E_2} = 1.\]

This paper uses TNorm to normalize the raw data. As mentioned before, the node variables \(E_1\) and \(E_2\) are Boolean variables with two states of positive and negative. Therefore, the following expressions are obtained:

\[P(E_1 = P) + P(E_1 = N) = 1 \quad P(E_2 = P) + P(E_2 = N) = 1.\]

After introducing equation (12) to equation (11), we can obtain equation (10). In equation (10), the probability expression of variable \(AT_3\) with state of positive can be extended to four items, which are four possible cases of the combination of \(E_1\) and \(E_2\).

\[
P(AT_3 = P) = P(E_3 = P) \times \beta_{E_1} + P(E_3 = P) \times \beta_{E_2}
\]

\[
= P(E_3 = P) \times (P(E_2 = P) + P(E_2 = N)) \times \beta_{E_1} + P(E_3 = P) \times (P(E_1 = P) \times \beta_{E_1} + P(E_3 = P) \times (E_1 = N) \times \beta_{E_2} + P(E_3 = P) \times (E_2 = P) + 0 \times P(E_1 = N) \times P(E_2 = N) \beta_{E_1} + \beta_{E_2} = 1.
\]

In BNM, the conditional probability relationships between a child node and its parent node can be written as follows:

\[P(T = t) = \sum_{i} P(T = t | X_1 = x_1, \ldots, X_n = x_n) \times P(X_1 = x_1, \ldots, X_n = x_n).\]
3. Case Study

3.1. Data Description. We selected eight megacities in China as a case study, namely, Beijing, Shanghai, Guangzhou, Shenzhen, Nanjing, Tianjin, Chengdu, and Chongqing. These eight cities are ranked top in China and present top-level urban economic development in China. The multisource data between 2010 and 2019 were obtained from various sources, such as the China National Bureau of Statistics, China Statistical Yearbook, the Yearbook of China’s Urban Transportation, and Alibaba’s Amap traffic group. There were only a small number of missing data in the original dataset, and this paper used the following methods to tackle the missing data: if the data had no obvious trend, we filled the data with the mean value. Take variable \( R_2 \) of Nanjing for example: the data in 2010 is missing; the figures for the remaining years have not changed much. We calculated the mean value of the variable \( R_2 \) from 2011 to 2019 and then filled the missing data with the calculated mean value. If the data had an obvious trend, then the missing data could be filled with forecast data through the Grey Model Theory. The Grey Model theory was founded by the Chinese Professor Julong Deng; it has the advantage of small-sample modeling and is considered as a new method to forecast and estimate parameters through extracting valuable information from the known information. Because of its advantages, it can be applied to parameter estimation. We used this method to estimate variable \( E_1 \) of Tianjin in 2015. Table 2 is a statistical summary of the collected variables in the indicator layer.

Note that some indicators such as \( A_4 \) and \( E_2 \) were calculated by using a combination of multisource data. \( A_4 \) can be calculated as the area of paved roads divided by vehicles.

3.2. Data Processing. We set binary positive and negative states of all variable nodes in the proposed BNM and then used TNORM to normalize the data from 2010 to 2019. With the fitted distribution, the probability of variable \( A_1 \) being positive, \( P( A_1 = \text{positive} ) \) can be directly determined by obtaining the cumulative probability, and the probability of being negative, \( P( A_1 = \text{negative} ) \), can be simply calculated as \( 1 - P( A_1 = \text{positive} ) \).

Table 3 demonstrates the main estimated parameters of the TNORM modeling for the variables. With these parameters, one can convert data into prior probability as initial input values in the proposed BNM. As an example, Table 4 shows the converted probability values of variable \( A_2 \).

Figure 6 shows the determined CPT for variable \( A_4 \) —accessibility. In forward inference, the probability of \( A_2 \) can be calculated using all the inputs from \( A_1 \) to \( A_4 \) based on this conditional probability table.

With all the variables and probability determined, we can obtain the BNM, as shown in Figure 7. Then, we can carry out sustainability measurement analysis by the forward inference and sensitivity analysis in the following step. NETICA software was used to carry out BNM analysis in this study.

4. Results and Discussion

4.1. Forward Inference. The objective of the forward inference is to compute the probability of sustainability in the transportation system for the sampled cities. With input data prepared for root nodes, we can compute the probability of sustainability = positive as yearly evaluation.

