TRCLC 18-1
September 30, 2019

Sustainable and Smart-growth City Ranking: Multifaceted Transportation Performance Measures in Smart Cities

FINAL REPORT

Jun-Seok Oh, Valerian Kwigizile, Ahmad Feizi

Western Michigan University

Transportation Research Center
for Livable Communities

Western Michigan University | University of Texas at Arlington | Utah State University | Wayne State University | Tennessee State University

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
TRCLC 18-01	N/A	N/A

4. Title and Subtitle Sustainable and Smart-growth City Ranking: Multifaceted Transportation Performance Measures in Smart Cities	**5. Report Date** September 30, 2019 **6. Performing Organization Code** N/A
7. Author(s) Jun-Seok Oh, Valerian Kwigizile, Ahmad Feizi	**8. Performing Org. Report No.** N/A
9. Performing Organization Name and Address Western Michigan University 1903 West Michigan Avenue Kalamazoo, MI 49008	**10. Work Unit No. (TRAIS)** N/A **11. Contract No.** TRCLC 18-01
12. Sponsoring Agency Name and Address Transportation Research Center for Livable Communities (TRCLC) 1903 W. Michigan Ave., Kalamazoo, MI 49008-5316	**13. Type of Report & Period Covered** Final Report 4/1/2019 - 9/30/2019 **14. Sponsoring Agency Code** N/A

15. Supplementary Notes

16. Abstract

The concept of smart city is fast becoming a key instrument in transforming living environments in a way better to enhance operational efficiency of a transportation system. This study identifies a framework to assess transportation performance measures and smart-growth of cities around the U.S. The proposed assessment framework is comprised of the evaluation of individual criterion and the assessment of comprehensive results. The criteria are categorized into four groups including network performance, traffic safety, environmental impact, and physical activity. This study provides a multifaceted approach to integrate the criteria's performance measures. As a case example, the proposed performance measures were examined for forty-six cities in the U.S. and the required data were gathered from multiple sources. A multi-criteria decision analysis (MCDA) method was employed to integrate and evaluate the score associated with each city. The output of the framework contains a sustainable and smart-growth ranking of the selected cities as well as uncertainty and sensitivity analysis. The sensitivity analysis was utilized to determine the quantity that each performance measure or weighting factor requires to alter the smart-growth score. It has been illustrated that the dominancy between reversible pairs in the ranking are critically sensitive for almost 15% of cases. The results of the proposed framework can be an effective decision supporting tool in analyzing traffic management strategies. Results from the score sensitivity calculation indicate that the proposed framework can be adopted in multifaceted transportation system performance in sustainable and smart-growth of cities.

17. Key Words	18. Distribution Statement
Smart city, Performance evaluation, Sustainable transportation, City ranking, Multi-criteria decision analysis	No restrictions.

19. Security Classification - report	20. Security Classification - page	21. No. of Pages	22. Price
Unclassified	Unclassified		N/A

Disclaimer

The contents of this report reflect the views of the authors, who are solely responsible for the facts and the accuracy of the information presented herein. This publication is disseminated under the sponsorship of the U.S. Department of Transportation's University Transportation Centers Program, in the interest of information exchange. This report does not necessarily reflect the official views or policies of the U.S. government, or the Transportation Research Center for Livable Communities, who assume no liability for the contents or use thereof. This report does not represent standards, specifications, or regulations.

Acknowledgments

This research was funded by the US Department of Transportation through the Transportation Research Center for Livable Communities (TRCLC), a Tier 1 University Transportation Center at Western Michigan University.

Table of Contents

List of Figures

List of Tables

Chapter 1 Introduction

1.1 Background

As a fundamental component in modern human beings' livelihood, the performance of transportation systems influences the quality of life in numerous ways. The performance assessment of transportation systems refers to the process of determining how well these systems perform concerning their intended objectives. The necessity for this assessment is considered crucial during the last recent years. The widely used term of sustainable transportation as a part of sustainable development has been defined as a mission that serves a community through a fast, safe, efficient, accessible and convenient transportation system to increase the quality of life (DOT, 2016). Sustainable transportation is described through its impacts on the economy, environment, and general well-being and it is measured by the system efficiency and effectiveness (Mihyeon Jeon, & Amekudzi, 2005).

On the other hand, the concept of smart city is fast becoming a key instrument in transforming living environments in a way better managing future demand of people. The goal of smart cities is to increase operational efficiency, share information with the public, and improve both the quality of government services and citizen welfare (Ramaprasad et al., 2017, and Wey & Hsu, 2014). Thus, the smart-growth strategies are considered as solutions to enhance the sustainability of a transportation system by enhancing the operational efficiency and effectiveness. Using the smart-growth strategies collects more usable data and builds big data infrastructure for transportation management. As a result, the strategies help us in providing more comprehensive and integrated solutions regarding transportation systems.

1.2 Research Objectives

The purpose of this research is to develop a conceptual framework for assessing transportation performance and smart-growth of cities around the U.S. that takes smart, and sustainable outcomes into consideration. In order to develop the assessment framework, our study examines extracting data from public sources and deriving candidate performance measures. We aim to suggest a rather new framework that can be pervasively utilized in similar studies with different samplings. The proposed assessment framework is comprised of the evaluation of individual items and the assessment of comprehensive results. The items, according to the general definition of sustainable and smart-growth, are categorized into four groups including network performance, traffic safety, environmental, and physical activity performance. Ultimately, the study intends to provide an integrated sustainable and smart-growth ranking of forty-six cities in the U.S. and discuss the uncertainty and sensitivity of the analysis.

1.3 Research Scope and Overview

This report is organized as follows. Chapter two reviews previous studies aimed to develop integrated measures to evaluate transportation systems performance. Chapter three explains the data preparation concept associated with the candidate performance measures and the overall proposed framework. The fourth chapter presents the results of the research, focusing on case study, multi-criteria decision analysis and sensitivity analysis. Discussion section is provided prior to drawing conclusions and includes the implication of the results for future research into this area. Finally, the conclusion gives a brief summary and application of the results. Figure 1-1 shows the conceptual framework of the research that extracted from five tasks:

Task 1: Literature Review

Task 2: Selection of Performance Measures

Task 3: Multi-Criteria Decision Analysis

Task 4: Data Analysis and Discussion

Task 5: Conclusion

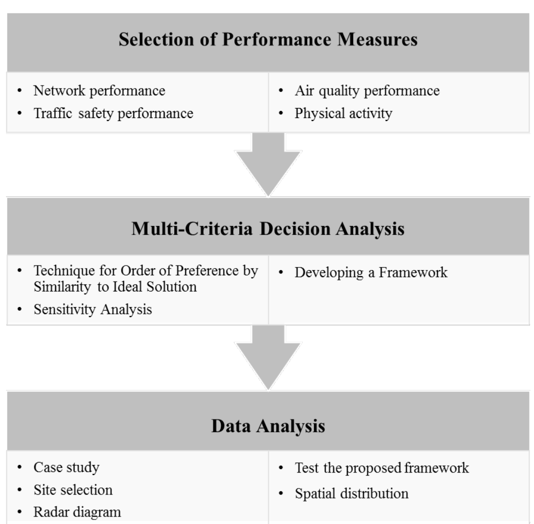

Figure 1-1: The conceptual framework of the research

Chapter 2 Literature Review

2.1 Overview

The recent years have been witnessed an increasing interest in developing performance indexes to determine the functionality of sustainable and smart transportation systems (Mihyeon Jeon, & Amekudzi, 2005; and Litman, 2009). This chapter presents a review of findings from previous studies on transportation performance evaluation in smart and sustainable cities. The existing methods to integrate the performance measures will also be presented. In the end, the research gap found in the literature review will be discussed.

2.2 Smart City

The widely used term of smart cities has become more popular in the last decades. There are several existing definitions of smart cities. According to Caragliu et al. (2011), a city is smart when "investment in human and social capital, transport, and modern communication infrastructure fuel sustainable economic growth and a high quality of life, with a wise management of natural resources, through participatory governance." Smart cities need sustainable urban development policies where all residents, including the poor, can live well and the attraction of the cities is preserved. Additionally, smart cities should be sustainable, converging economic, social, and environmental goals (Thuzar, 2011). The ultimate goal of smart cities is to provide real-time status updates of a city to solve problems such as traffic congestion and environmental pollution by combining technology, data analytics, and urban services.

Today's societies are facing challenges in transforming living environments in a way better managing future demand of people. A key point in this transformation is to redesign cities as *smart cities*, where the main services are integrated in a way that ensures a high quality of life while minimizing the usage of resources (Caragliu et al., 2011). Intelligent and multi-modal transportation concepts are widely seen as key components of smart sustainable cities (Motta et al., 2015). Such systems usually involve combinations of various modes of individual mobility (private cars, bicycles, walking), public transportation, and shared mobility (e.g. car sharing, Uber). The issue arises of how cities, surrounding regions and rural areas can evolve towards sustainable open and user-driven environment and how they can be synchronized and coordinated with each other.

Smart cities, as shown in Figure 2-1, are constituted from number of components, which are interrelated. Most of the previous literature have focused on how to integrate and connect different constitutes of a smart city (Lee et al., 2013; Ruiz-Romero et al., 2014; and Jin et al., 2014). From transportation perspective, however, it is crucial to have a comprehensive and integrated framework to evaluate the transportation performance in smart cities. To the best of our knowledge, there is no standard or constraint guideline to evaluate the constitutes of a transportation system in smart cities. Transportation in smart cities is largely being described through its impacts on the economy, environment, and general social well-being; and measured by system effectiveness and efficiency, and the impacts of the system on the natural environment (Mihyeon Jeon & Amekudzi, 2005).

