Future-Proof Transportation Infrastructure through Proactive, Intelligent, and Public-involved Planning and Management

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About the Transportation Infrastructure Durability Center

The Transportation Infrastructure Durability Center (TIDC) is the 2018 US DOT Region 1 (New England) University Transportation Center (UTC) located at the University of Maine Advanced Structures and Composites Center. TIDC's research focuses on efforts to improve the durability and extend the life of transportation infrastructure in New England and beyond through an integrated collaboration of universities, state DOTs, and industry. The TIDC is comprised of six New England universities, the University of Maine (lead), the University of Connecticut, the University of Massachusetts Lowell, the University of Rhode Island, the University of Vermont, and Western New England University.

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List of Key Terms

Transportation infrastructure planning: *Transportation infrastructure planning can be defined as the process of making decisions concerning the potential changes required for transportation-related infrastructures to improve the quality of life.*

Future-proofing: *The process of anticipating the distant future, factors that may affect it, and taking actions to minimize risks and maximize opportunities for value realization.*

Text mining: *Text mining is a sub-discipline of data mining that extracts interesting information and knowledge from unstructured or semi-structured text.*

Topic modeling: *Topic modeling is an unsupervised machine learning technique that is primarily used for document clustering.*

Association rule mining: *Association rule mining is a procedure that aims to observe frequently occurring patterns or associations from datasets found in various kinds of databases, such as relational databases, transactional databases, and other forms of repositories.*

Taxonomy: *Taxonomy is the practice and science of categorization or classification in which things are organized into groups or types.*

Inter-relationship: *Inter-relationship refers to the process concerning how two or more planning factors are connected and affect one another.*

Present Serviceability Rating (PSR): *PSR is a surface-condition rating scheme developed by the American Association of State Highway Officials (AASHO), which is based on a numeric scale between 0 and 5.*

Annual Average emission: *It refers to the lb of* Co_2 *equivalent generated from vehicles on average in a given year.*

ESAL: *ESAL is the acronym for equivalent single axle load. It refers to an 18,000 pound load on a single axle with dual tires.*

CESAL: *CESAL is the acronym for cumulative equivalent single axle load. It measures the cumulative weights arising from different types of vehicles operating on the same road over a specific time period.*

EV: *EV is the acronym for electric vehicles.*

CV: *CV is the acronym for conventional fuel vehicles.*

ET: *ET is the acronym for electric trucks.*

CFT: *CFT is the acronym for conventional fuel trucks.*

Abstract

Transportation infrastructure planning is a complex process, which requires the consideration of a multitude of factors. While many existing studies have investigated the impacts of different factors individually, a holistic framework that encompasses a comprehensive list of influencing factors on transportation infrastructure planning and their inter-relationships is still missing. Especially, many forward-looking factors are often overlooked in current planning frameworks. To this end, this study aims to develop a future-proofed transportation infrastructure planning framework with a focus on roadways, bridges, and transit. Three parts of work are included in this study: (1) First, a list of important and emerging factors that affect or may affect transportation infrastructures was identified from 48 published technical reports and journal articles on future-proofed transportation infrastructure planning via two topic modelling techniques: Latent Dirichlet Allocation (LDA) and Non-negative Matrix Factorization (NMF). These factors were later compiled and converted to a four-level taxonomy via bottom-up grouping. For example, public transportation programs and public-private partnerships were grouped together as the two primary sources of funding for transportation infrastructures. (2) Second, association rule mining (ARM) was then used to discover relationships among these factors. Specifically, two quantitative association rule mining metrics: confidence (frequency of association) and lift (strength of association were used. In total, 102 inter-relationships were identified, among which eight inter-relationships were found to be significant. For example, a significant association was found between societal trends with environmental performance. It implies that in order to achieve a better environmental performance of transportation infrastructure, capturing and taking advantage of societal trends could be useful, since societal trends such as less dependency on personal vehicles can significantly reduce the environmental impact of transportation infrastructures (e.g., less emission). (3) Finally, based on the significant association rules identified between new technology and other factors, two case studies were conducted to quantify the impacts of the electric vehicle as an example of new technologies on different aspects of transportation infrastructure. Quantitative scenario analysis was performed to facilitate informed decision-making under uncertainty. This framework has the potential to turn into a smart decision-making system that can help transportation infrastructure owners, designers, builders, governments, and operators to have a holistic approach to plan, build, and manage our transportation infrastructures in the face of future risks and uncertainties.

Chapter 1: Introduction

1.1 Problem Statement

Transportation infrastructure is one of the most important determinants of a country's progress. The USA is no different, and the $20 trillion economy relies heavily on a vast network of infrastructures such as roads, bridges, freight rails, and ports (McBride and Moss 2020). However, the existing transportation infrastructure systems were built decades ago and are in poor condition. According to ASCE's 2021 infrastructure report card, the U.S.'s overall infrastructure grade was C- (ASCE 2021). Among the different infrastructure categories that were considered, roads, bridges, and transit received grades of D, C, and D-, respectively. The majority of the economists agree that transportation delays and rising maintenance costs are holding USA's economic performance back. By increasing transportation infrastructure efficiency and reliability, the long-term competitiveness of the USA can be significantly enhanced, which can potentially insulate the economy from disruptions (Petroski 2016).

Transportation infrastructure planning is the process of making decisions regarding transportation infrastructure design, construction, maintenance, and operation to improve people's quality of life (Chowdhury and Zhu 2019). Transportation infrastructure planning is a complex process. This process can arguably become more challenging when incorporating future events and changes into consideration. With the ever-increasing occurrence of unexpected or uncontrollable events (e.g., various types of natural disasters) and rapid development of modern technologies (e.g., autonomous and connected vehicles), there is a pressing need to future proof transportation infrastructure systems so that they can be fit for the future in addition to satisfying current needs (Chowdhury and Zhu 2021). If transportation infrastructure planning is conducted in a silo with only a few dimensions, it can result in inefficient funding allocation, inaccurate travel demand forecasting, unpopular and unwarranted transportation project initiation, and many more. The scope of transportation infrastructure planning should be multi-dimensional as a multitude of factors may affect transportation infrastructure (e.g., innovation and public perception). Moreover, it should consider and quantify the inter-relationships among different factors as the effect of multiple factors may be combined and demonstrate a unique effect on transportation infrastructure. Essentially, a lack of consideration of such inter-dependencies can lead to planning agencies not having a plan of action against the potential combined effect of different factors. In essence, a holistic understanding of critical factors and their inter-relationship is needed that can minimize undesirable impacts and capitalize on opportunities of transportation infrastructure in the face of future events, changes, and opportunities.

1.2 Objectives

To achieve a transportation infrastructure system that meets the challenges of the 21st century, a holistic approach to transportation infrastructure planning is needed. Holistic transportation infrastructure planning can contribute to increasing efficiency and reliability by accurately, critically, and objectively defining future policies, goals, investments, and designs to prepare for future needs regarding the movement of people and goods (Transportation Planning Capacity Building Program 2015). Three research objectives were proposed in this study that can lead to holistic transportation infrastructure planning:

Objective 1: Identify the critical factors that currently impact transportation infrastructure or may impact in the future;

Objective 2: Identify the inter-relationships and quantify them in order to capture the effect of one factor on the implementation of other factors as well as the strength of the effect;

Objective 3: Develop computational simulation models that can be used to facilitate future-proofed transportation infrastructure planning decision-making.

1.3 Expected Contributions

The potential contributions of this project are threefold. First, this project provides a systematic way to understand and classify future risks and opportunities via identifying critical factors that should be carefully incorporated into transportation infrastructure planning. Second, this research helps to quantify the associations among future-proofed factors and helps pinpoint strong inter-dependencies that need attention. Third, this research introduces an innovative computational approach to discover new knowledge and hidden relationships in transportation infrastructure planning. Ultimately, planners and decision-makers at federal, state, and local levels can benefit as this research provides a technical guideline to understand critical factors and their interdependency and incorporate them into planning actions in order to plan, build, and manage our transportation infrastructures.

1.4 Report Overview

Chapter 2 briefly discusses existing research on transportation infrastructure planning and the underlying technique used to carry it out in this research: text mining. Chapter 3 presents the proposed method for identifying future-proofing critical factors and the results. Chapter 4 presents the proposed method for quantifying inter-relationships among the future-proofing critical factors and also highlights the most significant inter-relationships. Chapter 5 demonstrates the potential impacts of inter-relationships in transportation infrastructure using computational scenario analysis. Chapter 6 provides key managerial insights identified from this research alongside potential future research directions.

Chapter 2: Literature Review

This section details the existing literature on two key aspects of this project, i.e., transportation infrastructure planning and text mining. Essentially, the knowledge gaps concerning transportation infrastructure planning and the potential contributions of this research are discussed in section 2.1. Existing studies using text mining techniques for different transportation-related contexts and the potential of text mining techniques in transportation infrastructure planning are discussed in section 2.2.

2.1 Transportation Infrastructure Planning

Existing studies in transportation infrastructure planning mostly adopt fragmented approaches that are lacking in two important aspects. First, most of these studies focused only on one or a few factors and their effects on transportation infrastructures. Examples of such factors include funding (Cradock et al. 2009; Chase, 2011; Gransberg et al. 2013; Wood & Brown, 2019), traffic throughput and volume (Xu et al. 2013; Song et al. 2019; Xiao et al. 2019; Hardegen et al. 2019), land use (Badoe and Miller 2000; Waddell 2011; Hawkins and Nurul Habib 2019), and public participation (Majumdar 2017). Such studies contributed to knowledge development on how individual factors affect transportation infrastructure planning. However, without a comprehensive list of all important factors, systematic transportation infrastructure planning is hard to achieve and planning could be conducted in silo. Especially, existing studies mostly focused on solving current problems while failing to put enough emphasis on future-proofing factors, such as future changes and associated uncertainties (Moon et al. 2009; Alderson et al. 2018). Future-proofing can be defined as the process of anticipating the distant transportation future, factors that may affect it, and taking actions to minimize risks and maximize opportunities for value realization. If future needs are not addressed, the benefits of transportation infrastructure planning can only be realized in the short term and may require substantial additional investment and planning modifications to meet future needs.

Second, most of these studies did not consider the inter-relationships among different factors (Handy and McCann 2010). Different planning factors may be interdependent and have significant impacts on one another. For example, societal trends (e.g., pursuing a green lifestyle) can be important drivers for the adoption of new technologies (e.g., electric and autonomous vehicles) in transportation. These technologies will transform traditional transportation infrastructure through different investment, development, and maintenance plans. The performance of next-generation transportation infrastructure will then influence people's perception and reinforce certain social values in turn. Therefore, it is important to consider the close relationships between various transportation infrastructure planning factors, such as new technologies and societal trends.

2.2 Text Mining

Text mining is a sub-discipline of data mining that extracts interesting information and knowledge from unstructured or semi-structured text (Gupta and Lehal 2009). In transportation-related domains, text mining techniques have been used for various purposes such as identifying the contributing factors to rail, maritime, and aviation accidents, identifying the types of construction work that lead to a lane closure, stakeholder opinion classification in transportation projects, and bridge deterioration prediction (Kuhn 2018; Sun and Yin 2017; Brown 2016; Park et al. 2018; Liu and El-Gohary 2020; Liu and El-gohary 2018; Lv and El-Gohary 2017; Liu and El-Gohary 2017).

These studies primarily used published reports, social media data, and scholarly articles to implement text mining techniques to gain useful insights into their particular research context. Text mining can help identify (1) the key concepts and the main entities (e.g., DOT) described in the large text corpus, as well as their relationships with minimum human intervention, (2) can be applied with different formats text appears in, and (3) help unlock hidden information that can lead to new knowledge and improved understanding.

Such benefits and applicability of text mining techniques make them suitable for being applied in the transportation infrastructure planning domain. However, text mining techniques have not been applied to identify and examine a broad spectrum of critical factors and their inter-relationships. Transportation-related text documents encompass a wide variety of concepts (e.g., funding, technological innovation), entities (e.g., U.S. department of transportation (DOT), private agencies), and focus (e.g., strategic plans, vision statements). These text documents have different formats such as technical reports and scholarly articles. Integrating information from all these text documents with varying substances could result in large text datasets with a high number of variables, which makes manual processing to get key insights challenging. To this end, this study explored the potential of adopting text mining techniques as a new and efficient way toward the development of a future-proofed infrastructure planning framework.

Chapter 3: Future-proofing Critical Factor Identification

3.1 Topic Modeling

Topic modeling is an unsupervised machine learning technique that is primarily used for document clustering. Topic modeling is capable of finding out a text body's latent semantic structures (Wang and Taylor 2019). Essentially, it can scan documents, detect words and phrase patterns within them, and automatically cluster word groups and similar expressions (Lim et al., 2017). Topic modeling has been implemented in various transportation domain problems, such as extracting relevant semantics (e.g., traffic conditions, road conditions) from social media (Lau 2017), discovering representative and interpretable activity categorization from individual-level spatiotemporal data (Zhao et al. 2020), and sentiment analysis by extracting meaningful information from social network platforms (Ali et al. 2019). Topic modeling was adopted in this study to identify the important topics compiled across the large text datasets produced by different transportation planning authorities that often cover a variety of topics, resulting in a complex semantics structure.

Two topic modeling techniques: LDA and NMF were implemented in this study. Latent Dirichlet Allocation (LDA) and Non-negative Matrix Factorization (NMF) are two of the most popular topic modeling techniques used for identifying important topics from large text data as they are (1) fast and easily implementable methods for text mining, (2) do not require previously established labels or training data, (3) can reduce the dimension of text datasets, and (4) provide most relevant topics from large text datasets (Kuhn 2018). LDA is based on generative probabilistic modeling, while NMF relies on multivariate analysis and linear algebra (Chen et al. 2017). While LDA and NMF have significantly different theoretical structures, both models are capable of returning the most pertinent topics in a record. Both of these models were implemented in this study. The results were compared to ensure that a comprehensive list of concepts could be developed. Both LDA and NMF considered each sentence in the text files as a unique record and created topics accordingly. The algorithm and implementation procedure of LDA and NMF are provided below.

3.1.1 Latent Dirichlet Allocation (LDA)

The modeling process of LDA can be described as finding a mixture of topics from a text corpus with D records. In general, LDA begins with a random assignment of topics to each word and iteratively improves the assignment of topics to words. Assuming there are W words across the D records, the allocation of words across K different topics can be achieved following the steps described below (Wang and Taylor 2019):

Step 1: Loop through each record $d \in D$ and randomly assign each word in $d \in D$ to one of the $k \in K$ topics.

Step 2: For each record $d \in D$, loop through each word $w \in W$ and compute: (1) the proportion of words in $d \in D$ that are currently assigned to topic k: $p(k|d)$; and (2) the proportion of assignments to topic $k \in K$ over all D records that come from the word w: $p(w|k)$.

Step 3: Update $p(w|k,d)$ such that $p(w|k,d) = p(k|d) * p(w|k)$.

Step 4: Loop through each word $w \in W$ in each record $d \in D$, and reassign the topic for the currently selected word based on $p(w|k,d)$.

Step 5: Repeat steps 2-4 a large number of times to reach a steady state solution.

3.1.2 Non-negative Matrix Factorization (NMF)

NMF approximates a nonnegative data matrix X with a low-rank matrix such that

$$X(:,n) \approx \sum_{k=1}^{r} V(:,k)\, H(k,n) \quad with\, V, H \geq 0 \tag{1}$$

where r is the rank of X, and each entry (m, n) can be interpreted as the number of times the mth word appears in the $nth\ d \in D$. It must be noted that since the weights in the linear combinations are nonnegative (i.e., $H \geq 0$), only the union of the sets of words defined by the columns of V can be used to reconstruct the original records. Hence, the columns of matrix V can be interpreted as topics coded across different words. Matrix H illustrates how to sum contributions from different topics to reconstruct the word mix of a given original record. This means that given a set of records, NMF identifies topics and simultaneously classifies the records among these different topics. The ultimate goal is to find the best possible factorized matrixes that minimize the following objective function

$$\underset{V,H\geq 0}{minimize} ||X - VH||^2 \tag{2}$$

NMF will modify the initial values of V and H so that the matrix multiplication approaches X until either the approximation error converges or the max iterations are reached. Figure 1 shows the conceptual illustration of LDA and NMF, respectively.