4.1.1. Sustainability Analysis. The yearly sustainability analysis from 2010 to 2019 is shown in Figure 8. We categorize the eight cities into three groups, representing different levels of sustainability based on the values of the measurement. Values above 0.50 indicate good relative sustainability, between 0.40 and 0.50 are normal relative sustainability, and less than 0.40 are weak relative sustainability. As shown in Figure 8, most of the cities’ transportation systems are at the moderate level. Taking Nanjing and Guangzhou as examples, more than five years are labeled as normal relative sustainability, whereas those of Chengdu and Tianjin are classified as weak relative sustainability. This prominent feature indicates that the transportation system in these megacities might not be as sustainable as we had anticipated, thus requiring further improvement.

During the research period, Beijing demonstrated a growing trend throughout the 10-year observation, and the other seven cities experienced dynamic fluctuation and upward movement. Among them, Guangzhou, Shenzhen, Tianjin, and Chengdu had a rough “N” shape in the overall trend during the ten years of development, whereas Shanghai and Nanjing had a rough “bathtub” shape. Despite the year-to-year fluctuations, the mean values of sustainability from 2017 to 2019 are higher than those before 2017 in all eight cities, reflecting the gradual growing trend in the sustainability of the transportation systems. In terms of growth rate, Beijing and Shanghai had relatively higher growth rates from 2014 to 2019, whereas the growth rates of
the other cities remained relatively steady during the research period.

Figure 9 reveals the sustainability differences among the eight cities based on the mean values of the 10-year observation. The eight cities are ranked in descending order based on the evaluated sustainability, which presents a gradient distribution pattern. The mean values of the sustainability of Beijing and Shanghai in the past 10 years are 0.57 and 0.63, respectively, showing good relative sustainability. The mean values of Shenzhen, Guangzhou, Chengdu, Nanjing, and Chongqing are 0.45, 0.44, 0.40, 0.41, and 0.49, respectively, showing medium sustainability. Tianjin’s mean

### Table 2: Summary of the collected variables in the indicator layer.

| Variables | Data collected for the variables | Unit | Collection frequency | Max | Min | Mean |
|-----------|----------------------------------|------|----------------------|-----|-----|------|
| $S_1$    | Ratio of fatalities on traffic accidents | N/A | Yearly | 5.29 | 0.75 | 2.43 |
| $A_1$    | Area of paved roads | 10000 Sq.m | Yearly | 30839 | 6460 | 14148 |
| $A_2$    | Length of paved roads | km | Yearly | 18546 | 2610 | 8075 |
| $A_3$    | Per capita area of paved roads | Sq.m | Yearly | 24.3 | 4.46 | 12.69 |
| $A_4$    | Per vehicle area of paved roads | Sq.m | Yearly | 163.7 | 16.43 | 51.39 |
| $R_1$    | Congestion index | N/A | Yearly | 6.14 | 1.59 | 2.30 |
| $R_2$    | Average commute speed | km/h | Yearly | 34.44 | 2.08 | 27.18 |
| $R_3$    | Passenger capacity of urban public transport | 10000 persons | Yearly | 815849 | 15269 | 309167 |
| SE$_1$   | Number of public transport operating vehicles | Vehicles | Yearly | 40499 | 5952 | 16657 |
| SE$_2$   | Length of public transport operation line | km | Yearly | 304140 | 3467 | 44834 |
| SE$_3$   | Number of vehicles | 10000 vehicles | Yearly | 653.95 | 8.31 | 345.48 |
| $E_1$    | Per capita households expenditure on transportation | Yuan | Yearly | 5701 | 1384 | 3584 |
| $E_2$    | Ratio of per capita households expenditure on transport | N/A | Yearly | 18.64 | 7.65 | 12.64 |
| $R_1$    | Toxic air contaminants’ emission by transport | μg/m$^3$ | Yearly | 77 | 10 | 30.17 |
| $R_2$    | Greenhouse gases by transportation | μg/m$^3$ | Yearly | 71.94 | 10 | 30.17 |
| $R_3$    | Noise pollution | Decibel | Yearly | 70.9 | 65.6 | 68.34 |
| $L_1$    | Electricity consumed by transportation | 10000kwh | Yearly | 993081 | 2039.96 | 279435 |
| LA$_1$   | Land consumed by transportation infrastructure | Sq.km | Yearly | 485.27 | 13.43 | 185 |
| EC$_1$   | GDP of the transportation industry | 100 million Yuan | Yearly | 16500 | 260 | 743 |
| $F_1$    | Fiscal expenditures on transport | 100 million Yuan | Yearly | 1045 | 10 | 162 |
| $F_2$    | Fixed asset investment on transportation | 100 million Yuan | Yearly | 2713 | 37 | 667 |
| $I_1$    | Length of rail transit line | km | Yearly | 704.91 | 17.6 | 283.31 |
| $I_2$    | Number of new-energy vehicles | Vehicle | Yearly | 307075 | 0 | 42206 |