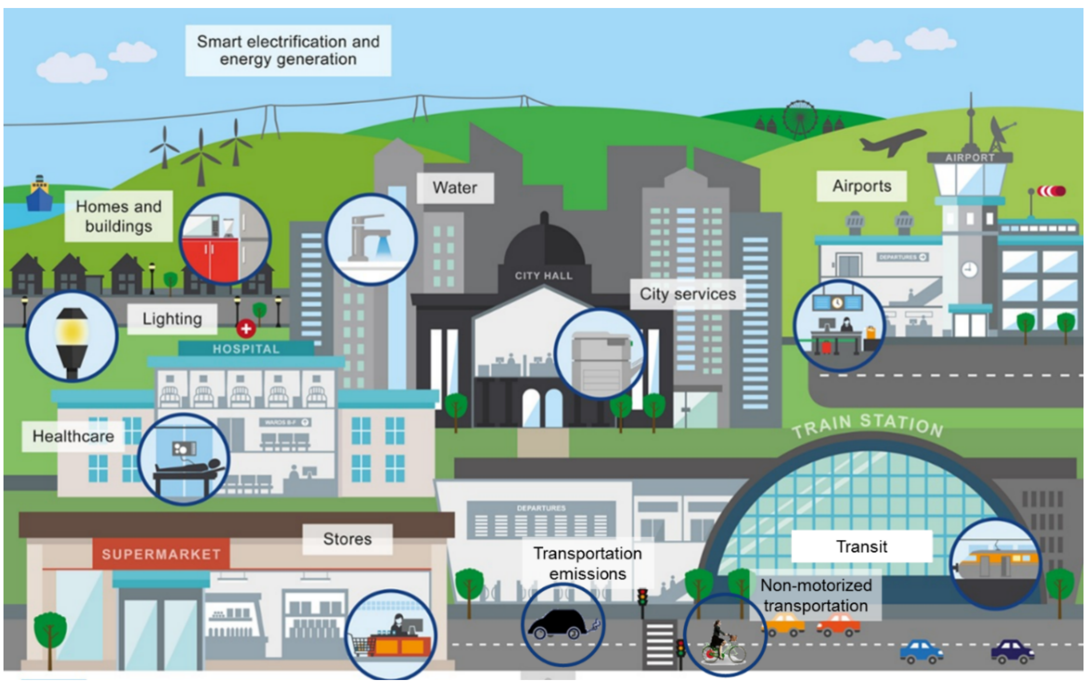

Figure 2-1: A Typical smart city constitutes (Source: www.iec.ch)

2.3 Performance Evaluation

Several studies have been conducted to adopt frameworks, indicators and metrics for transportation systems assessment (Gilbert et al., 2003; Litman, 2009; Haghshenas & Vaziri, 2012; and Castillo & Pitfield, 2010, for instance), however, there is no standard way in which smart cities' transportation is being evaluated. Preliminary work on transportation system performance was undertaken by World Health Organization (WHO, 2017). The study examined economic valuation of health effects of cycling and walking and proposed a technique, which is called Health Economic Assessment Tool (HEAT). HEAT is a comprehensive study that has introduced a harmonized method for economic evaluation based on available evidence. The tool can be used for assessing changes over time, such as before-and-after situations or scenario A versus scenario B. HEAT, however, is designed to be applied for assessment on groups of people not individuals. Another gap recognized in the evaluation steps of the tool is that HEAT follows the four-step model assumptions to generate the travel demand pattern.

According to the general definition of transportation in smart cities, constitutes can be categorized into five major groups, which are including, *network performance*, *traffic safety*, *environmental*, *equity and social*, and *public health*. Because of causal relationships among categories (e.g. environmental and public health), they would not be defined as utterly independent categorizes. To overcome this problem, this study identifies the categories with various subcategories and factors. Moreover, there are interrelationships among subcategories to each other that should be considered for evaluations. This approach can facilitate the performance evaluation process, which will be describing later. Figure 2-2 shows the major constitutes as well as the subcategories contributed to each group.

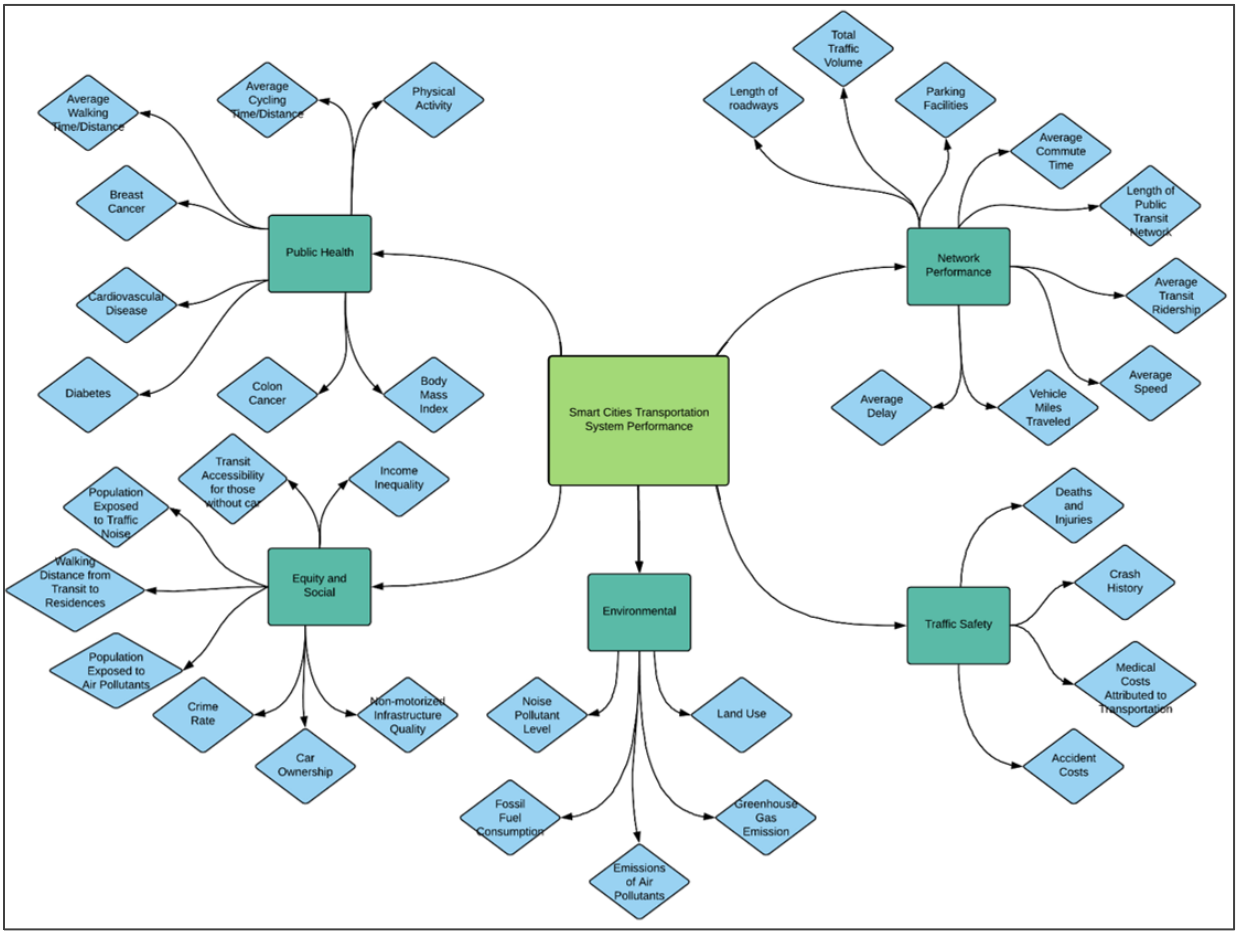

Figure 2-2: Constitutes and Subcategories of Smart Cities' Transportation System

The relationship complexity between categories indicates that there is a strong need for investigating effects of smart cities transportation elements on a transportation system performance associated with interrelationship between them in large-scale level.

2.4 Comprehensive and Integrated Frameworks

Traffic measures incorporation to develop a comprehensive and integrated transportation measure has been largely examined. One of the widely-used approach is the conversion the performance measures to monetary values as an output of the integration process (Weisbrod et al., 2009; Hezaveh et al., 2019; and Co & Vautin, 2014). The limitation of the conventional approach raises in long-range analysis due to the uncertainty associated with monetary conversion in different times and areas. Ramani et al. (2009) developed a methodology based on sustainable performance measures for strategic plan of Texas Department of Transportation (TxDOT), which included thirteen performance measures according to five goals of TxDOT's strategic plan. In another major study (Haghshenas & Vaziri, 2012), urban transportation sustainability was classified into environmental, economical, and social indicators. The researchers utilized the indicator to develop a city-based ranking. Appleton et al. (Appleton et al., 2008) have also developed performance targets for their variables and attempted to list 27 largest urban areas in Canada based on transportation improvements. In order to quantify the smartness of a city, Lopez and Monzon (2018) suggested an indicator covering not only the mobility system, but also the technological transportation aspect. They evaluated six different cities in Spain to examine the indicators.

2.5 Transportation and Public Health

Although some research has been carried out on transportation systems in smart and sustainable cities, the mechanism through which the public health incorporates into the analysis has not been widely established. There has been ample effort to synthesize a health impact assessment in transportation, but the application is still in early stages (Boehmer et al., 2017). The current available method for decision-making bodies often focuses on one objective over the others. Moreover, there is a synthesis lacking in the relationship between different transportation infrastructure elements and public health objectives. Boehmer *et al.* (2017) introduced a transportation and health tool released by the U.S. Department of Transportation (U.S. DOT) and the Centers for Disease Control and Prevention (CDC). The tool mainly deals with land use, physical activity, and fatalities caused by traffic crashes. One flaw of this tool was the lack of a direct indicator relating to the air quality and causing by the road traffic. In one outstanding recent study, the Health Impact Assessment (HIA) tool was set out to help agencies and decision-making bodies to determine policy alternatives by estimating adverse public health effects associated with the changes in various pollutants as monetized units (Davidson et al., 2007). The HIA is a combination of procedures, methods and tools used for assessing policies, programs and projects that have potential impacts on the public health (WHO, 1999).

The Integrated Transport and Health Impact Model (ITHIM) was originally adopted by Woodcock et al. (2013). The model intended to assess the public health impacts of alternative transportation, land use, and policy scenarios. They utilized Comparative Risk Analysis (CRA) to evaluate expected changes in number of crashes, physical activity, and air quality to link transportation plans with public health outcomes. They initially compared London, UK and Delhi, India through four scenarios (Woodcock et al., 2009) and examined the model in Wales and England downtown area (Woodcock et al., 2013). ITHIM has been applied worldwide through various geographic area using local estimates of baseline health burdens and population exposures. Whitfield et al. (2017) applied ITHIM to implement the health outcomes of a stepwise increase in walking and cycling in Nashville, Tennessee. Rabl & De Nazelle (2012) utilized ITHIM to quantify the health benefits of a change to exposure in ambient air pollution. They also conducted cost and benefit analysis associated with the transportation mode shift according to WHO recent review for active transportation benefits. A health impact assessment study, conducted in Spain, focused on the recent bike-sharing program, Bicing, in Barcelona (Rojas-Rueda et al., 2011). They used relative risks of all cause of mortality for commuters who use bicycles compared with other modes of transportation. In later work, Maizlish et al. (2017) applied ITHIM to quantify the health outcomes of preferred regional transportation plan scenarios in the five most populous California MPO regions. The results of the study demonstrate that increasing rate of active travel contribute to significant health benefits for area's population.

2.5.1 Air Pollutants

In the current study, the public health is evaluated according to two major factors: air pollutants and physical activity. Air pollutants (e.g. CO, CO_2, and NO_x) and particulate matters (PMs) negatively affect the human body due to the emissions of vehicles and the weather conditions. These pollutants are heavily generated by motor vehicles. They are correlated with public health in local communities. Air pollutants have adverse impacts on public health by threatening lung functionality (e.g., chest pain, coughing, throat irritation, and asthma) (US EPA, 2019). Children and elderly people, directly exposed to vehicle emissions, are more susceptible to experience induced respiratory diseases. An analysis of the relationship between long-term exposure to the PMs and the mortality rate from lung cancer and cardiovascular disease shows that the mortality rate heightens by the increase the exposure of PMs (Pope III et al., 2002; and AQEG, 2005). Therefore, a reasonable approach to tackle this issue is considering air pollutants as one of the evaluation factors of sustainability and smart-growth of a transportation system in the assessment framework.