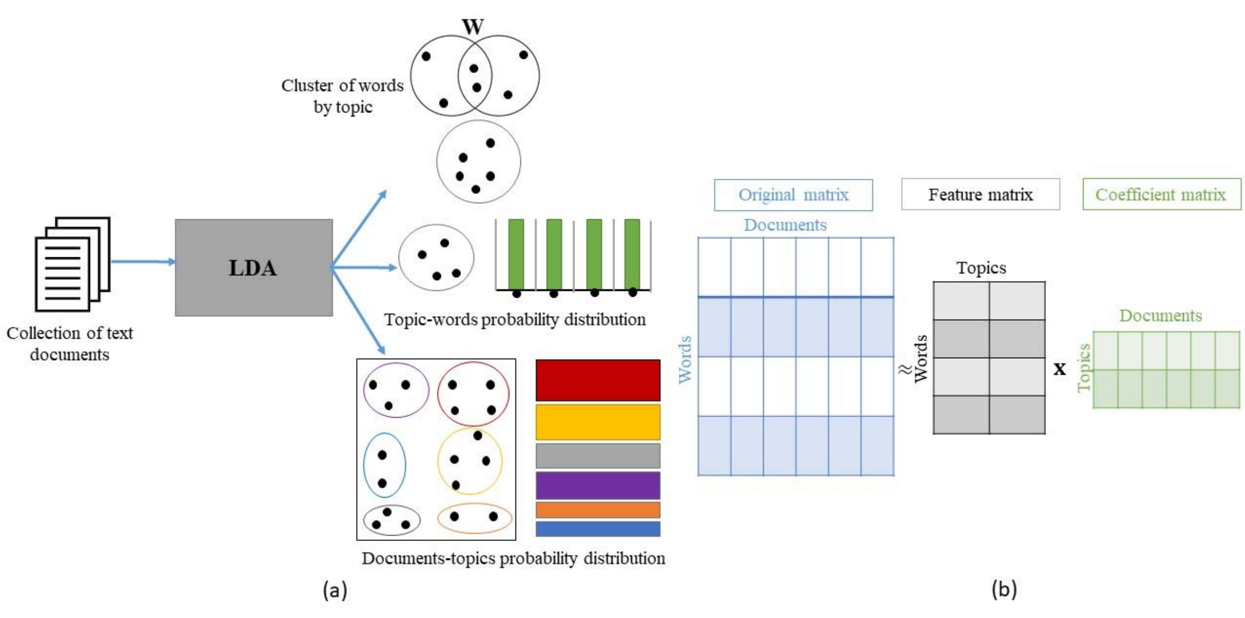


Figure 1. Conceptual illustration of (a) LDA and (b) NMF

3.2 Future-proofing Critical Factor Identification Steps

Future-proofing critical factor identification consists of two steps: (1) data collection and pre-processing and (2) taxonomy development.

3.2.1 Data Collection and Pre-processing

First, published documents related to transportation infrastructure planning were collected by using Google and Google Scholar search engines. The following keywords were used during the search: transportation planning vision, transportation long-term plan, strategic transportation plan, intelligent transportation system, transportation agency plan, and smart transportation planning. The goal was to collect a broad spectrum of views on the transportation infrastructure planning needs, policies, challenges, and opportunities in different parts of the U.S. In total, 48 documents whose focus areas cover most states of the U.S. were identified and used for this study (Figure 2). Table 25 in Appendix (A1) lists all the documents considered in this study. These documents included transportation vision statements, long-term regional transportation plans, infrastructure strategic investment plans, and several scholarly journal articles. These documents were developed by a variety of bodies such as state DOTs, local and regional transportation agencies, legislative bodies at the city level, external consultants, and renowned academic scholars. To obtain the most relevant text from these documents, data pre-processing was conducted by searching the keyword "infrastructure" within each document. Paragraphs with an infrastructure focus were extracted from each document and collated into separate text files as records. These text files were then further processed to eliminate the possibility of encoding errors. For example, different punctuation marks (e.g., apostrophe characters, hyphen) and ASCI characters (e.g., $, *) were removed from the text files.

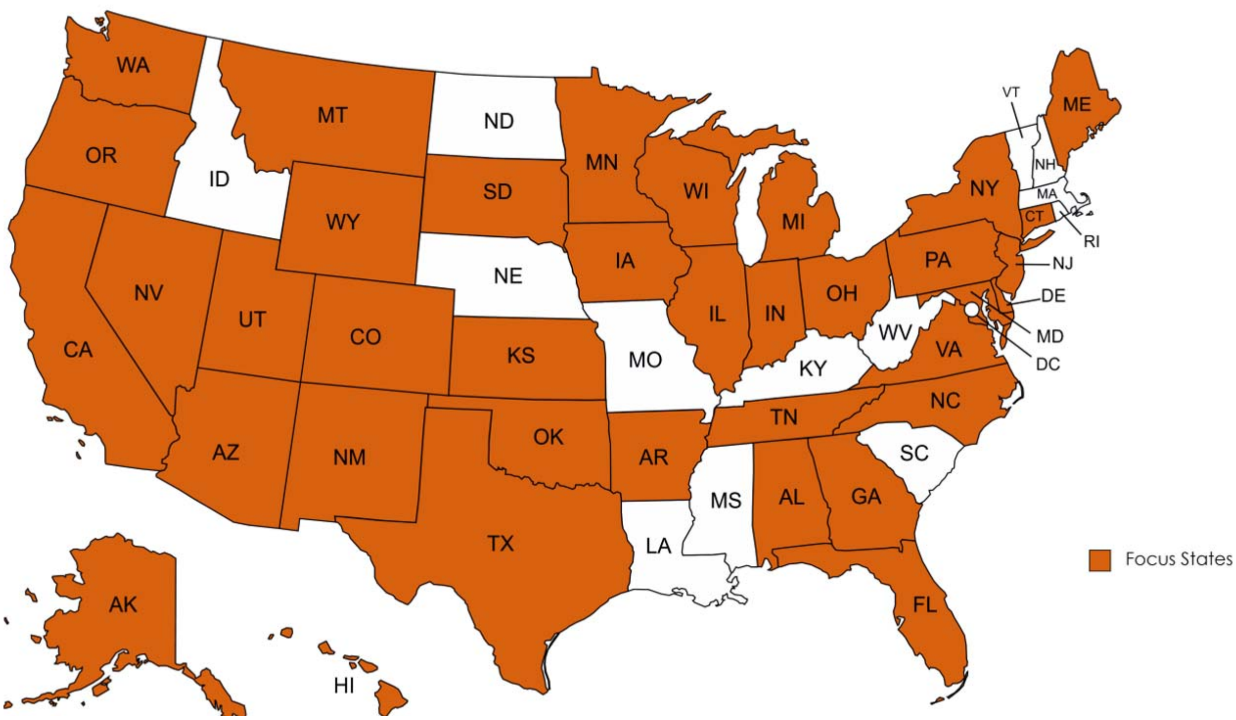


Figure 2. Focus areas of documents collected in this study

3.2.2 Taxonomy Development

In this step, topic modeling techniques were applied to the text files generated in the last step. Based on the topics identified, a four-level taxonomy for future-proofed transportation infrastructure planning was then developed. The taxonomy developed provides a clarified conceptual and theoretical framework to integrate the large variety of topics under the future-proofed transportation infrastructure planning theme (Hakeem and Shah 2004).

Each text file was analyzed by both LDA and NMF using the machine learning library Scikit-learn in conjunction with Python 2.7.0, returning a set of topics as output. The topics were identified based on estimating the (1) probability distributions for topics in documents, (2) probability distributions for words in topics, and (3) term frequency-inverse document frequency. Related python code is available in Appendix A3. Each topic is represented as a list of words. A sample output of the topic models is provided in Table 1. This example topic identified by NMF covered a set of 5 words that included private, public, sector, partnership, and payments. A similar topic identified by LDA covered a set of 5 words that included public, infrastructure, private, program, and transportation. Although the words are slightly different in the results generated by NMF and LDA, by reviewing the contexts, it was evident that both results were primarily related to an alternative source of transportation infrastructure funding, i.e., public-private partnership programs and the flexibility they provide. Therefore, they can be consolidated into one primary topic as "public-private partnership." Essentially, for each text file, five top topics were identified using LDA and NMF independently. Table 2 presents the ten topics identified in total via NMF and LDA with five representative words after analyzing a text file. Each of these topics primarily corresponds to a major theme or concept that was discussed in the text file. Topics generated using NMF and LDA were ultimately compared and consolidated into a final list of transportation infrastructure planning factors.

After identifying a comprehensive list of topics from all the documents, a bottom-up approach was used for grouping topics with similar themes under broader topics or concepts until a structured hierarchy of knowledge was built. For example, crash, terrorism, and cyber-attack were identified as the major man-made disruptions/risks in the transportation infrastructure sector (New Mexico Department of Transportation 2015). Six types of natural disruptions/risks that included drought/heatwave, rising sea level/flooding, wildfire, landslide, earthquake, and cold winter weather were also identified as major threats to transportation infrastructure (Washington Department of Transportation 2017). Naturally, the two topics: man-made disruptions/risks and natural disruptions/risks were further grouped into a general theme of Disruptions/risks. In this study, four levels (i.e., level 0, level 1, level 2, and level 3) in total were identified in the taxonomy to organize all the important concepts in a structured way. Level 3 is the lowest level with the finest granularity, followed by level 2, level 1, and finally, level 0. Figure 3 illustrates the four-level taxonomy developed in this study. In total, there were six level-1 topics identified under "Future-proofed Transportation Infrastructure Planning," each with a number of level-2 and level-3 topics.

Table 1. A sample output of the application of topic models (Oklahoma Department of Transportation 2010)

Topic Model	Topic Example	Contexts
NMF	Private, public, sector, partnership, payments	• In its simplest form, a public-private partnership is an agreement between public and private sector parties that transfers infrastructure delivery functions to private entities. • Depending on the restrictions of the public sector, this approach may close the gap on under-funded projects without raising taxes. • The most successful partnerships have included the transfer of both risk and responsibility together. • For example, the private partner in a toll road has the potential to profit from the venture but also risks a loss if toll revenues do not equal projections. • Restrictions on public sector debt capacity have been another reason why some public agencies have entered into public-private partnerships. • Many reasons have been offered as to why a DOT should consider using a public-private partnership approach.
LDA	Public, infrastructure, private, program, transportation	• In its simplest form, a public-private partnership is an agreement between public and private sector parties that transfers infrastructure delivery functions to private entities. • The most successful partnerships have included the transfer of both risk and responsibility together. • For example, the private partner in a toll road has the potential to profit from the venture but also risks a loss if toll revenues do not equal projections. • Many reasons have been offered as to why a DOT should consider using a public-private partnership approach. • Because of inadequate Highway Trust Fund revenues, explore various alternatives for funding the States surface transportation program, such as consider weight and vehicle miles travelled for fuel tax; fund transportation capital improvements from the (Federal) general fund; increase car tag fees; index the motor fuel tax to inflation; and charge user fees to provide maintenance funds for freight-related infrastructure. • Oklahoma Department of Transportation participates in the federally funded reimbursement program, Safe Routes to School (SRTS), which encourages students and their parents to make biking or walking to school a routine activity instead of driving.

Table 2. Sample output from a text file (City of Largo 2010)

Topic Model	Topics	Major theme/concept
NMF	Vehicles, infrastructure, damage, minimize, transportation	Infrastructure damage due to traffic vehicle type and volume
	Florida, global, integrated, growth, plan	Need and benefits of an integrated and forward-looking transportation infrastructure planning
	Community, regional, plans, visions, development	Developing transportation plans reflecting community values
	Safety, security, transportation, modes, emergency	Need for a comprehensive approach to safe and secure transportation across all transportation modes
	Areas, systems, urban, rural, economic	The link between transportation systems in rural and urban areas and their economic vitality
LDA	Infrastructure, people, freight, increase, critical	Increasing the efficiency and reliability of travel for people and freight
	Transportation, growth, objectives, performance, local	Evaluation of transportation objectives against predefined performance measures
	Transportation, resources, facilities, community, responsible	Planning and developing transportation facilities after coordinating and communicating with different community resources
	Transportation, infrastructure, systems, security, safety	Need for a comprehensive approach to enhance transportation infrastructure safety/security
	Transportation, florida, floridas, facilities, condition	Planning based on the physical condition of roads and other transportation facilities

Level 3

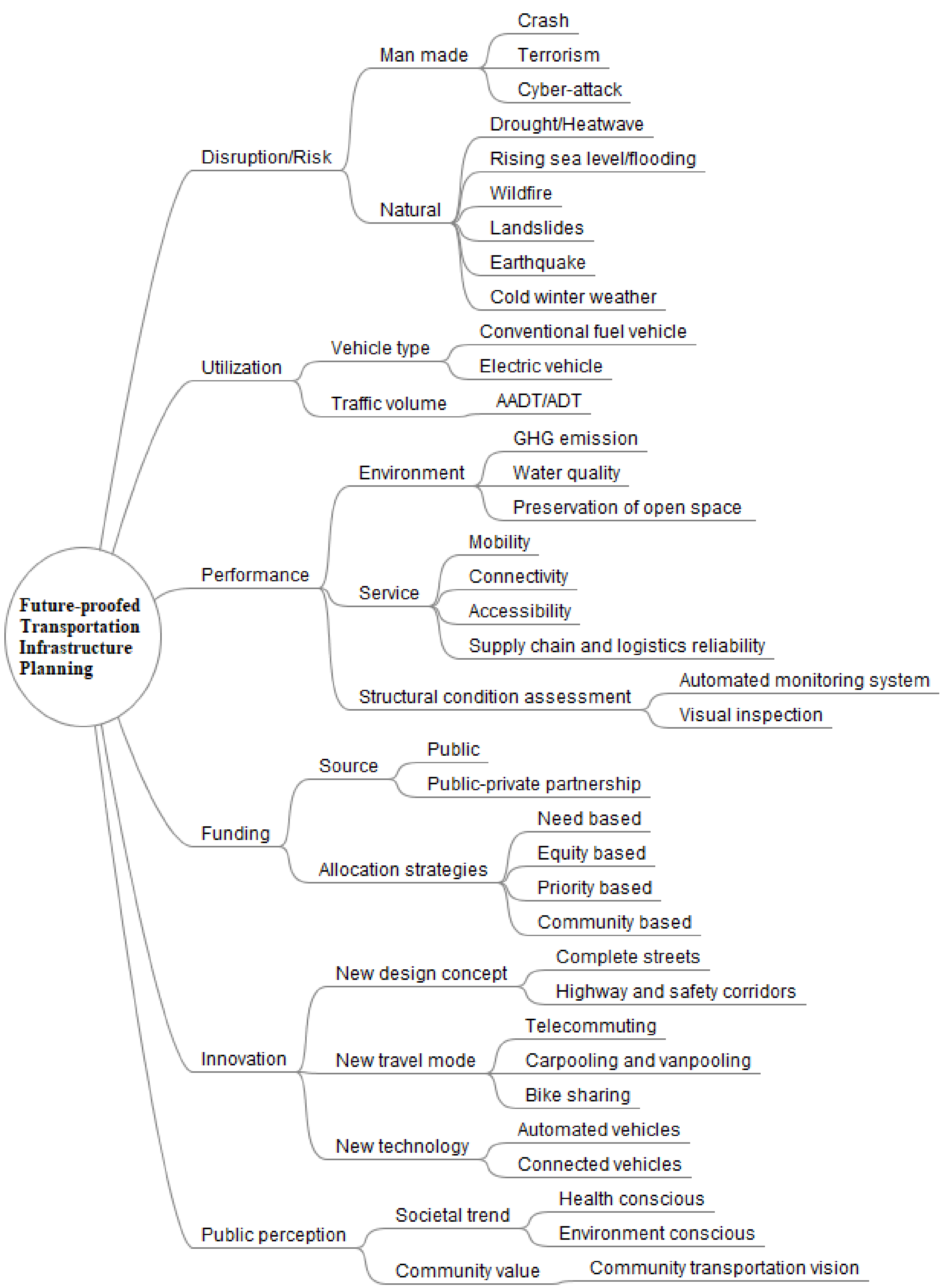


Figure 3. Four-level taxonomy

3.2.2.1 Disruption/Risk

Two types of disruption/risk were identified, i.e., natural and man-made. Natural and man-made disruptions/risks negatively impact transportation infrastructure. Natural disruptions/risks are associated with natural phenomena that may derail transportation (e.g., road closure) and cause structural damage. In contrast, man-made disruptions/risks are human-induced events with similar consequences (City of Largo 2010). Six major types of natural disruptions/risks that might have significant impacts on transportation infrastructure were identified, including drought/heatwave, rising sea level/flooding, wildfire, landslide, earthquake, and cold winter weather. Three major man-made disruptions/risks: crash, terrorism, and cyber-attack were also identified to have significant impacts on future-proofed transportation infrastructure planning.

3.2.2.1.1 Natural Disruptions/risks

Drought/Heatwave:

Drought is an insidious natural hazard that may cause tremendous loss to agriculture, ecosystems, and other sectors. A heatwave is a period of excessively hot weather, which may be accompanied by high humidity. The excessive heat experienced during drought/ heatwave can cause the pavement to soften and expand. This can create rutting and potholes, particularly in high-traffic areas, and can place stress on bridge joints. Drought/heatwave can also limit construction activities or increase the cost of construction activities, particularly in areas with high humidity.

Rising sea level/Flooding:

Global warming is causing the sea level to rise. The added water from melting ice sheets and glaciers and the expansion of seawater as it warms are two major causes of sea level rise. Flooding may occur as an overflow of water from a river, lake, or ocean overtops or breaks levees, resulting in some water escaping its usual boundaries. Flooding could also occur due to an accumulation of rainwater on saturated ground. Rising sea level/flooding can flood low-lying communities, resulting in downtime for transportation systems. Transportation infrastructures such as roads, railroads, and tunnels are highly vulnerable to flooding risks, especially on shorelines.

Wildfire:

A wildfire is an unplanned, uncontrolled, and unpredictable fire. Due to climate change, wildfires are getting more intense and frequent. Wildfires in close proximity can result in structural damage to transportation infrastructure. Wildfire, same as drought/heatwave, softens and deteriorates pavements.

Landslides:

A landslide is defined as the down-slope movement of a mass of rock, debris, or earth down a slope. Landslides could be activated by other types of natural disasters such as heavy rains, droughts, and earthquakes. Landslides result in road closing due to structural damage to pavements or mass of debris piled up, impeding regular traffic flow and emergency rescue.

Earthquake:

An earthquake is a violent and abrupt shaking of the surface of the Earth. Earthquake leads to structural failure in highway/roadway/bridge. More specifically, masonry and frame structures can be destroyed by the sudden release of energy. Failure or crack can be attributed to liquefaction, landslide, fault rupture, and failure of subgrade and subbase. Depending on the extent of the earthquake and the soil they were built on, bridges can also be susceptible to significant structural damage.