### Table 3: Parameter estimations for truncated normal distribution modeling.

| Label | Variable | $\mu$ | STD | UB | LB |
|-------|----------|-------|-----|----|----|
| $A_1$ | Area of paved roads | 14147.57 | 6228.17 | 30839 | 6460 |
| $A_2$ | Length of paved roads | 8074.95 | 4196.48 | 18546 | 2610 |
| $A_4$ | Per vehicle area of paved roads | 51.39 | 31.75 | 163.72 | 16.43 |
| $R_1$ | Congestion index | 2.30 | 31.75 | 6.14 | 1.59 |
| SE$_1$ | Number of public transport operating vehicles | 16657.38 | 8663.66 | 40499 | 5952 |
| $L_1$ | Electricity consumed by transportation | 279435.48 | 257792.88 | 993081 | 2039.96 |
| $F_2$ | Fixed asset investment on transportation | 667.61 | 455.46 | 2713.30 | 36.57 |
| $I_1$ | Length of rail transit line | 283.31 | 193.78 | 704.91 | 17.6 |

### Table 4: Probability inputs for indicator $A_2$.

| Year | $A_2 = \text{positive}$ | Beijing | Shanghai | Guangzhou | Shenzhen | Nanjing | Tianjin | Chengdu | Chongqing |
|------|--------------------------|---------|----------|-----------|----------|---------|--------|---------|----------|
| 2010 | Mean = 8074.95           | 56.45%  | 62.39%   | 18.86%    | 24.88%   | 0.85%   | 3.90%  | 0       | 4.63%    |
| 2011 | STD = 4196.48            | 60.16%  | 58.48%   | 96.08%    | 39.33%   | 1.57%   | 5.54%  | 3.25%   | 6.06%    |
| 2012 | UB = 18546               | 60.92%  | 60.13%   | 97.40%    | 35.14%   | 1.56%   | 9.12%  | 12.48%  | 7.47%    |
| 2013 | LB = 2610               | 61.71%  | 61.96%   | 99.02%    | 35.50%   | 2.58%   | 13.85% | 18.71%  | 18.34%   |
| 2014 |                           | 64.64%  | 61.96%   | 99.21%    | 37.84%   | 6.80%   | 20.04% | 19.96%  | 20.03%   |
| 2015 |                           | 64.47%  | 60.16%   | 99.52%    | 38.07%   | 6.96%   | 22.17% | 22.44%  | 23.29%   |
| 2016 |                           | 62.84%  | 55.33%   | 99.63%    | 39.94%   | 7.95%   | 28.82% | 27.95%  | 24.78%   |
| 2017 |                           | 60.48%  | 50.67%   | 99.07%    | 50.00%   | 8.20%   | 28.21% | 32.52%  | 30.24%   |
| 2018 |                           | 60.39%  | 48.66%   | 99.98%    | 48.70%   | 9.89%   | 38.66% | 40.17%  | 38.30%   |
| 2019 |                           | 90.32%  | 38.49%   | 99.66%    | 48.36%   | 7.98%   | 45.95% | 40.40%  | 45.28%   |
score (0.38) is the lowest. In general, the great disparities among the eight cities in terms of sustainability indicate the need for improvement.

