FLORIDA STATE UNIVERSITY

Florida Index for Transportation: A System of Systems Approach to Understanding the Changing Nature of Transportation

Final Report

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16. Abstract
This study aimed to (i) identify and track external factors that are associated with all modes of transportation (i.e., auto, truck, transit, bicycle and pedestrian, aviation, rail, and seaport), (ii) understand the evolutionary and emergent nature of the Florida transportation system, and (iii) facilitate informed policy and decision making in transportation planning. External factors are those that affect transportation system performance but are outside of the control of transportation agencies. FDOT needs to track and evaluate a broad range of external factors in order to prepare for rapid changes in the transportation environment and take timely and proper actions. This study developed a novel system-of-systems (SoS) approach to identify and track external factors associated with all transportation modes and understand the changing behavior of the Florida transportation system. In this regard, a composite index framework (i.e., Florida Index for Transportation [FIT]) is developed as a means to streamline abundant information derived from a large number of external factors and interpret the results for data-driven decision making. This study demonstrated two aspects of the proposed approach: (i) the implementation of FIT for transportation planning and (ii) the understanding of the changing nature of the Florida transportation system. The first capability of FIT was demonstrated through two virtual meetings with FDOT planners; as a result, two planning scenarios were developed to guide the use of FIT. Through statistical analysis, this study also confirmed that FIT enables planners to understand the impact of disruptive events on different transportation modes through investigation of their relevant external factors.

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EXECUTIVE SUMMARY

Transportation systems do not remain static but rather are dynamic over time due in part to the influences of external factors. These factors are those that affect transportation system performance but are outside of the control of transportation agencies. To prepare for such changes in the transportation environment, FDOT should be able to track and evaluate a broad range of external factors and integrate any derived insights into the broader transportation planning process. The FSU team proposed a novel system-of-systems (SoS) approach to identify and track external factors associated with all transportation modes, understand the evolutionary and emergent nature of the Florida transportation system, and develop data-driven decision making in transportation planning.

To provide a comprehensive understanding of the proposed SoS approach, this report consists of three chapters:

Chapter II. Identification of External Factors and Transportation Performance Measures

As the first step toward understanding the changing nature of transportation, the FSU team performed a literature review to (i) identify possible external factors affecting all travel modes of the Florida transportation system along with their relevant performance measures and (ii) understand the use of these factors in state, regional, and local transportation planning. The literature suggests that while there are quite a few studies on evaluating external factors on a single transportation mode's performance, almost no relevant studies exist on the evaluation of external factors on a multimodal transportation system. In most existing studies, only a few transportation performance factors are included, such as a highway travel time index, planning time index, and congested hours. To fully capture the performance of individual transportation modes, additional well-designed performance measures should be added for each mode, if a multimodal system is considered.

In addition, an extensive review of state, regional, and local transportation plans and planning documents was conducted to understand how transportation planning agencies evaluate external factors' effects on the transportation system. This review uncovered that most DOTs do not evaluate the impact of external factors on the performance of the transportation system for planning purposes. The only exception to this is travel demand. All state DOTs monitor several measures of travel demand, but less attention is given to the external factors shaping people's transportation choices. Similarly, due to the novelty of many emerging modes of transportation and the proprietary nature of private company's data, DOTs are struggling with systematically incorporating emerging modes into their performance measurements.

Furthermore, an online survey and phone interviews with transportation experts were also conducted to (i) augment the understanding of the external factors and (ii) identify additional external factors that were not captured during the literature review. The interactions with the experts enabled the identification of several external factors that have been considered by current practices for planning. For example, the top three identified factors in the population, environmental, economic, and technology categories are reported as below.

Population

- Suburbanization
- Population Growth
- Traffic Safety

Economic

- Viability of Revenue Streams
- Economic Growth
- Freight Transport

Environment

- Climate Change
- Weather-related inland flooding
- Coastal Flooding/Storm Surge

Technology

- Autonomous Vehicles
- Shared Vehicles
- Electric Vehicles

Chapter III. A System-of-Systems Framework to Understand the Changing Nature of Florida Transportation Systems

In this chapter, an SoS framework was developed to address the following two challenges. The first challenge was the lack of useful tools to track and interpret the changing behavior of transportation systems. Meanwhile, transportation consists of multiple heterogeneous distributed systems that are involved in networks across many levels. Such characteristics qualify transportation as an SoS. According to the SoS theory, changes in transportation result from evolutionary and emergent processes occurring at lower levels and become observable only at the upper levels of the hierarchical system, which necessitates a holistic approach. The second challenge is the overwhelming amount of information that needs to be analyzed to track relevant external factors for state- or higher-level decision making in transportation planning.

The SoS framework was developed in three phases: definition, abstraction, and implementation. In the definition phase, the systems' characteristics, attributes, drivers, disruptors, and stakeholders are identified at three different levels: the transportation mode level (α level), the Florida transportation system level (ground transportation, air transportation, and sea transportation; β level), and the national transportation system (γ level). In the abstraction phase, the scope of the SoS was further delineated to fit the goals of the study without losing any critical information. The overall resource network of the SoS is presented as a hierarchical structure with primary entities at multiple levels. In the implementation phase, the FSU team developed a composite index (i.e., FIT) to streamline the abundant amount of information derived from multiple external factors and detect the appearances of changing properties at the lower of the transportation SoS from the perspective of the higher levels. FIT comprises the influential external factors for each transportation mode at its base level along with their aggregations. Lastly, this chapter also provides some applications of FIT to illustrate how it can serve transportation planners and aid them in interpreting the changing nature of the transportation system.

Chapter IV. Demonstration of FIT Application

In this chapter, the FIT application in (i) improving FDOT's planning process and (ii) facilitating the understanding of the changing nature of the Florida transportation system was demonstrated.

With regard to improving FDOT's planning process, the FSU team organized two demonstration sessions with FDOT planners and decision makers. During the meetings, the FSU team introduced the FIT and its application for decision making purposes. Moreover, the FSU team addressed the FDOT decision makers' questions regarding the FIT development process and acquired their feedback to validate the overall FIT approach. During the second meeting, the FSU team received the FDOT planners' inputs regarding the usability of the FIT for transportation planning. Considering the FDOT planners' input, two sample scenarios were designed to demonstrate the FIT application for decision making purposes. Using the sample scenarios, it was shown that FIT can facilitate mode level and cross-modal decision making problems.

To demonstrate the FIT application in facilitating the understanding of the changing nature of the Florida transportation system, the FSU team investigated the changes in the composition of influential external factors and in FIT dimensions (i.e., underlying dimensions of the external factors). In this regard, the FIT was developed in four different time frames. In the next step, changes in the influential external factors and FIT dimensions for each transportation mode across different time frames were investigated. The followings are the major conclusions from this analysis:

1) Economic factors, housing factors, and employment factors are the most frequent new external factors emerging in different transportation modes.
2) Most of the new external factors arise within the 2009–2016 and 2010–2017 time frames, indicating a significant impact of the 2007–2009 market crisis on transportation performance measures.
3) FIT dimension level was found to be more stable than FIT external factors level. In other words, less variation was observed in mode dimensions compared to the composition of influential external factors.

Many federal and state agencies have acknowledged the importance of external factors and tried to integrate them into the planning process. However, because transportation planning is complex and multifaceted by nature, decision makers often must handle an overwhelming amount of information or sets of external factors in policy and decision making. In this regard, FIT can advance the current planning practices and enable FDOT planners to better understand external factors and make data-driven and -informed plans. While the FIT approach is compatible with the current practices of measuring mode performances, the team also faced challenges during the development of FIT. First, some transportation modes (e.g., seaport) have only a few performance measures. Increasing the number and types of performance measures helps to identify more diverse influential external factors and thus to improve the FIT results. Also, existing performance measures data are only available on an annual basis while the majority of the measures were available after 2008. As a result, a limited number of data points is available for statistical analyses, which may affect the reliability of some statistical analyses (e.g., Granger causality analysis). As more data become available with time, FIT will better support decision making.

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CHAPTER I: INTRODUCTION

The transportation system consists of multiple heterogeneous distributed systems that are involved in networks across many levels. The Florida transportation system, in particular, is composed of heterogeneous subsystems ranging from ground transportation (e.g., auto, truck, transit, bicycle and pedestrian, and rail) to water transportation (e.g., seaport) and air transportation (e.g., aviation). Each transportation system is distributed across various parts of the state and is operated and managed independently of the others even though they often communicate to improve the efficiency of the overarching transportation system. However, understanding and evaluating the dynamics of transportation is often difficult due to the substantial number of independent systems and their heterogeneity, the distributed but communicative nature of these systems, and the presence of uncertainty concerning their coevolution. According to Maier (1998), such challenging features qualify transportation as a system of systems (SoS)—a collection of subsystems that evolve over time and that are independently managed and operated at multiple levels (Figure 1).

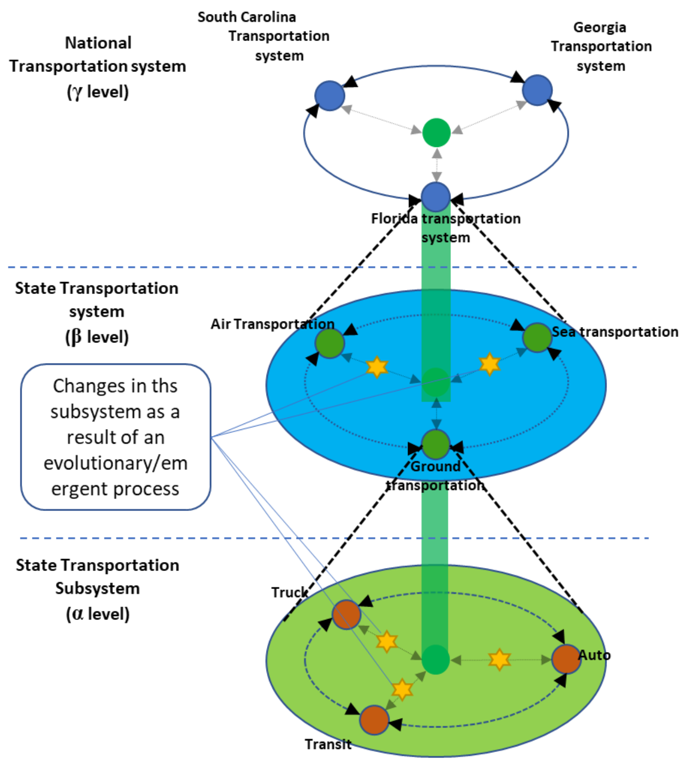


Figure 1: Florida transportation system of systems

Influenced by external factors, a transportation SoS does not remain static but instead is dynamic over time. In other words, in response to the changing transportation environment, the transportation SoS's constituent systems change the structure of the SoS over time (i.e., through the evolutionary process) or affect the interplay between and within subsystems, thus causing emergent behaviors that impact the entire system (i.e., through the emergent process). For instance, due to the increase in the aging population (i.e., a demographic change [external factor]), FDOT (2015) has been investigating new mobility solutions, such as shared autonomous vehicles. These new technologies are expected to enhance the safety of Florida transportation as well as the mobility of the aging population (Duncan et al. 2015). The adoption of new technology will subsequently require new infrastructure and gradually change the way the transportation SoS operates (i.e., through the evolutionary process). On the other hand, increased interactions between vehicles, infrastructure, and cyber systems may make the transportation SoS more vulnerable to cyberattacks (i.e., through the emergent process), thereby incurring unintended consequences. While this phenomenon would occur at the lowest level (i.e., the α level in Figure 1), it would become observable only at the upper levels of the SoS hierarchy (i.e., the β level or γ level in Figure 1) through the comparison of expected behaviors at the upper levels to the system's performance as a result of interactions at the lowest level. This necessitates a holistic understanding of the system to better comprehend its changing nature.

After the transportation SoS has undergone changes, associations with its external factors may change as well. In some cases, the performance of the transportation system becomes insensitive to otherwise influential external factors. Meanwhile, these changes may enhance the SoS's correlations with previously insignificant external factors. For example, the predominance of autonomous vehicle technology may contribute to offering aging and transportation-disadvantaged populations equal access to enhanced mobility. Consequently, automation in transportation may minimize the effects of demographic factors as a result of the transportation SoS's evolution. However, the SoS's increased vulnerability to cyberattacks may result in more security-related external factors (e.g., information shared under the U.S. Department of Homeland Security's Automated Indicator Sharing program about malicious internet protocol addresses or known senders of phishing emails) being taken into consideration. As such, tracking external factors enhances our understanding of the changing nature of transportation, but this process still requires a holistic approach to the transportation SoS so as to track the evolutionary and emergent behaviors of the system and better inform the planning process.

Considering the hierarchical nature of transportation planning, state- and national-level planning efforts require handling a large number of external factors, which often makes it hard to interpret the implications of their trends. While regional planning agencies devise plans with a focus on system entities (e.g., road pavement and traffic signals) at the bottom level, state- or federal-level agencies make plans and decisions at higher levels (e.g., highway systems and railway systems). While low-level decision makers align their choices to the policies issued at higher levels, higher-level decision makers use the cumulative information from the lower levels of the hierarchy to make informed decisions while juggling the uncertainty caused by external factors. This results in an overwhelming amount of information that needs to be regularly collected and analyzed by higher-level decision makers. As the level of decision making increases toward the national level (i.e., the higher levels), the number of external factors to be considered for planning purposes also increases. Without proper methods to streamline the abundant amount of information that comes from multiple external factors, it is hard for transportation decision- and policymakers to effectively interpret the results of any analysis of external factors.

Meanwhile, SoS approaches have been proposed to understand emergent and evolutionary properties in complex system problems. Previously, the SoS approach has been used to study several infrastructure system problems, including wastewater maintenance (Altarabsheh et al. 2019), construction bidding (Awwad et al. 2015), disaster management (Fan and Mostafavi 2018), and the impact of climate change on civil infrastructure (Mostafavi 2018), to name but a few. In this project, an SoS school of thought will be employed to understand the changing nature of the Florida transportation system. Meanwhile, researchers have used data analytics to inform decision making in transportation planning due to its ability to recognize the trends and patterns of system dynamics. In this project, a composite index framework is developed as a means to detect the appearances of evolutionary and emergent properties at lower levels of the transportation SoS hierarchy from its higher levels. This framework forms a hierarchy of influential external factors to effectively streamline and integrate abundant information from the system's lower levels into higher-level information, thus enabling decision makers to cope with the challenges concerning the volume of external factors data (Stigliz et al. 2012). Moreover, the idea of the composite index is also aligned with an SoS framework to study the evolutionary and emergent behavior of the SoS.

Project Objective(s)

The main objectives of this project are to (i) identify and track external factors that are associated with all modes of transportation (i.e., auto, truck, transit, bicycle and pedestrian, aviation, rail, and seaport), (ii) understand the evolutionary and emergent nature of the Florida transportation system, and (iii) facilitate informed policy- and decision making in transportation planning. To achieve these objectives, this project performed five major tasks:

- Task 1: Literature Review
- Task 2: Selection of External Factors
- Task 3: Statistical Analysis
- Task 4: Development of a System of Systems Framework and a Composite Index
- Task 5: Demonstration of the Composite Index

Throughout these tasks, this project developed a novel SoS approach to identify diverse external factors that influence the Florida transportation system, understand its changing nature, and inform policy- and decision making in transportation. To be more specific, this project reviewed a collection of select articles across the social science (e.g., urban planning, economy, and geography) and engineering disciplines (e.g., transportation engineering, construction engineering, and systems engineering) to identify possible external factors along with their significance. Furthermore, an online survey and phone interview were conducted with transportation experts from different sectors (e.g., industry, education, and government) to augment the team's understanding of these factors and discuss their significance on the performance of the Florida transportation system. The possible external factors were statistically analyzed to identify the ones that are statistically correlated with the performance of each travel mode. An SoS approach was applied to understand planning issues concerning the external factors, thus addressing the overwhelming level of complexity on the subject and gaining insights into the changing nature of the Florida transportation system. As the product of this project, the team developed a composite index (i.e., FIT) as a new medium to facilitate communication between and within the Florida transportation SoS by aggregating relevant external factors. Lastly, the team organized two interactive virtual meetings with FDOT planners to demonstrate the implementation and usability of FIT and illustrated FIT analysis to investigate a past possible disruptive event for validation of its approach.