Cold winter weather:
The winter season brings a variety of adverse weather extremes. One may experience heavy snow, ice accumulation, freezing temperatures, and wind chill. Different natural events occur during winters, such as winter storms, blizzards, and many more. Snow and ice reduce pavement friction and vehicle maneuverability, causing slower speeds, reduced roadway capacity, and increased crash risk. They also increase road maintenance costs. Snow and ice accumulations and wind-blown debris can also obstruct roads resulting in traffic delays and road closures. Moreover, cold weather also creates an issue with the pavement condition. For example, cold weather can cause asphalt to contract, resulting in cracks. This weakens the asphalt significantly and reduces the life expectancy of the surface.

3.2.2.1.2 Man-made disruptions/risks

Crash:
A crash can be defined as a collision involving a device designed primarily for conveying persons or goods from one place to another. Reducing crashes can save lives. The number of crashes as well as the underlying reasons for crashes, should be considered to select, fund, and build/modify transportation infrastructures so that the number of crashes can be reduced.

Terrorism:
Terrorism encompasses a range of complex threats: organized terrorism in conflict zones, foreign terrorist fighters, radicalized “lone wolves”, and attacks using chemical, biological, radiological, nuclear and explosive materials to cause harm to both human lives and critical infrastructures. Terrorism threats could lead to significant damage to transportation infrastructures (e.g., the collapse of bridges). Hence, it is crucial to identify vulnerable transportation infrastructures, potential impact if attacked, steps to take in order to prevent the attack, and steps to be taken if it is attacked.

Cyber-attack:
A cyber-attack is a malicious and deliberate attempt to breach the information in computer systems, technology-dependent enterprises, and networks. Cyber-attacks could disrupt, disable, or destroy functioning systems by using malicious codes to alter existing codes, logic, or data. Analog controls in different transportation infrastructure entities are being replaced by networked digital counterparts, allowing remote monitoring and control of signs, signals, bridges, tunnels, and vehicles. Due to such a level of computerization, cyber-attacks have become highly probable. Cyber-attacks can lead to crashes as well as disruption in day-to-day operations of various transportation infrastructures (e.g., closing of bridges) due to issues such as hacking of message signs and traffic controllers.

3.2.2.2 Utilization

Utilization refers to the usage of transportation infrastructure in terms of vehicle type and traffic volume. Vehicle type refers to the different types of vehicles based on their various characteristics, such as energy sources (e.g., conventional gasoline or diesel vehicles, electric vehicles) (Portland Bureau of Planning and Sustainability 2018). Traffic volume refers to the number of vehicles that use transportation infrastructure. Accurate prediction of the future vehicle types and volume can help to better understand the load experienced by roads and bridges both at the structural (e.g., stresses and strains in pavements) and system level (e.g., level of congestion), which can be used for accurate infrastructure capacity estimation and maintenance planning (Arun et al. 2013). Not considering it may result in inaccurate capacity estimation resulting in sub-optimal funding allocation and construction strategies.

3.2.2.2.1 Vehicle Type

Conventional fuel vehicle:

Conventional fuel vehicle refers to conventional internal combustion engine (ICE) vehicles powered by gasoline or diesel fuel. These types of vehicles make up the majority market share in the U.S. In 2021, internal combustion engines (ICEs) amounted to just under 90% of the light vehicle sales by fuel type, including cars and light trucks (Statista 2021). By 2030, gasoline-powered cars may still account for nearly 80% of the market (Statista 2021).

Electric vehicle:

Electric vehicles are vehicles that are either partially or fully powered on electric power instead of an internal-combustion engine. This type of vehicle is seen as a possible replacement for current-generation automobiles to address rising pollution, global warming, depleting natural resources, and many more. The electric vehicle market in the United States has grown significantly in recent years. In 2020, the share of new electric vehicle sales was approximately 2.4%, an increase from about 2% in 2019 (Bui et al. 2021).

3.2.2.2.2 Traffic Volume

AADT/ADT:

As a simple but valuable measure, annual average daily traffic (AADT) can be calculated by dividing the total volume of vehicle traffic on a highway or road for a year by 365 days (Rossi et al. 2012). It informs how busy a road is. It is the most commonly used method to determine traffic flow. It helps to determine whether new road segments must be built, which design modifications should be made, etc.

3.2.2.3 Performance

Three important aspects of transportation infrastructure performance were identified: environment, service, and structural condition assessment. Environmental performance is related to the impacts of transportation infrastructure on pollution, waste, and emissions. Water quality, GHG emission level, and open space preservation are often used to measure how transportation infrastructure impacts the environment (Portland Bureau of Planning and Sustainability 2018). Service performance refers to the capability of transportation infrastructure to ensure efficient and effective movement of people and goods. Four major service performance measures were identified: mobility, accessibility, connectivity, and supply chain and logistics reliability (Nevada Department of Transportation 2008; State of Alaska Transportation & Public Facilities 2016). Finally, it was identified that structural condition performance assessment is important for future-proofed transportation infrastructure planning. Structural condition performance assessment could be conducted through visual inspection or automated monitoring system (Wisconsin Department of Transportation 2009).

3.2.2.3.1 Environmental

Emission level:

Emission level refers to the quantitative amount of specific air pollutants released from transportation-related sources over particular timeframes (EPA 2018). Emission levels can be measured at both regional and national scales. The U.S. transportation sector — which includes cars, trucks, planes, trains, and boats, emits significant amounts of carbon annually. There has also been significant scientific evidence of carbon emission due to transportation construction projects. If this is not addressed, the earth's temperature can significantly rise. Including emission levels into the transportation infrastructure planning framework can help track the emission level and determine the best mode of action with regards to the use of eco-friendly materials in construction, alternative fuel and transportation mode development, construction of eco-friendly infrastructures such as cycling and walking trails, better land use management to increase accessibility, and many more.

Water quality:

Water quality measures the condition of the water based on chemical, physical, biological, and radiological characteristics. Transportation affects water quality directly in various ways: 1) road construction and maintenance; 2) pollutants deposited such as vehicle exhaust, oil, dirt, and deicing chemicals; and 3) oil spills on inland waterways and coastal areas. While planning, the effect of the transportation sector on water quality should be closely considered. Appropriate actions (e.g., constructing higher quality pavements to reduce the rate of erosion and penetration by the pollutant, encouraging alternative fuel and transportation mode development) should be taken.

Preservation of open space:

Well-managed open space in a community protects the environment and could greatly enhance the quality of life of residents. Well-preserved open space provides places and opportunities for economic, social, and cultural activities, which is beneficial for the long-term development of a community. Transportation planning should consider the conservation of open space. If planning authority conducts their operation without consulting land and resource management agencies, it can have a significant negative impact, such as uncontrolled urban sprawl, shortage of groundwater, polluting stormwater runoff, and a decrease in air quality.

3.2.2.3.2 Service

Mobility:

Mobility refers to the efficient movement of people or goods (Litman 2011). A mobility perspective focuses on increasing the motor vehicle system capacity and speed. Population increases and economic growth have increased the demand for mobility (e.g., an increase in vehicle miles of travel (VMT)). If mobility needs are not addressed, various problems such as congestion can be observed, leading to reduced economic activity in the area. Hence, to spur continued economic growth and foster quality of life, it is critical to build/modify transportation infrastructures that can accommodate future mobility needs.

Connectivity:

Connectivity refers to the density of connections in path or road networks and the directness of links (Victoria transportation policy institute 2017). A well-connected network has many short links, numerous intersections, and minimal dead-ends. Less connectivity leads to more travel times, fewer trips, and ultimately loss of mobility. Poor connectivity also negatively affects freight movement.

Accessibility:

Accessibility refers to the ability to reach desired goods, services, activities, and destinations (collectively called opportunities) (Litman 2011). Access is the ultimate goal of most transportation. Higher accessibility leads to reduced travel times and oftentimes less use of personalized automobiles. More compact, mixed-use, walkable communities are critical if accessibility is to be improved in a particular region.

Supply chain and logistics:

Supply chain and logistics refer to the movement of products from the beginning of a supply chain to the customer's handle. If the freight movement is in a good state, it results in a higher level of business activities. Considering it in planning is crucial as a business activity is essential for any region to thrive.

3.2.2.3.3 Structural Condition Assessment

Visual inspection:

Visual inspection is a common method for the inspection and maintenance of civil infrastructure. Using raw human senses (e.g., vision and touch), professionals complete data acquisition and analysis tasks for infrastructure quality control. Accurate visual inspection can detect a variety of structural surface flaws, such as corrosion, contamination, surface finish, and surface discontinuities on joints in transportation infrastructures. Visual inspection results should be incorporated into planning to determine the required maintenance and funding needs.

Automated monitoring systems:

Automated monitoring refers to the use of tools and technologies (e.g., cameras) to determine structural flaws in transportation infrastructures such as pavements and bridges. Automated monitoring systems can detect defects that are not visible on the surface by humans. Like visual inspection, automated monitoring systems' results should be incorporated into planning.

3.2.2.4 Funding

Funding refers to the financing mechanism to develop, maintain, or rehabilitate transportation infrastructure. Two dimensions pertaining to funding were observed to be important to transportation infrastructure: source and allocation. Source refers to the authorities and financial entities that provide money for transportation infrastructure-related ventures. Allocation refers to allocating the funds to different areas or activities for transportation enhancements. It was observed that there are different types of allocation strategies, such as need-based, equity-based, priority-based, and community-based strategies.

3.2.2.4.1 Source

Public:

Public funding includes money from federal sources, usually allocated through US DOT, as well as from state and local authorities that come from various sources such as sales taxes and property taxes. Tracking previous public transportation funding and potential funding can help plan better for transportation infrastructure projects. If not done in due time, sub-optimal allocation of the public fund may occur, which may dilute the long-term strategic plans.

Public-private:

The public-private partnership (PPP) is a collaborative relationship and innovative funding model established between a public agency and a private entity to design, develop, finance, construct, operate or maintain public infrastructure projects. Fiscal constraints limit how much governments can do on their own. Agencies should incorporate new PPPs or the potential of upcoming PPPs in the near future so that they can undertake new infrastructure projects. Relying solely on public funding can reduce their flexibility in completing the required task, be it constructing, resurfacing, or restoring new or already built infrastructures.

3.2.2.4.2 Allocation Strategies

***Need-based funding*:**

Need-based funding is investment dictated by the needs of a region. This type of funding indicates transportation infrastructure deficiencies. This is the most critical type of funding allocation as it can be related to safety (incorporating countermeasures to reduce crashes), freight movement needs, etc. Not considering such type of strategy in planning may lead to investment allocation not reflective of the need in a region.

Equity-based funding:

Equity-based funding refers to the allocation of funding to regions depending on how much they contribute to revenue generation, the percentage of people living, usage of transportation infrastructure, etc. Equity-based funding ensures that each user/region is weighted equally. This type of funding allocation can be applied if the competing regions face similar needs, and selection among them is required due to funding constraints. Not considering it in planning can lead to uneven and unjustified funding distribution, which may create tension between local government officials.

Priority-based funding:

This is a special type of funding allocation strategy where a special fund is allocated to pay off previous expenses or invest in new projects that regional authorities have identified as crucial. Local jurisdictions can also submit their priority projects through a competitive process. Federal authority can also set a limit that a certain portion of funding must go to a particular region, such as rural areas. Priority-based funding should be considered in planning as it helps pay off debt accrued over the years and focuses on disadvantaged areas. Not considering it may lead to debt explosion and directed funding to specific, traditional areas.

Community-focused funding:
Each community is different. Community value dictates the funding needed for transportation infrastructure. It can be in the form of the development of bicycle lanes, shorter/longer road widths, etc. This type of allocation strategy is needed when a community's needs are significantly different from a region's needs. If not addressed appropriately, people in the community can leave or put pressure on the local officials.

3.2.2.5 Innovation

Innovation can be defined as the implementation of a new idea, process, or service, to improve the efficiency and effectiveness of transportation infrastructure. Innovations, including new design concepts, travel modes, and technologies, have brought significant changes to today's transportation infrastructure and are expected to bring more in the future.

3.2.2.5.1 New Design Concepts

Complete Streets:
Complete streets are designed and operated to enable safe access for all users, including pedestrians, bicyclists, motorists, and transit riders of all ages and abilities (Smart Growth America 2019). Complete streets improve safety by reducing crashes through safety improvements. By providing safe and efficient connections between different locations (e.g., residences, offices, retail stores, parks, schools), complete streets could promote the economic growth and stability of a community or region.

Highway and safety corridors:
Highway and transportation corridors refer to the designation and design of roadways that are beneficial to fulfilling an operational goal set by the authority. These corridors help alleviate the pressure of increased population that provide high connectivity and convenience for all users. Safety corridors can reduce the number of crashes by designating the roadway as a no-tolerance zone for traffic violations monitored by a higher presence of law enforcement officers.

3.2.2.5.2 New Travel Mode

Telecommuting:
Telecommuting (working from home or a location close to home) is a travel mode that is getting increasingly popular, especially in the post-covid time. For transportation systems, the most promising outcome of telecommuting is the removal of cars from the road during peak travel periods. Telecommuting could reduce the AADT/ADT as fewer people travel on the streets. This change should be incorporated into the planning process to make required design/operational changes.

Carpooling and vanpooling:
A vanpool is a form of ridesharing in which a group of people (appx. 5-15 depending on the size of the van) share a ride to work for convenience, to save money, or be more environmentally friendly. Carpooling is similar with fewer people. Car and vanpooling can reduce congestion and travel time. Due to fewer cars on the road, carpooling and vanpooling can also significantly help reduce the emission level.

Bike sharing:

Bike-sharing is a new transportation mode in which individuals can use shared bikes on a short-term basis, usually for a price. Bike share and shared micro-mobility have rapidly emerged as new transportation options that can increase cycling and reduce automobile usage. Bike sharing can increase the safety and livability of a region by reducing emissions.

3.2.2.5.3 Process/New Technology

Autonomous vehicle:

Autonomous vehicles (AV) use technology to partially or fully replace human drivers. Currently, some vehicles are already being deployed with autonomous functionality, such as self-parking or auto-collision avoidance features (Bagloee et al. 2016). In the future, it is expected that a fully autonomous vehicle can drive itself independently without any human input. Infrastructure enhancements, such as dedicated lanes or roadways that maximize vehicle utility and reduce parking requirements, would be required to facilitate the adoption of AVs. If the effect of the incorporation of AVs in the transportation domain is not fully understood, many problems may arise, such as miscalculating the road capacity, inadequate road infrastructures to monitor AVs, a potential increase in congestion if people shift from transit to personal autonomous vehicles, etc.

Connected vehicle:

Connected vehicle technologies allow vehicles to communicate with each other and the world around them (ITS 2019). The connected vehicle concept is about supplying useful information to a driver or a vehicle to help the driver make safer or more informed decisions. The use of a "connected vehicle" doesn't imply that the vehicle is making any choices for the driver. Rather, it supplies information to the driver, including potentially dangerous situations to avoid. Similar to autonomous vehicles, the introduction and adoption of connected vehicles will have significant requirements on the enhancement of transportation infrastructure.

3.2.2.6 Public Perception

Public perception, including societal trends and community values, represents the belief or opinion of the public towards future transportation (Atlanta Regional Commission 2011). Two types of societal trends, i.e., health conscious and environmentally conscious, and one type of community value, i.e., community's transportation vision, were identified.

3.2.2.6.1 Societal trend

Health conscious:

This relates to the societal trend of people especially the younger generations' focus on a healthy lifestyle. Due to this, they prefer healthier transportation choices such as cycling or walking for both recreational and professional purposes. If the societal trend is health-centric, certain transportation infrastructures have to be built. For example, cycling advocates argue that dedicated infrastructure is required to increase the rate and safety of cycling, even as opponents assert that the cost is too high and the benefits limited — particularly if it means adjusting the urban space dedicated to cars. If this need is not properly addressed, the political pressure may pile up and lead to increased future costs for innovation/modification in transportation infrastructure design.

Environment conscious:

A growing number of people have stronger biospheric and altruistic values, as opposed to egoistic. Those people are inclined to reduce their car use, since they strongly believe car use contributes to environmental problems. A conscious environmental view of a region may lead to infrastructure development such as bike-friendly infrastructure. Similar to the dimension discussed before, if this need is not adequately addressed, the political pressure may pile up and lead to increased future costs.

3.2.2.6.2 Community Value

Community's transportation vision:

Community values are the core principles or standards that the community's citizens wish to maintain. They must be acknowledged, honored, and defended to ensure that infrastructure change and development in a community follow these core principles and standards. Community support can help agencies avoid costly delays in the environmental review and ecological permitting stages. Agencies also may generate greater goodwill, which can translate into increased financial support for transportation-related activities. Not considering it may result in community pressure on elected officials to halt an ongoing transportation project, modify an already built infrastructure, or even cancellation of a particular project.

Chapter 4: Inter-relationships Among Future-proofing Factors

4.1 Association Rule Mining

In order to determine the semantic relationship among different concepts generated via the topic models, the association rule learning method was applied (Chowdhury and Zhu forthcoming). Association rule mining is a procedure that aims to observe frequently occurring patterns or associations from datasets found in various kinds of databases, such as relational databases, transactional databases, and other forms of repositories (Manimaran and Velmurugan 2013). Association rules are created in ARM by thoroughly analyzing data and looking for frequent if/then patterns in large datasets to identify hidden knowledge (Ampornphan and Tongngam 2020). Due to its capability in identifying inter-relationships in complex text datasets, ARM has been used in many transportation domain problems such as discovering associations between pairs of timestamped alarms (e.g., warnings) in railway transportation systems using floating train data (FTD) (Sammouri et al. 2012), exploring relationships between risk variables (e.g., improper loading, poor navigation visibility) identified from inland waterborne transportation accident reports (Wang and Yin 2020), and exploring association rules among key influence factors (e.g., monthly freezing index, service age) for thermal cracking using the Long-Term Pavement Performance (LTPP) program database (Dong et al. 2018).