For more in-depth analysis, the inner reasons for the superiority can be determined. The values of Shanghai’s transportation sustainability show a drastic increase from 0.56 in 2014 to 0.73 in 2016 and is maintained around 0.75 in the following years, which may be affected by the comprehensive policies to strengthen environmental protection in Shanghai. As an indicative example, the “Shanghai Clean Air Action Plan (2013–2017)” issued by the municipal government has curbed the total emission of motor vehicle pollutants by especially taking concrete measures to eliminate high emission and older vehicles. According to rough calculations by the Shanghai Environmental Protection Department, NO\textsubscript{X} emissions can be reduced by an average of 60,000 tons per year, and the PM2.5 concentrations can be reduced by approximately 3–4 \(\mu g/m^3\) each year. Thus, these factors have an obvious powerful positive effect on transport sustainability. The transportation industry is becoming more and more environmentally friendly. Thus, these factors have an obvious powerful positive effect on transport sustainability.

Figure 6: The determined CPT for variable AT\textsubscript{2}—accessibility.

![Diagram of CPT for AT2](image)

Figure 7: The proposed BNM.

![Diagram of BNM](image)
4.1.2. Sustainability-Economic Coupling Analysis. It is believed that the level of regional economic development, urban governance, and urbanization directly influence the sustainability of the transportation system. In particular, it is expected that there should be a strong and positive coupling effect between regional economic development and transport sustainability, which may not be the case. An analysis of the annual GDP development reveals that most case cities’
transport sustainability does not always positively correlate with economic growth. This can be confirmed by sustainability-economic coupling analysis (Figure 10). The regression and $R^2$ values indicate their coupling strength. A better $R^2$ value indicates a stronger positive coupling relationship between transportation sustainability and the regional economic level, such as Shenzhen and Beijing. Moreover, a lower $R^2$ value represents a nonlinear characteristic, such as Tianjin, whose $R^2$ is below 0.4. The $R^2$ values of the other cities are medium, indicating that the economic growth of these metropolises does not necessarily bring about continuous growth in transport sustainability.

It is expected that economic growth will increase investment in transportation infrastructure, leading to the development of a more mature transportation network, which will enhance the overall transport sustainability. However, the development of transport sustainability is an integration involving multiple fields in which economic prosperity is merely one dimension but will not necessarily enhance it. One possible reason is that positive economic development makes the city more attractive, attracting significant resources and talents from all over the world, causing high population density and substantially increasing transportation demand, which will result in new imbalances, negative burdens, and externalities. These in turn affect the sustainability of the entire transportation system. The nonlinear relationship between economic development and transport sustainability reveals the multidimensional characteristics of sustainable development. Therefore, achieving sustainable development of urban transportation is a complex system engineering, which requires the integration of the combined effect of multiple factors and systemic consideration.

4.2. Sensitivity Analysis. The proposed method can compute the sensitivity index (SI) for each variable in each year, which can help to identify the good or poor performing nodes. Correspondingly, policy-makers can pay extra attention to these checkpoints when making decisions. Two tendencies of downward or upward are shown in Figure 11; the former indicates that something has been tackled well and has a positive effect on traffic sustainability, and the latter indicates otherwise. Through sensitivity analysis, we can discover some of the reasons for superiority or inferiority.

The safety and security attributes are believed to be one of the most significant factors of transport sustainability. Due to safety management in recent years, which has been well incorporated into the entire life cycle of urban traffic systems in China, especially in megacities, these megacities have more effective enforcement of traffic safety. Moreover, many cities have started the construction of intelligent transportation, which can provide the sufficient information and diverse services to transport participants and improve the ability of traffic accident prevention and emergency disposal. Additionally, educational efforts have been paid to enhance the mutual awareness about traffic safety. China has designated December 2 as the National Traffic Safety Day. Various forms of traffic safety publicity activities have been carried out; moreover, traffic safety is an important course for Chinese primary school students. A better understanding of the standards of traffic safety, higher traffic safety awareness, and improvement of traffic safety management level have positively affected the safety, which in turn lead to a continuous downward trend in traffic accidents in recent years. This will have a positive effect on traffic sustainability, and the government should take measures to maintain this good situation.
The SI of “Accessibility,” “Reliability,” and “Serviceability” has had a clear upward trend in the past ten years. These three attributes are closely related to the contradictions between traffic demand and supply, playing an increasingly important role in enhancing transport sustainability. In recent years, although the government is dedicated to increasing the supply of transportation, the demand for transportation is also increasing. The imbalance between transportation supply and demand can only be improved temporarily, and new imbalance and other associated stress appear with time, which has become hard to address and has had a negative effect on the sustainable development of transportation. The government needs to pay attention and take effective measures to tackle it.