CHAPTER II: IDENTIFICATION OF EXTERNAL FACTORS AND TRANSPORTATION PERFORMANCE MEASURES

Identifying and monitoring possible external factors help planning agencies understand their impact on the transportation system's behavior. An extensive review of academic literature and planning documents were conducted to identify a broad range of external factors impacting transportation systems' performance. In particular, state DOTs' planning documents were reviewed to understand how transportation agencies measure the impact of external factors on transportation systems' performance. Furthermore, an expert survey was conducted to discover those external factors that were not captured during the literature review and to augment our understanding of how transportation planners consider external factors for their planning and decision making purposes.

2.1 Effect of external factors on transportation

External factors are defined as those factors that influence transportation system performance, and they fall outside the control of transportation agencies. Examples of external factors are fuel prices, economic activities, the employment rate, and environmental regulations. This section presents a comprehensive survey of external factors that are considered in existing scholarly studies and practice. This section presents the literature review results regarding the external factors to a single transportation mode and multiple transportation modes.

2.1.1 External factors to a single transportation mode

Wardman (2006) developed an enhanced demand forecasting model for rail travel in Great Britain using rail ticket sales data and travel survey data. A few factors influencing rail travel demand were considered, namely, Gross Domestic Product (GDP), car travel time, fuel cost, population, car ownership, and the time trend (or time index, which is an ordered set of natural numbers used in the rail travel demand forecasting model) in the post-privatization periods. Among all such external factors, GDP was found to be the dominant factor driving rail demand. The developed model was shown to be able to successfully explain the variation in rail demand growth in Great Britain since 1998.

Taylor and Fink (2013) presented an in-depth review of the transit ridership literature, focusing on what factors, both external and internal, influence transit ridership. Three groups of external factors are considered namely socio-economic (such as income and auto ownership), spatial (such as urban form and land use), and financial (such as availability of transit subsidies). Internal factors are related to pricing, service quantity, and service quality. This review is descriptive in nature, with no quantitative analyses presented.
In one related study by Taylor et al. (2009), a quantitative analysis of transit use in 25 U.S. urbanized areas based on data from the National Transit Database (NTD) was presented, considering dozens of possible factors. There were in total five categories, each of which contains multiple factors, as shown in Figure 2. Taylor et al. (2009) built a regression model and identified the most influential factors in each category. For example, among population characteristics, they found the percent of college students, recent immigrants, and Democratic voters were major drivers of transit demand. Although most influential factors were considered external, the authors concluded that transit policies about fare and service frequency also made a major difference by explaining 25% of the observed variance in per capita transit use.

Chen et al. (2011) empirically examined the effects of various factors (particularly, gasoline prices, transit fares, and service level) on transit ridership with commuter rail trip data in New York City. In addition to considering the effect of various factors on transit ridership, they also studied the reaction in transit demand (such as lags and leads) to changes in other factors. A time-series model, the ARFIMA (auto-regressive fractionally integrated moving average) model, was employed to quantify the relative impacts of various factors on transit ridership and examine the demand lags/leads. Results showed that the effect of gas price was most significant, leading to the policy suggestion that increasing gas prices over decreasing transit prices could encourage transit ridership. They also showed that transit demand was influenced by transit supply with a lag of zero to four months.

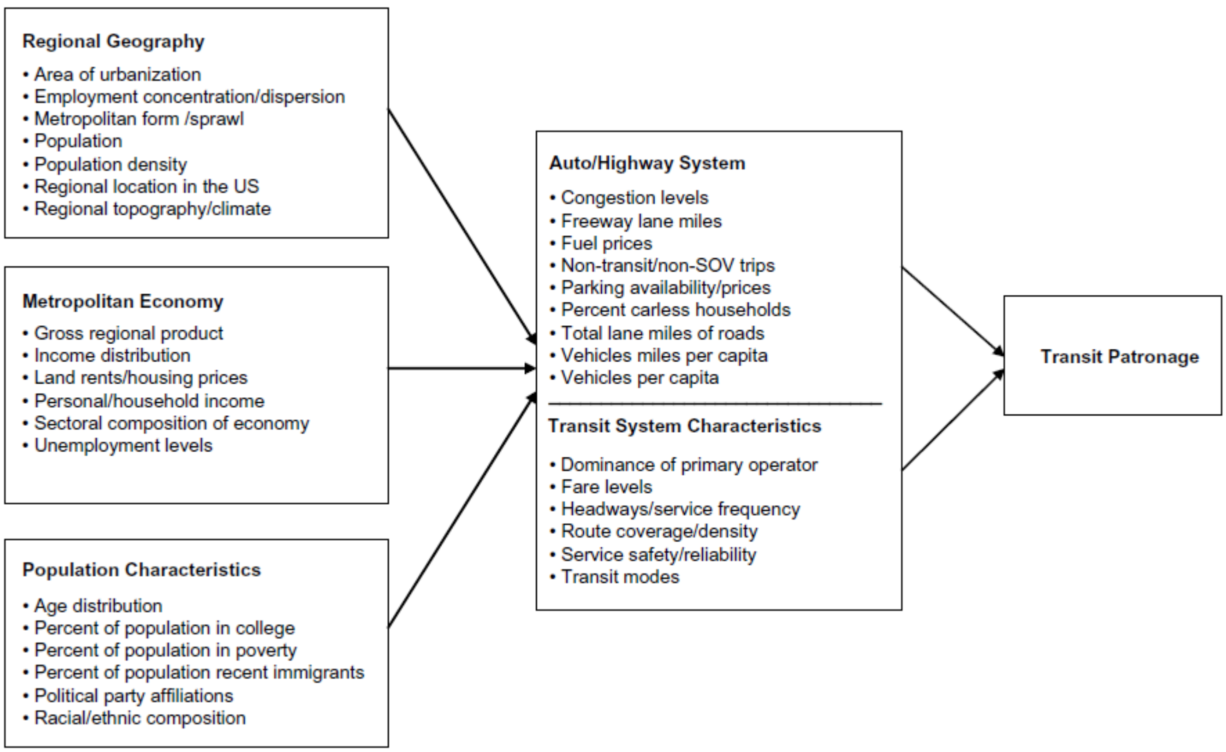


Figure 2: Possible factors influencing aggregate transit demand used in Taylor et al. (2009)

The TCRP Research Report 201 (Coogan et al. 2018) discussed how changes in demographics, attitudes, and transit levels of service (travel times and costs) might affect transit demand based on the assumption that an individual's demographics affect a person's long-term values, attitudes, and neighborhood choice, each of which affects the likelihood of choosing public transit. They found that demographic factors were critical to the prediction of future transit demand.

By contrast, there are not as many studies focusing on the effect of various factors (especially external ones) on highways as studies focusing on transit. Morris et al. (2011) considered the effects of a few factors, including precipitation and lighting conditions, on highway capacity. Wang and Zhang (2017) used a logistic regression model to study the impacts of roadway and environmental factors on traffic crash severity. A few influential factors were identified, such as road alignment, lighting condition, and road surface condition. The NCHRP Report 541 by Amekudzi and Meyer (2005) presented a series of procedures and methods for incorporating environmental factors (such as air quality) into transportation systems planning and decision making at the state and metropolitan levels.

The most relevant study on the evaluation of external factors on highway performance measures is an FHWA report by Dadashova et al. (2018). This report's objective was to identify key external factors that can impact highway performance and develop methods for including such factors in transportation performance reporting. Table 1 shows all the external factors used in Dadashova et al. (2018), which were grouped into four categories, namely Travel Demand, Economic, Employment and Price Indicators, Population and Housing Indicators, and Weather Conditions. Three performance measures, primarily for highways, were considered, namely a travel time index, a planning time index, and a count of roadway congested hours. Through statistical analyses, those highly correlated external factors with highway performance measures were identified. The second half of this FHWA report discussed how such external factors could be displayed with an emphasis on data visualizations.

The analyses presented in Dadashova et al. (2018) were at the aggregate national level, while certain data for some regions were not available. For example, the Bureau of Labor Statistics, U.S. Department of Labor (BLS) publishes Consumer Price Index (CPI) information for only 26 metropolitan areas. For other regions with no CPI information available, data for neighboring and closest regions were substituted. For example, the CPI data for the Columbus MSA (metropolitan statistical areas) in Ohio were not available; the Cincinnati MSA data were used. This national analysis suggests that the impacts of external factors on transportation systems performance in different regions could be "averaged" over space. Another issue with this report is that only highway performance was analyzed, with other transportation modes to be added.

There are very few studies available on evaluating external factors for other modes, especially in the academic literature. In air transportation, Cederholm (2014) qualitatively discussed how six groups of external factors impact the airline industry, namely, political, economic, social, technological, environmental, and legal; Distenfeld (2019) analyzed possible external factors on airline profits, including wage inflation, union strikes, labor shortage, fluctuating oil prices, competition, and consolidation. Such studies did not usually involve quantitative analyses and focused on one or two performance measures, such as safety and profitability. For other modes, especially those emerging ones, no studies in the literature have been found on the effect of external factors on such modes.

Table 1: Possible external factors considered in Dadashova et al. (2018)

External Factor Category	External Factor	Data Source	Reporting Frequency
Travel Demand	Average Daily Traffic Volumes	Federal Highway Administration Travel Monitoring Analysis System (TMAS)	Monthly
Economic, Employment, and Price Indicators	Gross Domestic Product (GDP) - All Industries	Bureau of Economic Analysis, U.S. Department of Commerce	Quarterly for States, annual for metropolitan statistical areas (MSAs)
	GDP - Construction		
	GDP - Manufacturing		
	GDP - Real Estate		
	GDP - Retail Trade		
	GDP - Transportation		
	Per Capita Income		
	Personal Income (PI)		
	Economic Conditions Index	Federal Reserve Bank	Monthly
	House Price Index	Federal Housing Finance Agency	Monthly
	Consumer Price Index (CPI)	Bureau of Labor Statistics, U.S. Department of Labor	Monthly, Semi-annual, Annual
	CPI - Rent Price Index		
	CPI - Fuel Price Index		
	Number of Employed	Bureau of Labor Statistics, U.S. Department of Labor	Monthly
	Number of Unemployed		
	Percentage of Unemployed		
Population and Housing Indicators	Population Estimate	U.S. Census Bureau	Annual
	Population Change		
	Natural Increase - Births		
	International Migration		
	Domestic Migration		
	Net Migration		
	Rental Vacancy Rate	U.S. Census Bureau	Quarterly
	Homeowner Vacancy Rate		
	Homeownership Rate		
	Total Building Permits	U.S. Census Bureau	Monthly
	Single Family (SF) Permits		
	Number of Structures		
Weather Conditions	Total Monthly Precipitation	National Oceanic and Atmospheric Administration	Monthly
	Total Monthly Snowfall		
	Average Monthly Temperature		

2.1.2 External factors to multiple transportation modes

There are very few relevant studies that have analyzed the effect of external factors on the performance of a multi-modal transportation system. Gransberg et al. (2013) presented an analysis of 18 complex transportation projects considering the impact of environmental legislation, public opinion, political influence, and source of construction funding on transportation projects. Porter et al. (2013) wrote a report on the effect of the built environment on transportation with an emphasis on transportation-related energy use and emissions. A dozen modeling tools and analysis methods were reviewed, which included the traditional "Four-Step" Model, a transportation land-use model, structural equations modeling, etc. Although there are many other factors that can be used to characterize the built environment, the most important factors that were identified from the literature and then used in the report Porter et al. (2013) were: density (population or number of jobs per square mile), diversity (the mix of different land uses), design (how friendly the local environment is to active transportation modes), and destination accessibility (ease of access to destinations). In particular, they found neighborhoods with higher densities, mixed land uses, and good walking environments contribute to lower vehicle travel and energy use. It was suggested that the federal government could influence local built environment through funding incentives and voluntary initiatives to reduce transportation-related energy use.

2.2 Transportation performance measures

To evaluate the effect of external factors on transportation systems performance as shown in Figure 3, a list of all transportation mode-specific performance measures should be compiled after identifying all possible external factors. In this section, the transportation performance metrics are explored in three groups: (i) FDOT performance metrics, (ii) state DOT performance metrics, and (iii) Metropolitan Planning Organizations (MPO) performance metrics.

2.2.1 FDOT performance metrics

The Florida Department of Transportation Forecasting and Trends Office publishes *The FDOT Source Book*, which contains all mobility measures in different categories (quantity, quality, accessibility, and utilization) for each mode that are considered by FDOT. Figure 4 shows the performance measures adopted for each mode, passenger and freight, in the 2018 edition of The FDOT Source Book. In this edition, some performance measures were removed, such as active rail access, time spent commuting, air demand to capacity ratio; other measures were added to reflect the latest transportation trends, such as transportation network company (TNC) employment and fuel consumption. It can be seen from Figure 4 that the number of performance measures varies across modes. More than 15 performance measures are used for highways, while for aviation, rail, and seaport, very few performance measures are used.

There is a trade-off between the number of performance measures and the complexity of data collection and analysis. When enough performance measures for a mode are identified, the performance of that mode is evaluated fully. Nonetheless, this inevitably complicates the data collection and analysis process. When the number of the performance measures is very small, it might be possible that some modal performance characteristics are not captured well. In the FHWA report (Dadashova et al. 2018), only three performance measures were included in the analysis. Therefore, this trade-off should be considered when determining the list of transportation performance measures for use with the external factors.

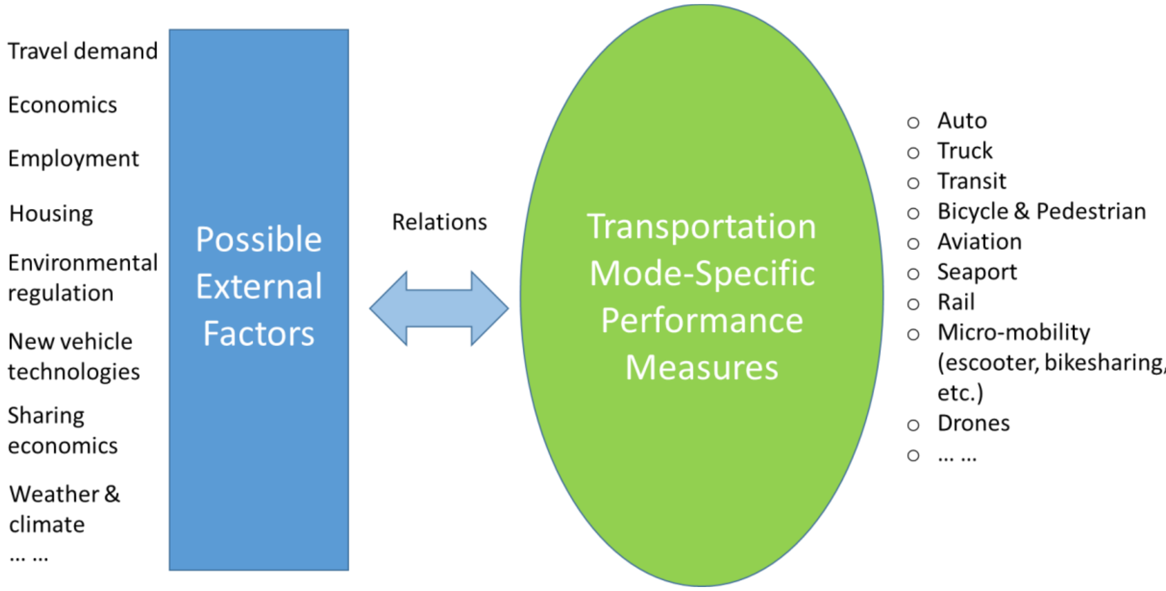


Figure 3: Relations between possible external factors and modal performance measures

MOBILITY MEASURES MATRIX

	MODE	QUANTITY	QUALITY	ACCESSIBILITY	UTILIZATION
PEOPLE	Auto/ Truck	• Vehicle Miles Traveled • Person Miles Traveled	• % Travel Meeting Level of Service Criteria • % Miles Meeting Level of Service Criteria • Travel Time Reliability: On-Time Arrival Planning Time Index • Vehicle Hours of Delay • Person Hours of Delay • Average Travel Speed • Number of Fatalities • Number of Serious Injuries • Rate of Fatalities • Serious Injuries Rate	• Job Accessibility: Auto	• % Travel Heavily Congested • % Miles Heavily Congested • Hours Heavily Congested • Vehicles per Lane Mile
PEOPLE	Transit	• Passenger Trips • Revenue Miles	• Revenue Miles between Failures	• Weekday Span of Service • Resident Access to Transit • Job Accessibility: Transit	• Passenger Trips per Revenue Mile
PEOPLE	Pedestrian & Bicyclist		• Pedestrian Level of Service • Pedestrian Fatalities and Serious Injuries • Bicycle Level of Service • Bicyclist Fatalities and Serious Injuries	• % Pedestrian Facility Coverage • % Bicycle Facility Coverage • % Population within 1 mile of Bike Lane and Shared-Use Paths	
PEOPLE	Aviation	• Passenger Boardings	• Departure Reliability		
PEOPLE	Rail	• Passengers	• On-Time Arrival		
PEOPLE	Seaport	• Seaport Passenger Movements			
FREIGHT	Truck	• Truck Miles Traveled • Combination Truck Miles Traveled • Combination Truck Ton Miles Traveled • Combination Truck Tonnage • Combination Truck Value of Freight	• Combination Truck Travel Time Reliability: On-Time Arrival Planning Time Index • Combination Truck Hours of Delay • Combination Truck Average Travel Speed • Combination Truck Cost of Delay		• Truck Empty Backhaul Tonnage • % Miles Heavily Congested • Vehicles per Lane Mile
FREIGHT	Aviation	• Tonnage • Value of Freight			
FREIGHT	Rail	• Tonnage			
FREIGHT	Seaport	• Tonnage • Twenty-Foot Equivalent Units • Value of Freight		• % of Seaports with Active Rail Access	

Figure 4: The mobility measure matrix from The FDOT Source Book – 2018 (Florida Department of Transportation 2018)

For each performance measure, The FDOT Source Book also provides the formula to compute this measure, the reporting period (peak hour, peak period, daily, or yearly), and the data source. Table 2 provides data sources for some performance measures included in The FDOT Source Book. For example, the measure “vehicles per lane mile” measures the average density on a roadway and is reported for the peak hour only. There are two data sources, namely the Traffic Characteristics Inventory and Roadway Characteristics Inventory of FDOT. This measure is also calculated for different regions, such as statewide, seven largest MPOs, other urbanized areas, and non-urbanized areas; this measure can also be calculated by facility type, for example, arterials, highways, and freeways. Clearly, for a single performance measure for one mode, there may be multiple reported values depending on the geographic coverage or time frame.