2.5.2 Physical Activity

The second components of public health, physical activity, is defined as any bodily movement produced by skeletal muscles that requires energy expenditure. Regular physical activity, such as walking or cycling, can reduce the risk of cardiovascular diseases, diabetes, colon cancer, breast cancer, and depression (Whitfield et al., 2017). Moreover, adequate levels of physical activity decreases the risk for hip and vertebral fractures and helps control weight (WHO, 2018). Active transportation is directly linked with the public health, and accordingly sustainability and smartness of a city. Woodcock et al. (2013) analyzed active travel using an Integrated Transport and Health Impact Model (ITHIM). ITHIM models the changes in population exposures to physical activity under different scenarios, such as population disease rate and air pollution exposures and traffic injury.

2.6 Research Gap

According to the literature review, previous studies focused on specific indicators to evaluate the smart-ness and sustainability of transportation systems in such a way that other indicators have been disregarded. In addition, some of the reviewed frameworks need access to various types of data that is not always achievable for all study areas. Therefore, a framework that takes desired components of smart and sustainable city into the consideration is required. This study, then, will develop a permissive framework to integrate such components, traffic safety, air quality, active transportation, and network performance, through publicly available datasets and explicit algorithm. The output of the study will provide decision-maker a ranking-based evaluation to have a better insight on sustainability and smart-growth of a numerous sets of cities.

Chapter 3 Methodology

3.1 Overview

In this chapter, we will propose an assessment framework to evaluate smart-growth ranking of US cities. The proposed assessment framework integrates four criteria including network performance, traffic safety, environmental impact, and physical activity. The framework requires traffic-related and environment-related data. This information is gathered from public data supported by the government agencies. Data review and derivation for each criterion is demanded, due to the fact that form and type of public data vary in different agencies

3.2 Data Preparation

The traffic-related data is employed to evaluate network performance, traffic safety, and physical activity. The U.S. Department of Transportation (DOT) has the independent statistical agency that named the Bureau of Transportation Statistics (BTS). BTS is a politically objective supplier for trusted and statistically sound baseline, contextual, and trend information. The data can be employed to frame transportation policies, investments, and research across the U.S. (BTS, 2018). BTS provides various traffic-related data including system performance and traffic safety as well as airline, energy, freight transportation, infrastructure, and economy statistic data. Also, Federal Highway Administration (FHWA), a division of the US DOT, serves the national source of transportation data including transportation system performance. The current study utilizes travel time and crash data, which are supported by the BTS and NHTSA to assess the network performance and traffic safety.

Active transportation modes, such as pedestrian and bicyclist, incorporate the amount of the physical activity. National Household Travel Survey (NHTS) provides number of pedestrian and bicycle trips made by households in the US. In order to evaluate active transportation and eventually equivalent physical activity in a city-level, this study examines weekly pedestrian and bicycle transportation. Additionally, environment-related data and records of air pollutant concentrations are collected from the Environmental Protection Agency (US EPA, 2019). The Environmental Protection Agency is an independent agency of the US federal government for environmental protection. They serve outdoor air quality data including Air quality Index (AQI), concentration of air pollutants, and various visualized maps and plots.

3.3 Performance Measures

3.3.1 Network Performance

Vehicle interactions can be quantified through congestion hours and the travel time to represent operational efficiency of the network. The congestion report serves congested hours, travel time index and total annual delay time for 101 cities in the US using archived traffic operations data from roadway sensors (Schrank et al., 2015). The Travel Time Index is the ratio of the peak-period travel time to the free-flow travel time. The peak period travel time is summation of delay time and free flow travel time. The deduced performance measure is applied to interpret network performance.

$$Travel\,Time\,Index\,(TTI) = \frac{T_p}{T_{FF}} = \frac{T_D + T_{FF}}{T_{FF}} \qquad (Eq.1)$$

Where, T_p is the peak period travel time, T_{FF} is free-flow travel time, and T_D is denoted as the delay time.

3.3.2 Traffic Safety

Safety performance is measured by recording the frequency and the severity of crashes. Number of crashes or the number of fatalities are possible ways to determine the safety performance. Safety performances have been adopted for different road users, such as pedestrians (Asadi-Shekari et al., 2015; and Santos, & Carvalheira, 2019), bicyclists (Daraei et al., 2019; and Feizi et al., 2019), and children (Williams et al., 2018). In addition, many agencies and organizations utilize performance measures related to the crash quantity. Herbel *et al.* (2009) considered crashes and injuries as a safety performance measure. Several attempts have been made so far to organize extensive safety measures (Arvin et al., 2019; and Sloan et al., 2018) and safety performance for the transportation safety plans (AHSO, 2013; and CTDOT, 2012).

One of the widely-used factors for calculating crash severity is KABCO weighting factor, which is determined based on the relative cost of a person-injury crash. The KABCO crash frequency measure weights crashes according to the crash severity to develop a combined frequency and severity score. The crash severity types include K: fatality, A: Suspected serious injury, B: Suspected minor injury, C: Possible injury, and O: No apparent injury. The weighting factors are calculated based on the national comprehensive crash unit costs (Harmon et al., 2018). A Two-year crash data (2016-2017) for each site was extracted from FARS Query website (2019), which provides the city-level statistics. In order to identify the safety performance, the KABCO score was divided by the area's population.

$$Crash\ Severity\ Score\ (CSS_s) = \frac{\sum_i N_i W_i}{P_s} * 1000 = \frac{\sum_i N_i * ({C_i}/{C_O})}{P_s} * 1000 \qquad (Eq. 2)$$

Where, P_s is the population in site s, N_i is the number of crashes with severity type i, W_i is the weighting factor for severity type i, C_i is the cost for severity type i, and C_O is the cost estimated for no apparent injury crashes.

3.3.3 Air Quality Performance

To determine the air quality, it is necessary to interpret the concentration of air pollutants instead of the total quantity of air pollution. The Air Quality Index (AQI), developed by Environmental Protection Agency (EPA), is an indicator of health status according to current atmospheric conditions. AQI provides results detailing the changes concentration of air pollutants, including NO_2, O_3, SO_2, $PM_{2.5}$, and PM_{10}, in consecutive years in a county-level or a city-level. This compound was built by adopting the procedure used by EPA (US EPA, 2019). So that, AQI for individual pollutant is calculated according to Eq. (3). Afterwards, the one with the maximum value will be picked for the daily AQI in a site.

$$AQI_{daily} = \max_i\{AQI_i\} = \max_i\{\frac{(C_{o,i} - C_{min,i}) * (AQI_{max,i} - AQI_{min,i})}{C_{max,i} - C_{min,i}} + AQI_{min,i}\} \qquad (Eq. 3)$$

Where, i is the pollutant type, $C_{o,i}$ is the 24-hour average concentration of the pollutant I; $C_{min,i}$ and $C_{max,i}$ are the lowest and the highest concentration of AQI category (ranged from good to hazardous) that contains pollutant i; and $AQI_{min,i}$ and $AQI_{max,i}$ are the lowest and the highest value allowed for that AQI category, which corresponds to pollutant i.

3.3.4 Physical Activity Performance

The prevalence of active transportation modes, including walking and cycling, is characterized as one of the key aspects of smart-growth of a city. The goal is to evaluate the physical activity per person based on Metabolic Equivalent of Tasks (METs). MET is one of the common approaches to determine health outcomes of physical activities (Woodcock et al., 2013; and Woodcock et al., 2014). MET is a unit of energy expenditure adjusted for body mass, with the reference category of 1 MET is the typical energy expenditure of an individual at rest. METs are ratios between the metabolic rates of an activity in relation with the resting metabolic rate.

Data required to examine the physical activity performance were gathered from multiple sources with different standing points. First, the number of bicycle and walking trips were derived from National Household Travel Survey (2019). Based on Census Bureau data, the site's population was adjusted with NHTS data to evaluate the number of bicycle and walking trips per person per year. The total trips were converted to trip durations, in order to be aligned with METs measurement. Kuzmyak & Dill (2012) have calculated the average duration of U.S. walking and bicycling trips for all purposes based on 2009 NHTS, which is more reliable than the active transportation commuting data provided by American Community Survey (ACS). Ultimately, an average of 14.9 min. and 19.4 min. were assumed respectively for one walking and bicycling trip. The last step is computing the total METs based on the trip durations. We converted active transportation time using the mostly common MET values, which are 2.5 METs/h for walking and 4 METs/h bicycling (Ainsworth, 2000).

3.4 Multi-Criteria Decision Analysis

To integrate four aspects of smart-growth of a city with different units and characteristics, the study employed Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) as a multi-criteria decision analysis (MCDA) method (Roszkowska, 2011; and Tzeng & Huang, 2011). The TOPSIS approach was utilized since it offers an effective way to scale values that account for both the best and the worst alternative simultaneously. Simplifying the calculating process and easily execution by transportation agencies and decision makers, are considered as other advantages of TOPSIS. These circumstances make TOPSIS a major MADA technique in comparison with other related techniques such as ELimination Et Choix Traduisant la REalité (ELECTRE) and Analytic Hierarchy Process (AHP). To evaluate weighting factors for TOPSIS analysis, we used entropy (Cha, 2000) as an objective method.

The first step to run a TOPSIS evaluation process is to make decision matrix and normalizing the matrix. A general decision matrix that with j criteria and each criterion has i alternatives, possesses $i \times j$ elements (Eq.4). Normalization the elements for each individual criterion generates a normalized matrix that $0 \leq r_{ij} \leq 1$ (Eq.5).

$$X_{ij} = \begin{bmatrix} x_{11} & \cdots & x_{1j} \\ \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} \end{bmatrix} \qquad (Eq. 4)$$

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{I} x_{ij}^2}} \qquad (Eq. 5)$$

The next step is to evaluate the weighting factors trough entropy approach. Entropy is the measurement of the disorder degree of a system. It can measure the amount of favorable information with the data provided. When the difference of the value among the quantified elements in the same criterion is large, the entropy is small. The lower the entropy, the more useful the criterion. On the other hand, if the difference is smaller and the entropy is higher, the relative weight would be smaller (Zou et al., 2006). Entropy for criterion j is computed through equation 6 and the corresponding weighting factors will be calculated through equation 7.

$$E_j = -\frac{1}{Ln(I)}\sum_{j=1}^{J} r_{ij}.Ln(r_{ij}) \qquad (Eq.6)$$

$$W_j = \frac{1-E_j}{\sum_{j=1}^{J}(1-E_j)} \qquad (Eq.7)$$

The weighted decision matrix is a product of the weighting factor matrix and the normalized decision matrix (Eq.8). Criteria are categorized into two categories, cost and beneficial. The positive ideal solution (PIS) for a beneficial criterion and a cost criterion occur for the maximum and the minimum quantified values respectively (Eq.9). Correspondingly, the negative ideal solution (NIS) for a beneficial criterion and a cost criterion occur for the minimum and the maximum quantified values respectively (Eq.10).