Figure 10: Analysis of sustainability-economic coupling effect.
The SI of “Equity” has also experienced a continuous downward trend in the past ten years due to the low price of public transportation after the government subsidy. For example, the public transportation in many cities in China is free for the elderly and disabled; the ratio of household expenditure on transportation has been declining, and the people’s sense of satisfaction and gain in transportation has been continuously enhanced. The growing social welfare and sense of social equity have had a positive effect on urban transportation sustainability.

The SI of “Reparability” and “Low carbon” has had a continuous upward trend in the past ten years. The problem of motor vehicle pollution has become increasingly prominent as the main source of air pollution. China is the largest CO₂ emitter in the world, with 103.13 million tons of CO₂ emissions in 2018 [3]. China’s transport-related CO₂ emissions account for 25% of the total CO₂ emissions, and liquid fuel consumption related to transport accounts for 65% of the total energy consumption in 2016. Moreover, the analyses of atmospheric PM2.5 sources in cities such as Beijing, Tianjin, and Shanghai indicate that almost 50% of the PM2.5 concentrations are caused by mobile sources. Therefore, issues of transport-related emission and energy consumption require more attention and action from the government.

The SI of “Innovation” has had an upward trend in the past ten years. Every coin has two sides, and technology innovation is no exception. For example, the marginal effects of specific applications of new-energy vehicles may diminish with time. The increase in the number of new-energy vehicles will bring about undesirable consequences, such as tight parking space and increased road congestion, which will directly swallow up or even exceed its initial benefits. More data do not necessarily mean more useful information; it may contain ambiguous or abnormal information. Therefore, constant technological innovation is needed to cope with the problems in the development of sustainable transport. Sufficient attention should be given to it, and a combination of various policy measures should be adopted to facilitate technological innovation.

5. Conclusion

5.1. Summary of Findings. This paper proposes a unique approach to quantitatively evaluate the sustainability of urban transportation systems. Eight megacities in China were used as a sample to illustrate the applicability and strength of the proposed model. Instead of finding a one-size-fits-all model for measuring transport sustainability, the ultimate purpose of this study is to introduce a new perspective on how we can interpret transport system sustainability as a multidimensional property and identify key checkpoints that should be given special attention. This study draws the following three conclusions.

Firstly, the overall levels of transportation sustainability in the selected cities are moderate, revealing that the transportation system of these cities is not sustainable as we anticipated. The trend of Shenzhen, Guangzhou, and the other cities has had a rough “N” shape, whereas that of Shanghai and Nanjing has had a rough “bathtub” shape. All the cities have exhibited an increasing trend in recent years, although they have had dynamic fluctuation. Moreover, certain disparities among the eight cities in terms of sustainability indicate the need for improvement.

Secondly, the sustainability-economic coupling analysis shows a nonlinear relationship between sustainability and economic level, revealing that economic growth does not necessarily lead to the enhancement of the transport sustainability.

Thirdly, the results of the sensitivity analysis demonstrate the upward tendency of “Accessibility,” “Serviceability,” “Reliability,” and “Innovation,” indicating their great effect on transport sustainability. More sustainable transportation systems will be achieved after managing these relationships well.

5.2. Managerial Implications. Some rational managerial implications can be discussed based on the study.

Firstly, systemic thinking is essential for decision-making. As previously stated, transport sustainability is a multifaceted property, which covers a vast domain, so quality of social life, economic prosperity, environmental integrity, and progressive technology should be integrated into it. Moreover, the systemic approach should not be a static consideration but should be incorporated into the entire life cycle of transportation systems, including the design, construction, and management of transportation systems. Stakeholders, including designers, constructors, operators, and managers, should closely work together.

Secondly, as a type of modern sociotechnical system, more attention should be paid to the attributes that had an upward trend in the research period, such as “Accessibility,” “Serviceability,” “Reliability,” and “Innovation.” Policies that will meet the travel needs of the residents, enhance human’s
environmental surroundings, and help to reduce economic costs should be implemented.