Table 2: Selected transportation performance measures from FDOT 2018 Source Book

Mode	Performance Measures	Sources
Auto	Vehicle Miles Traveled Person Miles Traveled % of non-Single Occupancy Vehicle Travel Travel Time Reliability Average Travel Speed Number of Fatalities Rate of Fatalities Hours Heavily Congested	FDOT, Traffic Characteristics Inventory FDOT, Roadway Characteristics Inventory FDOT, Florida Strategic Highway Safety Plan HERE Technologies, Travel Time Data U.S. Census Bureau, American Community Survey
Truck	Combination Truck Miles Traveled Truck Miles Traveled Truck Tonnage Truck Value of Freight Travel Time Reliability: On-time Arrival Combination Truck Average Travel Speed Truck Empty Backhaul Tonnage	FDOT, Traffic Characteristics Inventory FDOT, Roadway Characteristics Inventory FDOT, Weigh-In-Motion Data FHWA, Freight Analysis Framework
Transit	Revenue Miles Passenger Trips Revenue Miles Between Failures Job Accessibility–Transit Passenger Trips per Revenue Transit Subsidies	FDOT, Florida Transit Information and Performance Handbook FDOT Pooled Fund Study, Access Across America
Bicycle & Pedestrian	Number of Facilities involving Peds and Bicyclists % Pedestrian Facility Coverage % Bicycle Facility Coverage	FDOT, Pedestrian LOS Model FDOT, Florida Strategic Highway Safety Plan FDOT, Roadway Characteristics Inventory
Aviation	Tonnage Passenger Enplanements Aircraft Operations Gate Departure Delay Operating Cost per Passenger	Federal Aviation Administration–Air Carrier Activity Information System (ACAIS) U.S. Bureau of Transportation Statistics
Rail	Tonnage Passengers	Amtrak, Amtrak Fact Sheet SunRail–Ridership Data
Seaport	Tonnage Twenty-Foot Equivalent Units Value of Freight	Florida Ports Council, Five-Year Florida Seaport Mission Plan

Figure 5 provides an overview of high-level performance measures for different modes. For traditional modes, performance measures available in The FDOT Source Book can be adopted or modified. For emerging modes, proper performance measures should be designed. For example, with the advent of dockless bike-sharing, e-scooters, micro-transit, and ride-sourcing (such Uber and Lyft), travelers' transportation preferences change over time. New measures should be designed to properly evaluate the performance of such emerging services.

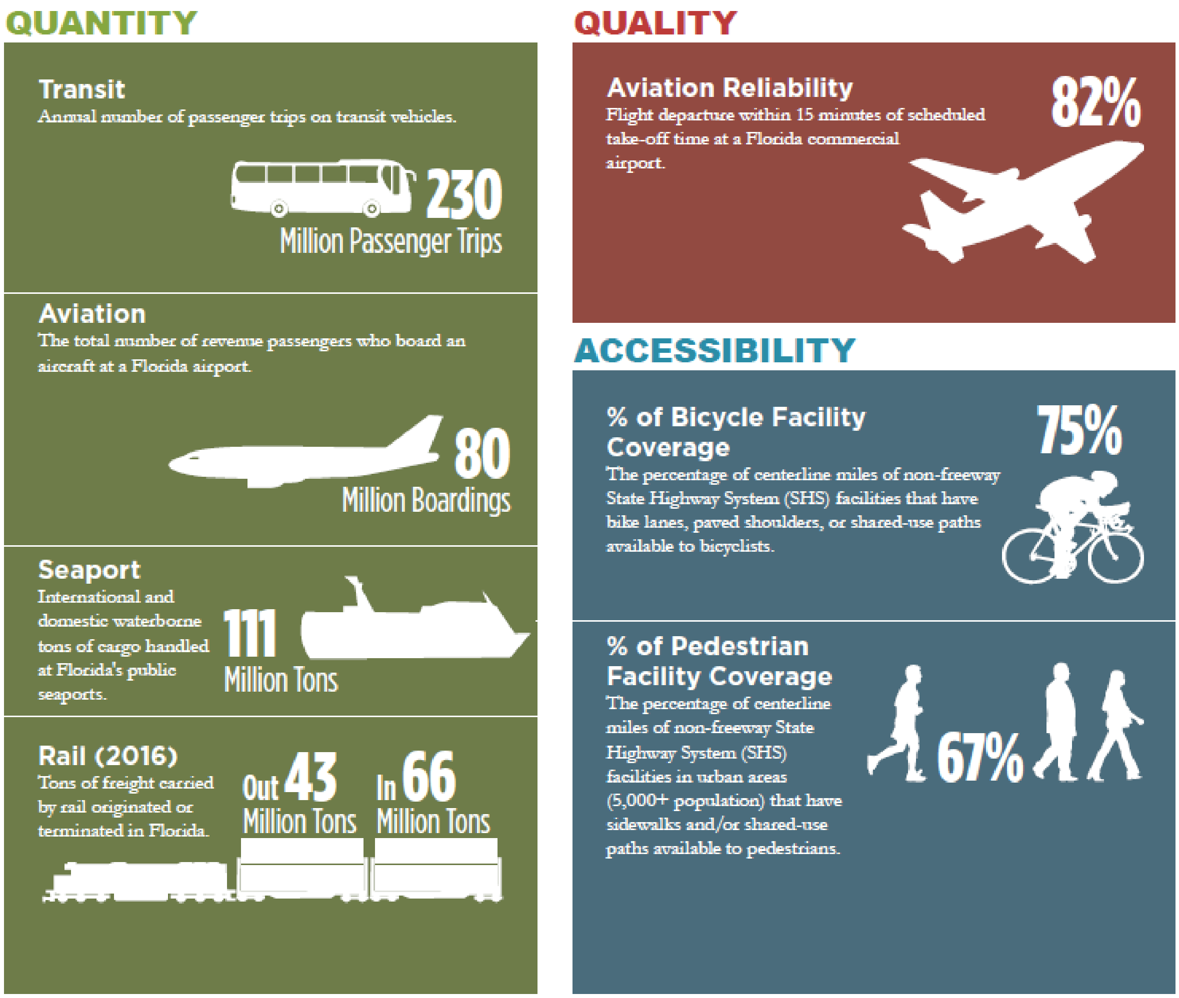


Figure 5: Part of 2017 modal performance summary from The FDOT Source Book–2018

2.2.2 State DOT mobility metrics

This section of the review examines transportation plans and planning documents to determine how state Departments of Transportation (DOTs) evaluate external factors' effects on the transportation system and how that influences their decision making processes. In particular, several states that offered innovative evaluation frameworks will be highlighted to provide insights into the state of practice in external factor evaluation. Special attention will be given to plans that are leading the way in assessing the performance and impacts of emerging modes of transportation such as on-demand mobility options, e-bikes, and e-scooters.

After reviewing the measures DOTs across the country use to evaluate transportation performance, the following DOTs are highlighted here for their insights into understanding and evaluating mobility performance measures: District of Columbia DOT, Washington DOT, Illinois DOT, and Wisconsin DOT.

Key findings of this evaluation include:

- Travel demand is the only external factor that is consistently evaluated by state DOTs
- State DOTs have yet to start systematically evaluating the performance or effects of emerging modes of transportation or how external factors affect them
- Contextual factors, such as the urban context (urban vs. rural), can determine which factors are relevant and which metrics are most informative.

2.2.2.1 District of Columbia Department of Transportation

The District of Columbia Department of Transportation (DDOT) contracted Kittelson and Associates to develop a toolbox of performance measures to better help guide DDOT to be more effective in determining the success of transportation projects. As seen in Figure 6, the performance measures in the toolbox are separated by priority measures and project-specific measures.

DDOT performance measures, as seen in Figure 6, are relatively similar to many state DOTs' metrics that were evaluated. Overall, it has a simpler performance evaluation system than FDOT's Source Book as it monitors significantly fewer metrics across fewer goal areas. In particular, it does not identify mode-specific metrics, opting instead to include mode share as one of its measures. More importantly, travel demand is the primary external factor evaluated. Multiple demand-related measures of congestion are assessed, including automobile delay, progression speed, travel time, but no other external factor is explicitly monitored in the priority measures. This was a common finding among most of the DOT's that were examined, including FDOT. It is common for DOTs to actively monitor multiple measures of travel demand, but the external factors that shape travel demand are usually not included.

PERFORMANCE MEASURE

PRIORITY MEASURES	**Safety and Comfort**	85th Percentile Speed
		Bicycle and Pedestrian Crashes
		Crash Frequency
		Crash Rate
		Crash Severity
		Level of Traffic Stress
	Mobility and Congestion	Automobile Delay
		Pedestrian Crossing Time
		Progression Speed
		Travel Time
		Travel Time Index
	Mode Share	Automobile Volume
		Bicycle Volume
		Pedestrian Volume
		Bus Ridership
PROJECT-SPECIFIC MEASURES	**Access to Jobs and Community Destinations**	Jobs and Destinations Served
	System Coverage	Residents Served
	Environment	Air Quality
		Green Space
		Impervious Surface
		Traffic Noise
		Traffic Diversion

10 PERFORMANCE MEASURES TOOLBOX

Figure 6: Example of performance measures (Kittelson and Associates 2016)

One unique aspect of the DDOT's performance measures is how project-specific measures are identified. Specifically, these measures address external environmental factors such as greenspace; however, these measures generally examine the project's effects beyond the transportation system instead of looking at how factors beyond the transportation system might affect the performance of the project.

Although none of the measures above relate specifically to emerging mobility, it would not be difficult for DDOT to adopt the current toolkit framework to incorporate those new performance measures. For each performance measure, a context is given, and then it is related back to the goals that DDOT has established for themselves, such as sustainability and health, public space, citywide accessibility and mobility, and more. Then data needs and sources are listed along with evaluation methods. One unique feature of this toolkit is that best practices are given as to how to calculate or gather data for the performance measures. There are also local example studies that are applied. This is useful for DDOT because they are able to reference other examples of how other entities or staff at DDOT looked at the performance measures previously (Kittelson and Associates 2016).

2.2.2.2 Washington Department of Transportation

The Washington Department of Transportation (WSDOT) contracted Fehr & Peers, Inc. to create a Mobility Performance Framework to support the Practical Solutions approach that WSDOT employs. The performance measures are for the overarching goal areas of accessibility, predictability, and efficiency. Furthermore, these metrics are directly related to WSDOT's decision points, including corridor sketch planning, system-level prioritization, and corridor/subarea strategy evaluation. An example of the system level prioritization performance metrics is shown in Figure 7.

Similar to DDOT, WSDOT does not directly evaluate many external factors beyond travel demand. However, WSDOT's evaluation matrix is unique in that it identifies the urban contexts (urban, suburban, rural) where each performance metric applies. It recognizes how external factors such as urban development patterns influence the viability of specific performance metrics. In this way, WSDOT highlights how these factors can affect the relative importance of individual metrics on decision making (Fehr & Peers Inc 2017). In short, different regions throughout Florida may require unique performance measures, and how much weight should be given to each measure may depend on the external factors shaping the study area, such as the built environment, development patterns, and demographic profile.

Measure	Metric	Context			
		Urban Core	Town/ Urban	Sub-urban	Rural
Transit Availability & Connectivity	Frequency of transit service*	●	●	○	○
	Presence of local transit/ regional service*	●	●	●	○
Access for Special Needs Populations	Percent accessibility for low-income, minority, youth/elderly or other disadvantaged populations	●	●	●	●
Goal: Accessibility | Category: Travel Experience					
Level of Service	Hours of Traffic Congestion	●	●	○	
	Travel Time (speed), by mode*	●	●	○	○
	Hours of Person Delay, by mode	●	●	○	
	Hours of Truck Delay*	○	○	○	○
Goal: Predictability | Category: Travel Reliability					
Modal Reliability	Travel time reliability buffer index*	●	●	○	○
	Ferry reliability	○	○	○	
Non-recurring Incidents	Number and rate of crashes	●	●	●	●
Goal: Predictability | Category: Network Resiliency					
Route and Mode Availability	Percent of corridor segments lacking a connecting and parallel network (by mode: roadway, pedestrian, bicycle, transit)	●	●	●	○
Goal: Efficiency | Category: Mode Usage					
Mode Share	Percent mode shares (by mode)*	●	●	●	○
Vehicle Occupancy	Number of persons per vehicle. (PMT/VMT)	●	●	○	○
Load Factor	Percent Capacity Used (by mode- Ferry, Rail, Transit) See count and forecast data below	●	●	○	
Goal: Efficiency | Category: Utilization					
Vehicle Throughput	VMT*	●	●	●	●
Freight Throughput	Ton Miles*	○	○	○	○
Person Throughput	PMT	●	●	●	○
	Ferry Persons and Vehicles carried*	○	○	○	
	Transit Persons and Vehicles carried*	●	●	○	
	Rail Persons and Vehicles carried*	●	●	○	

* Similar to WSDOT identified metric

Most applicable ●; Sometimes applicable ○; Least applicable [blank]

Figure 7: System-level prioritization metrics (Fehr & Peers Inc 2017)

2.2.2.3 Illinois Department of Transportation

The Mobility Chapter of the Illinois Department of Transportation (IDOT) Long Range Transportation Plan identifies key performance objectives. To evaluate whether IDOT achieves those goals, they established a series of performance metrics for each objective, as shown below.

Objective #1. Enhance intermodal freight connectivity and mobility to improve the continuity and accommodate the efficient movement of goods and services

- The relevant performance measures include modal breakdown of annual shipping volumes, number of intermodal facilities for freight movement, number of intermodal facilities with National Highway System connections, truck travel time reliability index, the Intelligent Transportation System (ITS) statewide architecture and strategic plan update, live internet-based intermodal dashboard of approved freight routes, and number of studies looking at commercial autonomous vehicles and their impacts on the freight transportation network

Objective #2. Invest in multi-modal transportation infrastructure improvements and strategic performance-based expansion of services that support the effective movement of passengers.

- It is important to note that there are no performance measures listed for this objective

Objective #3. Increase route efficiency and safety for all users by improving infrastructure conditions and addressing capacity issues.

- The performance measures for this objective are directly from the Moving Ahead for Progress in the 21st Century (MAP-21) Act and Fixing America's Surface Transportation (FAST) Act. These measures are listed in Figure 8. IDOT has also added additional measures that are not listed in this figure but include mileage of highly congested routes, the number of rail crossing-fatalities, serious injuries, and crashes reported, along with the number of congestion management strategies. Although performance measures are listed, they are vague and do not provide information on how they will be measured (Illinois Department of Transportation 2018).