An association rule has two major parts, i.e., an *antecedent* (if) and a *consequent* (then). An *antecedent* is something that is fixed by the user, and a *consequent* is an item that is found in combination with the *antecedent.* In the context of the current analysis, an antecedent would be any concept shown in the taxonomy (e.g., societal trend), and consequents would be the concepts that are most closely associated with it (e.g., societal trend changes based on the new travel mode). Two quantitative measures (confidence and lift) are used to determine the significance of the degree of association. The first measure, called confidence, captures how often the *antecedent* appear in transactions that contain only the *antecedent*. Finally, lift refers to the increase in confidence in claiming that the *antecedent* will be present in a combination, given that the *antecedent* was present.

ARM intends to identify strong rules discovered in databases using some measures of interestingness. Formally, let $I = \{I_1, . . . , I_m\}$ be a set of m items, and a database D = $\{t_1, . . . , t_n\}$be a set of n observations, where each observation is unique and has a subset of items in I. A rule in the ARM has the form "X→Y", where $X, Y \subseteq I$ and $X \cap Y = \emptyset$. This means that every rule is composed of two sets of items X and Y, where X is called the antecedent and Y is called the consequent.

Two common measures of interestingness, i.e., confidence and lift were adopted in this study to find interesting patterns in the data. Confidence is the conditional probability of the consequent occurring, given that the antecedent is true. It can be calculated as

$$Confidence(\mathrm{X} \rightarrow \mathrm{Y}) = \frac{Support(\mathrm{X} \rightarrow \mathrm{Y})}{Support(\mathrm{X})} \tag{3}$$

Where $Support(\mathrm{X})$ is the proportion of observations in the database which contains item X, $Support(\mathrm{X} \rightarrow \mathrm{Y})$ is the proportion of observations in the database, which contains both items X and Y. Confidence value represents the certainty of a rule. A higher confidence value indicates a stronger association between topics.

The lift metric is defined as the probability of the co-occurrence of the antecedent and consequent divided by the probability of their co-occurrence if the occurrence of the two items are independent. It can be calculated as

$$Lift(\mathrm{X} \rightarrow \mathrm{Y}) = \frac{Support(\mathrm{X}\rightarrow \mathrm{Y})}{Support(\mathrm{X}) * Support(\mathrm{Y})} \tag{4}$$

The lift value indicates the statistical dependence between X and Y. A lift value greater than 1 indicates a positive correlation, less than 1 indicates a negative correlation, and equal to 1 indicates that the two items are independent. Figure 4 shows the conceptual illustration of ARM adopted in this study.

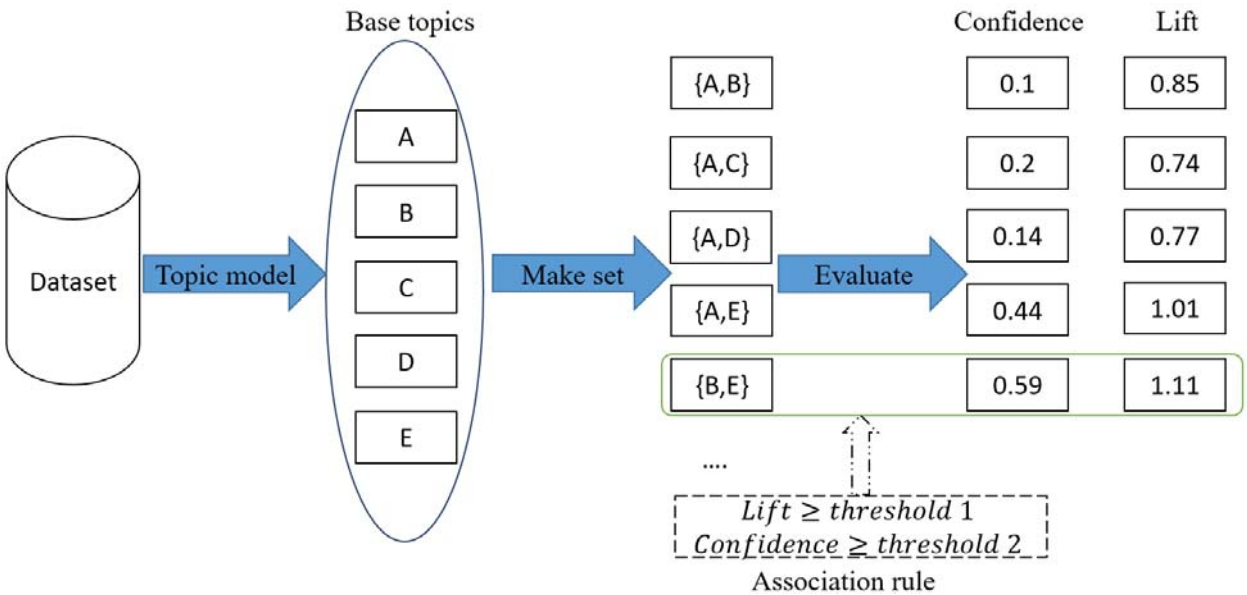


Figure 4. Conceptual illustration of ARM

4.2 Inter-relationship Identification

Based on the developed taxonomy, association rule mining was applied to level-2 topics to identify their inter-relationships. Level-2 topics were selected for the ARM analysis in this study since they have the appropriate level of detail. Using level-3 topics in the taxonomy for analysis would significantly increase the computational complexity, while using level-1 topics may result in losing useful insights due to the high level of granularity. For ARM analysis, a dataset with 14 items (i.e., level-2 topics) and 253 observations was first created. The observations were coded with regard to each individual topic as well as pairs of topics. The number of occurrences of each individual topic indicates the frequency of that topic appearing in the database. The number of occurrences of each pair of topics indicates the frequency of a specific rule appearing in the database. For example, in a document titled "*Moving Michigan Forward: 2040 State Long-Range Transportation Plan*", it was stated that "*Integrating sidewalks, bicycle lanes, shared use pathways, or other infrastructure supporting pedestrians and bicyclists into road construction projects results in both efficiency and opportunities to improve safety for all users of the roadway*" (Michigan Department of Transportation 2016). Based on this observation, one occurrence of a rule (i.e., a pair of level-2 topics) was identified as "new design concept→man-made disruptions/risks", as the observation indicates new design concept could reduce safety accidents in the future.

For each level-2 topic, association rules were created with regard to the rest of the 13 topics, resulting in a total of 102 rules in this study (Table 2). An R package for ARM was used to calculate the confidence and lift values for each rule (for code, see Appendix A4). For example, it was observed that a rule "New technology→man-made disruptions/risks" occurred 15 times among the 253 observations. The topics of "new technology" and "man-made disruptions/risks" were identified in 68 observations and 40 observations, respectively. Hence, according to Eq. (3), the confidence level of the rule "New technology→man-made disruptions/risks" was (15/253) / (68/253) =22.06%. According to Eq. (4), the lift value was (15/253)/ ((68/253) *(40/253)) =1.395. This shows that man-made disruptions/risks and new technology occurred more frequently than expected. Table 24 in the Appendix (A2) shows all the identified rules in this study.

4.2.1 Significant Inter-relationships

In this study, significant inter-relationships among different planning factors were identified based on both confidence and lift values. Two criteria were used to assess a rule and determine whether it is significant: first, the confidence value of the rule should be above the upper quartile among all the rules in this study (i.e., 0.1730); second, the lift value should be above 1. Based on these two criteria, eight rules were identified as significant in this study. Table 3 and Figure 5 show the identified significant inter-relationships.

Table 3. Significant association based on confidence and lift values

Rules	Confidence	Lift
Man-made disruption/risk and New technology	0.375	1.395
Man-made disruption/risk and Community value	0.286	1.807
Environmental performance and Societal trend	0.286	2.493
Structural condition assessment and Traffic volume	0.273	3.136
New technology and Traffic volume	0.381	1.417
New technology and Vehicle type	0.364	1.353
New technology and Societal trend	0.286	1.063
New technology and Environmental performance	0.276	1.027

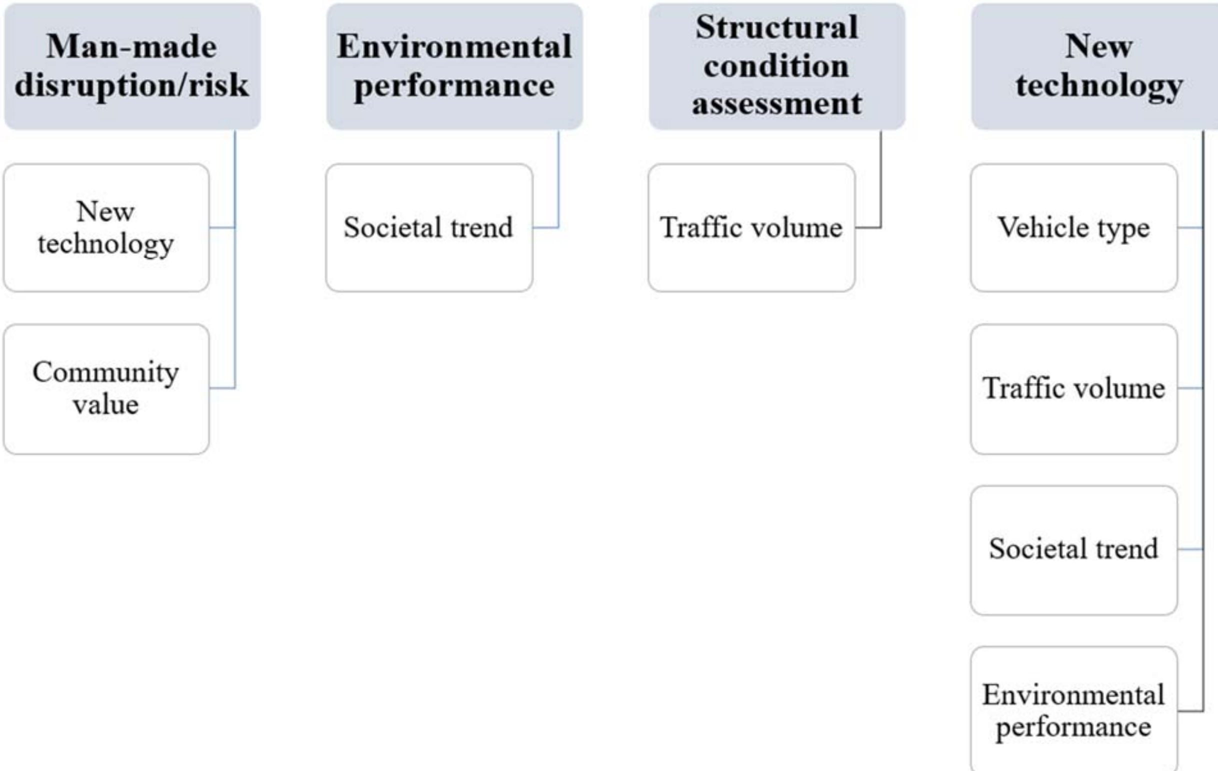


Figure 5. Significant associations identified among transportation planning factors

4.2.1.1 Association with Man-made Disruptions/risks

Two associations related to man-made disruptions/risks were found to be significant. First, there is a high degree of inter-dependency between new technologies and man-made disruptions/risks. New technologies such as automated and connected vehicles have the potential to reduce crashes due to various safety features of the vehicles (Rahman et al. 2019). Researchers estimated that these new features could reduce traffic fatalities by up to 94% by eliminating human error-induced traffic accidents (Maddox 2018). On the other hand, these new technologies increase security and privacy concerns due to the large volume of information being accessed and shared. A report from the European Union Agency for Cybersecurity (ENISA) pointed out that autonomous vehicles are highly vulnerable to a wide range of attacks, such as sensor attacks with beams of light, overwhelming object detection systems, and back-end malicious activity (ENISA 2021). Community value is another factor that was observed to be strongly associated with man-made disruptions/risks. Residents in local communities, as the ultimate users of transportation infrastructure, can help enhance transportation safety by directly participating or indirectly influencing transportation infrastructure planning and design. For example, The Seattle Department of Transportation (SDOT) has taken a city-resident partnership approach to ensure that both sides come to a common understanding of local transportation needs and challenges and make planning and design decisions accordingly (Seattle Department of Transportation 2017). They found that community-oriented solutions could lead to effective measures that reduce man-made disruptions and risks in transportation. Such measures may include displaying more signage, implementing traffic calming measures, new parking management, and driver awareness campaigns. Knowing these strong inter-relationships, transportation planning agencies should carefully examine the potential impacts of new and innovative technologies and actively incorporate community values into consideration in order to reduce the risks associated with man-made disruptions.

4.2.1.2 Association with Environmental Performance

Environmental performance and societal trend were found to be highly associated. There is a growing level of environmental consciousness in society. In a recent study, it was observed that more and more people believe that protecting the environment and dealing with global climate change should be two of the top priorities in the U.S. (Tyson and Kennedy 2020). This trend has a significant impact on transportation systems and their environmental performance. For instance, a growing number of people, especially the younger generation, call for a more environmentally friendly transportation system that promotes healthy living (Connecticut Department of Transportation 2015). People contribute to reduced carbon footprint by adopting more sustainable travel behaviors such as taking mass transit, switching to electric vehicles, and using shared mobility services (Wang and Wang 2021). The public is also calling for preserving open/green space and minimizing the urban sprawl to protect the environment (Gearin and Kahle 2006). Acknowledging this association between societal trend and environmental performance of transportation, transportation infrastructure planners should better capture the emerging social trends, and leverage the power of social trends to drive the development and design of environment-friendly transportation infrastructure (Fry 2020).

4.2.1.3 Association with Structural Condition Assessment

The inter-relationship between traffic volume and structural condition assessment techniques was observed to be significant. It was found that traffic volume would affect the selection of structural condition assessment tools and methods. For roads and bridges with light traffic, traditional visual inspection techniques might be adequate. However, for heavily used roads and bridges that play an important role in the overall transportation system efficiency, automated monitoring and assessment systems that provide a more accurate and faster evaluation of infrastructure conditions are preferred. The continuous health monitoring of infrastructure could facilitate informed maintenance and rehabilitation decisions and thus minimize the potential consequences of improper or delayed actions, such as sustained lane closure due to large-scale maintenance (Grosso et al. 2020). Therefore, transportation planners could use traffic volume as a criterion to prioritize the adoption of automated structure condition monitoring and assessment. This can lead to less maintenance cost in the long term as well as less loss of service in the transportation network.

4.2.1.4 Association with New Technology

New technology was found to be closely associated with four other topics: vehicle type, traffic volume, societal trend, and environmental performance. First, vehicle type will change with the advancement of new technologies. More electric and autonomous vehicles will be seen on the road. It is estimated that about 15% of the fleet in the U.S. will become autonomous by 2030, and about 50% of the light-duty vehicles sold in the U.S. will be electric by 2035 (Rissman 2017). Second, technologies such as AV would drastically change the traffic condition. It could smooth traffic flows and reduce congestion by better guiding and coordinating vehicles on the roads. At the same time, it might increase vehicle miles traveled (VMT) resulting from migration effects from other travel modes to private AVs (Soteropoulos et al. 2019). Third, technologies will bring or reinforce emerging societal trends. For example, self-driving and mobile computing will enable people to change their lifestyles, such as sharing vehicles instead of owning vehicles. The societal trends will, in turn, push the development of technologies. Finally, technologies (e.g., electric and automated vehicles) will help improve environmental performance in multiple ways, including using renewable energy sources and reducing GHG emissions. As new technologies are associated with so many aspects of future transportation, it is critical for planning agencies to understand the technological landscape and thoroughly incorporate the implications on traffic, society, and the environment into infrastructure design and management to meet future needs.

Chapter 5: Modeling the Effects of Future-proofed Factors and Associations

After the future-proofed transportation planning factors and their associations are identified, numerical models can be developed to incorporate them into risk-informed decision-making. In this study, based on the identified critical influence of electric vehicles as an example of new technology and vehicle type, the potential effects of electric vehicles (EV) on (1) pavement conditions and (2) environmental performance in the future were modeled in two case studies.

5.1 Effects of EV on Pavement Condition

Due to the massive battery, EVs weigh more than their internal combustion engine counterparts. Because of this larger weight, it could potentially cause more wear and tear to the pavements. To determine whether EV would have significant impact on pavement condition, Present Serviceability Rating (PSR) was used. PSR is a surface-condition rating scheme developed by the American Association of State Highway Officials (AASHO), which is based on a numeric scale between 0 and 5 (FHWA 2021). The value of 0 indicates extremely poor condition, whereas 5 indicates a theoretical distress-free pavement. The value of 4.5 is considered the highest practical PSR based on existing literature (Batouli et al. 2022). Pavement deterioration was quantified by using an empirical formulation for highway performance monitoring system (HPMS) suggested by Lee et al. (1993). This equation can be stated as follows.

$$PSR = PSR_i - A.F * a * SN^b * Age^c * CESAL^d \qquad (5)$$

$Where\ PSR_i$ denotes the initial value of PSR for a given road section right after construction or after a major rehabilitation,

$CESAL$ (Cumulative Equivalent Single Axle load) captures the impact of traffic load,

Age denotes the lifetime of the road since construction,

$A.F\ is$ an adjustment factor that is used to customize the prediction of PSR based on the effects of climate conditions,

SN (structural number) reflects the structural conditions of roads (i.e., the type of material and depth of surface, base, and subbase layers),

and $a, b, c,$ and d are coefficients whose values depend on the type of pavement.