5.3. Limitations and Future Studies. Although the proposed BNM can satisfactorily measure the sustainability of the urban traffic system and provide insights into the effect of the indicators on sustainability, certain limitations and future extensions are worth noting. Firstly, due to the availability and quality of the data used in this study, the measurement is only four-dimensional modeling. Future research can be extended with more information, including cultural, historical, and geographical; a more comprehensive model with a wide-angle view may be required. Secondly, this study is conducted based on a finite number of microdata, the application of big data will provide good supplements for future studies, and new methods of data mining and interaction analysis may be required to enhance analysis. Thirdly, this study is limited to a relatively small group of eight metropolitan areas in China; future research can extend to a large-scale group, which would help the planner to identify the condition of regions comparatively. These extensions will be researched in our future work to provide more meaningful findings to policy-makers, scholars, and other stakeholders.

Data Availability

The data were obtained from various sources, such as the China National Bureau of Statistics, China Statistical Yearbook, the Yearbook of China’s Urban Transportation, and Alibaba’s Amap traffic group.

Conflicts of Interest

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

Acknowledgments

This research was supported by the Special Funds for Basic Scientific Research in Central Universities of China (no. JBK2002011) and the Soft Science Research Project of Chengdu (no. 2017-RK00-00229-ZF).

References

[1] M. Diao, H. Kong, and J. Zhao, “Impacts of transportation network companies on urban mobility,” Nature Sustainability, vol. 4, no. 6, pp. 494–500, 2021.
[2] W.-M. Wey and J.-Y. Huang, “Urban sustainable transportation planning strategies for livable City’s quality of life,” Habitat International, vol. 82, pp. 9–27, 2018.
[3] World Bank, GHG Emissions, World Resources Institute, Washington, DC, USA, 2020, https://data.worldbank.org/indicator/EN.ATM.CO2E.KT?view=chart.
[4] I. Mahdiniia, M. Habibian, Y. Hatamzadeh, and H. Gudmundsson, “An indicator-based algorithm to measure transportation sustainability: a case study of the U.S. states,” Ecological Indicators, vol. 89, pp. 738–754, 2018.
[5] UN (United Nations), Report of the World Commission on Environment and Development, United Nations Publication, 1987.
[6] M. Sciamarelli, “Sustainable development goal 9: Build resilient infrastructure, promote inclusive and sustainable industrialisation and foster innovation,” in Proceedings of the Integrating Global Issues in the Creative English Language Classroom: with Reference to the United Nations Sustainable Development Goals, p. 91, 2017, https://www.teachingenglish.org.uk/article/integrating-global-issues-creative-english-language-classroom.
[7] H. Haghsenas and M. Vaziri, “Urban sustainable transportation indicators for global comparison,” Ecological Indicators, vol. 15, no. 1, pp. 115–121, 2012.
[8] T. Litman, “Developing indicators for comprehensive and sustainable transport planning,” Transportation Research Record: Journal of the Transportation Research Board, 2017, no. 1, pp. 10–15, 2007.
[9] C. M. Jeon, A. A. Amekudzi, and R. L. Guensler, “Sustainability assessment at the transportation planning level: performance measures and indexes,” Transport Policy, vol. 25, pp. 10–21, 2013.
[10] T. Litman, Well measured: developing indicators for sustainable and livable transport planning, Victoria Transport Policy Institute, Victoria Canada, 2011.
[11] H. Castillo and D. E. Pittfield, “ELASTIC - a methodological framework for identifying and selecting sustainable transport indicators,” Transportation Research Part D: Transport and Environment, vol. 15, no. 4, pp. 179–188, 2010.
[12] EPA, “Guide to sustainable transportation performance measures,” United States Environmental Protection Agency, EPA 231-K-004, 2011.
[13] A. M. Hassan and H. Lee, “Toward the sustainable development of urban areas: an overview of global trends in trials and policies,” Land Use Policy, vol. 48, pp. 199–212, 2015.
[14] U. Illahi and M. S. Mir, “Development of indices for sustainability of transportation systems: a review of state-of-the-art,” Ecological Indicators, vol. 118, p. 106760, 2020.
[15] M. Reisi, L. Aye, A. Rajabifard, and T. Ngo, “Transport sustainability index: Melbourne case study,” Ecological Indicators, vol. 43, pp. 288–296, 2014.
[16] J. Tang, H. Heinimann, K. Han, H. Luo, and B. Zhong, “Evaluating resilience in urban transportation systems for sustainability: a systems-based Bayesian network model,” Transportation Research Part C: Emerging Technologies, vol. 121, p. 102840, 2020.
[17] C. De Gruyter, G. Currie, and G. Rose, “Sustainability measures of urban public transport in cities: a world review and focus on the Asia/Middle East Region,” Sustainability, vol. 9, no. 1, p. 43, 2016.
[18] A. Alonso, A. Monzón, and R. Cascajo, “Comparative analysis of passenger transport sustainability in European cities,” Ecological Indicators, vol. 48, pp. 578–592, 2015.
[19] A. Stefaniec, K. Hosseini, J. Xie, and Y. Li, “Sustainability assessment of inland transportation in China: a triple bottom line-based network DEA approach,” Transportation Research Part D: Transport and Environment, vol. 80, p. 102258, 2020.
[20] S. Rajak, P. Parthiban, and R. Dhanalakshmi, “Sustainable transportation systems performance evaluation using fuzzy logic,” Ecological Indicators, vol. 71, no. 12, pp. 503–513, 2016.
[21] K. Baghizadeh, N. Cheikhrouhou, K. Govindan, and M. Ziyarati, “Sustainable agriculture supply chain network design considering water-energy-food nexus using queuing
system: a hybrid robust possibilistic programming,” *Natural Resource Modeling*, 2021.