✓ Number and rate of fatalities (per 100 Million VMT and mode)

✓ Number and rate of serious injuries (per 100 Million VMT and mode)

✓ Number of non-motorized fatalities and non-motorized serious injuries

✓ Percentage of NHS bridges classified as being in good condition

✓ Percentage of NHS bridges classified as being in poor condition

✓ Percentage of Interstate pavement in good condition

✓ Percentage of Interstate pavement in poor condition

✓ Percentage of non-Interstate NHS pavement in good condition

✓ Percentage of non-Interstate NHS pavement in poor condition

✓ Percentage of person-miles traveled on the Interstate considered reliable

✓ Percentage of person-miles traveled on the non-Interstate NHS considered reliable

✓ Truck travel time reliability index

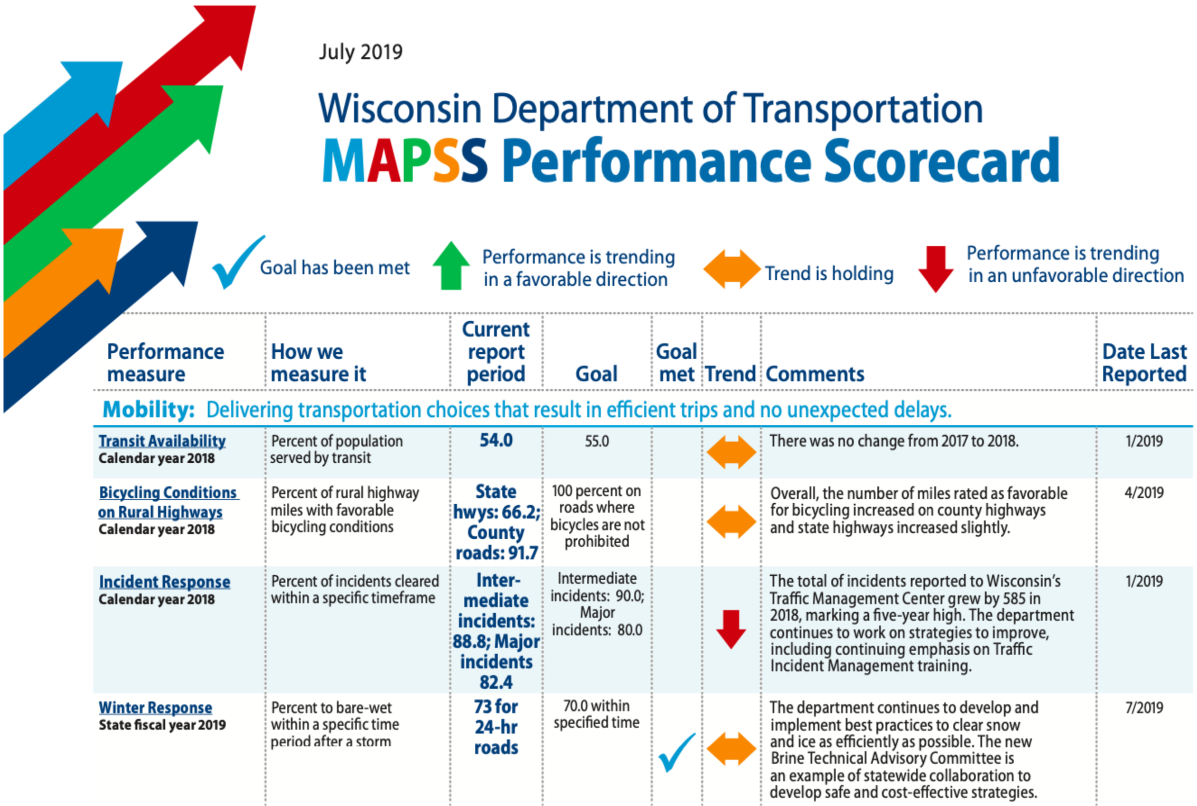
✓ Annual hours of peak hours excessive delay, per capita

✓ Percent of non-SOV travel

Figure 8: Example performance metric (Illinois Department of Transportation 2018)

2.2.2.4 Wisconsin Department of Transportation

The Wisconsin Department of Transportation (WisDOT) has a performance improvement program that looks at mobility, accountability, preservation, safety, and service (MAPPS). This measures the performance of Wisconsin's transportation system in a way resident of Wisconsin can understand and track the progress being made. Figure 9 shows the performance measures that WisDOT uses for mobility.



July 2019

Wisconsin Department of Transportation
MAPSS Performance Scorecard

Goal has been met — Performance is trending in a favorable direction — Trend is holding — Performance is trending in an unfavorable direction

Performance measure	How we measure it	Current report period	Goal	Goal met	Trend	Comments	Date Last Reported
Mobility: Delivering transportation choices that result in efficient trips and no unexpected delays.							
Transit Availability Calendar year 2018	Percent of population served by transit	54.0	55.0		Trend is holding	There was no change from 2017 to 2018.	1/2019
Bicycling Conditions on Rural Highways Calendar year 2018	Percent of rural highway miles with favorable bicycling conditions	State hwys: 66.2; County roads: 91.7	100 percent on roads where bicycles are not prohibited		Trend is holding	Overall, the number of miles rated as favorable for bicycling increased on county highways and state highways increased slightly.	4/2019
Incident Response Calendar year 2018	Percent of incidents cleared within a specific timeframe	Intermediate incidents: 88.8; Major incidents 82.4	Intermediate incidents: 90.0; Major incidents: 80.0		Unfavorable direction	The total of incidents reported to Wisconsin's Traffic Management Center grew by 585 in 2018, marking a five-year high. The department continues to work on strategies to improve, including continuing emphasis on Traffic Incident Management training.	1/2019
Winter Response State fiscal year 2019	Percent to bare-wet within a specific time period after a storm	73 for 24-hr roads	70.0 within specified time	Goal met	Trend is holding	The department continues to develop and implement best practices to clear snow and ice as efficiently as possible. The new Brine Technical Advisory Committee is an example of statewide collaboration to develop safe and cost-effective strategies.	7/2019

Figure 9: WisDOT MAPPS performance scorecard (Wisconsin Department of Transportation 2019)

The MAPSS report offers valuable insights because it has unique performance measures, and those of transit availability and bicycling conditions will be looked at. The performance measure of transit availability is measured by calculating the population that is within a quarter-mile walking distance from a fixed bus route and the population within the service area for rideshare and other transit systems. These populations are divided by the total population of Wisconsin to determine how many people have access to public transit. Through these calculations, it was found that 54% of Wisconsin residents have access to public transit in 2018.

The performance measure of bicycling conditions on rural highways is measured by the number of rural miles of state and county highways that were considered safe to bike on. The bike conditions are rated on a scale from best to moderate, and this is then divided by the number of non-freeway miles of state and county highways. Although undesirable bike infrastructure is considered, it is not used for this calculation. In 2018, 91.7% of rural highways were rated either best or moderate (Wisconsin Department of Transportation 2019).

The performance metrics developed by WisDOT are among the most comprehensive of all of the DOTs looked at. It provides specific information on how measures are accounted for and calculated. It also shows if the measure has been analyzed yet or not.

Key Findings from State DOT Plans

- <u>Travel demand is the only external factor that is consistently evaluated by state DOTs:</u> In terms of auto modes, planning agencies' primary concern is whether their system has enough capacity to handle the travel demand. Consequently, DOTs and other planning agencies often use several measures of travel demand (vehicle miles traveled, passenger miles traveled, etc.). They will then measure how well their system capacity is handling the demand (congestion, level of service, etc.). However, very few agencies explicitly evaluate the external factors that shape travel demand, such as demographic changes, economic factors, and technological changes.

- State DOTs have yet to start systematically evaluating the performance or effects of emerging modes of transportation or how external factors affect them: Determining how best to measure the demand for emerging modes of transportation is a growing challenge that transportation agencies are facing. The lack of available data on the use of emerging modes is particularly limiting. TNC's and e-scooter providers often keep their data proprietary, making it difficult to monitor how fast they are growing in popularity or what factors contribute to their use. Local agencies generally have developed more innovative ways of examining emerging modes than state agencies.

- Contextual factors, such as the urban context (urban vs. rural), can help determine which factors are relevant and which metrics are most informative: The factors shaping the demand for transportation as well as the factors that make up a successful transportation system are largely dependent upon contextual factors such as development patterns and the urban context. For example, the factors determining a successful intercity highway (i.e., throughput) are very different from the factors determining a successful urban neighborhood's street network (i.e., accessibility). Consequently, the performance metrics used to evaluate transportation systems should vary based on the context being evaluated. Evaluation systems monitoring the performance of the transportation system must be able to adapt to fit the unique characteristics of each region or context. This could be done by adjusting what factors are monitored or by adjusting the weight given to each performance metric.

2.2.3 Local and regional performance metrics

In addition to DOT's, Metropolitan Planning Organizations (MPO) and cities have also developed their own performance measures for mobility. The following cities are looked at: Twin Cities (St. Paul and Minneapolis), Minnesota; Portland, Oregon; and San Francisco, California. San Francisco was the only city that focused on emerging forms of mobility and had an in-depth matrix. However, the risk profile that the City of Portland has is an innovative way to understand how different risks can impact performance measures.

Key findings of this evaluation include:

- Local and regional agencies are examining emerging mobility modes but have yet to incorporate them into their key performance measures
- Equity is an important concern for emerging mobility plans
- Several cities have created emerging mobility plans that can be a component of a long-range transportation plan or serve as a standalone document.

2.2.3.1 Twin Cities Shared Mobility Plan

The Twin Cities Shared Mobility Plan was developed by the Shared Use Mobility Center (SUMC) to better understand mobility in the Twin Cities, which are St. Paul and Minneapolis. The Twin Cities region is a growing area and is seen as a pioneer for new forms of transportation systems. One of the plan’s goals is for residents to have a modal shift to remove more private cars from the roads in the Twin Cities. Consequently, there is a focus on new and emerging technologies as a means of achieving this goal. The Twin Cities Shared Mobility Plan goes into detail into modal pilots that have been conducted for car sharing, bike sharing, and more.

The Shared Mobility Plan also provides key metrics to ensure that shared mobility programs are adapted to serve the same population that uses public transit. In particular, Shared Use Mobility Center suggested the Twin Cities should track:

- “Jobs accessed as a result of new shared transportation services,
- Electrification of the sector as market forces and grant-based opportunities allow for the evolution of the industry,
- Approximation of monthly household spending on transportation before and after the introduction of service(s),
- Long-term retention of affordable housing units in developments featuring shared mobility services,
- Participation rates in comparison to the demographic background of the region and project area in terms of race, ethnicity, age, and income, and
- Measurements of coverage area and access for new services, to ensure that these services are being distributed equitably throughout the region and that they can be easily accessed and used by people in these communities following deployment.” (The Shared-Use Mobility Center 2017).

2.2.3.2 Portland Bureau of Transportation

The City of Portland along with the Portland Bureau of Transportation (PBOT), developed the Ubiquitous Mobility for Portland report to apply for the Smart Cities Grant from the U.S. Department of Transportation. If awarded the Smart Mobility grant, the City of Portland hopes to utilize it to create the Ubiquitous Mobility for Portland program, which includes a transportation system that is people-focused, autonomous, connected, and multi-modal, along with emitting low levels of carbon. The proposal includes key performance indicators for the vision elements defined in the Ubiquitous Mobility for Portland proposal. An example of a matrix is shown in Figure 10.

Objective	Measure	Monitoring Approach
Safety		
Reduce serious and fatal crashes at high crash locations	Number of serious and fatal crashes at high crash locations	Use vehicle Basic Safety Message (BSM) data to identify locations where driving events (such as speed, hard breaking, vehicle type, and windshield wiper use) indicate risk. Integrate BSM data from mobile devices as available.
Reduce serious and fatal crashes involving vulnerable users (including motorcycles, bicyclists, and pedestrians)	Number of serious and fatal crashes involving vulnerable users Participation in BSM broadcast for mobile devices	Use mobile BSM data utilization rates to track participation by vulnerable users.
Reduce over-limit speed and red light running infractions	85 percent speed compliance Red light violations	Use data generated by signal controllers to measure intersection entry on red light. Use combination of in-vehicle and infrastructure sensor data to measure vehicle speed by corridor.
Reduce driving under the influence by establishing a "ride home" partnership with TNCs and city parking services	TNC rides provided by target area Number of impairment citations Pre-paid "morning after" parking utilization	Use Portland Police DUII citations, Oregon Liquor Control Commission DUII data by retail location, transit, APC, TNC reports, and parking meter data to track impact on DUII citations in relationship to ride home program.

Figure 10: Measures for key objectives (Portland Bureau of Transportation 2016)

Furthermore, the Ubiquitous Mobility for Portland proposal focuses on emerging mobility modes. Although no performance measures are included, there are risk profiles developed for the following vision elements to support the proposal's objectives of safety, mobility, efficiency, sustainability, and climate change (Figure 11) (Portland Bureau of Transportation 2016).

Vision Elements Risk Profile			
Vision Element	**Risk Profile**	**Mitigation**	**Risk Rating**
#1: Urban Automation	Technical risks for the demonstration of semi-autonomous and fully autonomous vehicles on the transportation sites and campuses of project partners include equipment failures and accidents, as well as necessary state legislature approval. These include both program risks and operational risks. The program risks will be addressed by system engineering techniques to ensure delivery of workable solutions are on time and within budget. The operational risks will be covered by traditional insurance instruments associated with operations and maintenance of public transportation. There may be a need or opportunity for public participants to sign a limitation of liability for certain types of autonomous vehicle operation. Policy risks include the adoption of business rules for the operation of vehicles and public participation. Institutional risks include delays associated with implementing new technology.	Systems engineering Custom insurance coverage Limitation of liability	High

Figure 11: Vision element risk profile (Portland Bureau of Transportation 2016)

2.2.3.3 San Francisco County Transportation Authority

The San Francisco County Transportation profiles created an Emerging Trends Mobility Report to guide the Long Range Transportation Plan (Connect SF) and update the San Francisco Transportation Plan and provide guidance for future policy recommendations. San Francisco County has defined emerging mobility services as shown in Figure 12: electric standing scooter sharing, bike sharing, moped sharing, car sharing, ridesharing, ridehailing, microtransit, courier network services, autonomous vehicles, robots, and drones.

TYPE OF SERVICE	EXAMPLES OF SERVICE PROVIDERS (BOLDED COMPANIES ARE ACTIVE IN SAN FRANCISCO)
Electric Standing Scooter Sharing	Bird, Lime, Spin *
Bike sharing	B-Cycle, Bluegogo, **Bay Area Bike Share/Ford GoBike (operated by Motivate), JUMP Bike (operated by Social Bicycles)**, Limebike, Scoot, Zagster
Moped Sharing	Renault's Twizy, **Scoot**, Toyota's iRoad
Car sharing	Car2go, **Getaround**, GIG, **Maven, Zipcar**
Ride sharing	Blablacar, **Scoop**, Tripda, **Waze Carpool**
Ride hailing	**Flywheel, Lyft, Uber,** Via
Microtransit	Bridj, **Chariot**, Leap, Night School, Via**
Courier Network Services	**Amazon's Flex, Caviar, FedEx, Good Eggs, Grubhub, Instacart, Postmates, Omni, UPS**
TYPE OF TECHNOLOGIES	EXAMPLES OF TECHNOLOGY PROVIDERS (BOLDED COMPANIES ARE ACTIVE IN SAN FRANCISCO)
Autonomous Vehicles	Cruise/GM, EasyMile, Ford, Lyft, Mercedes, Renault/Nissan, Navia, Nvidia, Tesla, Uber, Waymo, Zoox***
Robots + Drones	Amazon Prime Air, Marble, Starship

* Electric standing scooter sharing was not included in the evaluation because their service was introduced after the evaluation period

** Bridj, Leap and Night School are no longer in operation but are presented as examples of microtransit services

*** The full list of autonomous vehicle developers and their activities is currently unknown

Figure 12: Identified forms of emerging mobility (San Francisco County Transportation Association 2018)

San Francisco County has also developed guiding principles to serve as a framework for emerging mobility which includes the following metrics: safety, transit, equitable access, disabled access, sustainability, congestion, accountability, labor, financial impact, and collaboration. Each of these has specific metrics that can be used to measure it, such as operational safety, transit competition, first and last mile, user statistics, access time, and more. The evaluation criteria have two components, which are (1) outcome metrics and (2) policy and design features. Outcome metrics are used to evaluate whether an emerging mobility service is aligned with a guiding principle. The policy and design feature are how emerging mobility services can achieve a guiding principle. An example of an outcome metric for safety is shown in Figure 13.