$$[V_{ij}] = [W_j] \times [r_{ij}] \qquad (Eq.8)$$

$$V_j^+ = \{\begin{matrix} \min(V_{ij}) \quad if\ j\ is\ a\ cost\ criteria \\ \max(V_{ij})\ if\ j\ is\ beneficial\ criteria \end{matrix} \qquad (Eq.9)$$

$$V_j^- = \{\begin{matrix} \max(V_{ij}) \quad if\ j\ is\ a\ cost\ criteria \\ \min(V_{ij})\ if\ j\ is\ beneficial\ criteria \end{matrix} \qquad (Eq.10)$$

Distances from the best and the worst solutions will be determined through equations 11 and 12. The closeness coefficient, a decimal number between 0 and 1, will indicate the closeness of each alternative to the negative ideal solution (Eq.13). The more the closeness coefficient, the higher the alternative ranking.

$$S_i^{+} = \sqrt{\sum_{i=1}^{J} \left(V_{ij} - V_j^{+}\right)^2} \qquad (Eq. 11)$$

$$S_i^{-} = \sqrt{\sum_{i=1}^{J} \left(V_{ij} - V_j^{-}\right)^2} \qquad (Eq. 12)$$

$$CC_i = \frac{S_i^{-}}{S_i^{-} + S_i^{+}} \qquad (Eq. 13)$$

3.4.1 Sensitivity Analysis

MCDA methods generally associate with a degree of uncertainty and robustness that should be reported to decision makers. Quantifying the uncertainty measurement that intertwines with weighting factors evaluation and the final ranking, this study examines two methods of sensitivity analysis developed by the previous studies (Triantaphyllou & Sánchez, 1997; and Song & Chung, 2016). Since we examined an objective method to find the criteria weighting factors, analyzing the effects of changes in a single-criterion weight was used to determine the robustness of criteria weights. The purpose of weighting factor sensitivity analysis is to evaluate the minimum required quantity for a criterion weighting factor to reverse the ranking between alternatives *i* and *α* (Eq.14). Equations 15 and 16 are respectively utilized to determine modified weighting factor of criterion *k* and the percentage change in criterion weight.

$$\delta_{i,\alpha,k} = \frac{CC_i - CC_\alpha}{x_{i,k} - x_{\alpha,k}} \qquad (Eq. 14)$$

$$\begin{cases} W_k^{*} = W_k - \delta_{i,\alpha,k} & if\ \delta_{i,\alpha,k} \le W_k \\ Not\ feasseable\ to\ reverse & if\ \delta_{i,\alpha,k} > W_k \end{cases} \qquad (Eq. 15)$$

$$\%W = \frac{W_k^{*} - W_k}{W_k} * 100 \qquad (Eq. 16)$$

In addition to weighting factors, the sensitivity analysis using a single performance measure value was applied for checking the uncertainty of the quantified values of individual alternative in each criterion. The purpose of the sensitivity analysis on quantified values is to find the minimum value that a single performance measure of alternative *i* in criterion *k* needs to change its position in the ranking with alternative α. Also, $\acute{\tau}_{i,\alpha,\gamma}$ indicates the threshold value of $x_{i,\alpha}$, which is the minimum change that has to occur on the current value in criterion *k* to change the current ranking between two alternatives of *i* and α (Eq.17). The minimum value of $\acute{\tau}_{i,\alpha,\gamma}$ is the critical degree of alternative *i* in terms of criterion *k*. (Eq.18) and the sensitivity coefficient is the reciprocal of the critical degree (Eq.19). The process repeats every time for a specific alternative with constant criteria's weighting factors.

$$\begin{cases} \acute{\tau}_{i,\alpha,\gamma} < \dfrac{CC_i - CC_\alpha}{W_k} * \dfrac{100}{x_{i,k}} \; if \; i < \alpha \\ \acute{\tau}_{i,\alpha,\gamma} > \dfrac{CC_i - CC_\alpha}{W_k} * \dfrac{100}{x_{i,k}} \; if \; i > \alpha \\ \acute{\tau}_{i,\alpha,\gamma} \leq 100 \end{cases} \qquad (Eq.17)$$

$$\Delta_{i,k} = \min\left|\acute{\tau}_{i,\alpha,k}\right| \qquad (Eq.18)$$

$$SC(x_{i,k}) = \frac{1}{\Delta_{i,k}} \qquad (Eq.19)$$

3.5 Proposing the Sustainability and Smart-Growth Ranking Framework

The proposed assessment framework began with suggesting the sources of data required for the performance measures to generate a raw dataset and initiate the analysis. Evaluation the performance measures and methods to compute them were presented in the second step of the framework. A specific index for each performance measure has been developed in the third step of the framework. Ultimately, an integrated output and comprehensive results that will be generated by TOPSIS approach were shown in the last step of the framework. The output of the framework provides a sustainability and smart-growth ranking of cities as well as uncertainty and sensitivity analysis. Figure 3-1 presents the proposed conceptual framework in this study.

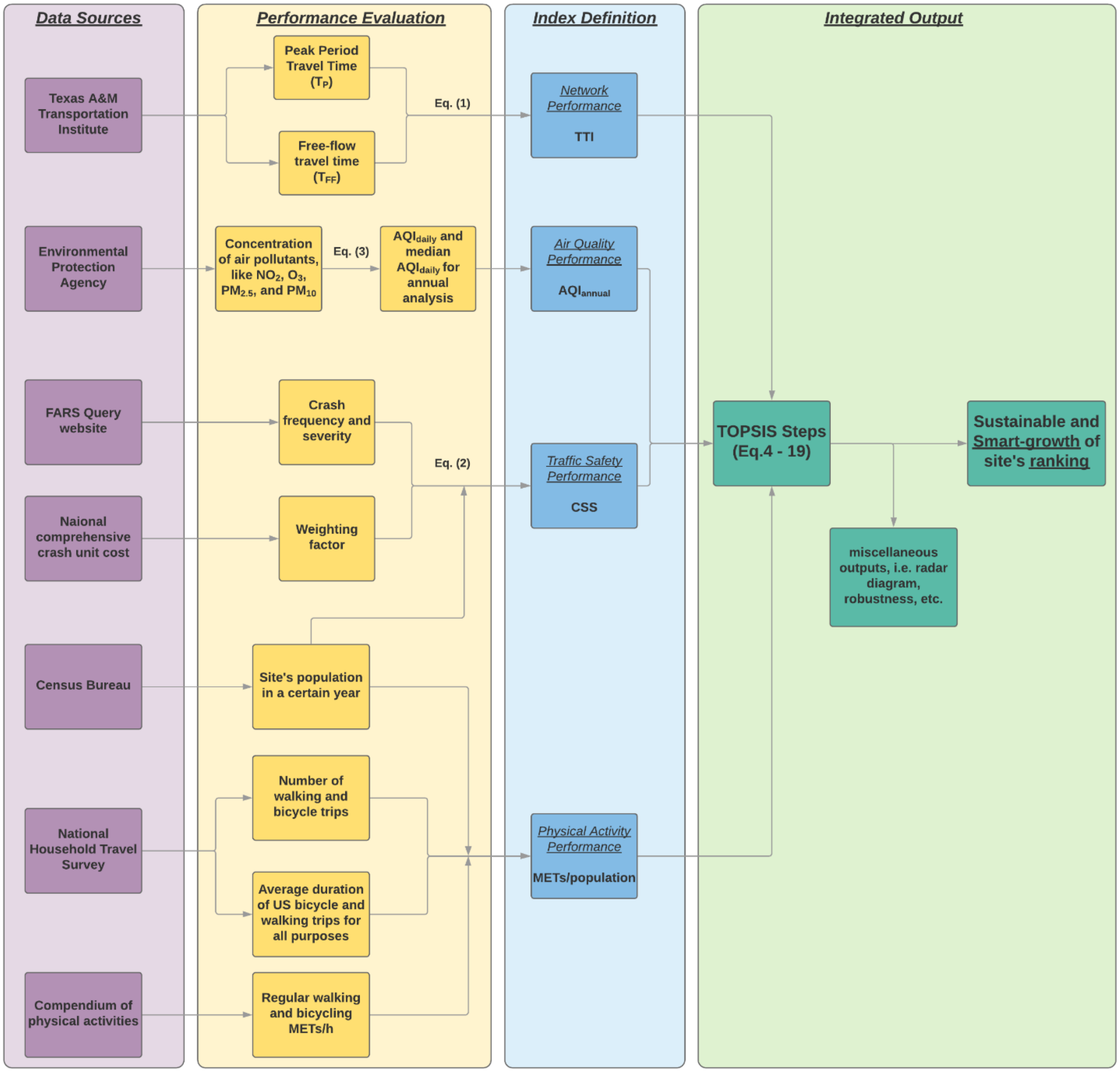

Figure 3-1: The conceptual framework of the proposed method to assess the sustainability and smart-growth city ranking

Chapter 4 Examining the Framework

4.1 Overview

This study applied the proposed assessment framework for assessing sustainability and smart-growth of transportation performance to draw a comparison between a set of populated cities in the United States. Data availability and a population with more than 1 million constituted two primary criteria for selecting the cities.

4.2 Study Areas

A set of forty six populated cities in the U.S. were chosen to examine the proposed framework. Table 4-1 presents alternative codes assigned to each city as well as cities' population in 2010.

Table 4-1: Case study characteristics

City	State	Alternative code	Population	City	State	Alternative code	Population
Atlanta	GA	A01	420,003	Minneapolis-St. Paul	MN	A24	667,646
Austin	TX	A02	790,390	Nashville-Davidson	TN	A25	626,681
Baltimore	MD	A03	620,961	New Orleans	LA	A26	343,829
Boston	MA	A04	617,594	New York	NY	A27	8,175,133
Buffalo	NY	A05	261,310	Orlando	FL	A28	238,300
Charlotte	NC	A06	731,424	Philadelphia	PA	A29	1,526,006
Chicago	IL	A07	2,695,598	Phoenix	AZ	A30	1,445,632
Cincinnati	OH	A08	296,943	Pittsburgh	PA	A31	305,705
Cleveland	OH	A09	396,815	Portland	OR	A32	583,776
Columbus	OH	A10	787,033	Providence	MA	A33	178,042
Dallas-Fort Worth	TX	A11	2,304,460	Raleigh	NC	A34	632,222
Denver	CO	A12	925,236	Riverside	CA	A35	513,795
Detroit	MI	A13	713,777	Sacramento	CA	A36	466,488
Houston	TX	A14	2,099,451	Salt Lake City	UT	A37	226,379
Indianapolis	IN	A15	829,718	San Antonio	TX	A38	1,327,407
Jacksonville	FL	A16	821,784	San Diego	CA	A39	1,307,402
Kansas City	MO-KS	A17	459,787	San Francisco	CA	A40	1,195,959

Las Vegas	NV	A18	583,756	San Jose	CA	A41	945,942
Los Angeles	CA	A19	4,579,406	Seattle	WA	A42	608,660
Louisville	KY	A20	597,337	St. Louis	MO	A43	319,294
Memphis	TN	A21	646,889	Tampa	FL	A44	580,478
Miami	FL	A22	399,457	Virginia Beach	VA	A45	437,994
Milwaukee	WI	A23	594,833	Washington	DC	A46	601,723

4.3 Performance Evaluation and Index Definition

The data sources for each performance measure have been addressed in Figure 3-1. Performance evaluations for the network and the safety performance were respectively calculated based upon Eq. (1) and Eq. (2). In terms of air quality measure, the maximum daily AQI was determined by Eq. (3). The median of the daily AQI for an entire year was then considered as the annual AQI for each city. Physical activity performance was evaluated through the total number of walking and bicycling trips for each city, which were extracted from NHTS. Since the spatial data for walking and bicycling durations were not available, the U.S. average duration was multiplied by the number of active transportation trips and the corresponding METs/h for each of the activities. In the end, the total physical activity for each city was adjusted by its population. Table 4-2 indicates the calculated performance measures to determine the sustainability and smart-growth of the case studies. The table also presents the cities' ranking with regards to each performance measure (criterion).