5.1.1 Case Description

Five road sections with varying lengths and types in Connecticut were identified (Connecticut Department of Transportation 2022). These road sections were located across different towns in Connecticut, including East Haddam, Old Lyme, East Haven, Bridgeport, and Killingly. Among these road sections, two of them are of composite types, whereas three are flexible types. With regard to the functional class type, three of them are interstates, one is minor arterial, and the final one is other principal arterial. The values of $a, b, c,$ and d coefficients are based on the type of pavements. These values were collected from the study done by Lee et al. (1993). Table 4 shows the value of the coefficients and the summary statistics of different predictive models for five major pavement types. In the Table, FLEX refers to the flexible pavement-based regression model and COMP refers to the composite pavement-based regression model. The coefficient values from only these two predictive models were collected.

Table 4. PSR coefficients identified from Lee et al. (1993)

	Model				
	FLEX	COMP	JPCP	JRCP	CRCP
$\log_{10}a$	1.1550	-0.4185	0.5104	1.7241	0.7900
b	-1.8720	-0.1458	-1.7701	-2.7359	-1.3121
c	0.3499	0.5732	1.0713	0.3800	0.1849
d	0.3385	0.1431	0.2493	0.6212	0.2634
R^2	0.52	0.58	0.79	0.57	0.37
SEE	0.45	0.38	0.26	0.40	0.31
N	522 (31)	509 (0)	117 (3)	254 (21)	1204 (65)

As the A.F value is based on the climate conditions and road section functional class, the climate zone of Connecticut was also identified. It was found that Connecticut falls in the wet-freeze long-term pavement performance (LTPP) climate zone; hence, the adjustment factors (A.F) for the considered road sections need to be collected accordingly (Figure 6). Lee et al. (1993) provided two estimates for the A.F. The first set of estimates was obtained using the statistical package SAS (Table 5). The second set of estimates provided the recommended mean adjustment factors for use as defaults in the HPMS analytical process (Table 6). For the flexible and composite pavement types, both the A.F. estimates were observed to be similar. For example, the A.F value for a flexible pavement in other principal arterial was found to be 0.59 in both Tables 4 and 5. The PSR_i value was assumed to be 4.5 for all road segments based on different existing studies (Chootinan et al. 2006; Lee et al. 1993). Other values, such as the age of the road and AADT, were collected from different state and local transportation agencies (e.g., Connecticut Department of Transportation (2022)). Table 7 summarizes these parameters for the five road sections.

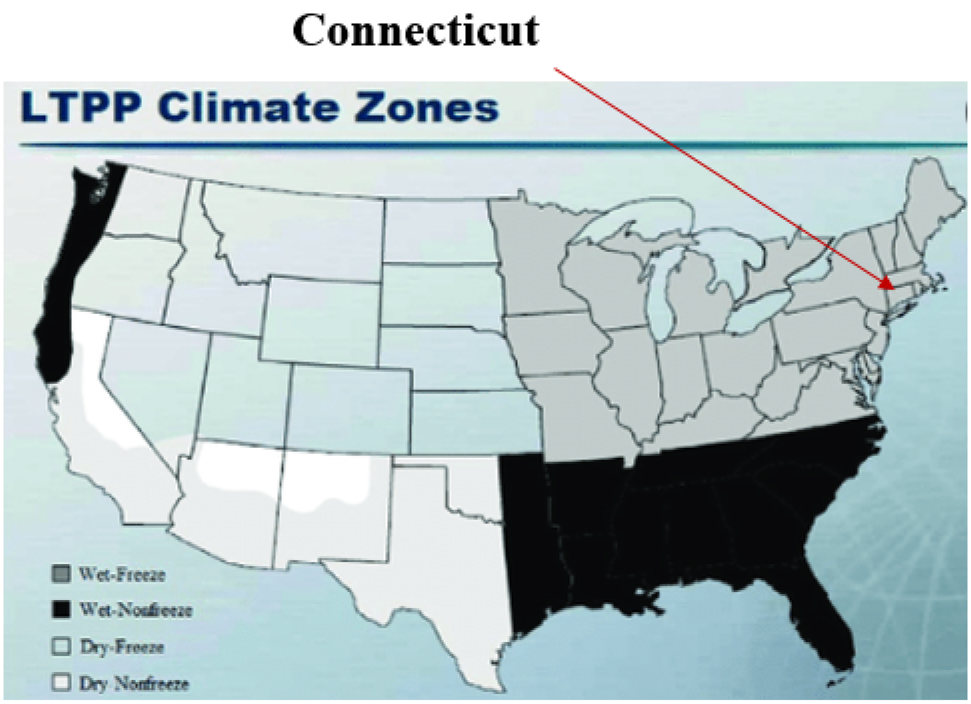


Figure 6. Long-term Pavement Performance (LTPP) climate zone of Connecticut (Coffey et al. 2018)

Table 5. Mean adjustment factors directly generated from SAS program in Lee et al. (1993)

	PTYPE									
	FLEX		COMP		JPCP		JRCP		CRCP	
	FGROUP		FGROUP		FGROUP		FGROUP		FGROUP	
	INT/-OPA	MA/C-OL	INT/-OPA	MA/C-OL	INT/-OPA	MA/C-OL	INT/-OPA	MA/C-OL	INT/-OPA	MA/C-OL
	AF	AF	AF	AF	AF	AF	AF	AF	AF	AF
	MEAN	MEAN	MEAN	MEAN	MEAN	MEAN	MEAN	MEAN	MEAN	MEAN
ZONE										
1. Wet; Freeze	0.59	0.81	1.04	1.11	0.56	0.99	0.87	2.27	0.57	-0.18*
2. Wet; Freeze-Thaw	0.37	0.85	1.13	1.07	0.33	0.64	1.25	1.46	0.39	2.12*
3. Wet; No Freeze	0.44	0.69	0.78	0.31	0.60	0.55	0.57	0.97	1.08	1.74*
4. Intermediate; Freeze	0.27	0.49	0.55	1.15	0.46	0.52	0.23	0.12*	0.94	0.00*
5. Intermediate; Freeze-Thaw	0.52	0.71	0.26	0.64*	0.66	1.61*	2.09	1.00*	1.10*	1.56*
6. Intermediate; No Freeze	0.43	0.65	0.71	0.87	0.27	1.34	1.71	2.61	2.02	.
7. Dry; Freeze	0.22	0.43	0.76*	2.53*	0.79	0.79	0.22	0.00*	0.17	.
8. Dry; Freeze-Thaw	0.32	0.39	-0.44*	0.00*	1.80	.	0.49*	0.00*	-0.13	.
9. Dry; No Freeze	0.38	0.79	0.26	.	0.22	0.66*	-0.30*	2.10*	0.45*	.

Note:
INT/OPA = Interstate highways and other principal arterials, FGROUP=1
MA/COL = minor arterials and collectors, FGROUP=2
* = mean AFs based on 25 data points or less
. = data unavailable

Table 6. Recommended mean adjustment factors for different pavement groups in Lee et al. (1993)

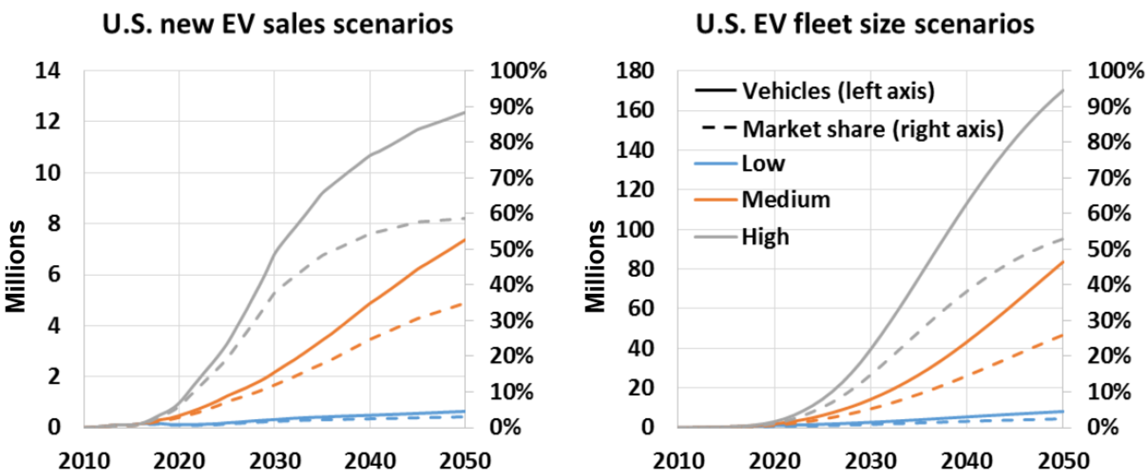
	PTYPE									
	FLEX		COMP		JPCP		JRCP		CRCP	
	FGROUP		FGROUP		FGROUP		FGROUP		FGROUP	
	INT/-OPA	MA/C-OL	INT/-OPA	MA/C-OL	INT/-OPA	MA/C-OL	INT/-OPA	MA/C-OL	INT/-OPA	MA/C-OL
	AF	AF	AF	AF	AF	AF	AF	AF	AF	AF
	MEAN	MEAN	MEAN	MEAN	MEAN	MEAN	MEAN	MEAN	MEAN	MEAN
ZONE										
1. Wet; Freeze	0.59	0.81	1.04	1.11	0.56	0.99	0.87	1.50	0.57	1.00
2. Wet; Freeze-Thaw	0.40	0.85	1.13	1.07	0.40	0.64	1.25	1.46	0.40	1.00
3. Wet; No Freeze	0.44	0.69	0.78	0.40	0.60	0.55	0.57	0.97	1.08	1.00
4. Intermediate; Freeze	0.40	0.49	0.55	1.15	0.46	0.52	0.40	0.40	0.94	1.00
5. Intermediate; Freeze-Thaw	0.52	0.71	0.40	0.64	0.66	1.50	1.50	1.00	1.10	1.00
6. Intermediate; No Freeze	0.43	0.65	0.71	0.87	0.40	1.34	1.50	1.50	1.50	1.00
7. Dry; Freeze	0.40	0.43	0.76	1.50	0.79	0.79	0.40	0.40	0.40	0.50
8. Dry; Freeze-Thaw	0.40	0.40	0.40	0.40	1.50	0.40	0.49	0.40	0.40	0.50
9. Dry; No Freeze	0.40	0.79	0.40	0.40	0.40	0.66	0.40	1.50	0.45	0.50

Table 7. Road section characteristics

Parameters	Road sections				
	A	B	C	D	E
Pavement type	Composite	Composite	Flexible	Flexible	Flexible
Functional class	Interstate	Interstate	Interstate	Other principal Arterial	Minor Arterial
AADT (2020)	129100	61900	23000	27500	4068
Age (years)	13	4	4	13	20
A.F	1.04	1.04	0.59	0.59	0.81
a	0.381505	0.381505	14.28894	14.28894	14.28894
b	-0.1458	-0.1458	-1.8720	-1.8720	-1.8720
c	0.5732	0.5732	0.3499	0.3499	0.3499
d	0.1431	0.1431	0.3385	0.3385	0.3385
SN	8.21	8.21	4.61	4.61	4.61
PSR_i	4.5	4.5	4.5	4.5	4.5

5.1.2 AADT Projection

Traditionally PSR has been estimated using conventional fuel vehicles (CV). One key phenomenon that has not been investigated is the effect of EVs on pavements. EVs are expected to increase their market share, resulting in higher EV AADTs on the road. The Electric Power Research Institute (EPRI) developed a series of three market penetration scenarios (i.e., low, medium, and high) based on actual EV sales through 2016. These scenarios were informed by various sources, such as the National Research Council of the National Academies of Science, Engineering, and Medicine (National Research Council 2013) and the National Renewable Energy Laboratory (Mai et al. 2018). Figure 7(a) and 7(b) illustrate the low, medium, and high EV market penetration scenarios as new annual sales and total EV fleet size (i.e., cumulative vehicles in service), respectively. Using the dotted line in Figure 7(b), the low, medium, and high EV fleet projection scenarios were estimated. EV fleet size projection can be referred to as EV adoption as both indicate the people's acceptance level towards driving EVs. The low scenario illustrates the pessimistic case with the lowest EV adoption, and the high scenario depicts the optimistic case. The medium scenario demonstrates the most likely case. Table 8 shows these three potential EV adoption scenarios that may occur in the future.



(a) (b)

Figure 7. Electric Power Research Institute (EPRI) low, medium, and high EV market penetration scenarios, shown both as (a) annual sales and (b) total EV fleet (US Drive 2019)

Table 8. EV adoption scenarios

Year	Scenario		
	Low	Medium	High
2025	0.75%	4.0%	8.0%
2030	1.0%	5.0%	15.0%
2035	1.5%	10.0%	22.0%
2040	2%	14.0%	39.0%
2045	2.5%	20.0%	45.0%
2050	3.0%	27.0%	52.0%

Based on the adoption scenarios shown in Table 8, EV AADT could be projected for different road sections. Table 7 identified the overall AADT values of the five road segments (i.e., A, B, C, D, and E) in 2020. Using a yearly growth factor of 0.8375%, first, overall AADT values of these roads were projected till 2050 using the equation $Previous\ year\ AADT(1 + 0.8375\%)$. Table 8 shows the projected AADT for the five road sections from 2020 to 2050 with five years increment. The growth factor value was approximated based on existing studies conducted across different road segments in Connecticut (Milone & Macbroom 2011; Fuss & O'Neill 2020). Using the EV adoption scenarios in Table 8, the projected overall AADT values (Table 9) were divided into CV and EV AADTs. For example, in 2030, assuming high adoption scenario, approximately 21,049 EVs and 119,280 CVs would be operating daily on average on road A, respectively, resulting in a total AADT of 140,328 vehicles. Tables 10, 11, and 12 demonstrate the EV and CV AADT under low, medium, and high EV adoption scenarios, respectively. Results show that with the increase in EV adoption, the total number of EVs increases on the roads significantly.

Table 9. Projected AADT till 2050

Year		Road sections				
		A	B	C	D	E
2020	**AADT**	129,100	61,900	23,000	27,500	4,068
2025		134,597	64,535	23,979	28,671	4,241
2030		140,328	67,283	25,000	29,891	4,421
2035		146,304	70,149	26,065	31,164	4,610
2040		152,534	73,136	27,174	32,491	4,806
2045		159,029	76,250	28,332	33,875	5,011
2050		165,801	79,497	29,538	35,317	5,224

Table 10. EV and CV AADT under low EV adoption scenario

Year		Road sections									
		A		B		C		D		E	
		EV	CV	EV	CV	EV	CV	EV	CV	EV	CV
2025	**AADT**	1,009	133,588	484	64,052	180	23,800	215	28,456	32	4,209
2030		1,403	138,926	673	66,611	250	24,750	299	29,593	44	4,378
2035		2,195	144,110	1,052	69,097	391	25,674	467	30,697	69	4,541
2040		3,051	149,484	1,463	71,673	543	26,631	650	31,842	96	4,710
2045		3,976	155,054	1,906	74,344	708	27,624	847	33,029	125	4,886
2050		4,974	160,827	2,385	77,112	886	28,652	1,060	34,258	157	5,068

Table 11. EV and CV AADT under medium EV adoption scenario

Year		Road sections									
		A		B		C		D		E	
		EV	CV	EV	CV	EV	CV	EV	CV	EV	CV
2025	**AADT**	5,384	129,213	2,581	61,954	959	23,020	1,147	27,524	170	4,072
2030		7,016	133,312	3,364	63,920	1,250	23,750	1,495	28,397	221	4,201
2035		14,630	131,674	7,015	63,134	2,607	23,459	3,116	28,048	461	4,149
2040		21,355	131,180	10,239	62,897	3,804	23,370	4,549	27,943	673	4,134
2045		31,806	127,224	15,250	61,000	5,666	22,666	6,775	27,100	1,002	4,009
2050		44,766	121,035	21,464	58,033	7,975	21,563	9,536	25,782	1,411	3,814

Table 12. EV and CV AADT under high EV adoption scenario

Year		Roads									
		A		B		C		D		E	
		EV	CV	EV	CV	EV	CV	EV	CV	EV	CV
2025	**AADT**	10,768	123,830	5,163	59,373	1,918	22,061	2,294	26,377	339	3,902
2030		21,049	119,280	10,093	57,191	3,750	21,250	4,484	25,408	663	3,759
2035		32,187	114,117	15,433	54,716	5,734	20,331	6,856	24,309	1,014	3,596
2040		59,488	93,046	28,523	44,613	10,598	16,577	12,672	19,820	1,875	2,932
2045		71,563	87,466	34,313	41,938	12,749	15,583	15,244	18,631	2,255	2,756
2050		86,217	79,585	41,339	38,159	15,360	14,179	18,365	16,953	2,717	2,508

5.1.3 CESAL and PSR Estimation

The concept of an equivalent single-axle load (ESAL) is typically used to measure the effects of axle loads on the pavement (Hajek 1995). By convention, an 18,000-pound single axle is considered 1.00 ESAL. Essentially, the ESAL values for other axles express their effect on pavement wear relative to 1.00 ESAL. CESAL refers to cumulative ESAL estimation based on different types of vehicles operating on a pavement. Different truck categories are defined in terms of standard ESAL loadings due to their load being comparable to 1.00 ESAL value. Other types of automobiles are not considered as they do negligible damage to the pavement structure due to lower weights. The CESAL value can be estimated using the following equation

$$\sum_{i \in I, k \in K} CESAL_{ikt} = \frac{\sum_{k \in K} AADT_{tk} * \sum_{i \in I} P_i * \sum_{i \in I} L_i}{100} \qquad \forall t \in T \tag{6}$$

Where $K = \{Type\ of\ vehicle: CV, EV\}$,

$I = \{Truck\ categories: 2, 3, 4, 5, 6\ or\ more\ axles\}$,

$T = \{Time\ periods: 2025, 2030, 2035, 2040, 2045, 2050\}$,

$AADT_{tk} = AADT\ of\ vehicle\ type\ k \in K\ in\ a\ given\ year\ t \in T$,

$P_i = Percentage\ of\ AADT\ of\ truck\ category\ i \in I$, and

$L_i = load\ factor\ for\ truck\ category\ i \in I$.