Safety

Emerging Mobility Services and Technologies must be consistent with the City and County of San Francisco's goal for achieving Vision Zero, reducing conflicts, and ensuring public safety and security.

OUTCOME METRIC	
1	OPERATIONAL SAFETY Number of collisions per 100,000 service miles
POLICIES AND DESIGN FEATURES	
2	OPERATIONAL SAFETY Service avoids in-app messaging and navigation during vehicle operation (during revenue and non-revenue hours)
3	OPERATIONAL SAFETY Safety training is required
4	OPERATIONAL SAFETY Service has hours of service program for both revenue and non-revenue hours and checks DMV Record Duty of Service log
5	UNSAFE DRIVING PENALTIES Service penalizes user for speeding, traffic tickets, blocking bicycle and pedestrian facilities, DUIs, reckless driver complaints, and leads to corrective action
6	PERSONAL SECURITY Service requires background checks of operators.
7	PERSONAL SECURITY Service provides 24-hour service with a human response in a timely manner.

Figure 13: Outcome metric for safety (San Francisco County Transportation Association 2018)

The outcome metrics were then evaluated in relation to strategies the County is trying to accomplish to achieve these goals. An example is shown in Figure 14.

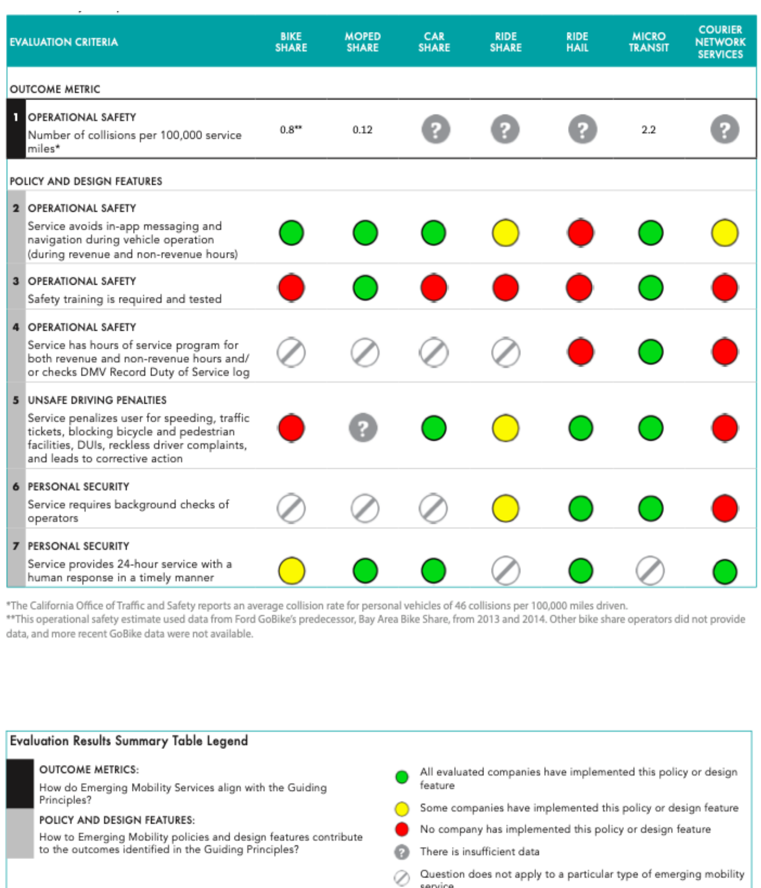


Figure 14: Evaluation of outcome metrics (San Francisco County Transportation Association 2018)

By evaluating emerging mobility through community outreach, workshops, and questionnaires, the San Francisco County Transportation Authority found the following results:

- Pilots and permits lead to better performance
- Inadequate data
- Opportunities for equitable access
- Conflicts with public transit
- Impacts on safety
- Impacts on congestion

From these results, the following recommendations were then developed:

1. Proactively Partner: Partner with companies to pilot and develop innovative mobility solutions
2. Collect Emerging Mobility Data and Conduct Research: Centralize data streams into a warehouse strategy and incorporate data from pilot projects
3. Regulate and Recover Costs: Consider developing an emerging mobility permit program and a regulatory or impact fee to cover the costs emerging modes have on city resources
4. Bridge Mobility and Access Gaps: Focus on the equity gaps of low-income users and issues related to disabled access
5. Support and Prioritize Public Transit: Pursue Transit First Policies by expanding transit priority facilities and considering rights-of-way prioritization
6. Enforce Safe Streets: Enforce Safe Streets Policies (i.e., addressing failure to yield and speeding issues) in known emerging mobility conflict areas.
7. Manage Congestion at Curbs and on Roadways: Develop a curb management strategy that allocates and prices curb access appropriately (San Francisco County Transportation Association 2018).

Key Findings from Local and Regional Plans

- <u>Local and regional planning agencies are more likely to measure demographic factors because it is much easier to monitor, model, and make decisions based on these factors at the local level than at the state leve</u>l. Yet, even at the local level, most agencies incorporate external factors by examining retroactive data on trip generation instead of looking toward how the external factors may reshape the nature of travel demand in the future.

- <u>Local and regional agencies are examining emerging mobility modes but have yet to incorporate them into their key performance measures:</u> All of the plans examined discuss emerging modes of mobility but have yet to develop key performance measures. Similarly, the focus has been on preparing for emerging modes instead of how external factors impact these emerging modes. This is likely due in large part to the lack of available data on emerging modes, but it could also be because cities are waiting to see if people are actually using the modes and if they are viable before developing performance measures.

- <u>Equity is an important concern for emerging mobility plans:</u> Local agencies' discussion of emerging modes is often framed around improving the mobility of transportation disadvantaged populations. Emerging mobility is seen as a solution to problems such as congestion, transportation equity, and more. Most local and regional planning agencies are waiting to see if emerging modes address these problems before diving deeper into external factors.

- Several cities have created emerging mobility plans that can be a component of a long-range transportation plan or serve as a standalone document: Cities have created standalone planning documents that fall within their Long Range Transportation Plans or other plans. This is important because it shows that emerging mobility is looked at separately but it also helps a city achieve its overall transportation goals.

2.3 Expert survey

In order to augment our understanding of the external factors, we performed a survey of local-, state-, and national-level transportation experts from different sectors. The survey was designed to further help identify external factors that can be used to understand the changing nature of transportation, evaluate their efficacy, and understand how and where these factors were being used to support decision making in transportation planning.

2.3.1 Survey methodology

Surveys are a long-standing tool employed by social science researchers to collect data on factors, trends, and outcomes (Misro et al. 2014). More so than other data collection methods, surveys provide researchers with an opportunity to query a large targeted population, thereby increasing the ability to collect larger amounts of information. Following decades of academic guidance, a well-designed survey can also uncover heretofore unknown information while offering a high degree of statistical power (Rossi et al. 2013).

Web-based surveys, like the one employed in this project, offer an opportunity to reach an even greater population but can include respondent biases that reduce the quality of responses and response rates (Dillman et al. 1998; Solomon 2001). Web-based surveys can also be weakened by a lack of consistent or comprehensive reporting on the methods of survey design and recruitment (Turk et al. 2018). To address these issues, we employed the guidance offered by Turk (2018) under advisement to ensure a robust reporting of our methods of design and analysis, but we did experience a lower than anticipated response rate.

To best assess the real-world use of external factors in decision support, the following steps were taken:

- A list of transportation experts from industry, academia, and the government was provided to the FDOT Project Manager for review and approval. The final list included 253 potential contacts: 86 with representation from local/regional government, 77 from the state government, nine from federal government agencies, 30 industry/trade associations, 13 academic institutions, and 36 other organizations. Figure 15 presents the relative number of transportation experts surveyed based on their sector.

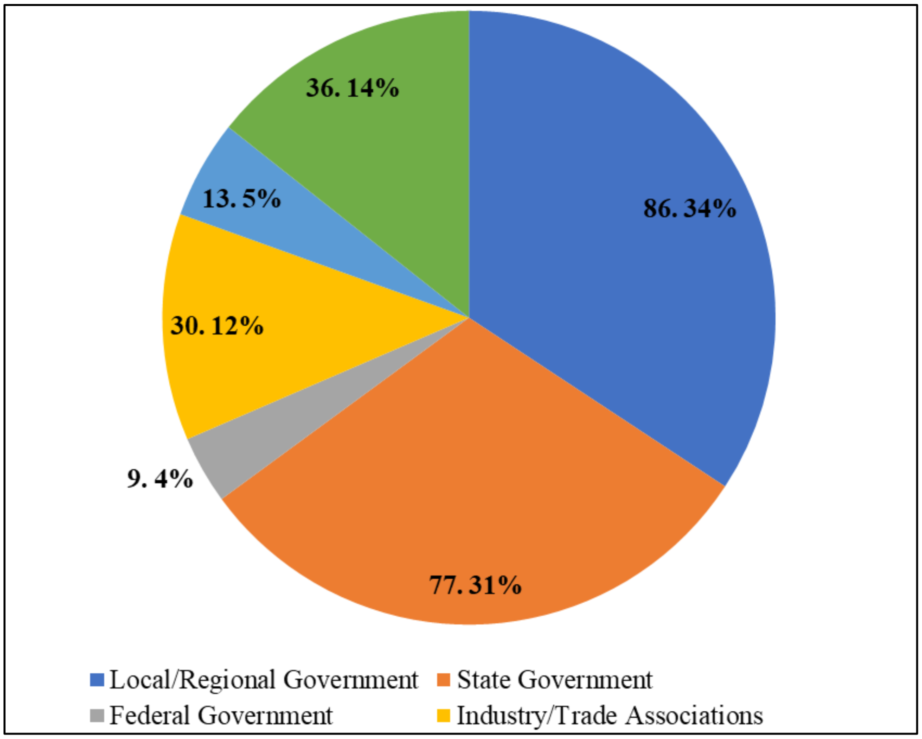


Figure 15: Transportation experts surveyed by sectors

- A survey instrument was developed in coordination with an interdisciplinary team of researchers with backgrounds in engineering, geography, and urban and regional planning following standard survey design guidance. The intent of the survey was to help the researchers understand the selection and application of external factors in transportation planning. It was approved by the FSU Institutional Research Board and the FDOT Project Manager.

- The survey questionnaire was comprised of two parts. The first part collected background information and asked respondents about perceptions of the relative importance of each of seven-goal areas included the *2060 Florida Transportation Plan*, the single overarching statewide plan guiding Florida's transportation future (FDOT 2010). The second part asked specific questions about how respondents identified, used, and measured external factors. The second set of questions, as well as many of the survey results presented in this report, subdivided external factors into four overarching categories based on recently completed research by FDOT, entitled, *Assessment of Planning Risks and Alternative Futures for the Florida Transportation Plan*, which looked at the dynamic risks affecting future transportation planning in four areas: demographics, economics, the environment, and technology. It should be noted that the FDOT research included a fifth category, global/geopolitical events, which the researchers determined was not a useful category of analysis for this study (FDOT 2019). The complete Survey Questionnaire can be found in Appendix A.

- The survey, which was designed to preserve the anonymity of the respondents, was disseminated electronically via email on Qualtrics. A follow-up reminder email was sent to the entire contact list on Monday, November 18, 2019. It should be noted that a limited number of contacts were returned due to an addressee error (e.g., agency email change, staff person no longer with the agency). In these instances, the project team immediately determined a valid contact and re-transmitted the survey.

- A script of follow-up questions was developed (see Appendix B). On December 4, 2019, the research team began calling survey respondents that asked for a follow-up call as part of their survey responses. They also began calling contacts within sectors that showed lower response rates with the intent of boosting participation.

2.3.2 Survey results

As of December 1, 2019, 19 out of a total of 253 potential respondents, or 7.5%, had responded to the survey. The majority of our respondents were highly educated planning professionals with significant professional experience. 64.3% of respondents had a graduate degree, and the average respondent had 21 years of work experience.

Our respondents came from a wide array of transportation backgrounds. Figure 16 shows the response totals by sector.

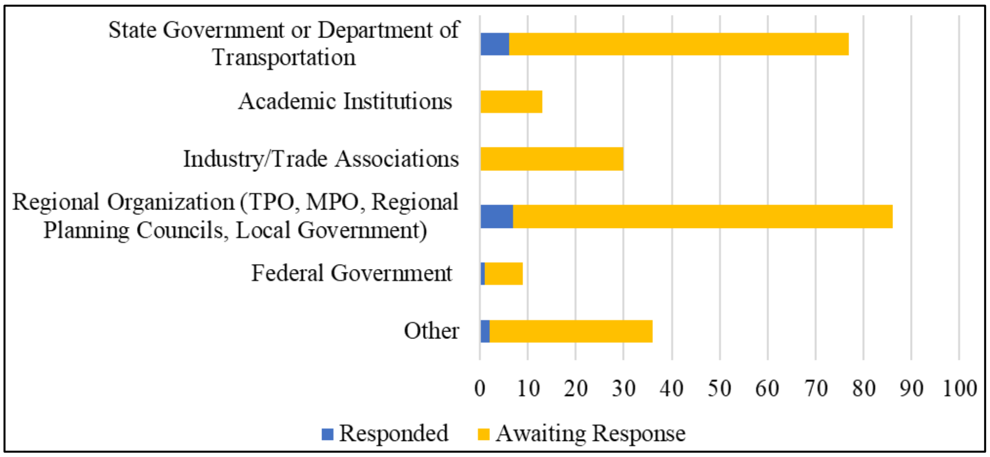


Figure 16: Respondents by sector (n=19)

Survey results imply that there is a relationship between the type and use of external factors in decision making by program experts to that found in the academic literature. The following table (Table 3) documents this relationship.

Table 3: External factors identified by the literature and the survey

External Factor	Noted in Literature	Referenced by Some Experts	Referenced by All Experts
Demographic Factors			
Population Growth	X		X
# of Licensed Drivers		X	
Suburbanization			X
Immigration		X	
Aging Populations	X		X
Tourism			X
Traffic Safety			X
Traffic Volumes	X		
Economic Factors			

Table 3: External factors identified by the literature and the survey (continued)

External Factor	Noted in Literature	Referenced by Some Experts	Referenced by All Experts
Economic Growth (GDP)	X		X
Per Capita Income	X	NA*	
Unemployment	X	X	
Fuel Costs		X	
Financial Markets		X	
Housing Markets	X	X	
Freight transport			X
Emerging Industries (Tech, Aerospace)		X	
Viability of Revenue Streams (gas tax, etc.)			X
Environmental Factors			
Development/Open land conversion	X		X
Sea Level Rise		X	
Weather-related inland flooding			X
Coastal flooding and hurricane-related storm surge		X	
Air Quality		X	
Climate-Change based natural hazards (intensifying hurricanes, tornadoes, etc.)			X
Technological Factors			
Autonomous Vehicles			X
Connected Vehicles		X	
Electric Vehicles		X	
Shared Vehicles		X	
E-commerce	X	NA**	
Cyber Security	X	NA**	
Emerging modes of personal transportation (e-bikes, e-scooters)	X	NA**	
* The survey did not ask about per capita income ** No survey responses were recorded for these factors			

In addition to augmenting the literature review, the survey data enable us to identify the external factors that professionals believe have the greatest impact upon the future transportation system. Table 4 lists the top three factors from each category that respondents rated as having the greatest impact on the transportation system. Each factor was rated on a scale from 0 to 5, with 0 being “No Impact” and 5 being “Extreme Impacts.”

As previously noted, respondents were provided with four categories of external factors in the questionnaire to help respondents understand the survey’s sequence and flow to boost the number and thoroughness of responses. It should be noted that while these categories were derived from other FDOT research related to long-range planning, as with any classification system, some factors, while relevant, may not fit perfectly into a single category. As an example, shared vehicles were grouped under technology rather than demographics because it is expected to rely upon technology-driven applications for ridership management, routing, and billing.

General trends that were observed in the survey results as it related to each of these broad categories as employed in this study follow:

- **Demographic Factors**: Florida's expected population growth, particularly in suburban areas, was expected to have the greatest impact on the transportation system. The suburbanization trends that have contributed to the congestion issues experienced by most metropolitan areas today are expected to continue and will need to be monitored to anticipate future travel demand.

- **Economic Factors**: While the impact of Florida's economic growth on travel demand was considered an important factor, the viability of revenue streams to fund future infrastructure investments was considered the most important external factor among all four categories.

- **Environmental Factors**: Climate change and the increasing frequency and intensity of flooding events both inland and along the coast were considered to be the most significant environmental factors.