Table 4-2: Performance measures for the set of sixty four cities

Alt. Code	Performance Measures							
	Network		Traffic safety		Air quality		Physical activity	
	TTI (no unit)	Rank	CSS (/1000 person)	Rank	AQI (no unit)	Rank	METs (/person)	Rank
A01	1.24	22	124.2	36	48	24	170.35	12
A02	1.33	37	93.8	27	44	11	164.62	16
A03	1.26	27	28.3	3	47	21	175.83	8
A04	1.29	32	38.8	5	45	17	135.73	43
A05	1.17	4	57.2	14	40	4	159.62	23

A06	1.23	20	120.6	34	45	17	171.73	11
A07	1.31	35	44.4	7	57	39	160.43	22
A08	1.18	7	92.6	26	52	32	177.01	7
A09	1.15	1	118.4	33	48	24	152.76	29
A10	1.18	7	67.8	17	44	11	135.83	42
A11	1.27	30	122.9	35	50	28	137.14	41
A12	1.30	34	70.2	20	61	40	161.30	21
A13	1.24	22	138.9	42	54	35	133.28	45
A14	1.33	37	107.4	30	51	30	168.15	13
A15	1.18	7	108.3	31	50	28	137.28	40
A16	1.18	7	164.7	46	41	6	193.90	2
A17	1.15	1	130.9	38	47	21	126.86	46
A18	1.26	27	80.7	23	61	40	146.24	32
A19	1.43	46	69.8	19	77	44	143.13	34
A20	1.20	15	136.1	41	48	24	142.99	36
A21	1.19	12	157.5	44	44	11	138.38	39
A22	1.29	32	104.8	29	43	7	158.89	25
A23	1.17	4	91.5	25	44	11	152.41	30
A24	1.26	27	26.0	1	51	30	164.45	17
A25	1.21	17	102.0	28	43	7	141.30	37
A26	1.32	36	125.8	37	46	20	164.05	20
A27	1.34	40	27.6	2	53	33	177.30	6
A28	1.21	17	134.4	40	38	3	174.34	10
A29	1.24	22	57.6	16	55	37	159.16	24
A30	1.27	30	148.6	43	77	44	149.71	31
A31	1.19	12	55.1	13	55	37	193.59	3
A32	1.35	42	70.7	21	37	2	184.56	4
A33	1.20	15	32.2	4	44	11	134.65	44
A34	1.17	4	68.6	18	45	17	165.62	15
A35	1.33	37	88.7	24	97	46	143.13	34
A36	1.23	20	112.9	32	61	40	166.70	14
A37	1.18	7	72.2	22	54	35	199.08	1

A38	1.25	26	53.5	12	43	7	145.53	33
A39	1.24	22	57.5	15	64	43	154.62	27
A40	1.41	45	44.5	8	53	33	164.30	18
A41	1.38	43	51.8	11	47	21	164.30	18
A42	1.38	43	44.9	9	44	11	157.68	26
A43	1.16	3	164.3	45	40	4	141.08	38
A44	1.21	17	131.2	39	43	7	181.53	5
A45	1.19	12	45.1	10	36	1	153.72	28
A46	1.34	40	44.0	6	49	27	175.83	8

4.4 Indexes Integration

TOPSIS approach, as one of the MCDA techniques, was applied to assess the sustainability and smart-growth of cities. The TOPSIS adopted in this study consists of multiple steps, such as vector normalization and weighting factors evaluation. The computation result of vector normalization itself may not be useful for the comparison illustration because of small-scale values. However, in an attempt to make an applicable comparison of criteria distribution between cities, cumulative percentage can be used. For instance, Figure 4-1 presents the comparison between five cities in a radar diagram. The diagram provides a visual representation that shows the strengths and weaknesses of each city through a multi-dimensional graph. The cumulative percentage in this figure indicates the probability of more sustainable and smart transportation system performance. Therefore, performance measures for travel time, traffic safety, and air quality were inversely applied.

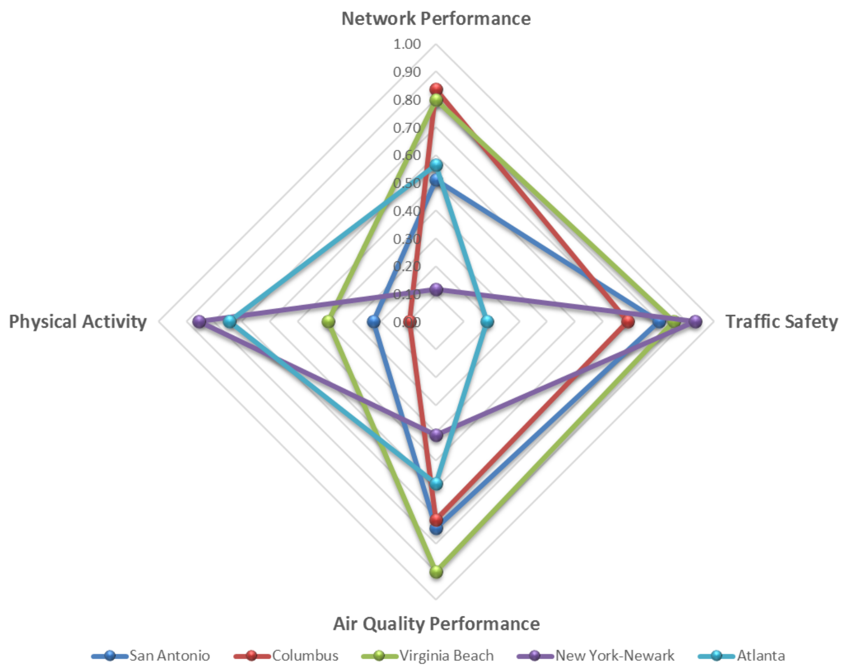

Figure 4-1: The proposed performance measures comparison between five example cities

Entropy analysis was applied to calculate the criteria weighting factors. The result reveals that the travel time performance measure, as a factor of delay and congestion, had the highest weight (W_{TTI}=0.261) and traffic safety performance measure had the least weight ($W_{CSS}=0.226$) among criteria. For other criteria, $W_{AQI}=0.253$ and $W_{MET}=0.259$ were calculated.

In order to integrate the performance measures and conduct the TOPSIS analysis, the concept of individual criterion has to be determined. In our study, the physical activity performance measure, indicating the annual metabolic equivalent tasks for walking and bicycling hours per person, was considered as a beneficial criterion. Therefore, the highest and the lowest values of this criterion were analyzed respectively for PIS and NIS in Eq. (9) and Eq. (10). For the rest of the criteria, the process was applied inversely.

The result of the TOPSIS analysis provides the closeness coefficient (Eq. (13)), which indicates the distance to the ideal solution. The more the coefficient, the better the transportation system in terms of sustainability and smart-growth of the criteria. Baltimore (A03) ranked in the first place in smart-growth, and Phoenix (A30) ranked as the last city. Table 4-3 shows the result of the TOPSIS adopted in this study as well as the smart-growth ranking of the alternatives (cities).

Also, Figure 4-2 provides the spatial distribution of the cities with different closeness coefficient on the map.

Table 4-3: The result of the TOPSIS method for forty-six alternatives (cities)

Rank	Alternative code	City	CC_i	Rank	Alternative code	City	CC_i
1	A03	Baltimore	0.855	24	A08	Cincinnati	0.622
2	A45	Virginia Beach	0.827	25	A22	Miami	0.603
3	A24	Minneapolis	0.808	26	A25	Nashville	0.600
4	A46	Washington	0.801	27	A18	Las Vegas	0.575
5	A27	New York	0.800	28	A14	Houston	0.559
6	A05	Buffalo	0.795	29	A06	Charlotte	0.555
7	A42	Seattle	0.792	30	A28	Orlando	0.547
8	A33	Providence	0.783	31	A15	Indianapolis	0.543
9	A41	San Jose	0.769	32	A44	Tampa-St.	0.539
10	A32	Portland	0.767	33	A09	Cleveland	0.536
11	A04	Boston	0.766	34	A01	Atlanta	0.527
12	A38	San Antonio	0.765	35	A26	New Orleans	0.525
13	A31	Pittsburgh	0.751	36	A11	Dallas	0.494
14	A40	San Francisco	0.747	37	A19	Los Angeles	0.494
15	A34	Raleigh	0.742	38	A17	Kansas City	0.488
16	A07	Chicago	0.725	39	A36	Sacramento	0.482
17	A29	Philadelphia	0.708	40	A16	Jacksonville	0.479
18	A10	Columbus	0.703	41	A20	Louisville	0.477
19	A37	Salt Lake City	0.701	42	A43	St. Louis	0.458
20	A23	Milwaukee	0.645	43	A21	Memphis	0.449
21	A02	Austin	0.641	44	A13	Detroit	0.427
22	A39	San Diego	0.638	45	A35	Riverside	0.343
23	A12	Denver-Aurora	0.624	46	A30	Phoenix	0.244

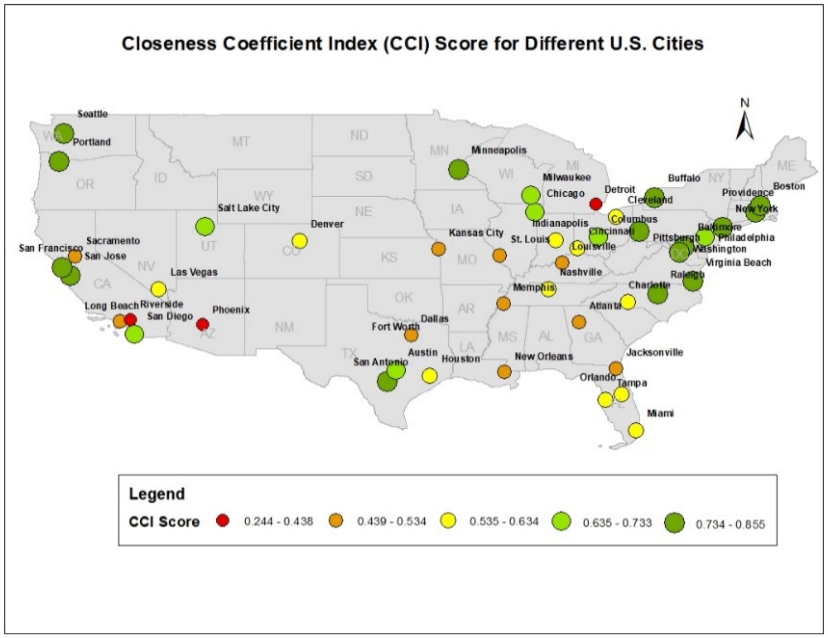

Figure 4-2: Closeness coefficient score calculated by TOPSIS for different cities

4.5 Sensitivity Analysis

4.5.1 Quantified Values of Alternatives

The sensitivity analysis was conducted as a complementary examination to measure the uncertainty of the proposed ranking. The relative sensitivities were analyzed by using Eq. (17) to measure the functionality of each criterion among the forty-six cities. The analysis required a matrix of 46*46 pairwise comparisons for each criterion, and total of 2,116*4 comparisons for all criteria.