[22] S. Ling, S. Ma, and N. Jia, “Sustainable urban transportation development in China: a behavioral perspective,” *Frontiers of Engineering Management*, pp. 1–15, 2021.

[23] T. Afrin and N. Yodo, “A probabilistic estimation of traffic congestion using Bayesian network,” *Measurement*, vol. 174, 2021.

[24] K. Baghizadeh, J. Pahl, and G. Hu, “Closed-loop supply chain design with sustainability aspects and network resilience under uncertainty: modelling and application,” *Mathematical Problems in Engineering*, vol. 2021, pp. 1–23, Article ID 9951220, 2021.

[25] W. C. Chan, W. H. W. Ibrahim, M. C. Lo, M. K. Suaidi, and S. T. Ha, “Sustainability of public transportation: an examination of user behavior to real-time GPS tracking application,” *Sustainability*, vol. 12, no. 22, p. 9541, 2020.

[26] T.-A. Shiau and J.-S. Liu, "Developing an indicator system for local governments to evaluate transport sustainability strategies," *Ecological Indicators*, vol. 34, no. 11, pp. 361–371, 2013.

[27] S. Bray, L. Caggiani, M. Dell’Orco, and M. Ottomanelli, “Measuring transport systems efficiency under uncertainty by fuzzy sets theory based data envelopment analysis,” *Procedia - Social and Behavioral Sciences*, vol. 111, pp. 770–779, 2014.

[28] A. Awasthi and S. S. Chauhan, “Using AHP and Dempster-Shafer theory for evaluating sustainable transport solutions,” *Environmental Modelling & Software*, vol. 26, no. 6, pp. 787–796, 2011.

[29] D. Staš, R. Lenort, P. Wicher, and D. Holman, “Green transport balanced scorecard model with analytic network process support,” *Sustainability*, vol. 7, pp. 15243–15261, 2015.

[30] R. Sayyadi and A. Awasthi, “An integrated approach based on system dynamics and ANP for evaluating sustainable transportation policies,” *International Journal of Systems Science: Operations and Logistics*, pp. 1–10, 2020.

[31] S. Sabet, F. Namdarpour, and M. Mesbah, “A cost-effective methodology to compare travel time and speed: a tale of 11 cities,” *Municipal Engineer*, vol. 5, pp. 1–24, 2020.

[32] K. Baghizadeh, D. Zimon, and L. Jum’a, “Modeling and optimization sustainable forest supply chain considering discount in transportation system and supplier selection under uncertainty,” *Forests*, vol. 12, no. 8, p. 964, 2021.

[33] X. Wu, H. Liu, L. Zhang, M. J. Skibniewski, Q. Deng, and J. Teng, “A dynamic Bayesian network based approach to safety decision support in tunnel construction,” *Reliability Engineering & System Safety*, vol. 134, pp. 157–168, 2015.