Five categories of trucks were identified that could have a significant impact on the pavements. These trucks had different axles and were classified into seven classes (i.e., 5, 6, 7, 8, 9, 10, 11, 12, and 13) based on their weights (Figure 8). Class 5, 6, 7, and 8 truck weights could range from 16001-19500 lbs, 19,501-26,000 lbs, 26,001-33,000 lbs, and 33,001 lbs- and up, respectively (US Department of Energy 2022). Each truck class has its respective number of axles. Weights for the 2, 3, and 4 axle trucks were assumed to fall between these ranges of class 5, 6, 7, and 8 vehicles. For example, the weight of all 3-axle trucks running with conventional fuels was assumed to be 23,000 lbs (Table 13).

Weight range data for truck classes 9, 10, 11, 12, and 13 could not be directly found in the existing literature. A typical 5-axle semi-truck that belongs to truck class 9 was found to weigh 35,650 lbs and was used as the weight of all 5-axle trucks running with conventional fuels (Big Truck Guide 2020). The weight for 6 or more axle trucks (i.e., class 10, 12, 13) running with conventional fuels was assumed to be 40,650 lbs. The load factors (i.e., L_i) for these conventional fuel trucks (CFTs) were also collected from existing literature (Alaska Department of Transportation 2020). Load factor refers to the average number of ESALs associated with each truck of a truck size category. It was observed that higher CFT weights resulted in higher load factors (Table 13).

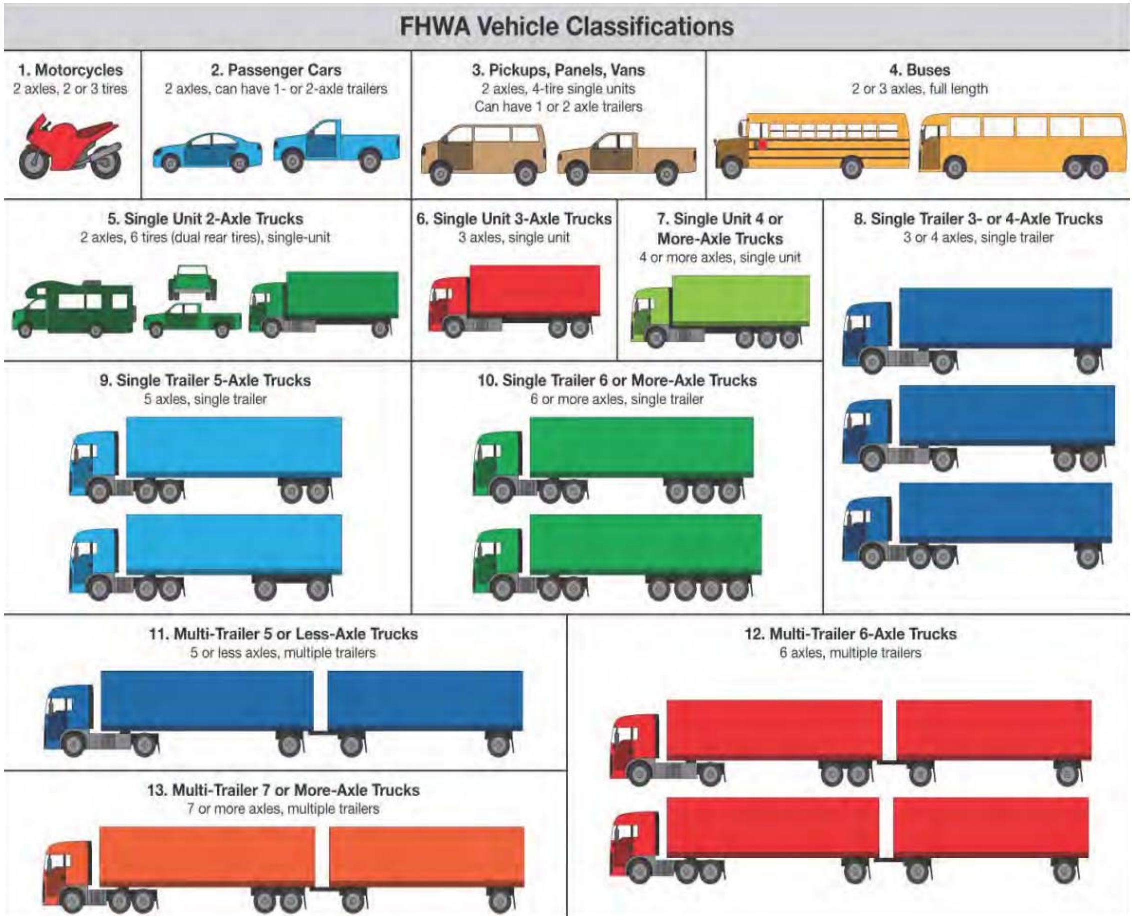


Figure 8. Federal Highway Administration (FHWA) vehicle classification (Refai et al. 2014)

To estimate the equivalent electric truck (ET) weights, it is important to determine the number of axles. Harvey et al. (2020) identified three ET types: short-haul (with a range less than 150 miles), medium-duty (with a range between 150 and 300 miles), and long-haul trucks (with a range exceeding 300 miles). Short-haul trucks were assumed to consist of a tractor with one steering single axle and one single axle (in total 2 axles). Medium-duty trucks were assumed to have a steering single axle and a back axle. It was assumed that 25 percent of the back axles were singles and 75 percent were tandems (in total either 2 axles or 3 axles). Long-haul trucks were assumed to consist of a tractor with one steering single axle and one tandem axle on the tractor (in total 3 axles). Based on this, all the 2-axle ETs in this study were assumed to be medium-duty trucks, whereas all the 3-axle ETs were assumed to be heavy-duty trucks. Harvey et al. (2020) also estimated that in 2030, the medium-duty 2-axle ET weights would be approximately 1,440 lbs higher than comparative CFT weights. Long-haul 3-axle ETs would be 5,328 lbs heavier than comparative CFTs. Data concerning 4, 5, and 6 or more axle ETs were not found from the existing literature as ETs are relatively new in the market. It was assumed that 4, 5, and 6 or more axle ET weights would be at the minimum 5,328 lbs higher than their counterparts (Table 13). For example, the 4-axle CFT weight was 30,000 lbs. The 4-axle ET weight was assumed to 35,328 lbs. ET load factor was estimated based on the following equation.

$$ET\ load\ factor = \frac{CFT\ load\ factor * ET\ weight}{CFT\ weight} \quad (7)$$

For different classes, the equivalent vehicle percentage (P_i) was estimated using Table 14 and inserted into Table 13. For example, 2.34% of the vehicles were observed to belong to truck class 5 (i.e., 2-axle). However, concerning 4-axle, 5-axle, and 6 or more axle truck categories, multiple truck classes belong to each of them. In such cases, the percentages of vehicles in several classes were added together. For example, truck classes 7 and 8 belong to the 4-axle truck category. The percentages of class 7 and 8 class trucks on the road were 0.0875% and 1.325%, respectively. Hence, the P_i for 4-axle trucks was estimated to be 0.0875%+1.325%=1.41%.

Table 13. Summary of truck categories for CESAL estimation

Truck categories	Federal Highway Administration (FHWA) truck classification	% of AADT (P_i)	CFT weight (lbs)	CFT load factor (L_i)	ET weight (lbs)	ET load factor (L_i)
2-axle	5	2.34	18,000	0.5	19,440	0.54
3-axle	6	0.68	23,000	0.85	28,328	1.05
4-axle	7, 8	1.41	30,000	1.2	35,328	1.41
5-axle	9, 11	5.45	35,650	1.55	40,978	1.78
6 or more axle	10, 12, 13	0.675	40,650	2.24	45,978	2.53

Table 14. Vehicle percentage chart for different truck classes (Hallenbeck et al. 1997)

Class	Vehicle (%)
1	0.125
2	72.21
3	16.85
4	0.275
5	2.34
6	0.68
7	0.0875
8	1.325
9	5.125
10	0.2625
11	0.325
12	0.125
13	0.2875

Tables 10, 11, 12, 13, and 14 were used together to estimate the CESAL values for both CFT and ET+CFT mix. Tables 15, 16, and 17 demonstrate the CESAL values estimated using Eqn. (6) for both CFT only and ET+CFT mix under low, medium, and high EV adoption scenarios. Results show that the

- ESAL value was highest for road section A, followed by B, D, C, and E. This is due to the fact that road section A had the highest AADT whereas E had the lowest AADT.
- Road sections with lower AADTs also had lower variation in CESAL under different EV adoption scenarios.
- Primarily road sections A and B demonstrated a noticeable impact in CESAL with changes in EV adoption scenarios.
- In general, the CESAL change is not significant when EV adoption is low. However, it becomes more significant when the EV adoption rate is higher in later years.

Table 15. CESAL (millions) for CFT and ET+CFT mix in the low adoption scenario

Year		Road sections									
		A		B		C		D		E	
		ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT
2025	**CESAL (millions)**	6.5902	6.5829	3.1598	3.1563	1.1741	1.1728	1.4038	1.4022	0.2077	0.2074
2030		6.8734	6.8632	3.2956	3.2907	1.2245	1.2227	1.4641	1.4620	0.2166	0.2163
2035		7.1714	7.1555	3.4385	3.4309	1.2776	1.2748	1.5276	1.5242	0.2260	0.2255
2040		7.4823	7.4602	3.5876	3.5770	1.3330	1.3291	1.5938	1.5891	0.2358	0.2351
2045		7.8067	7.7778	3.7431	3.7293	1.3908	1.3857	1.6629	1.6568	0.2460	0.2451
2050		8.1452	8.1090	3.9054	3.8881	1.4511	1.4447	1.7350	1.7273	0.2567	0.2555

Table 16. CESAL (millions) for CFT and ET+CFT mix in the medium adoption scenario

Year		Road sections									
		A		B		C		D		E	
		ET+ CFT	CFT	ET+ CFT	CFT	ET+ CFT	CFT	ET+ CFT	CFT	ET+CFT	CFT
2025	**CESAL (millions)**	6.6220	6.5829	3.1751	3.1563	1.1798	1.1728	1.4106	1.4022	0.2087	0.2074
2030		6.9142	6.8632	3.3152	3.2907	1.2318	1.2227	1.4728	1.4620	0.2179	0.2163
2035		7.2617	7.1555	3.4818	3.4309	1.2937	1.2748	1.5468	1.5242	0.2288	0.2255
2040		7.6152	7.4602	3.6513	3.5770	1.3567	1.3291	1.6221	1.5891	0.2400	0.2351
2045		8.0087	7.7778	3.8400	3.7293	1.4268	1.3857	1.7060	1.6568	0.2524	0.2451
2050		8.4340	8.1090	4.0439	3.8881	1.5026	1.4447	1.7966	1.7273	0.2658	0.2555

Table 17. CESAL (millions) for CFT and ET+CFT mix in the high adoption scenario

Year		Road sections									
		A		B		C		D		E	
		ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT
2025	**CESAL (millions)**	6.6611	6.5829	3.1938	3.1563	1.1867	1.1728	1.4189	1.4022	0.2099	0.2074
2030		7.0160	6.8632	3.3640	3.2907	1.2499	1.2227	1.4945	1.4620	0.2211	0.2163
2035		7.3891	7.1555	3.5429	3.4309	1.3164	1.2748	1.5740	1.5242	0.2328	0.2255
2040		7.8920	7.4602	3.7840	3.5770	1.4060	1.3291	1.6811	1.5891	0.2487	0.2351
2045		8.2973	7.7778	3.9783	3.7293	1.4782	1.3857	1.7674	1.6568	0.2615	0.2451
2050		8.7349	8.1090	4.1881	3.8881	1.5562	1.4447	1.8606	1.7273	0.2752	0.2555

The CESAL values obtained from Tables 15, 16, and 17 were later used together with Table 7 to predict the PSR values for the five road sections under different EV adoption scenarios using Eqn. (5). It must be noted that the calculations of PSR values here were just for investigating the impacts of EVs on pavement conditions. No maintenance activities for roads were considered.

Results show that, in general, electric trucks do not bring discernible differences in expected pavement performance (i.e., PSR) under any of the three adoption scenarios (Tables 18, 19, and 20). The highest difference was observed in road section A, which has a significantly higher AADT than other road sections. To further compare how the PSR for different road sections in the six time periods varied with different EV adoption scenarios, the following equation was developed.

$$PSR\ Decrease = \frac{PSR(CFT) - PSR(CFT + ET)}{PSR(CFT)} * 100\% \tag{8}$$

Table 21 lists the PSR decrease for different road sections in the six time periods. Figure 9 illustrates the average percentage decrease across the six time periods. For example, on average, across the six time periods, PSR for road A with ET+CFT mix decreased by almost 0.0753%, 0.5892%, and 1.2717% with low, medium, and high EV adoption scenarios, respectively, compared to CFT vehicle only.

Key takeaways for the stakeholders from these results:

- In general, the additional weight of EV does not seem to bring a significant impact on pavement conditions directly.
- Although insignificant, higher adoption of EVs will have an effect on pavement conditions compared with low adoption of EVs.
- The effect on pavement conditions may be more severe for highly used and older roads. Cities/towns with a higher population density that have higher traffic volume may experience more deterioration in their pavements due to EV adoption. Moreover, pavements that are reaching or have exceeded their lifecycle may see greater EV-related impacts.
- Although the direct influences on individual road sections' PSR values seem trivial, the corresponding impacts on maintenance requirements and the associated cost at the network level may be significant. Future work needs to be conducted to understand the impacts on cost.

Table 18. Expected PSR in the low adoption scenario

Year		Road sections									
		A		B		C		D		E	
		ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT
2025	**PSR**	2.5605	2.5608	2.7541	2.7544	3.1274	3.1280	3.0419	3.0424	3.4517	3.4521
2030		2.2380	2.2384	2.4638	2.4643	2.9763	2.9771	2.8813	2.8821	3.3362	3.3368
2035		1.9407	1.9415	2.1963	2.1970	2.8394	2.8407	2.7359	2.7372	3.2317	3.2327
2040		1.6618	1.6630	1.9451	1.9462	2.7122	2.7140	2.6007	2.6027	3.1345	3.1359
2045		1.3967	1.3983	1.7065	1.7080	2.5918	2.5942	2.4729	2.4754	3.0426	3.0444
2050		1.1425	1.1446	1.4777	1.4796	2.4764	2.4795	2.3503	2.3535	2.9545	2.9568

Table 19. Expected PSR in the medium adoption scenario

Year		Road sections									
		A		B		C		D		E	
		ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT
2025	**PSR**	2.5591	2.5608	2.7529	2.7544	3.1252	3.1280	3.0395	3.0424	3.4500	3.4521
2030		2.2361	2.2384	2.4621	2.4643	2.9733	2.9771	2.8781	2.8821	3.3339	3.3368
2035		1.9361	1.9415	2.1921	2.1970	2.8324	2.8407	2.7284	2.7372	3.2263	3.2327
2040		1.6546	1.6630	1.9387	1.9462	2.7015	2.7140	2.5894	2.6027	3.1264	3.1359
2045		1.3853	1.3983	1.6963	1.7080	2.5753	2.5942	2.4553	2.4754	3.0299	3.0444
2050		1.1257	1.1446	1.4626	1.4796	2.4524	2.4795	2.3248	2.3535	2.9361	2.9568

Table 20. Expected PSR in the high adoption scenario

Year		Road sections									
		A		B		C		D		E	
		ET+ CFT	CFT	ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT	ET+CFT	CFT
2025	**PSR**	2.5575	2.5608	3.3649	3.3668	3.4418	3.4460	3.0366	3.0424	3.3129	3.3177
2030		2.2313	2.2384	2.9895	2.9942	3.2236	3.2331	2.8700	2.8821	3.2092	3.2188
2035		1.9297	1.9415	2.6662	2.6746	3.0444	3.0602	2.7179	2.7372	3.1112	3.1262
2040		1.6400	1.6630	2.3696	2.3866	2.8783	2.9089	2.5662	2.6027	3.0100	3.0381
2045		1.3695	1.3983	2.0981	2.1202	2.7331	2.7713	2.4306	2.4754	2.9192	2.9535
2050		1.1087	1.1446	1.8414	1.8696	2.5957	2.6430	2.2988	2.3535	2.8298	2.8713