According to Eq. (18) the most critical degree was calculated to find the minimum value that changes the pairwise ranking between the alternatives (cities). As Figure 4-3 demonstrates, the most critical degree belongs to A09 in the criteria AQI and MET, where the most sensitivity occurs between A09 and A44. The results suggest that the current ranking of alternative A09 could be switched to 32 effortlessly, by a limited change in either the performance value of the criterion MET or AQI. The two alternatives' ranking appears remarkably sensitive. Consequently, the decision making for them should be treated carefully.

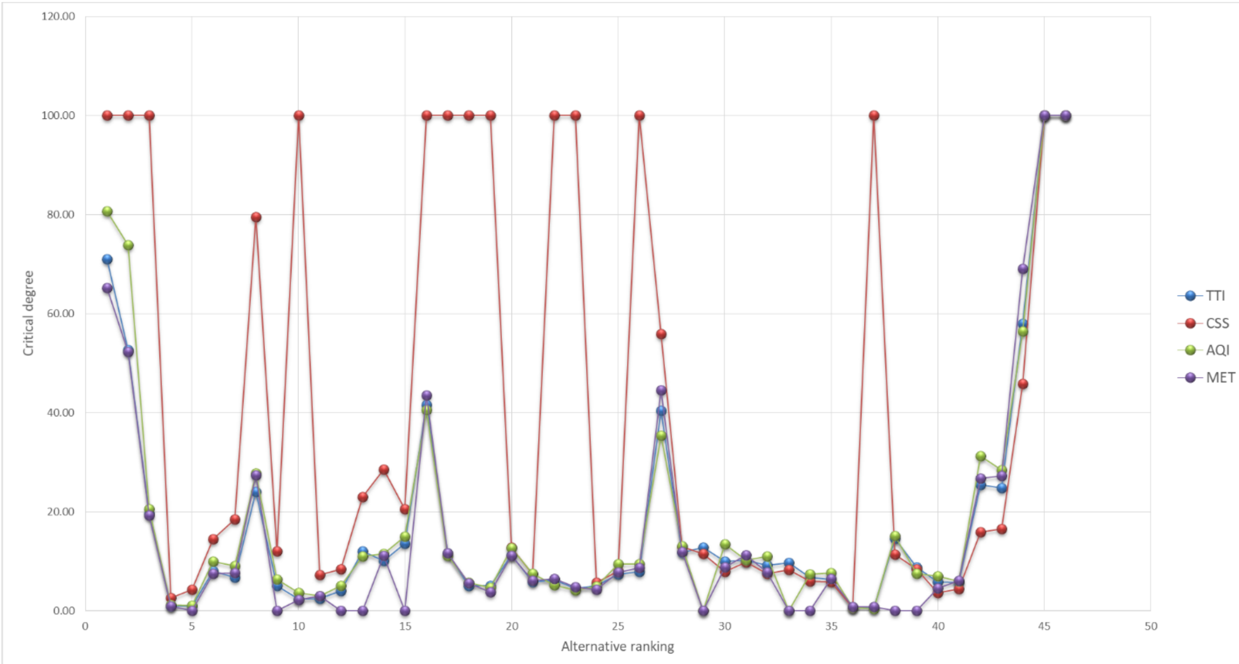

Figure 4-3: Critical degrees for performance measures in different criteria

According to Table 4-4, critical degrees in criterion MET were more often repeated comparing to other criteria. Meaning that, the performance values in this criterion become more sensitive in terms of reversing the ranking between two consecutive alternatives ($\Delta_{A27,MET}$, $\Delta_{A06,MET}$, $\Delta_{A01,MET}$, $\Delta_{A17,MET} \approx$ 0.01%). The results of uncertainty and sensitivity analysis reveal that the ranking between A11 and A26 occurs to be sensitive. Because, the lowest critical degree in criterion TTI occurred between the two aforementioned alternatives. Also, critical degrees in other criteria for A11 and A26 show values lower than one, which is considered critical. Although the critical uncertainty was detected between few pairs, more than 60% of the rankings was allocated to the dominant alternatives. In another significant finding, the sensitivity analysis unveiled that no critical degrees were identified in the first three and the last three ranking places. This finding confirms the robustness of the ranking between the first and the last three alternatives. Note that the shaded cells in the table below indicate the robust ranking in terms of the sensitivity coefficient.

Table 4-4: Critical degrees and sensitivity coefficient for performance measures sensitivity analysis

Rank	Alt. (*i*)	$\Delta_{i,k}$ (%)				SC($x_{i,k}$)			
		TTI	CSS	AQI	MET	TTI	CSS	AQI	MET
1	A03	71.09	100	80.76	65.25	0.01	0.01	0.01	0.02
2	A45	52.72	100	73.85	52.27	0.02	0.01	0.01	0.02
3	A24	19.67	100	20.59	19.30	0.05	0.01	0.05	0.05
4	A46	0.99	2.68	1.15	0.97	1.01	0.37	0.87	1.03
5	A27	0.99	4.26	1.06	**0.01**	1.01	0.23	0.94	**111.11**
6	A05	8.00	14.52	9.92	7.51	0.12	0.07	0.10	0.13
7	A42	6.78	18.49	9.02	7.60	0.15	0.05	0.11	0.13
8	A33	24.06	79.57	27.81	27.47	0.04	0.01	0.04	0.04
9	A41	5.10	12.03	6.34	**0.01**	0.20	0.08	0.16	**90.91**
10	A32	2.35	100	3.63	2.20	0.43	0.01	0.28	0.45
11	A04	2.46	7.24	2.99	2.99	0.41	0.14	0.33	0.33
12	A38	4.07	8.44	5.02	**0.01**	0.25	0.12	0.20	**74.63**
13	A31	12.05	23.08	11.05	0.02	0.08	0.04	0.09	45.45
14	A40	10.17	28.57	11.47	11.18	0.10	0.03	0.09	0.09
15	A34	13.60	20.57	14.98	0.02	0.07	0.05	0.07	46.08
16	A07	41.60	100	40.52	43.51	0.02	0.01	0.02	0.02
17	A29	11.70	100	11.18	11.68	0.09	0.01	0.09	0.09
18	A10	5.02	100	5.71	5.59	0.20	0.01	0.18	0.18
19	A37	5.02	100	4.65	3.81	0.20	0.01	0.22	0.26
20	A23	11.32	12.82	12.75	11.13	0.09	0.08	0.08	0.09
21	A02	5.86	7.36	7.50	6.06	0.17	0.14	0.13	0.16
22	A39	6.28	100	5.16	6.45	0.16	0.01	0.19	0.15
23	A12	4.62	100	4.17	4.77	0.22	0.01	0.24	0.21
24	A08	5.09	5.75	4.89	4.34	0.20	0.17	0.20	0.23
25	A22	7.43	8.11	9.44	7.72	0.13	0.12	0.11	0.13
26	A25	7.92	100	9.44	8.69	0.13	0.01	0.11	0.12
27	A18	40.40	55.90	35.37	44.59	0.02	0.02	0.03	0.02
28	A14	11.83	12.98	13.07	11.98	0.08	0.08	0.08	0.08
29	A06	12.79	11.56	0.01	**0.01**	0.08	0.09	71.43	**111.11**

30	A28	9.97	7.96	13.45	8.86	0.10	0.13	0.07	0.11
31	A15	10.22	9.88	10.22	11.25	0.10	0.10	0.10	0.09
32	A44	9.19	7.52	10.96	7.85	0.11	0.13	0.09	0.13
33	**A09**	9.67	8.33	**0.01**	**0.01**	0.10	0.12	**111.11**	**166.67**
34	A01	6.73	5.96	7.37	**0.01**	0.15	0.17	0.14	**128.21**
35	A26	6.32	5.88	7.69	6.51	0.16	0.17	0.13	0.15
36	A11	0.69	**0.63**	0.74	0.82	1.45	1.58	1.34	1.22
37	A19	**0.61**	100	0.48	0.79	1.63	0.01	2.07	1.27
38	A17	14.59	11.36	15.12	**0.01**	0.07	0.09	0.07	**166.67**
39	A36	8.78	8.47	7.50	0.02	0.11	0.12	0.13	58.14
40	A16	5.79	3.68	7.07	4.52	0.17	0.27	0.14	0.22
41	A20	5.70	5.46	6.04	6.13	0.18	0.18	0.17	0.16
42	A43	25.42	15.91	31.23	26.77	0.04	0.06	0.03	0.04
43	A21	24.78	16.60	28.40	27.29	0.04	0.06	0.04	0.04
44	A13	58	45.90	56.44	69.11	0.02	0.02	0.02	0.01
45	A35	100	100	100	100	0.01	0.01	0.01	0.01
46	A30	100	100	100	100	0.01	0.01	0.01	0.01

A simple example of the sensitivity analysis clarifies the application of the results. Based on Table 2 we realize that the performance value of alternative A41 in criterion CSS is 51.8. On the other hand, the critical degree (Table 4-4) of this alternative is 12.03%. Meaning that if the performance value is reduced (because this is a cost criterion) by 51.8*12.03% = 6.23, consequently the ranking will be reversed and A41 will be placed instead of A33. Using Eq. (2) and the alternative population (P_{A41}=945,942) we can extract the KABCO weighting factor for reducing 6.23 in the crash severity score. Thereafter, we can calculate number of crashes with no apparent injury (O-severity) through a simple calculation: 6.23*945.942=5,893. Which, in this case, equals to 107 crashes with serious injury (A), or 6 fatal crashes (K).

4.5.2 Weighting Factor Sensitivity

Using Eq. (14), enabled us to calculate the minimum quantity that a criterion weight needs to reverse the ranking between two alternatives. If the minimum quantity exceeds the criterion weight, no feasible reverse change happens between the two coupled alternatives. Otherwise, the modified weight and percentage change would be respectively determined through Eq. (15) and Eq. (16). The sensitivity analysis was conducted for the weight factors of the all criteria. Table 4-5 presents sensitive ranks to a single-criterion weight change. Shaded cells in the table indicate critical rankings (%W<20%).