[34] J. Y. Zhu and A. Deshmukh, “Application of Bayesian decision networks to life cycle engineering in Green design and manufacturing,” *Engineering Applications of Artificial Intelligence*, vol. 16, no. 2, pp. 91–103, 2003.

[35] S. Hosseini, A. Al Khaleel, and M. Sarder, “A general framework for assessing system resilience using Bayesian networks: a case study of sulfuric acid manufacturer,” *Journal of Manufacturing Systems*, vol. 41, pp. 211–227, 2016.

[36] S. Hosseini and K. Barker, “Modeling infrastructure resilience using Bayesian networks: a case study of inland waterway ports,” *Computers & Industrial Engineering*, vol. 93, no. 5, pp. 252–266, 2016.

[37] L. Zhang, X. Wu, L. Ding, M. J. Skibniewski, and Y. Yan, “Decision support analysis for safety control in complex project environments based on Bayesian networks,” *Expert Systems with Applications*, vol. 40, no. 11, pp. 4273–4282, 2013.

[38] T. D. Phan, J. C. R. Smart, S. J. Capon, W. L. Hadwen, and O. Sahin, “Applications of Bayesian belief networks in water resource management: a systematic review,” *Environmental Modelling & Software*, vol. 85, no. 11, pp. 98–111, 2016.

[39] K. W. Przytula and D. Thompson, “Construction of Bayesian networks for diagnostics,” in *Proceedings of the IEEE Aerospace Conference Proceedings*, vol. 5, Big Sky, MT, USA, March 2000.

[40] Y. Huang, R. McMurran, G. Dhadyalla, and R. Peter Jones, “Probability based vehicle fault diagnosis: Bayesian network method,” *Journal of Intelligent Manufacturing*, vol. 19, no. 3, pp. 301–311, 2008.

[41] L. Sun, Y. Lu, J. G. Jin, D.-H. Lee, and K. W. Axhausen, “An integrated Bayesian approach for passenger flow assignment in metro networks,” *Transportation Research Part C: Emerging Technologies*, vol. 52, pp. 116–131, 2015.

[42] P. Verma and A. S. Raghubanshi, “Urban sustainability indicators: Challenges and opportunities,” *Ecological Indicators*, vol. 93, pp. 282–291, 2018.

[43] M. A. Siddique and M. A. Quaduddus, “Modelling sustainable development planning: a multicriteria decision conferencing approach,” *Environment International*, vol. 27, no. 2, pp. 89–95, 2001.

[44] D. Krajnc and P. Glavic, “A model for integrated assessment of sustainable development,” *Resources, Conservation and Recycling*, vol. 43, no. 2, pp. 189–208, 2005.

[45] G. A. Tanguay, J. Rajaonson, J.-F. Lefebvre, and P. Lanoie, “Measuring the sustainability of cities: an analysis of the use of local indicators,” *Ecological Indicators*, vol. 10, no. 2, pp. 407–418, 2010.

[46] Y. Shi, T. Arthanari, X. Liu, and B. Yang, “Sustainable transportation management: integrated modeling and support,” *Journal of Cleaner Production*, vol. 212, pp. 1381–1395, 2019.

[47] R. Mehmoond and G. Graham, “Big data logistics: a health-care transport capacity sharing model,” *Procedia Computer Science*, vol. 64, pp. 1107–1114, 2015.

[48] S. Suma, R. Mehmoond, N. Albugami, I. Katib, and A. Albeshti, “Enabling next generation logistics and planning for smarter societies,” *Procedia Computer Science*, vol. 109, pp. 1122–1127, 2017.

[49] R. Daniels and C. Mulley, “Explaining walking distance to public transport: the dominance of public transport supply,” *Journal of Transport and Land Use*, vol. 6, no. 2, pp. 5–20, 2011.

[50] C. Andre, H. Anne, and L. W. Joan, “Passengers’ perception of and behavioral adaptation to unreliability in public transportation,” *Transportation Research Record*, vol. 2351, no. 1, pp. 153–162, 2013.

[51] R. Joumard and H. Gudmundsson, “Indicators of environmental sustainability in transport,” *Indicators of Environmental Sustainability in Transport*, vol. 4, no. 3, p. 168, 2010.