Table 21. Decrease in PSR under low, medium, and high EV adoption scenarios

Year		Low EV Adoption Scenario				
		Road Sections				
		A	B	C	D	E
2025	PSR Decrease (%)	0.0121	0.0101	0.0165	0.0180	0.0114
2030		0.0214	0.0175	0.0257	0.0282	0.0175
2035		0.0419	0.0334	0.0440	0.0485	0.0295
2040		0.0724	0.0557	0.0661	0.0732	0.0437
2045		0.1176	0.0867	0.0922	0.1026	0.0600
2050		0.1864	0.1298	0.1226	0.1373	0.0785
Year		Medium EV Adoption Scenario				
		Road Sections				
		A	B	C	D	E
2025		0.0642	0.0537	0.0880	0.0961	0.0609
2030		0.1069	0.0874	0.1282	0.1407	0.0873
2035		0.2781	0.2212	0.2920	0.3220	0.1960
2040		0.5028	0.3867	0.4597	0.5093	0.3039
2045		0.9304	0.6857	0.7310	0.8138	0.4757
2050		1.6528	1.1509	1.0910	1.2211	0.6988
Year		High EV Adoption Scenario				
		Road Sections				
		A	B	C	D	E
2025		0.1280	0.0569	0.1224	0.1918	0.1427
2030		0.3188	0.1587	0.2931	0.4199	0.2978
2035		0.6073	0.3145	0.5145	0.7042	0.4805
2040		1.3792	0.7159	1.0518	1.4018	0.9253
2045		2.0617	1.0432	1.3801	1.8096	1.1586
2050		3.1352	1.5048	1.7906	2.3243	1.4456

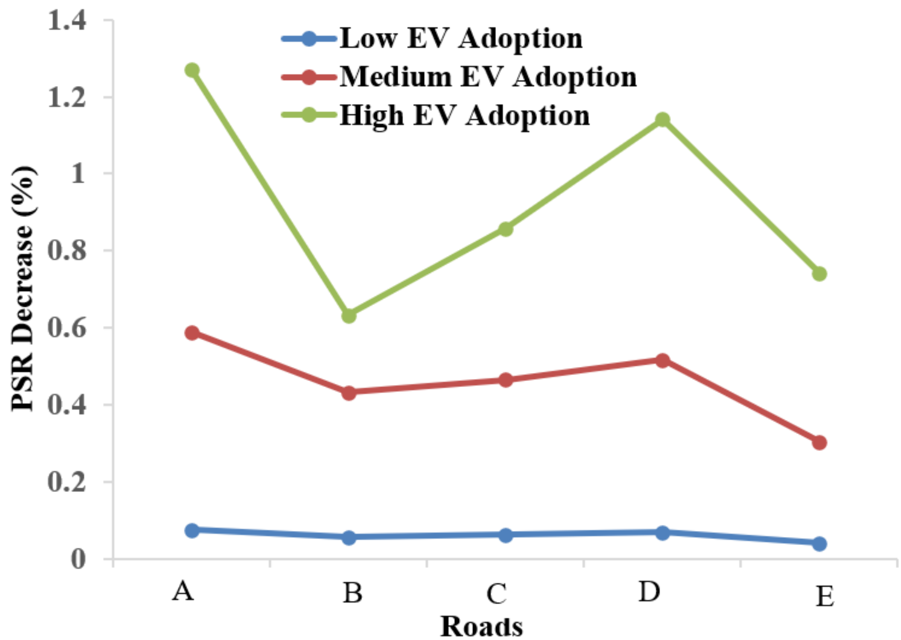


Figure 9. Average percentage of PSR decrease due to ET adoption

5.2 Effects of EV on Environmental Performance

The effects of EVs on environmental performance have also been investigated. The entire state of Connecticut was used as the testbed. The total number of vehicles operating on Connecticut roads was collected, which was observed to be 2,826,350 in 2017 (Federal Highway Administration 2021). Using the growth factor of 0.8375%, the projected total number of vehicles for 2025, 2030, 2035, 2040, 2045, and 2050 was estimated (Table 22). Using the low, medium, and high EV adoption scenarios shown in Table 8, the projected number of EVs and conventional vehicles (CVs) were also estimated. For example, it was estimated that under the high adoption scenario, in 2035, the projected number of EVs and CVs in Connecticut would be 722,513 and 2,561,638, respectively.

Data was also collected for the annual emission per vehicle (U.S. Department of Energy 2022). EVs typically have zero tailpipe emissions (i.e., direct emissions) (Manjunath and Gross 2017). However, emissions may be produced by the source of electrical power, such as a natural gas/oil/hydro power plant. In geographic areas that use relatively low-polluting energy sources for electricity generation, EVs typically only have lower emissions well-to-wheel than similar conventional fuel vehicles. Well-to-wheel emissions refer to the emissions associated with fuel production, processing, distribution, and use. Concerning CVs, emissions are produced during extraction, refining, distribution, and burning of fuels in vehicles (i.e., both direct and well-to-wheel).

Annual emission per EV was observed to be 2,597 lb of Co_2 equivalent in Connecticut (U.S. Department of Energy 2022). This is significantly lower than the national average of 3,932 lb of Co_2 equivalent. It shows that Connecticut produces electricity or receives a supply of electricity from cleaner and more efficient power plants. On the other hand, annual emission per CV was observed to be 11,435 lb of Co_2 equivalent in Connecticut. Figure 10 and Figure 11 illustrate the national and Connecticut annual emissions per vehicle, respectively.

Using the average emission per vehicle in Connecticut values alongside the total number of projected vehicles identified in Table 22, the annual emissions for EVs and CVs under different adoption scenarios were identified. For example, under the high adoption scenario, in 2035, 722,513 EVs generated 1.88E+09 lb of Co_2 equivalent. For the same time period, 2,561,638 conventional fuel vehicles resulted in 2.93E+10 lb of Co_2 equivalent. Due to the higher per vehicle emission rate, the overall emission was significantly higher for CVs. Table 23 details the annual emission (lb of Co_2 equivalent) for EVs and CVs under different adoption scenarios in Connecticut.

Table 22. Number of EVs and CVs under different adoption scenarios in Connecticut

Year			EV Adoption Scenario					
			Low		Medium		High	
		EV+CV	EV	CV	EV	CV	EV	CV
2025	Vehicles on road	3,021,360	22,660	2,998,700	120,854	2,900,506	241,709	2,779,651
2030		3,150,017	31,500	3,118,516	157,501	2,992,516	472,502	2,677,514
2035		3,284,152	49,262	3,234,889	328,415	2,955,736	722,513	2,561,638
2040		3,423,998	68,480	3,355,518	479,360	2,944,639	1,335,359	2,088,639
2045		3,569,800	89,245	3,480,555	713,960	2,855,840	1,606,410	1,963,390
2050		3,721,810	111,654	3,610,156	1,004,889	2,716,922	1,935,341	1,786,469

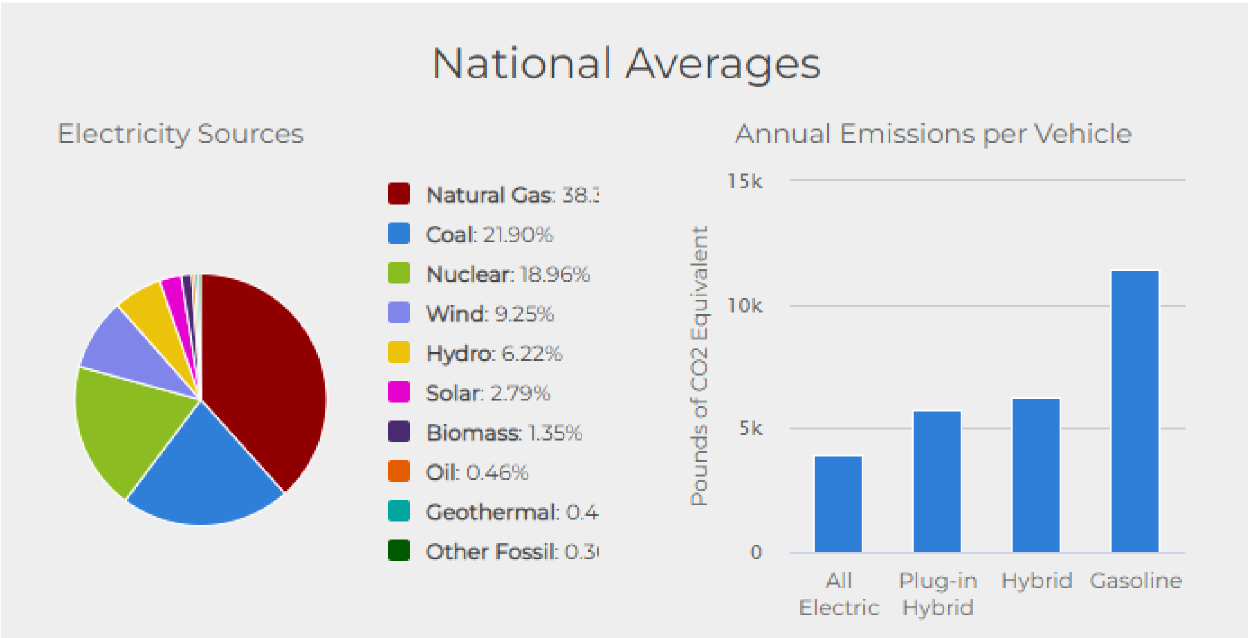


Figure 10. National annual average emissions per vehicle in the US (U.S. Department of Energy 2022)

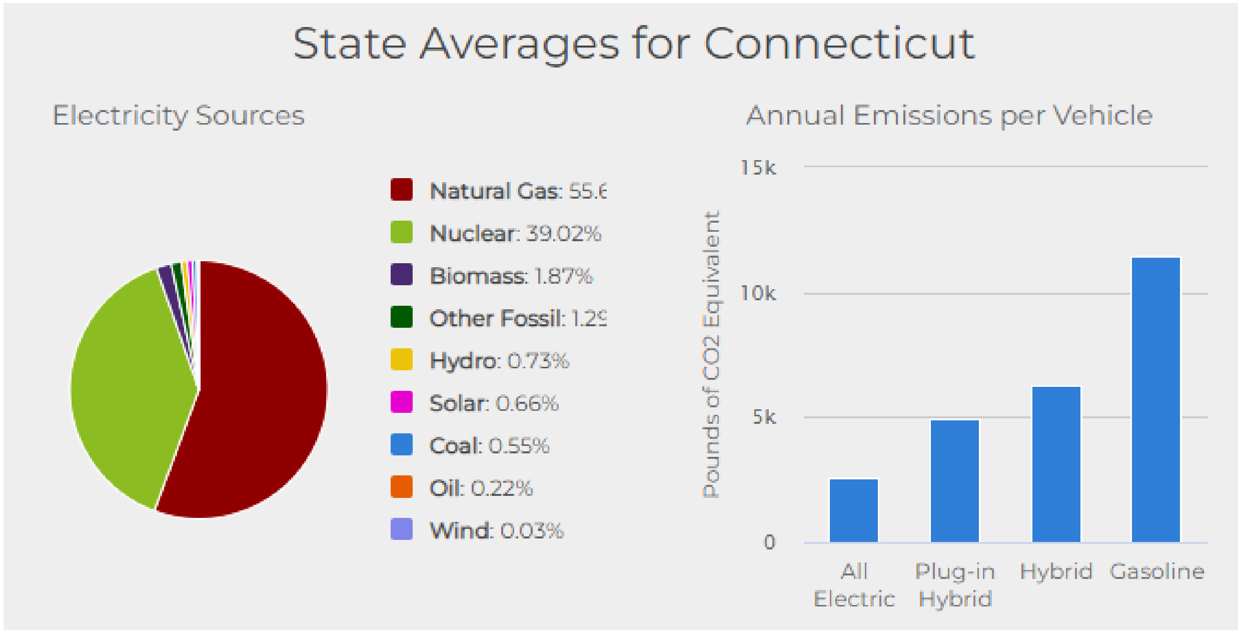


Figure 11. Annual average emissions per vehicle in Connecticut (U.S. Department of Energy 2022)

Table 23. Annual emission (lb of Co_2 equivalent) for EVs and CVs under different adoption scenarios in Connecticut

Year		EV Adoption Scenario					
		Low		Medium		High	
		EV	CV	EV	CV	EV	CV
2025	Annual emission (lb of Co_2 equivalent)	5.88E+07	3.43E+10	3.14E+08	3.32E+10	6.28E+08	3.18E+10
2030		8.18E+07	3.57E+10	4.09E+08	3.42E+10	1.23E+09	3.06E+10
2035		1.28E+08	3.70E+10	8.53E+08	3.38E+10	1.88E+09	2.93E+10
2040		1.78E+08	3.84E+10	1.24E+09	3.37E+10	3.47E+09	2.39E+10
2045		2.32E+08	3.98E+10	1.85E+09	3.27E+10	4.17E+09	2.25E+10
2050		2.90E+08	4.13E+10	2.61E+09	3.11E+10	5.03E+09	2.04E+10

In order to better quantify the impacts of EV on the environment, the emissions under two situations (i.e., EV+CV and CV only) were compared. EV+CV means electrical vehicles and conventional fuel vehicles both operating on the road based on the EV adoption scenario. CV only means only conventional fuel vehicles operating on the road. Table 24 compares the annual emission (lb of Co_2 equivalent) for EV+CV mix and CV only scenario. An index was created to assess the decrease in emissions due to the adoption of EV.

$$Emission\ Decrease = \frac{Emission(CV) - Emission(EV + CV)}{Emission\ (CV)} * 100\% \tag{9}$$

The values of the index under different potential EV adoption scenarios were calculated. Figure 12 details these results concerning emission decrease due to EV adoption.

Results show that with an increase in the total number of vehicles on the road, the adoption of EVs has a more significant impact on reducing the emission level. For example, in the low EV adoption scenario, the level of emission decrease changes from 1.55% to 2.32% from 2040 to 2050 due to switching from CV only to EV+CV mix. This is because more vehicles on the road increase the potential for more EVs, resulting in a higher emission decrease. This, coupled with higher EV adoption, has a more significant impact on the emission level. For instance, in the high EV adoption scenario, the level of emission decrease changes from 30.14% to 40.19% from 2040 to 2050. Another key observation is that under the low adoption scenario, the impacts of EVs on emission reduction are insignificant. Under the medium adoption scenario, it also does not change significantly until 2030. Then, there is a linear increase. Under the high adoption scenario, the impacts of EVs on emission reduction were observed to be significant. There is a tipping point between the years 2035 and 2040. After 2040, there is again an almost linear increase in the emission decrease level.

Key takeaways for the stakeholders from these results:

- The effects of EVs on transportation infrastructure environment performance are significant.
- The emission level of EVs is dependent on the source of electricity. Sustainable and efficient sources (e.g., natural gas, oil) should be prioritized over other sources (e.g., coal) to further reduce emissions.
- Both the gradual increase in the total number of vehicles over the years and the higher EV adoption rate have a positive impact on reducing EV emission levels.
- Transportation is a major contributor to emissions and global warming. The adoption of EVs can help reduce the projected temperature increase and help reach different climate goals, such as the Paris agreement (i.e., to limit warming to 1.5°C) (United Nations 2022).

Table 24. Annual emission (lb of Co_2 equivalent) equivalent for EV+CV mix and CV only scenarios

Year		Adoption Scenario					
		Low		Medium		High	
		EV+CV	CV	EV+CV	CV	EV+CV	CV
2025	Annual emission (lb of Co_2 equivalent)	3.43E+10	3.45E+10	3.35E+10	3.45E+10	3.24E+10	3.45E+10
2030		3.57E+10	3.60E+10	3.46E+10	3.60E+10	3.18E+10	3.60E+10
2035		3.71E+10	3.76E+10	3.47E+10	3.76E+10	3.12E+10	3.76E+10
2040		3.85E+10	3.92E+10	3.49E+10	3.92E+10	2.74E+10	3.92E+10
2045		4.00E+10	4.08E+10	3.45E+10	4.08E+10	2.66E+10	4.08E+10
2050		4.16E+10	4.26E+10	3.37E+10	4.26E+10	2.55E+10	4.26E+10

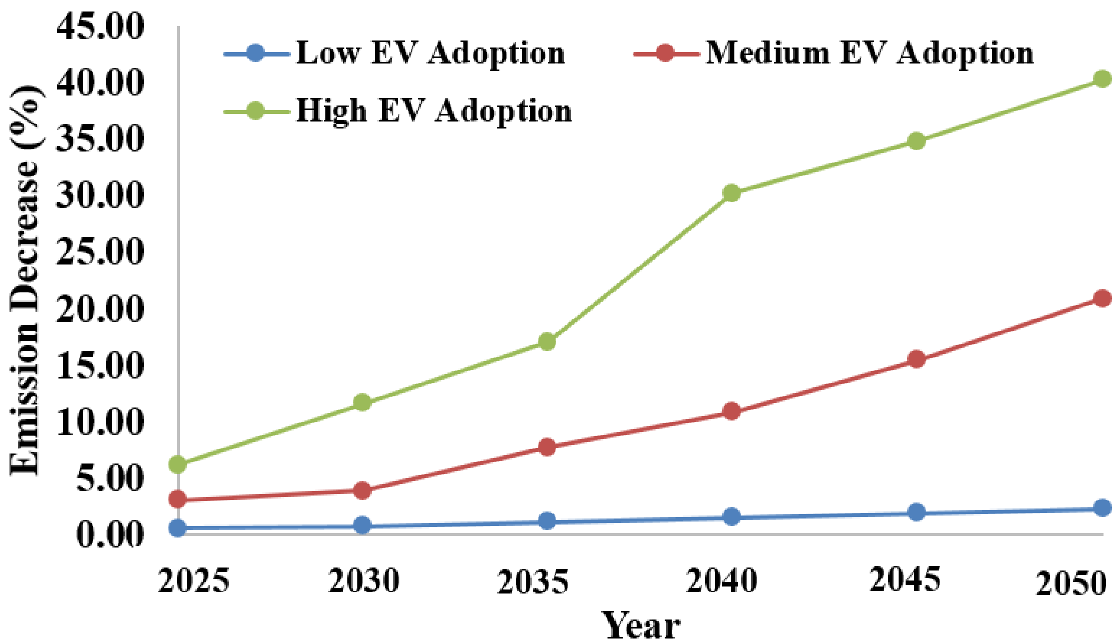


Figure 12. Emission decrease due to EV adoption

CHAPTER 6: Conclusions and Future Research Directions

This study provides a step-by-step delineation with regards to identifying a comprehensive list of critical factors for future-proofed transportation infrastructure planning and their inter-relationships in the U.S. While identifying these factors, using text mining techniques, documents from different parts of the U.S. were collected to ensure that the list of factors was comprehensive and deemed important by different transportation planning authorities across the U.S. The developed procedure to identify these critical factors and their inter-relationships is scalable and flexible. By incorporating the latest transportation infrastructure publications, the critical future-proofed factors and their inter-relationships can be updated to reflect the emerging trends. Modeling the effects of future-proofed factors and their inter-relationships further shows that there are potentially significant implications for the stakeholders to consider the developed taxonomy and the associations of its topics/concepts during the planning process.