- **Technological Factors**: Emerging technologies were expected to significantly impact the performance of the transportation system. While shared and electric vehicles will have a significant impact, autonomous vehicles are the technology expected to have the greatest impact.

Please see Appendix C for the table of the complete results for every external factor.

Table 4: Top three most significant factors on the transportation system by category (average score is bounded from 1 to 5; n=19)

Population 1. Suburbanization (3.64) 2. Population Growth (3.58) 3. Traffic Safety (3.18)	**Economic** 1. Viability of Revenue Streams (gas tax, etc.) (3.89) 2. Economic Growth (GDP) (3.52) 3. Freight Transport (3.31)
Environment 1. Climate Change (3.79) 2. Weather-related inland flooding (3.53) 3. Coastal Flooding/Storm Surge (3.48)	**Technology** 1. Autonomous Vehicles (3.82) 2. Shared Vehicles (3.75) 3. Electric Vehicles (3.14)

We were also interested in identifying how external factors impact each of the Florida Transportation Plan's (FTP) seven goals as identified in the FTP Vision Element. The Florida Transportation Plan is the overarching statewide plan guiding Florida's transportation future. The FTP identifies seven goal areas that are critical to achieve the Florida future transportation vision. The FTP's goals are:

1. Safety and security for residents, visitors, and businesses,
2. Agile, resilient, and quality transportation infrastructure,
3. Efficient and reliable mobility for people and freight,
4. More transportation choices for people and freight,

5. Transportation solutions that support Florida's global economic competitiveness,
6. Transportation solutions that support quality places to live, learn, work, and play, and
7. Transportation solutions that enhance Florida's environment and conserve energy.

Based on the preliminary survey results, Table 5 displays the top three external factors that experts believed would have the greatest impact on FDOT's ability to achieve each FTP goal, expected to have the greatest impact on FDOT's ability to achieve each FTP goal. Please see Appendix C for a complete table of the results for every external factor.

Table 5: Top three factors with the greatest impact on each FTP goal area

FTP Goal	External Factor	Average Score
Goal 1: Safety and Security	Traffic Safety	4.43
	Autonomous, Connected, Electric, Shared Vehicles (ACES)	4.29
	Climate Change	3.92
Goal 2: Resilient Infrastructure	Climate Change	4.38
	Coastal Flooding/Hurricane Storm Surge	4.15
	Suburbanization	4.14
Goal 3: Efficient and Reliable Mobility	Autonomous Vehicles	4.38
	Suburbanization	4.29
	Viability of Revenue Streams	4.00
Goal 4: More Transportation Choices	Shared Vehicles	4.15
	Autonomous Vehicles	4.00
	Viability of Revenue Streams	3.92
Goal 5: Economic Competitiveness	Economic Growth	4.46
	Viability of Revenue Streams	4.21
	Connected Vehicles	4.08
Goal 6: Quality Places	Air Quality	4.46
	Development/Open Land Conversion	4.00
	Climate Change	3.92
Goal 7: Environmental and Energy Conservation	Development/Open Land Conversion	4.31
	Air Quality	4.15
	Climate Change	3.92

In addition to identifying what external factors significantly impact the transportation system, the survey was also designed to assess the current state of practice in external factor evaluation and how practitioners incorporate external factors into the planning process. More specifically, it sought to uncover (1) which factors transportation professionals monitor to assess the performance of their transportation system, (2) how they measure those factors, and (3) what data sources they use for each metric. Table 6 displays the percentage of respondents that monitor each external factor to assess their community's transportation system. Over 70% of respondents said they evaluated factors highlighted in green. Between 50% and 70% of respondents monitored factors highlighted in yellow. Less than 50% of respondents measured factors highlighted in red.

Table 6: Percent of respondents who use external factors in the planning process

Demographic Factors	%Yes	Economic Factors	%Yes
Traffic Safety	87%	Economic Growth (GDP)	77%
Population Growth	87%	Freight transport	64%
Aging Populations	80%	Viability of Revenue Streams (gas tax, etc.)	64%
Tourism	67%	Emerging Industries (Tech, Aerospace)	57%
Suburbanization	53%	Unemployment	50%
Licensed drivers	47%	Fuel Costs	50%
Immigration	21%	Housing Markets	43%
		Financial Markets	25%
Environmental Factors	**%Yes**	**Technological Factors**	**%Yes**
Weather related inland flooding	73%	Emerging modes of personal transportation (e-bikes, e-scouters, etc.)	77%
Air Quality	58%	Autonomous Vehicles	60%
Development/Open land conversion	57%	Electric/Connected/Shared Vehicles	50%
Coastal flooding and hurricane related storm surge	54%	Cyber Security	38%
Climate-Change based natural hazards (intensifying hurricanes, tornadoes, etc.)	54%	E-commerce	38%
Sea Level Rise	50%		

2.4 The final list of external factors and performance measures

Based on the literature review findings and the result of the survey, potential external factors are compiled in Table 7. Please refer to Appendix D for further details regarding external factors' data sources and data frequency.

Table 7: External factors impacting Florida transportation systems

Code	External factor name	Level
EF01	VMT (NL)	National
EF02	Population Estimate (NL)	National
EF03	Population Change (NL)	National
EF04	Natural Increase - Births (NL)	National
EF05	International Migration (NL)	National
EF06	Domestic Migration (NL)	National
EF07	Net Migration (NL)	National
EF08	Rental Vacancy Rate (NL)	National
EF09	Homeowner Vacancy Rate (NL)	National
EF10	Homeownership Rate (NL)	National
EF11	Total Building Permits (NL)	National
EF12	Single Family (S.F.) Permits (NL)	National
EF13	Number of Housing Units (NL)	National
EF14	Population in College (NL)	National
EF15	Percentage of Population in Poverty (NL)	National
EF16	Political Party Affiliation - Democratic (NL)	National

Table 7: External factors impacting Florida transportation systems (continued)

Code	External factor name	Level
EF17	Political Party Affiliation - Republican (NL)	National
EF18	Political Party Affiliation - Independent (NL)	National
EF19	Racial/ethnic composition (NL)	National
EF20	Immigration (NL)	National
EF21	Aging Populations (NL)	National
EF22	GDP–All industries (NL)	National
EF23	GDP–Construction (NL)	National
EF24	GDP–Manufacturing (NL)	National
EF25	GDP–Real Estate (NL)	National
EF26	GDP–Transportation (NL)	National
EF27	Per Capita Income (NL)	National
EF28	Personal Income (NL)	National
EF29	Financial Condition Index (NL)	National
EF30	House Price Index (NL)	National
EF31	Consumer Price Index (CPI) (NL)	National
EF32	CPI–Rent Price Index (NL)	National
EF33	CPI–Fuel Price Index (NL)	National
EF34	Number of Employed (NL)	National
EF35	Number of Unemployed (NL)	National
EF36	Percentage of Unemployed (NL)	National
EF37	Financial Markets (Dow Jones Avg Closing Price) (NL)	National
EF38	Emerging Industries tech, aerospace (NL)	National
EF39	Total Precipitation (NL)	National
EF40	Average Temperature (NL)	National
EF41	Number of Smartphone Users (NL)	National
EF42	Number of Mobile Internet Users (NL)	National
EF43	Hours of Service (HOS) Rules (Driving Limit Without Breaks) (NL)	National
EF44	Subsidies for Renewable Fuels (Millions) (NL)	National
EF45	Level of Highway Funding (NL)	National
EF46	Investments and Incentives for Alternative Fuel Infrastructure and Vehicles (NL)	National
EF47	Florida Population (SL)	State (Florida)
EF48	Georgia Population (SL)	State
EF49	Alabama Population (SL)	State
EF50	FL Population Change (SL)	State (Florida)
EF51	International Migration (SL)	State (Florida)
EF52	Domestic Migration (SL)	State (Florida)
EF53	Net Migration (SL)	State (Florida)
EF54	Population in College (SL)	State (Florida)
EF55	Percentage of Population in Poverty (SL)	State (Florida)
EF56	Political Party Affiliation (republican) (SL)	State (Florida)
EF57	Political Party Affiliation (democrat) (SL)	State (Florida)
EF58	Political Party Affiliation (other) (SL)	State (Florida)
EF59	Seniors Population (65+) (SL)	State (Florida)

Table 7: External factors impacting Florida transportation systems (continued)

Code	External factor name	Level
EF60	Rental Vacancy Rate (SL)	State (Florida)
EF61	Homeowner Vacancy Rate (SL)	State (Florida)
EF62	Homeownership Rate (SL)	State (Florida)
EF63	Total Building Permits (SL)	State (Florida)
EF64	Single Family (S.F.) Permits (SL)	State (Florida)
EF65	Number of Housing Units (SL)	State (Florida)
EF66	Number of Licensed Drivers (SL)	State (Florida)
EF67	Tourism (SL)	State (Florida)
EF68	Viability of Streams (Gas, tax, etc.) (Millions) (SL)	State (Florida)
EF69	GDP- F.L. All Industries (In Millions of Dollars) (SL)	State (Florida)
EF70	GDP of FL- Construction (In Millions of Dollars) (SL)	State (Florida)
EF71	GDP of FL- Manufacturing (In Millions of Dollars) (SL)	State (Florida)
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)	State (Florida)
EF73	GDP of FL- Retail Trade (In Millions of Dollars) (SL)	State (Florida)
EF74	GDP of FL- Transportation (In Millions of Dollars) (SL)	State (Florida)
EF75	Per Capita Income (SL)	State (Florida)
EF76	Personal Income (In Millions of Dollars) (SL)	State (Florida)
EF77	Economic Condition Index (SL)	State (Florida)
EF78	House Price Index (SL)	State (Florida)
EF79	Average CPI for all MSAs (SL)	State (Florida)
EF80	CPI–Rent Price Index (SL)	State (Florida)
EF81	CPI–Fuel Price Index (SL)	State (Florida)
EF82	Number of Employed (SL)	State (Florida)
EF83	Number of Unemployed (SL)	State (Florida)
EF84	Percentage of Unemployed (SL)	State (Florida)
EF85	Total Precipitation (SL)	State (Florida)
EF86	Average Temperature (SL)	State (Florida)
EF87	Number of Hurricane Strikes + Tropical Storms (SL)	State (Florida)
EF88	Sea Level Rise (SL)	State (Florida)
EF89	Weather-related inland flooding (SL)	State (Florida)
EF90	Transportation Electric Vehicle Retail Sales (SL)	State (Florida)
EF91	Highway Operations and Maintenance Decisions (Millions) (SL)	State (Florida)
EF92	Level of Highway Funding (Payments into Highway Trust Fund) (SL)	State (Florida)
EF93	Florida Total Amount of Highway Trust Fund Money (Allocations) (SL)	State (Florida)
EF94	Fuel Taxes (SL)	State (Florida)
EF95	Privatization of Roads (SL)	State (Florida)
EF96	Number of Launches at Kennedy Space Center (SL)	State (Florida)
EF97	International Trade Through Miami-Dade (Billions) (SL)	State (Florida)
EF98	Number of Tourists to Orlando (SL)	State (Florida)

Note: NL: national level, SL: state level, CPI: consumer price index, GDP: gross domestic product, MSA: metropolitan statistical area

As discussed previously, the Florida Department of Transportation Forecasting and Trends Office publishes *The FDOT Source Book*, which contains all mobility measures in different categories (quantity, quality, accessibility, and utilization) for each mode that FDOT considers. This project will use the performance measures available from the 2019 edition of *The FDOT Source Book* to statistically test the relevance of the external factors to each transportation mode. Some of the performance measures do not have enough data points to run statistical analyses and get statistically significant results because these factors started to be reported in the FDOT Source Book in recent years. As such, the team has further selected the performance measures for each mode to be considered for analysis. The final list of the performance measures is available in Table 8 along with their identifiable codes (PM01 to PM67). Please refer to Appendix D for further details regarding performance measures data.

Table 8: List of transportation performance measures

Code	Performance measure name	Level
PM01	Safety Belt Use	Auto
PM02	Bicycle Fatalities	Pedestrian and Bike
PM03	Pedestrian Fatalities	Pedestrian and Bike
PM04	Motorcyclist Fatalities	Pedestrian and Bike
PM05	Vehicle Miles Traveled (Million) (Daily)	Auto
PM06	Vehicle Miles Traveled (Million) (Peak Hours)	Auto
PM07	Person Miles Traveled (Millions) (Daily)	Auto
PM08	Person Miles Traveled (Millions) (Peak Hour)	Auto
PM09	Percentage of Travel Meeting LOS Criteria (Daily)	Auto
PM10	Percentage of Travel Meeting LOS Criteria (Peak Hour)	Auto
PM11	Percentage of Miles Meeting LOS Criteria (Peak Hour)	Auto
PM12	% of non-Single Occupancy Vehicle Travel	Auto
PM13	Travel Time Reliability (On Time Arrival) (Daily)	Auto
PM14	Travel Time Reliability on Freeways: On-Time Arrival (Peak hour)	Auto
PM15	Travel Time Reliability (Planning Time Index) (Daily)	Auto
PM16	Travel Time Reliability on Freeways: Planning Time Index (Peak hour)	Auto
PM17	Vehicle Hours of Delay, Thousands (Peak hour)	Auto
PM18	Vehicle Hours of Delay, Thousands (Daily)	Auto
PM19	Vehicle Hours of Delay, Thousands (Yearly)	Auto
PM20	Person Hours of Delay, Thousands (Peak hour)	Auto
PM21	Person Hours of Delay, Thousands (Daily)	Auto
PM22	Person Hours of Delay, Thousands (Yearly)	Auto
PM23	Average Travel Speed	Auto
PM24	Percentage of Travel Heavily Congested (Peak hour)	Auto
PM25	Percentage of Travel Heavily Congested (Daily)	Auto
PM26	Percentage of Miles Heavily Congested	Auto
PM27	Hours Heavily Congested (Daily)	Auto
PM28	Hours Heavily Congested (Yearly)	Auto
PM29	Vehicles Per Lane Mile	Auto
PM30	Number of Fatalities	Auto
PM31	Rate of Fatalities	Auto
PM32	Passenger Trips	Transit

Table 8: List of transportation performance measures (continued)

Code	Performance measure name	Level
PM33	Revenue Miles (Millions)	Transit
PM34	Revenue Miles Between Failures	Transit
PM35	Weekday Span of Service (Hours)	Transit
PM36	Passenger Trips per Revenue Mile	Transit
PM37	Job Accessibility–Transit	Transit
PM38	Transit Subsidies	Transit
PM39	% Pedestrian Facility Coverage (Total Statewide urban)	Pedestrian and Bike
PM40	% Bicycle Facility Coverage (Total Stat)	Pedestrian and Bike
PM41	% Bicycle Facility Coverage (Total State Urban)	Pedestrian and Bike
PM42	Passenger Enplanements	Aviation
PM43	Gate Departure Delay	Aviation
PM44	Tonnage	Aviation
PM45	Aviation Value of Freight (Billions)	Aviation
PM46	Aircraft Operations	Aviation
PM47	Operating Cost per Passenger	Aviation
PM48	Tonnage (Millions)	Rail
PM49	Passengers	Rail
PM50	Rail On-Time Arrival	Rail
PM51	Tonnage	Seaport
PM52	Twenty-Foot Equivalent Units	Seaport
PM53	Value of Freight	Seaport
PM54	Seaport Passengers	Seaport
PM55	Truck Miles Traveled (Millions)	Truck
PM56	Combination Truck Miles Traveled (Millions)	Truck
PM57	Combination Truck Ton Miles Traveled (Billion Ton Miles)	Truck
PM58	Combination Truck Tonnage (kiloton)	Truck
PM59	Combination Truck Value of Freight (Millions of dollars)	Truck
PM60	Truck Travel Time Reliability (Peak Hour or Peak Period)	Truck
PM61	Travel Time Reliability: On-time Arrival (Daily)	Truck
PM62	Combination Truck Planning Time Index (Peak Hour or Peak Period)	Truck
PM63	Combination Truck Planning Time Index (Daily)	Truck
PM64	Combination Truck Hours of Delay, Vehicle Hours (Thousands) (Daily)	Truck
PM65	Combination Truck Average Travel Speed	Truck
PM66	Combination Truck Cost of Delay	Truck
PM67	Combination Truck Empty Backhaul Tonnage (kiloton)	Truck

CHAPTER III: A SYSTEM-OF-SYSTEMS FRAMEWORK TO UNDERSTAND THE CHANGING NATURE OF FLORIDA TRANSPORTATION SYSTEMS

In this section, an SoS approach is applied to understand planning issues concerning the external factors, thus addressing the overwhelming level of complexity on the subject and gaining insights into the changing nature of the Florida transportation system. This project has adopted the three-phase approach proposed by DeLaurentis (2005): the definition phase, the abstraction phase, and the implementation phase. The definition phase aims to understand the dimensions and characteristics of the SoS and its structure as it currently exists. In the abstraction phase, the main actors, effectors, disturbances, and networks, and interdependencies of the entities are identified. Finally, the implementation phase employs an approach such as modeling and statistical analysis to represent all or part of the abstraction (DeLaurentis 2005). In the following sections, we explain each phase of the framework.