As a part of the analysis results, it is illustrated that the ranking of A02 and A23 will be equal if there is an increase of 0.22 in the TTI criterion weight. Besides, either a decrease of 0.14 in TTI weight or an increase of 0.02 in CSS weight factor will equalize the ranking of A04 and A32. Also, the most critical criteria weight for rank equivalence between coupled alternatives is between A11 and A19. Where, an increase more than 5% in W_{TTI} or a decrease less than 1% in W_{CSS} will reverse the ranking between two alternatives. Note that the shaded cells in the table below indicate the sensitive ranking in terms of the sensitivity coefficient. Pairwise comparisons not mentioned in the table below were not sensitive to a weight change ($\delta_{i,\alpha,k} > W_k$).

Table 4-5: Sensitivity analysis for criteria weighting factor (W_k)

Alt. i	Alt. α	k	W_k	$\delta_{i,\alpha,k}$	W^*_k	%W	Alt. i	Alt. α	k	W_k	$\delta_{i,\alpha,k}$	W^*_k	%W
A02	A23	TTI	0.26	-0.22	0.48	83%	A16	A17	CSS	0.23	-0.16	0.39	72%
	A39	TTI	0.26	0.23	0.04	-87%			MET	0.26	-0.14	0.40	53%
		CSS	0.23	**0.04**	0.18	-19%		A19	CSS	0.23	-0.10	0.33	46%
		AQI	0.25	**-0.04**	0.30	17%			AQI	0.25	0.15	0.11	-58%
		MET	0.26	0.26	0.00	-100%		A20	CSS	0.23	0.05	0.18	-21%
A04	A32	TTI	0.26	0.14	0.12	-53%			AQI	0.25	-0.10	0.36	41%
		CSS	0.23	**0.02**	0.21	-9%			MET	0.26	**0.04**	0.21	-17%
		AQI	0.25	-0.04	0.30	17%		A36	CSS	0.23	**-0.04**	0.27	19%
		MET	0.26	**0.02**	0.24	-8%			MET	0.26	-0.13	0.39	51%
	A38	CSS	0.23	-0.07	0.30	31%			AQI	0.25	0.06	0.20	-23%
		MET	0.26	-0.17	0.43	67%	A17	A19	TTI	0.26	0.20	0.06	-77%
	A41	CSS	0.23	0.16	0.07	-70%			CSS	0.23	-0.07	0.30	31%
		MET	0.26	0.12	0.14	-46%			AQI	0.25	0.08	0.18	-30%
A05	A27	CSS	0.23	-0.12	0.35	53%		A36	CSS	0.23	0.19	0.04	-83%
		AQI	0.25	0.15	0.11	-58%			AQI	0.25	-0.13	0.38	51%
	A42	TTI	0.26	-0.12	0.38	45%			MET	0.26	-0.14	0.40	54%

		CSS	0.23	0.15	0.07	-68%	A19	A20	CSS	0.23	-0.17	0.40	75%
		AQI	0.25	-0.25	0.50	99%			AQI	0.25	0.21	0.05	-82%
	A46	AQI	0.25	0.23	0.03	-90%		A36	CSS	0.23	-0.18	0.40	79%
A08	A12	TTI	0.26	0.13	0.13	-50%	A20	A36	CSS	0.23	-0.15	0.38	68%
		CSS	0.23	-0.05	0.28	24%			AQI	0.25	0.15	0.11	-57%
		AQI	0.25	0.07	0.18	-28%			MET	0.26	0.25	0.01	-95%
		MET	0.26	-0.13	0.39	49%	A22	A25	MET	0.26	0.18	0.08	-70%
A09	A44	CSS	0.23	0.17	0.05	-77%	A23	A39	CSS	0.23	0.12	0.10	-55%
		AQI	0.25	-0.24	0.49	94%	A27	A46	CSS	0.23	0.02	0.21	-7%
		MET	0.26	0.13	0.13	-50%			AQI	0.25	-0.04	0.29	14%
A10	A29	AQI	0.25	0.14	0.11	-56%	A29	A37	MET	0.26	-0.17	0.43	66%
		MET	0.26	0.21	0.05	-80%	A31	A40	TTI	0.26	-0.17	0.43	65%
	A37	AQI	0.25	-0.06	0.32	25%			MET	0.26	0.16	0.10	-63%
		MET	0.26	**-0.03**	0.29	12%	A32	A38	TTI	0.26	0.22	0.05	-83%
A11	A19	TTI	0.26	**-0.01**	0.28	5%			CSS	0.23	-0.07	0.30	33%
		CSS	0.23	**0.01**	0.22	-1%			AQI	0.25	-0.15	0.40	58%
		AQI	0.25	**0.01**	0.26	1%			MET	0.26	0.07	0.19	-27%
		MET	0.26	**-0.05**	0.31	19%		A41	CSS	0.23	0.10	0.13	-43%
A15	A28	CSS	0.23	0.09	0.13	-41%			AQI	0.25	0.08	0.18	-30%
		AQI	0.25	-0.11	0.36	43%			MET	0.26	-0.12	0.37	44%
		MET	0.26	0.11	0.15	-42%	A34	A40	TTI	0.26	0.17	0.09	-66%
	A44	CSS	0.23	-0.11	0.34	50%			CSS	0.23	-0.13	0.36	59%
		AQI	0.25	0.20	0.06	-78%			AQI	0.25	0.21	0.04	-84%

Chapter 5 Discussion and Conclusion

5.1 Discussion

This study set out with the aim of proposing a new framework for multifaceted transportation performance in terms of sustainability and smart-growth of smart cities. We attempted to fill out the gap and the lack of studies in the existing literature regarding the assessment of smart cities with respect to transportation systems as well as health outcomes and the concentration of pollutants. The comprehensive tools developed so far (i.e. ITHIM and GHGE) were more applicable for strategic policy assessment in a single-city level (Whitfield et al., 2017; and Maizlish et al., 2017). However, the framework proposed in this study (Figure 3-1) presents an integrated approach that includes factors corresponding to a city's transportation system and can be applied by multiple sources of data. The method helps understanding transportation performances in a comprehensive manner through integrating multifaceted measures for sustainability and smart-growth of cities' evaluation.

A case study approach including forty-six cities with 1 million or more population was used to examine the implementation of the framework. The results obtained from TOPSIS analysis (Table 4-3) illustrated that Baltimore (A03), Virginia Beach (A45), and Minneapolis (A24) are ranked as the first three cities in the United States. Correspondingly, the last three cities in the ranking of sustainability and smart-growth include Detroit (A13), Riverside (A35), and Phoenix (A30). Moreover, the result of the uncertainty and sensitivity analysis of the performance measures (Table 4-4) confirmed the robustness of the ranking of the six cities. However, the sensitivity analysis result revealed that the overall ranking correspond to the all alternatives (cities) is still sensitive to the performance measures. Table 4-4 depicted that the dominancy between reversible pairs for almost 15% of cases are critically sensitive.

Sensitivity analysis also provides applicable results for transportation agencies engaging with performance measures monitoring. The sensitivity analysis is applicable to appraise any hypothetical changes within a transportation system setting, including network and traffic-related features, crash frequency and severity, air pollutant concentrations, and transportation and non-transportation physical activities. For instance, we have demonstrated that a reduction of only 6 fatal crashes, which is equal to 107 crashes with serious injury, in San Jose, CA will alter the city's ranking. This change will ultimately promote San Jose's ranking and relocate it to an upper ranking place that is currently occupied by Providence, MA.

The method employed for weighting factor determination was an objective method. One criticism of applying this method is that weight factors can be changed by altering the performance measures in different sets of data. The answer to this possible comment is the entropy method embedded into the framework incorporates with the model flexibility. That is, we can avoid sticking to fix weights for the various type of data sets. On the other hand, sensitivity analysis as a complementary tool offered at the end of the framework (Figure 3-1), helps decision maker to interpret the effect of each criterion weight change on the ranking output. In this study, we have examined the minimum value that each criterion weight needs to equalize the closeness coefficient score between two alternatives. The results revealed that the most critical criteria weight for rank equivalence occurs between Dallas (Rank 36) and Los Angeles (Rank 37). Where an increase of 5% in network performance criterion weight or a reduction of 1% in safety performance criterion weight will equalize the cities' score.

5.2 Limitations

We acknowledge that the example presented in the study was not free from limitations as it used the provided data. But, the proposed framework is not necessarily supposed to be examined only by a city-level transportation network data. In fact, to examine the effects of alternative strategies, performance measures could be derived from micro-level activity-based travel demand models or simulations in a small network. Simulation-based assessments can serve as a decision-supporting tool for evaluation and selection of various treatment options for sustainable and smart strategies prior to an actual implementation. The application of activity-based travel demand models makes it possible to quantify various measures in the proposed approach by providing the effects of alternative strategies. Results from an activity-based simulation approach could be used as an input for the proposed performance measures. The inputs can be derived from other available sources, as long as the required data to execute the framework is available.

The findings of this study were subjects to a hypothetical assumption of homologues population in an individual study area. One needs to keep in mind that different socio-economy population characteristics may produce a distinctive travel pattern, driving behavior, physical activity, and eventually different performance measures in an area. More research on different population characteristics and effects of social equity on sustainability and smart-growth of a city is recommended for future investigations.

5.3 Conclusion

This study proposed a conceptual assessment framework of multifaceted transportation performances for sustainability and smart-growth in cities considering network performance, safety, air quality, and physical activity. The performance measures reflected the recent paradigm shift in transportation. The framework provides each of individual performance measures as well as the integrated score and the comprehensive results. The proposed framework was applied to forty-six cities in the United States each considered as a case study. The example was limited in that it only used existing data rather than testing alternatives. However, the sensitivity analysis demonstrated its capacity to present multifaceted performance measures and their relative performance among different study areas.

The results of the proposed framework can be an effective decision supporting tool in analyzing traffic management strategies. Results from the score sensitivity calculation indicate that the proposed framework can be adopted in multifaceted transportation system performance in sustainability and smart-growth of cities. For future studies, various strategies and simulated data could be applied in order to verify and calibrate the comprehensive framework. Ultimately, extensive analyses should be performed to determine the contributing factors and associated weights.

Bibliography

Ainsworth, B. E., Haskell, W. L., Whitt, M. C., Irwin, M. L., Swartz, A. M., Strath, S. J., ... & Jacobs, D. R. (2000). Compendium of physical activities: an update of activity codes and MET intensities. *Medicine and science in sports and exercise*, *32*(9; SUPP/1), S498-S504.

Air Quality Expert Group (AQEG). (2005). Particulate Matter in the United Kingdom. London: Department for Environment, Food and Rural Affairs.

Alaska Highway Safety Office (AHSO). (2013). Alaska Highway Safety Performance Plan.

Appleton, B., Davies, M., Tansey, J., Atwal, P., Dore, G. P., & Muzyka, D. (2008). GreenApple Canada 2008: SMART Transportation Ranking Report. *Sauder School of Business, University of British Columbia*.

Arvin, R., Kamrani, M., & Khattak, A. J. (2019). *Examining the Role of Speed and Driving Stability on Crash Severity Using SHRP2 Naturalistic Driving Study Data* (No. 19-01981).