This study essentially provides a systematic way to understand and classify future risks and opportunities that should be carefully incorporated into infrastructure planning. Stakeholders and practitioners in planning agencies such as DOTs would benefit from this study in different ways:

- First, for planners and stakeholders unfamiliar with future-proofed transportation infrastructure planning (e.g., new employees), the developed taxonomy can be used for training purposes. It could help them to better comprehend the vast array of factors that may affect future transportation infrastructure and enrich their knowledge of each dimension. Different "realities" of what might happen in the future with regards to the identified critical factors could be created to facilitate scenario planning. For example, traditionally, planners and stakeholders may mostly consider the characteristics of CVs and their effects during transportation infrastructure planning. The taxonomy developed in this study highlighted the potential infrastructure utilization and emission level change due to a shift in vehicle type, drawing stakeholders' attention to the effects of increased weights of EVs on pavement and bridges and less emission potential. Learning such changes and corresponding impacts from the taxonomy, planners and decision-makers can conduct predictive modeling and analysis with different EV market penetration scenarios and better understand the impacts. Planners and stakeholders can then evaluate budget proposals, infrastructure development plans, and design and construction alternatives under various plausible scenarios and make informed decisions based on quantitative analysis.
- Second, for planners and stakeholders who already know many of these critical factors, they can best benefit from the inter-relationships identified in this study. Since some of the critical planning factors are closely interrelated, planners and stakeholders could use the identified significant association rules to understand the possible ripple effects of their decision-making and adjust their plans accordingly to achieve optimal outcomes. The significant inter-relationships identified facilitate system thinking and could cultivate innovative solutions to certain planning challenges, bringing future-proofed transportation infrastructure planning to the next level. For example, based on the finding that there is a

close association between environmental performance and societal trends, planners and stakeholders could consider encouraging the adoption of environmentally friendly transportation alternatives (e.g., bike-share, e-scooters) through social media networks to improve environmental performance. Innovative social media strategies such as using young social media influencers to promote environmentally friendly transportation alternatives via paid campaigns could also emerge.

- Third, at the organizational level, the identified factors in the taxonomy and the inter-relationships can help transportation agencies to develop their own knowledge bases. Organizations and agencies can identify their subject matter experts (SME) or data sources with regard to different factors and develop a systematic database to foster the exchange of knowledge. Location-specific and community-specific data will be collected and stored in a customized database for individual organizations and agencies based on their traits and needs. This could facilitate a sustainable way of ensuring a future-proofed planning culture across different functional units, different projects, and different employees spanning generations in the workforce.
- Fourth, transportation agencies may have varying degrees of preparedness and response capabilities toward a highly complex and uncertain future. Based on the findings of this study, different organizations and agencies could communicate and learn from each other using the same language, fostering the creation of "future-proofed transportation infrastructure planning best practices" across agencies.

This study has a few limitations that should be addressed in future studies. These limitations and potential future research directions include:

- One limitation of the presented study is that a limited number of documents, mainly published in the U.S., were included in the text mining analysis. The taxonomy developed and presented in this study cannot guarantee to encompass all future terminology covering emerging technologies and unexpected disruptions in the transportation infrastructure domain. More data need to be collected in the future so that a more comprehensive list of factors that contribute to future-proofed transportation infrastructure planning could be identified, and more interesting inter-relationships among different factors could be discovered. A dynamic process for constant modification of the taxonomy should be developed in the future to provide opportunities for the merging of new terminologies.
- A more detailed quantitative exploration of the taxonomy and inter-relationships is needed. In this study, using EVs as an example of new technology and vehicle type, the potential effects of EVs on (1) pavement conditions and (2) environmental performance in the future were modeled in two case studies. The results showed that EVs have minimal impacts on pavement conditions but significant impacts on environmental performance. Such type of quantification, be it on a city, county, or national level, is needed to better realize the applicability of this research.

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Appendices

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Table 25. Publications considered in this study

Author(s)	Publication title
Wisconsin Department of Transportation (2009)	Connections 2030: statewide long-range transportation plan
State of Alaska Transportation & Public Facilities (2016)	Alaska statewide long-range transportation plan: let's keep moving 2036
Seattle Department of Transportation (2015)	Move seattle: 10-Year strategic vision for transportation
Portland Bureau of Planning and Sustainability (2018)	2035 comprehensive plan
Oklahoma Department of Transportation (2010)	The 2010-2035 Oklahoma long range transportation plan
New Mexico Department of Transportation (2015)	The New Mexico 2040 plan
Nevada Department of Transportation (2008)	Statewide transportation plan – moving Nevada through 2028
Michigan Department of Transportation (2016)	Moving Michigan forward: 2040 state long-range transportation plan
City of Largo (2010)	2060 Florida transportation plan
Connecticut Department of Transportation (2015)	Connecticut's bold vision for a transportation future
Washington Department of Transportation (2017)	Washington transportation plan (WTP), phase 2 – Implementation
Atlanta Regional Commission (2011)	Volume I : 2040 regional transportation plan
San Francisco Municipal Transportation Agency (2018)	San Francisco municipal transportation agency strategic plan
Maine Department of Transportation (2010)	Statewide long-range transportation plan: 2008 - 2030
Minnesota Department of Transportation (2009)	Minnesota statewide transportation policy plan: 2009-2028
Illinois Department of Transportation (2018)	Long range transportation plan
Arizona Department of Transportation (2011)	Long-range transportation plan 2010-2035
New Jersey Department of Transportation (2008)	New Jersey's Long-Range Transportation Plan: 2030
Pennsylvania Department of Transportation (2016)	Long range transportation and comprehensive freight movement plan
City of Chicago (2017)	Vision zero Chicago: Action plan
Austin Department of Transportation (2017)	Vision zero annual report
New York Metropolitan Transportation Council (2009)	A shared vision for a shared future: 2010-2035 NYMTC regional transportation plan
Auburn-Opelika Metropolitan Planning Organization (2015)	2040 long range transportation plan
Wilmapco Council (2011)	2040 regional transportation plan update

Author(s)	Publication title
City of Largo (2010)	2060 Florida transportation plan
Northwestern Indiana Regional Coordinating Council (2013)	2035 transportation plan
Northwest IOWA Planning and Development Commission (2012)	2031 long range transportation plan
Lawrence Transportation Commission (2018)	Transportation 2040: Metropolitan transportation plan
Metroplan (2005)	Metro 2030: Metropolitan transportation plan
Salisbury/Wicomico Metropolitan Planning Organization (2015)	Connect 2045: Long range transportation plan
Nelson/Nygaard Consulting Associates Inc. (2012)	Long Range Transit Plan Final Report
Atkins (2012)	North Carolina statewide transportation plan
Clark County-Springfield Transportation Coordinating Committee (2016)	2040 long range transportation plan
South Dakota Department of Transportation (2010)	South Dakota statewide long range transportation plan
Wyoming Department of Transportation (2018)	Long range transportation plan
Texas Department of Transportation (2015)	Texas transportation plan 2040
Utah Department of Transportation (2015)	2015-2040 long-range transportation plan
Cambridge Systematics (2012)	TransAction 2040: Northern Virginia transportation plan
Hawaii Department of Transportation (2014)	Statewide federal aid highways 2035 transportation plan
Georgia Department of Transportation (2006)	2005-2035 Georgia statewide transportation plan
Northwestern University Transportation Center (2016)	Mobility 2050: A vision for transportation infrastructure
Meehan and Whitfield (2017)	Integrating health and transportation in Nashville, Tennessee, USA: From policy to projects
Sinha et al. (2017)	Transportation infrastructure asset management in the new millennium: continuing issues, and emerging challenges and opportunities
Bagloee et al. (2016)	Autonomous vehicles: challenges, opportunities, and future implications for transportation policies
Asadabadi and Miller-Hooks (2017)	Assessing strategies for protecting transportation infrastructure from an uncertain climate future
Plakandaras et al. (2019)	Forecasting transportation demand for the U.S. market
Sumalee and Ho (2018)	Smarter and more connected: Future intelligent transportation system

A2

Table 26. Identified rules with confidence and lift values

Antecedent	Consequent	Confidence	Lift
Community value	Man-made disruption/risk	0.05	1.80714
	New design concept	0.0278	1.00397
	Service performance	0.0175	0.63409
	Funding source	0.0172	0.62315
	Funding allocation strategies	0.0172	0.62315
Societal trend	Environmental performance	0.068966	2.492611
	Traffic volume	0.047619	1.721088
	New process/technology	0.029412	1.063025
	Service performance	0.017544	0.634085
New travel mode	Environmental performance	0.06897	1.454023
	Service performance	0.04386	0.924708
	Funding allocation strategies	0.03448	0.727012
	Man-made disruption/risk	0.025	0.527083
	Funding source	0.01724	0.363506
	New process/technology	0.01471	0.310049
New design concept	Man-made disruption/risk	0.15	1.054167
	Community value	0.142857	1.003968
	Funding allocation strategies	0.137931	0.969349
	Funding source	0.12069	0.84818
	Environmental performance	0.103448	0.727012
	Service performance	0.096491	0.678119
New process/technology	Traffic volume	0.38095	1.417367
	Man-made disruption/risk	0.375	1.395221
	Vehicle type	0.36364	1.352941
	Societal trend	0.28571	1.063025
	Environmental performance	0.27586	1.026369

	Service performance	0.21053	0.783282
	Structural condition assessment	0.13636	0.507353
	Natural disruption/risk	0.13043	0.485294
	New travel mode	0.08333	0.310049
	Funding allocation strategies	0.01724	0.064148
Funding allocation strategies	Service performance	0.22807	0.994858
	New design concept	0.222222	0.969349
	Man-made disruption/risk	0.175	0.763362
	Environmental performance	0.172414	0.752081
	New travel mode	0.166667	0.727011
	Community value	0.142857	0.623153
	Structural condition assessment	0.136364	0.594828
	Traffic volume	0.095238	0.415435
	Natural disruption/risk	0.086957	0.37931
	New process/technology	0.014706	0.064148
Funding source	Service performance	0.22807	0.994858
	Structural condition assessment	0.22727	0.991379
	New design concept	0.19444	0.84818
	Environmental performance	0.17241	0.752081
	Man-made disruption/risk	0.15	0.65431
	Community value	0.14286	0.623153
	Natural disruption/risk	0.13043	0.568966
	Traffic volume	0.09524	0.415435
	New travel mode	0.08333	0.363506
Structural condition assessment	Traffic volume	0.272727	3.136364
	Vehicle type	0.142857	1.642857
	Natural disruption/risk	0.086957	1.0
	Funding source	0.086207	0.991379
	Funding allocation strategies	0.051724	0.594828
	New process/technology	0.044118	0.507353
	Man-made disruption/risk	0.025	0.2875

Service performance	Funding source	0.44828	0.994858
	Funding allocation strategies	0.44828	0.994858
	Natural disruption/risk	0.43478	0.964912
	New travel mode	0.41667	0.924708
	New process/technology	0.35294	0.783282
	New design concept	0.30556	0.678119
	Community value	0.28571	0.634085
	Societal trend	0.28571	0.634085
	Traffic volume	0.19048	0.422723
	Man-made disruption/risk	0.025	0.055482
Environmental performance	Societal trend	0.285714	2.492611
	New travel mode	0.166667	1.454023
	Natural disruption/risk	0.130435	1.137931
	New process/technology	0.117647	1.026369
	Funding source	0.086207	0.752081
	Funding allocation strategies	0.086207	0.752081
	New design concept	0.083333	0.727012
	Traffic volume	0.047619	0.415435
Traffic volume	Societal trend	0.14286	1.721088
	Structural condition assessment	0.13636	3.136364
	New process/technology	0.11765	1.417367
	Service performance	0.03509	0.422724
	Environmental performance	0.03448	0.415435
	Funding source	0.03448	0.415435
	Funding allocation strategies	0.03448	0.415435
	Man-made disruption/risk	0.025	0.301191
Vehicle type	Structural condition assessment	0.136364	1.642857
	New process/technology	0.058824	1.352941
	Man-made disruption/risk	0.025	0.575
Man-made disruption/risk	Community value	0.28571	1.807143
	New process/technology	0.22059	1.395221

	New design concept	0.16667	1.054167
	Funding allocation strategies	0.12069	0.763362
	Funding source	0.10345	0.65431
	Vehicle type	0.09091	0.575
	New travel mode	0.08333	0.527083
	Traffic volume	0.04762	0.30119
	Structural condition assessment	0.04545	0.2875
	Service performance	0.00877	0.055482
Natural disruption/risk	Environmental performance	0.103448	1.137931
	Structural condition assessment	0.090909	1.0
	Service performance	0.087719	0.964912
	Funding source	0.051724	0.568966
	New process/technology	0.044118	0.485294
	Funding allocation strategies	0.034483	0.37931

A3

Python code for LDA Latent Dirichlet Allocation (LDA) and Non-negative Matrix Factorization (NMF)

```
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.datasets import fetch_20newsgroups
from sklearn.decomposition import NMF, LatentDirichletAllocation
import numpy as np
def display_topics(H, W, feature_names, documents, no_top_words, no_top_documents):
    for topic_idx, topic in enumerate(H):
        print "Topic %d:" % (topic_idx)
        print " ".join([feature_names[i]
                        for i in topic.argsort()[:-no_top_words - 1:-1]])
        top_doc_indices = np.argsort( W[:,topic_idx] )[::-1][0:no_top_documents]
        for doc_index in top_doc_indices:
            print documents[doc_index]
documents = []
with open('sss.txt', 'r') as f:
    documents  = [line.strip() for line in f]
no_features = 1000
tfidf_vectorizer = TfidfVectorizer(max_df=0.95, min_df=2, max_features=no_features, stop_words='english')
tfidf = tfidf_vectorizer.fit_transform(documents)
tfidf_feature_names = tfidf_vectorizer.get_feature_names()
tf_vectorizer = CountVectorizer(max_df=0.95, min_df=2, max_features=no_features, stop_words='english')
tf = tf_vectorizer.fit_transform(documents)
tf_feature_names = tf_vectorizer.get_feature_names()
no_topics = 5
# Run NMF
nmf = NMF(n_components=no_topics, random_state=1, alpha=.1, l1_ratio=.5, init='nndsvd').fit(tfidf)
nmf_W = nmf.transform(tfidf)
nmf_H = nmf.components_
lda = LatentDirichletAllocation(n_topics=no_topics, max_iter=5, learning_method='online', learning_offset=50.,random_state=0).fit(tf)
lda_W = lda.transform(tf)
lda_H = lda.components_
no_top_words = 5
no_top_documents = 8
print("nmf Model:")
display_topics(nmf_H, nmf_W, tfidf_feature_names, documents, no_top_words, no_top_documents)
def print_topics(model, vectorizer, top_n=15):
    for idx, topic in enumerate(model.components_):
        print("Topic %d:" % (idx))
        print([(vectorizer.get_feature_names()[i], topic[i])
```

```
                    for i in topic.argsort()[:-top_n - 1:-1]])
print_topics(nmf, tfidf_vectorizer)
print("=" * 20)
print("LDA Model:")
display_topics(lda_H, lda_W, tf_feature_names, documents, no_top_words, no_top_documents)
print_topics(lda, tf_vectorizer)
print("=" * 20)
```

A4

R code for Association Rule Mining

```
library(arules)
library(arulesViz)
library(RColorBrewer)
mydata<-read.csv("~/R/new_data.csv",header=T,colClasses = "factor")
rules<-apriori(mydata)
#sample rule with Man-made disruption/risk
rules <- apriori(mydata,parameter = list(minlen=2, maxlen=2,supp=0, conf=0.001),
 appearance=list(rhs=c("Man.made.disruption.risk=yes"), lhs=c("Natural.disruption.risk=yes",
"Total.number.of.vehicles=yes","Vehicle.Type=yes",  "Service.performance=yes",
"Funding.allocation.strategies=yes", "New.travel.mode=yes", "New.design.concept=yes",
"Environmental.performance=yes", "Community.value=yes", "Societal.trend=yes",
"New.technolgy=yes", "Funding.source=yes", "Structural.condition.assessment=yes")))
inspect(rules)
plot(rules)
plot(allrules, method = "grouped matrix", measure = "confidence", shading = "lift")
subrules2 <- head(allrules,  size = "confidence",by = "lift")
plot(subrules2)
plot(allrules, method = "matrix")
plot(allrules,method='grouped')
plot(rules,method='graph',control=list(type="items", cex=2.02),measure = "lift", shading =
"confidence",  nodeCol = brewer.pal(n=4, "Greens"),    edgeCol = brewer.pal(5, "BuPu"), alpha
= 1)
```

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