3.1 Definition phase

The first phase of the framework is the definition phase. This phase identifies the SoS as it exists, which helps researchers imagine a schematic structure of the SoS and, later, understand the influence of external factors on the Florida transportation SoS. This phase identifies the systems' characteristics, attributes, drivers, disruptors, and the stakeholders who impact each system (Mostafavi 2018). Additionally, the definition phase defines the categories and levels that will later be required to detect the evolutionary and emergent properties of the SoS (DeLaurentis 2005).

This study first divides the transportation system into seven modes (auto, truck, transit, pedestrian and bike, aviation, rail, and seaport) aligned with the FDOT Source Book. Moreover, three levels are considered for mapping the Florida transportation system's hierarchical nature, which also reflects the various levels of decision making in transportation planning (e.g., system [ground, air, and sea transportation], state-, and national levels). Several categories of information were investigated for each level to identify different aspects of the Florida transportation SoS. These categories, described in Table 9, include resources, operations, stakeholders, and policies. An SoS lexicon is developed to define the Florida transportation SoS in Table 10.

The SoS lexicon encompasses corresponding resources forming a system at each level along with some collective functionalities and their disruptors and drivers. For example, resources at the base level (i.e., the α level in Figure 17) include the auto, transit, truck modes of ground transportation, seaport for sea transportation, and aviation for air transportation. The collection of resources at the base level constitutes the intermediate level resources (i.e., β level in Figure 17): ground transportation, sea transportation, and air transportation. A network of such transportation systems becomes a resource (i.e., a state transportation system) at a top-level (i.e., γ level in Figure 17)

Policies at different levels impact the resources and their operations. The manufacturing of resources and their operations at each level are highly governed by regulations and policies devised by corresponding transportation authorities. Such regulations are mostly in place to ensure safe and secure transportation. Meanwhile, the stakeholders of each mode may have different objectives and intentions for each transportation system. These objectives also impact the economics of the system. For example, users are more concerned about transportation safety and cost. Resource manufacturers are focused on improving their products to gain a higher share in the market. Transportation operators are interested in the improvement of system performance in terms of safety and operation. Furthermore, the interaction of the stakeholder's goals and objectives impacts the economics of the system. For example, a resource manufacturer may lose its market share due to some safety incidents. Such events may cause a shift in the travel demand to other transportation mode types in some severe cases.

According to SoS theory, emerging and evolutionary changes occur at a base level (α level) and become observable only at its higher levels (γ or β levels). This phenomenon requires a comprehensive investigation of system entities at the α level. In this regard, the FSU team performed a literature review for each mode; the resources, operations, stakeholders, and policies related to subsystems for each transportation mode were studied. The findings of this review were utilized in the development of the Florida SoS framework and SoS lexicon matrix (Table 10).

Table 9: Transportation SoS lexicon

Categories	Descriptions
Resources	Physical entities that support the provision of transportation services
Operations	Provision of transportation services by using resources
Stakeholders	Non-physical entities(stakeholders) that give the intent to operate the transportation SoS
Policies	The external forcing functions that impact the operation of physical & non-physical entities
Levels	**Descriptions**
Alpha (α)	Florida transportation subsystem
Beta (β)	Florida transportation system (i.e., collections of α-level systems in a network)
Gamma (γ)	National transportation system (i.e., collections of β-level systems in a network)

Table 10: Transportation system of systems lexicon matrix

Level	Resources	Operations	Stakeholders	Policies
α	Resources in one transportation subsystem in regional level • Vehicle • Airplane • Train	Operation of a resource like aircraft, truck	Users Freight companies Private taxi companies Economics of building/ operating/ buying/selling /leasing a single Resource	Policies relating to single resource use (e.g., type certification, flight procedures, etc.)
β	Collection of resources for a transportation mode: For example: • Roadway network	Operation of resource networks for common function (e.g., airline, highway network)	Airlines Railway companies Economics of operating / buying/selling /leasing resource networks	Policies relating to sectors using multiple vehicles. (safety, accessibility, etc.)

Table 10: Transportation system of systems lexicon matrix (continued)

Level	Resources	Operations	Stakeholders	Policies
ϒ	Resources in a state and interstate level: For example: • Florida transportation system	Operation of resources in the state and interstate level	FDOT District Authorities Economics of total national transportation system (All Transportation Companies)	Policies relating to national transportation policy.

3.2 Abstraction phase

The abstraction phase aims to reduce the overwhelming complexity of the SoS by abstracting the primary entities in a hierarchy along with their interrelationships (DeLaurentis 2005; Mostafavi 2018), thereby guiding the development of a composite index. In this phase, the overall resource network of the SoS is presented as a hierarchical structure. This network captures the main entities of the SoS at multiple levels, spanning from the national level to the single model.

3.2.1 Resources network

Multiple interdependent heterogeneous distributed systems constitute a transportation SoS. Each of these systems involves networks across several levels in a hierarchy. The Florida transportation SoS, in particular, consists of multiple subsystems ranging from ground transportation (e.g., auto, truck, transit, bicycle and pedestrian, and rail) to water transportation (e.g., seaport) and air transportation (e.g., aviation). These heterogeneous transportations systems are interdependent to one another for efficient operation. To properly map the Florida transportation SoS, it is critical to consider both the hierarchical and interdependent nature of the system.

Figure 17 shows the Florida transportation SoS hierarchy. In this framework, the Florida transportation systems exist within a three-level hierarchy. Specifically, the base level (α level) consists of interrelated single transportation modes as subsystems in Florida. These single subsystems are then aggregated to form the state transportation systems at the middle level (β level). Finally, at the top level (γ level), the state transportation systems are aggregated to represent the Florida transportation system along with other states' transportation systems.

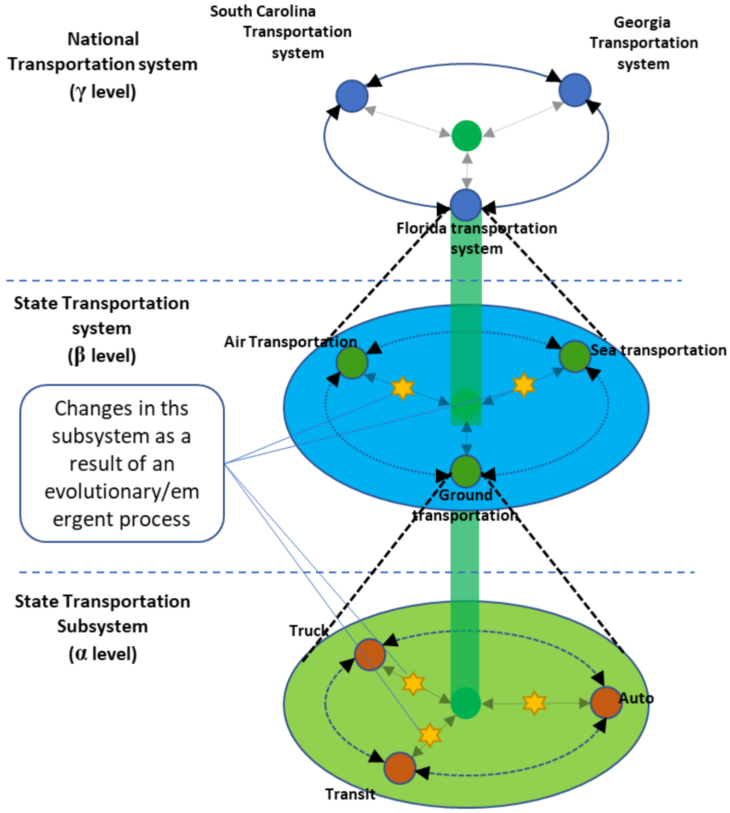


Figure 17: Florida transportation system of systems hierarchy

Figure 18 provides more detailed information on how systems at lower levels are combined to form higher transportation systems. We have divided the Florida transportation system into three systems (i.e., ground, air, and sea transportation systems) that are further broken into seven modes: auto, truck, transit, rail, bike, aviation, and seaport. This configuration aligns with the performance measures reported in the FDOT Source Book.

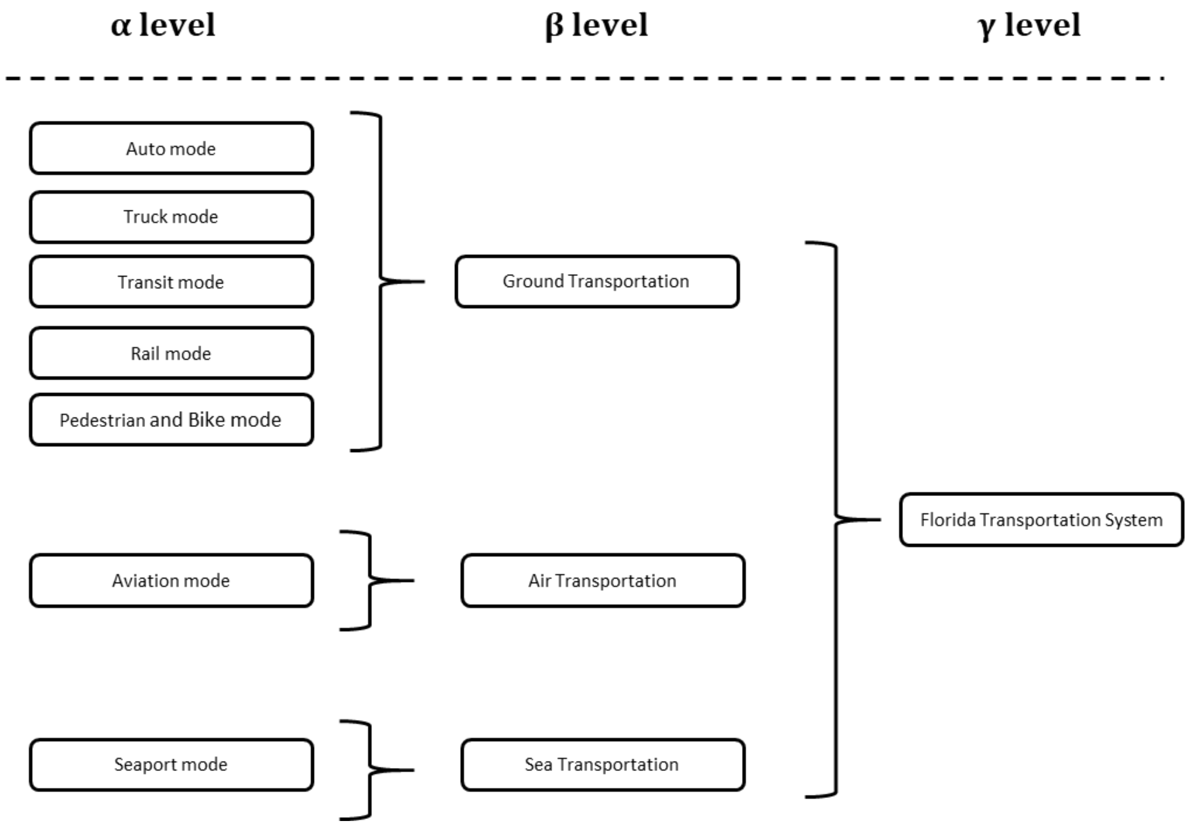


Figure 18: Aggregation of Florida transportation systems

3.3 Implementation phase

A composite index, the Florida Index for Transportation (FIT), is proposed to understand the changing nature of the Florida transportation SoS. To be more specific, FIT is developed as the means to detect the appearance of evolutionary and emergent properties at lower levels in the transportation SoS hierarchy from its higher levels by making it possible to trace the roots of the dynamics of the external factors. Moreover, FIT streamlines the abundant information generated from the analysis of a large number of external factors at the bottom of the SoS. FIT will serve as an overall indicator of the transportation demand or infrastructure needs as a result of changes induced by various external factors.

Figure 19 depicts the structure of the FIT. Like the hierarchy of the Florida transportation SoS, the composite index consists of multiple levels. The base level (i.e., the α level) contains select external factors for each transportation mode. The external factors are aggregated to form a higher level of information (i.e., FIT dimensions). These dimensions reflect the overall contexts of the external factors' impact and provide information useful for transportation planning. Combining the dimensions of the transportations modes yields transportation mode indexes. Aggregating transportation mode indexes construct three transportation system indexes (i.e., FIT system indexes) at the β level for ground transportation, air transportation, and sea transportation. These indexes are then integrated into a single index (i.e., FIT) at the γ level.

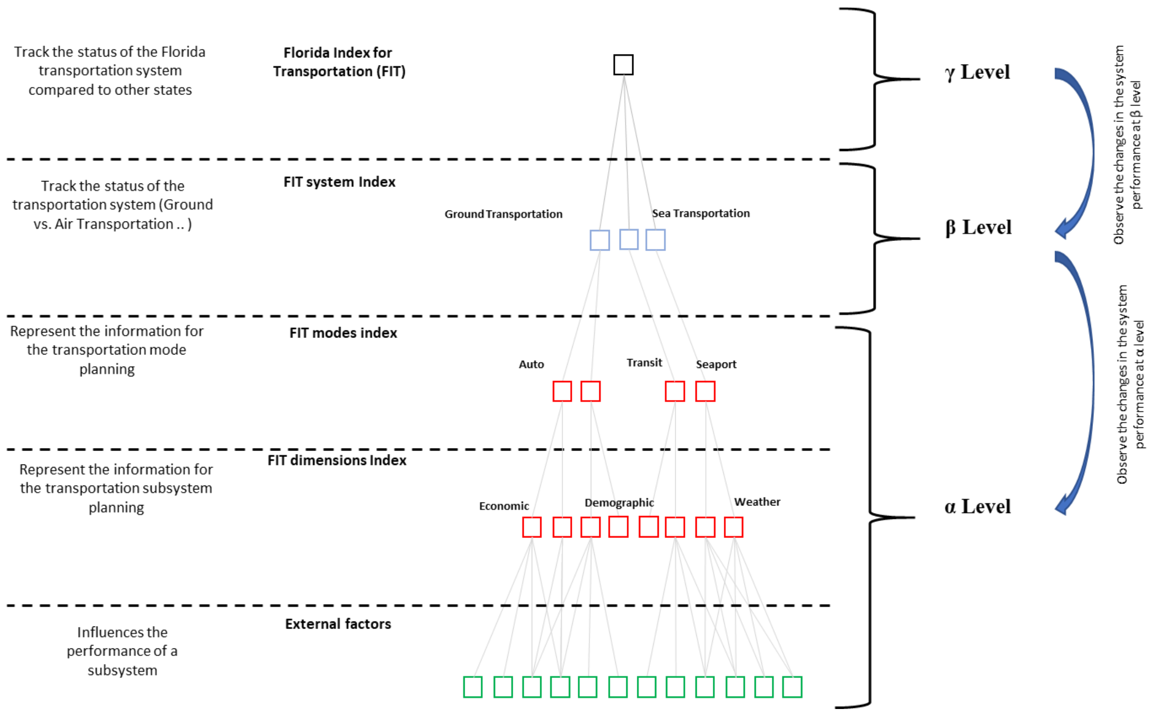


Figure 19: Structure of the FIT

FIT's structure effectively handles the abundant amount of information gathered from the analysis of external factors for transportation planning. Specifically, FIT enables transportation planners to first look at the broad spectrum of external factors, locate the roots of dynamics in a trend, and then track down and find the origins of emergent and evolutionary properties within the SoS.

To guide the planning process, FIT is proposed to measure changes in transportation demand or infrastructure need as a result of external factors. In other words, increasing FIT trends implies increasing transportation needs as the result of external factors, while decreasing FIT trends indicate decreasing transportation demand. However, just understanding how much demand exists is not useful to guide transportation planning. In addition to demand changes, planners also need to know how much demand the current transportation system has been able to accommodate. In other words, it is essential to compare FIT trends (i.e., demand) with transportation supply trends (i.e., capacity) for more informed planning. In this regard, a separate composite index called the "Florida Performance Index (FPI)" is developed with performance indicators available from the FDOT Source Book (Florida Department of Transportation 2018). Comparing the capacity of the transportation system (i.e., FPI) with transportation needs (i.e., FIT) enables decision makers to identify which transportation mode (α level) and system (β level), for example, require more investments as a result of the changing impact of external factors.