Asadi-Shekari, Z., Moeinaddini, M., & Shah, M. Z. (2015). Pedestrian safety index for evaluating street facilities in urban areas. *Safety science*, *74*, 1-14. https://doi.org/10.1016/j.ssci.2014.11.014

Boehmer, T. K., Wendel, A. M., Bowers, F., Robb, K., Christopher, E., Broehm, J. E., ... & Ralph, J. (2017). US Transportation and Health Tool: Data for action. *Journal of Transport & Health*, *6*, 530-537.

Breau of Transportation Statistics, *Learn About BTS and Our Work*, https://www.bts.gov. Accessed July 10, 2018.

Caragliu, A., Del Bo, C., & Nijkamp, P. (2011). Smart cities in Europe. *Journal of urban technology*, *18*(2), 65-82.

Castillo, H., & Pitfield, D. E. (2010). ELASTIC–A methodological framework for identifying and selecting sustainable transport indicators. *Transportation Research Part D: Transport and Environment*, *15*(4), 179-188.

Cha, X. J. (2000) Information analysis and prediction (Book style), Wuhan: Wuhan University Press.

Co, S., & Vautin, D. (2014). *Benefit-Cost Analysis of Public Health Outcomes in Long-Range Transportation Planning in the San Francisco Bay Area* (No. 14-3223).

Connecticut Department of Transportation (CTDOT). (2012). Highway Safety Plan. Bureau of Policy and Planning Highway Safety Office.

Daraei, S., Pelechrinis, K., & Quercia, D. (2019). A Data-Driven Approach for Assessing Biking Safety in Cities. *arXiv preprint arXiv:1902.05015*.

Davidson, K., Hallberg, A., McCubbin, D., & Hubbell, B. (2007). Analysis of PM2. 5 using the environmental benefits mapping and analysis program (BenMAP). *Journal of Toxicology and Environmental Health, Part A*, *70*(3-4), 332-346.

Department of Transportation. (2016 June). *2016 Strategic Sustainability Performance Plan*. Office of Sustainability and Safety Management, Department of Transportation.

Feizi, A., Oh, J. S., Kwigizile, V., & Joo, S. (2019). Cycling environment analysis by bicyclists' skill levels using instrumented probe bicycle (IPB). *International Journal of Sustainable Transportation*, 1-11. https://doi.org/10.1080/15568318.2019.1610921

Gilbert, R., Irwin, N., Hollingworth, B., & Blais, P. (2003). Sustainable transportation performance indicators (STPI). *Transportation Research Board (TRB), CD ROM*.

Haghshenas, H., & Vaziri, M. (2012). Urban sustainable transportation indicators for global comparison. *Ecological Indicators*, *15*(1), 115-121.

Harmon, T., Bahar, G., & Gross, F. (2018). Crash costs for highway safety analysis (No. FHWA-SA-17-071).

Herbel, S., Meyer, M. D., Kleiner, B., Gaines, D., & Systematics, C. (2009). *A primer on safety performance measures for the transportation planning process* (No. FHWA-HEP-09-043). United States. Federal Highway Administration.

Hezaveh, A. M., Arvin, R., & Cherry, C. R. (2019). A geographically weighted regression to estimate the comprehensive cost of traffic crashes at a zonal level. *Accident Analysis & Prevention*, *131*, 15-24. https://doi.org/10.1016/j.aap.2019.05.028

Jin, J., Gubbi, J., Marusic, S., & Palaniswami, M. (2014). An information framework for creating a smart city through internet of things. *IEEE Internet of Things Journal*, *1*(2), 112-121.

Kuzmyak, J. R., & Dill, J. (2012). Walking and bicycling in the United States: The Who, What, Where, and Why. *TR News*, (280).

Lee, J. H., Phaal, R., & Lee, S. H. (2013). An integrated service-device-technology roadmap for smart city development. *Technological Forecasting and Social Change*, *80*(2), 286-306.

Litman, T. A. (2009). *Sustainable transportation indicators: a recommended research program for developing sustainable transportation indicators and data* (No. 09-3403).

Lopez-Carreiro, I., & Monzon, A. (2018). Evaluating sustainability and innovation of mobility patterns in Spanish cities. Analysis by size and urban typology. *Sustainable Cities and Society*, *38*, 684-696.

Maizlish, N., Linesch, N. J., & Woodcock, J. (2017). Health and greenhouse gas mitigation benefits of ambitious expansion of cycling, walking, and transit in California. *Journal of transport & health*, *6*, 490-500.

Mihyeon Jeon, C., & Amekudzi, A. (2005). Addressing sustainability in transportation systems: definitions, indicators, and metrics. *Journal of infrastructure systems*, *11*(1), 31-50.

Motta, G., Sacco, D., Ma, T., You, L., & Liu, K. (2015, March). Personal mobility service system in urban areas: The IRMA project. In *Service-Oriented System Engineering (SOSE), 2015 IEEE Symposium on* (pp. 88-97). IEEE.

National Household Travel Survey. *NHTS Table Designer*. U.S Department of Transportation. Federal Highway Administration, Washington DC. https://nhts.ornl.gov/tables09/ae/TableDesigner.aspx. Accessed July 19, 2019.

Pope III, C. A., Burnett, R. T., Thun, M. J., Calle, E. E., Krewski, D., Ito, K., & Thurston, G. D. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *Jama*, *287*(9), 1132-1141. Rabl, A., & De Nazelle, A. (2012). Benefits of shift from car to active transport. *Transport policy*, *19*(1), 121-131.

Query FARS Data. Fatality Analysis Reporting System. https://www-fars.nhtsa.dot.gov//QueryTool/QuerySection/SelectYear.aspx. Accessed July 18, 2019.

Ramani, T., Zietsman, J., Eisele, W., Rosa, D., Spillane, D., & Bochner, B. (2009). *Developing sustainable transportation performance measures for TXDOT's strategic plan: technical report* (No. FHWA/TX-09/0-5541-1). Texas Transportation Institute.

Ramaprasad, A., Sánchez-Ortiz, A., & Syn, T. (2017, September). A unified definition of a smart city. In *International Conference on Electronic Government* (pp. 13-24). Springer, Cham.

Rojas-Rueda, D., de Nazelle, A., Tainio, M., & Nieuwenhuijsen, M. J. (2011). The health risks and benefits of cycling in urban environments compared with car use: health impact assessment study. *Bmj*, *343*, d4521.

Roszkowska, E. (2011). Multi-criteria decision making models by applying the TOPSIS method to crisp and interval data. *Multiple Criteria Decision Making/University of Economics in Katowice*, *6*, 200-230.

Ruiz-Romero, S., Colmenar-Santos, A., Mur-Pérez, F., & López-Rey, Á. (2014). Integration of distributed generation in the power distribution network: The need for smart grid control systems, communication and equipment for a smart city—Use cases. *Renewable and sustainable energy reviews*, *38*, 223-234.

Santos, B., & Carvalheira, C. (2019). Pedestrian Road Accident Index for Municipalities: The Portuguese Case. In *IOP Conference Series: Materials Science and Engineering* (Vol. 603, No. 4, p. 042084). IOP Publishing.

Schrank, D., Eisele, B., Lomax, T., & Bak, J. (2015). 2015 urban mobility scorecard. Texas A&M Transportation Institute.

Sloan, J., Nargesi, S. R., Bezboruah, K., & Mattingly, S. (2018). Are Bicyclists and Pedestrians Victims or Villains When Struck By a Vehicle?. *Journal of Transport & Health*, *9*, S26-S27.

Song, J. Y., & Chung, E. S. (2016). Robustness, uncertainty and sensitivity analyses of the TOPSIS method for quantitative climate change vulnerability: A case study of flood damage. *Water Resources Management*, *30*(13), 4751-4771.

Thuzar, M. (2011). Urbanization in SouthEast Asia: Developing Smart Cities for the Future?. *Regional Outlook*, 96.

Triantaphyllou, E., & Sánchez, A. (1997). A sensitivity analysis approach for some deterministic multi-criteria decision-making methods. *Decision sciences*, *28*(1), 151-194.

Tzeng, G. H., & Huang, J. J. (2011). *Multiple attribute decision making: methods and applications*. Chapman and Hall/CRC.

United States Census Bureau; 2016 American Community Survey 1-Year Estimates, Table S0801: Commuting characteristics by sex. Using American FactFinder; (21 March 2018), http://factfinder2.census.gov

US Environmental Protection Agency. *Air Quality System Data Mart*. http://www.epa.gov/ttn/airs/aqsdatamart. Accessed July 19, 2019.

US Environmental Protection Agency Office of Air and Radiation, *Good Up High Bad Nearby - What is Ozone?* https://airnow.gov/index.cfm?action=gooduphigh.index. Accessed July 27, 2019.

Weisbrod, G., Lynch, T., & Meyer, M. (2009). Extending monetary values to broader performance and impact measures: Transportation applications and lessons for other fields. *Evaluation and program planning*, *32*(4), 332-341.

Wey, W. M., & Hsu, J. (2014). New urbanism and smart growth: Toward achieving a smart National Taipei University District. *Habitat International*, *42*, 164-174.

Whitfield, G. P., Meehan, L. A., Maizlish, N., & Wendel, A. M. (2017). The integrated transport and health impact modeling tool in Nashville, Tennessee, USA: Implementation steps and lessons learned. *Journal of transport & health*, *5*, 172-181.

Williams, G. C., Borghese, M. M., & Janssen, I. (2018). Neighborhood walkability and objectively measured active transportation among 10–13 year olds. *Journal of Transport & Health*, *8*, 202-209.

Woodcock, J., Edwards, P., Tonne, C., Armstrong, B. G., Ashiru, O., Banister, D., ... & Franco, O. H. (2009). Public health benefits of strategies to reduce greenhouse-gas emissions: urban land transport. *The Lancet*, *374*(9705), 1930-1943.

Woodcock, J., Givoni, M., & Morgan, A. S. (2013). Health impact modelling of active travel visions for England and Wales using an Integrated Transport and Health Impact Modelling Tool (ITHIM). *PLoS One*, *8*(1), e51462.

Woodcock, J., Tainio, M., Cheshire, J., O'Brien, O., & Goodman, A. (2014). Health effects of the London bicycle sharing system: health impact modelling study. *Bmj*, *348*, g425.

World Health Organization. (1999). Health impact assessment: Main concepts and suggested approach. *Gothenberg consensus paper. Geneva: WHO*.

World Health Organization. (2017). Health economic assessment tool (HEAT) for walking and for cycling: Methods and user guide on physical activity, air pollution, injuries and carbon impact assessments. *Copenhagen: WHO Regional Office for Europe*.

World Health Organization, *Physical Activity*, http://www.who.int/topics/physical_activity/en. Accessed July 10, 2018.

Zou, Z. H., Yi, Y., & Sun, J. N. (2006). Entropy method for determination of weight of evaluating indicators in fuzzy synthetic evaluation for water quality assessment. *Journal of Environmental sciences*, *18*(5), 1020-1023.