Figure 20 depicts the hierarchical structure of the FPI. Following the FDOT Source Book's categorization, the performance indicators at the base level (i.e., α level) are classified into two groups: mobility and safety. In the next level, FPI aggregates performance indicators to construct the transportation mode performance index. Similar to FIT, model-level indices are aggregated to develop system-level indices (i.e., β level). State transportation decision makers may use the information at the system level to compare performance trends among different transportation systems and investigate whether each transportation system meets desired performance levels. Finally, at its top-level (i.e., γ level), the FPI combines transportation system indices to develop a single index representing the Florida transportation system's overall performance.

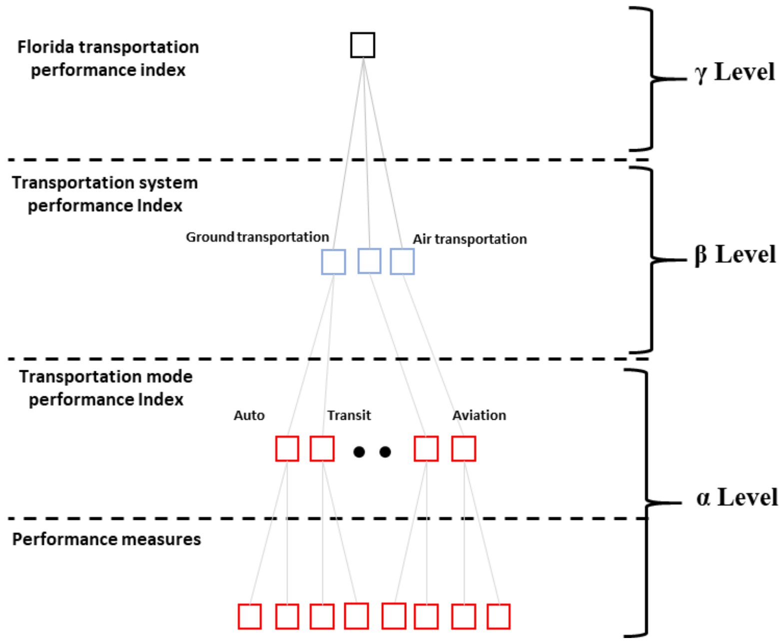


Figure 20: Structure of the FPI

Following the guidelines described in the handbook on constructing composite indicators (Joint Research Centre-European Commission 2008), the following steps were taken to develop the FIT and FPI.

1. Data selection to collect the required data for the analysis
2. Imputation of missing data to account for the different reporting frequencies of the data
3. Statistical analysis to assess the suitability of the data and explain methodological choices
4. Weighting of the indicators to account for the importance of and preferences concerning the external factors
5. Aggregation of the indicators to construct the composite index

In this section, the composite index development process is explained step by step, and the results are presented for each step.

3.3.1 Step 01: Data collection

Two sets of data are required to construct the composite indexes. The first dataset consists of information on the performance measures, and the second dataset includes information on the external factors. The team used performance measures data available in the 2019 FDOT Source Book. Table 8 contains the list of performance measures used in this study. The data for the external factors can be found by querying a variety of publicly available data sources. For example, many of the demographic and socioeconomic factors such as population, migration, percent of older adults, employment, and poverty rate were available from the US Census Bureau. For more obscure factors related to the regulatory framework or emerging technologies, data was often available from related federal or state agencies. For example, data on the availability of subsidies for and investments in renewable fuels were available from the

Department of Energy. Similarly, data for many environmental factors were available from the US Department of Environmental Protection, while data on many economic factors were obtained from the Federal Reserve Bank.

Proxy data for external factors

Unfortunately, data was not readily available for all of the factors identified through the factor identification process. However, this did not always mean that the factor was not measurable. When data to measure the factor directly was not available, the FSU research team identified proxies that would provide an indirect performance measure of each factor. For example, to measure weather-related inland flooding events, the team gathered data on the number of flood insurance claims filed (EF89 in Table 7). While this proxy does not measure flooding directly, it provides an effective proxy by measuring the impact of flooding.

Similarly, the viability of revenue streams (EF68 in Table 7) is an essential factor because it will determine transportation agencies' ability to adapt to external factors; however, since transportation funding is comprised of a range of funding sources, these factors proved too broad to measure directly. Consequently, the research team chose to use gas tax revenue as a proxy since it represents one of Florida's primary sources of transportation funding.

3.3.2 Step 02: Imputation of missing data

In this project, external factors and performance measures are observed at successive times (i.e., both are time series data). Different external factors or performance measures have various reporting frequencies, and data for analysis may be available only at a certain time frame. Data conversion methods from one frequency to another are thus needed. For example, population data are available on an annual basis. To obtain quarterly data, linear interpolation can be used, as illustrated in Figure 21. Assume that there is one observation of the population at the end of 2009 while another observation is available at the end of 2010. To estimate the population at the end of the second quarter of 2010, linear interpolation can be used, assuming that the population grows linearly over time. Clearly, such a data imputing method may introduce inaccuracies, while this is arguably the only viable way to derive quarterly population data with no further information.

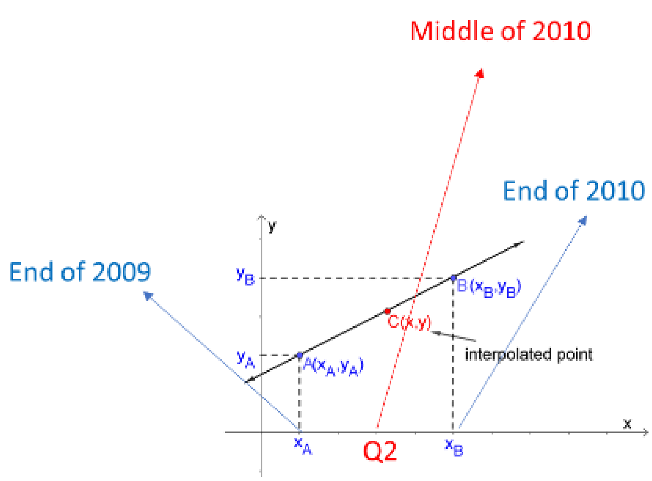


Figure 21: Illustration of linear Interpolation

In some cases, simply taking the sum or average yields the data at a new frequency. For example, summing up the monthly precipitation over months yields the quarterly precipitation. Dividing the annual net migration by four gives the quarterly net migration, assuming no seasonal effects are available.

Using such data conversion methods, both external factor and performance measure data were prepared on a quarterly basis. The documentation for external factors (Appendix D) provides details on what data conversion methods are used (if any) for an external factor; the documentation for performance measures (Appendix D) provides details on some performance measures data are converted. Table 11 lists all data conversion methods.

Table 11: Data conversion methods

Direction	Conversion Methods	Explanations
Monthly to Quarterly	Sum	To aggregate the number in each month over three months.
	Average	To take the average of three monthly values.
Annual to Quarterly	Equal Division	To divide the annual number equally by four.
	Linear Interpolation	The missing values between two annual values are filled with linearly interpolated values

Data cleaning. Data ranging from the first quarter of 2011 to the last quarter of 2018 was selected for the study. Other periods were not included primarily due to a lack of data. As there are eight years of data, the number of observations for each variable (external factor or performance measure) is 32 if no data is missing. We removed any variables with missing data in the selected time frame because the Granger causality analysis is not compatible with missing data. The number of external factors we analyzed thus dropped from 98 to 86, and the number of performance measures decreased from 67 to 58.

3.3.3 Step 03: Statistical analysis

In this section, the statistical analysis required for the development of FIT is explained. Statistical analysis was conducted to identify the most influential external factors at the FIT's base level (i.e., α level in Figure 19). In this regard, three types of statistical analyses were performed. Table 12 presents each statistical analysis, along with the purpose of the analysis. In the following subsections, each analysis is briefly explained, followed by the results in each section. Please note that the FPI is constructed using all performance measures. Therefore no statistical analysis was required to selected specific performance measures and develop FPI.

Table 12: Types of statistical analysis

Statistical Method	**Purpose**
Granger causality test	- Verifying whether values of an external factor help predict the value of a performance measure, i.e., whether the Granger causality exists between an external factor and a performance measure
Cross-correlation calculation	- Quantifying the correlation between an external factor and a performance measure, which can then be used to identify influential external factors for a transportation mode
Factor analysis	- Identify the latent factors in each set of external factors - Weigh each latent factor (or dimension) based on the explained variance of each factor.

3.3.3.1 Granger causality analysis

The Granger causality test is a statistical hypothesis test to determine whether a time series is useful in forecasting another. If so, the Granger causality is said to exist between the two time series; otherwise, not. The concept of Granger causality was first introduced by the Nobel prize winner, Clive W. J. Granger, in 1969 (Granger 1969, 1980). This technique enables the researchers to investigate the Granger causal relationships using a data-driven approach (Chicharro 2011). If changes in the values of variable X predict the changes in variable Y, then, observationally speaking, X is thought to cause Y. In its original formulation, the Granger causality test infers a causal interaction relying on the reduction of the prediction error of Y when including the past values of X. It should be noted that Granger causality means that the past values of X have a statistically significant effect on the current value of Y, taking past values of Y into consideration. The term "Granger causality" is used rather than true "causality" to avoid mistaking correlation as causation (Levendis 2018).

Intuitively, if we control for the history of y and find that the history of x could help predict y, we say x Granger causes y. The Granger causality test is performed in the following three-step procedure:

Step 1: Regress y on y lags without x lags (restricted model)

$$y_t = a_1 + \sum_{j=1}^{m} \gamma_j y_{t-j} + e_t \qquad \text{Equation 1}$$

Step 2: Add in x lags and regress again (unrestricted model)

$$y_t = a_1 + \sum_{i=1}^{n} \beta_i x_{t-i} + \sum_{j=1}^{m} \gamma_j y_{t-j} + e_t \qquad \text{Equation 2}$$

Step 3: Test null hypothesis that $\beta_i = 0 \ \forall i$ using an F-test. In other words, the null hypothesis is that X does not Granger cause Y.

The null hypothesis is that x does not Granger cause y, i.e., all β coefficients corresponding to past values of x are zero, or lagged values of x are not retained in the regression. The p-value from the F-test is used to determine whether the null hypothesis is rejected or not. If the p-value is less than a significance level (e.g., 0.05), then the null hypothesis can be rejected, and it can be concluded that the said lag of x is indeed useful. Therefore:

- If p-value < 0.05, the null hypothesis is rejected, and we would consider x is helpful in forecasting y or x Granger causes y.

- If p-value >= 0.05, the null hypothesis is not rejected, and x is not considered to be useful in forecasting y or x does not Granger cause y.

In this study, the Granger causality test was employed to study whether a specific external factor is helpful in forecasting the future values of a particular performance measure. Thus, the Granger causality test was conducted for all pairs of external factors and performance measures, and the presence of Granger causality relationship for each pair was reported

3.3.3.2 Cross-correlation analysis

The Pearson correlation coefficient is widely used to measure the linear association between two variables X and Y. However, the Pearson correlation coefficient may result in misleading results when time-series data are involved. The left two figures of Figure 22 show two randomly generated time series (data1 and data2), which are independent of each other. The Pearson correlation coefficient between data1 and data2 is -0.028, which is close to zero. That means there is no significant correlation between data1 and data2, as expected. When a common trend that grows over time is added to either random time series, the resulting time series are shown on the right of Figure 22. After adding a trendline, the new Pearson correlation coefficient is 0.996, which indicates a very strong correlation. Then, one may conclude that those two resulting time series are strongly correlated, which is not really true. The main reason for this very high Pearson correlation coefficient is that both the two resulting time series depend on the common trend or time. As a time series consists of a few components, including trend, seasonality, and noise, the Pearson correlation coefficient is not a good measure to quantify the correlation between two time series.

When analyzing the correlations between the two time series, the leading or lagging effect should be properly considered. Analyzing the potential lag is necessary because one variable might have a statistical effect on the other while the effect is not immediate and occurs only after a certain time or delay. This amount of time or delay is called a lag. As illustrated in Figure 23, the pattern in time series X is observed again in time series Y only after a certain time (a lag), which implies a lagging effect of X on Y. Figure 24 shows another example of the lagging effect. Two identical time series are shown; while one time series starts earlier than the other. The time series that starts earlier (in red) can be shifted to the right until it has the maximum overlap with the other series (blue). This amount of shifting is the time delay between two time series. If this shifting is not considered, directly measuring the correlation between two time series may show that those two identical time series are not strongly correlated. However, the correlation between those two time series should be very strong if this lagging effect is properly identified. Clearly, the Pearson correlation coefficient does not capture this effect.

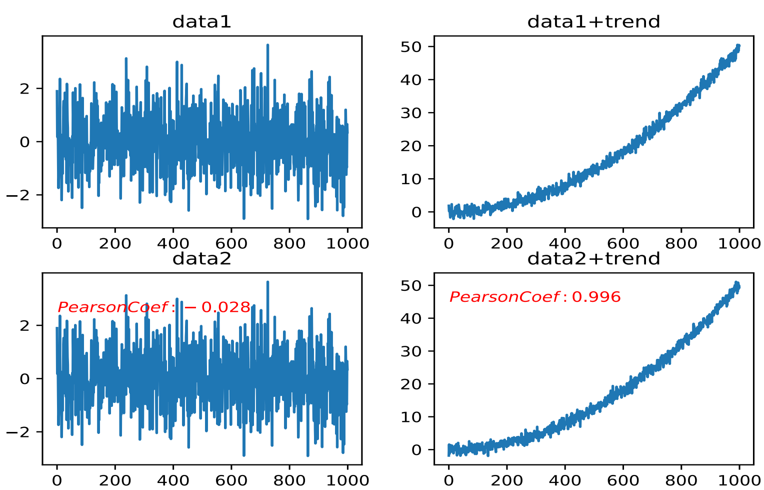


Figure 22: Examples of misleading results

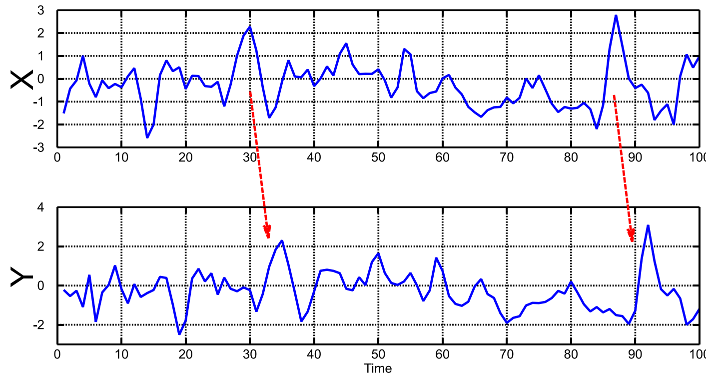


Figure 23: Illustration of lagging effect
(source: https://en.wikipedia.org/wiki/Granger_causality)

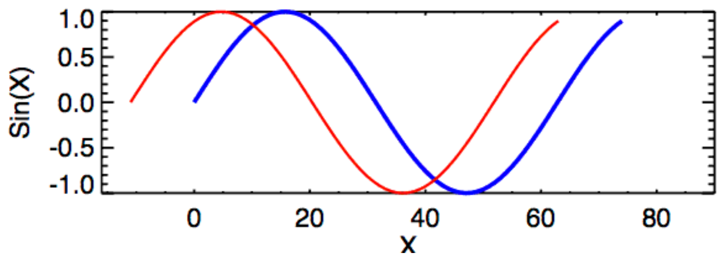


Figure 24: Illustration of two identical time series with an offset
(source: http://robosub.eecs.wsu.edu/wiki/ee/hydrophones/start)

Therefore, in a time series analysis, cross-correlation is used to quantify the correlation of two time series X and Y, which can be calculated as follows:

$$r_k = \frac{\sum_{i=1}^{n-k}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{(\sum_{i=1}^{n}(X_i - \bar{X})^2)(\sum_{i=1}^{n}(Y_i - \bar{Y})^2)}} \qquad \text{Equation 3}$$

For each possible lag, a cross-correlation value can be computed. The "optimal" lag can be found when the highest correlation coefficient is achieved.

The cross-correlation analysis is performed on all pairs of external factors and performance measures. Figure 25 shows the correlation matrix, which depicts the correlation results among all pairs of external factors and performance measures.

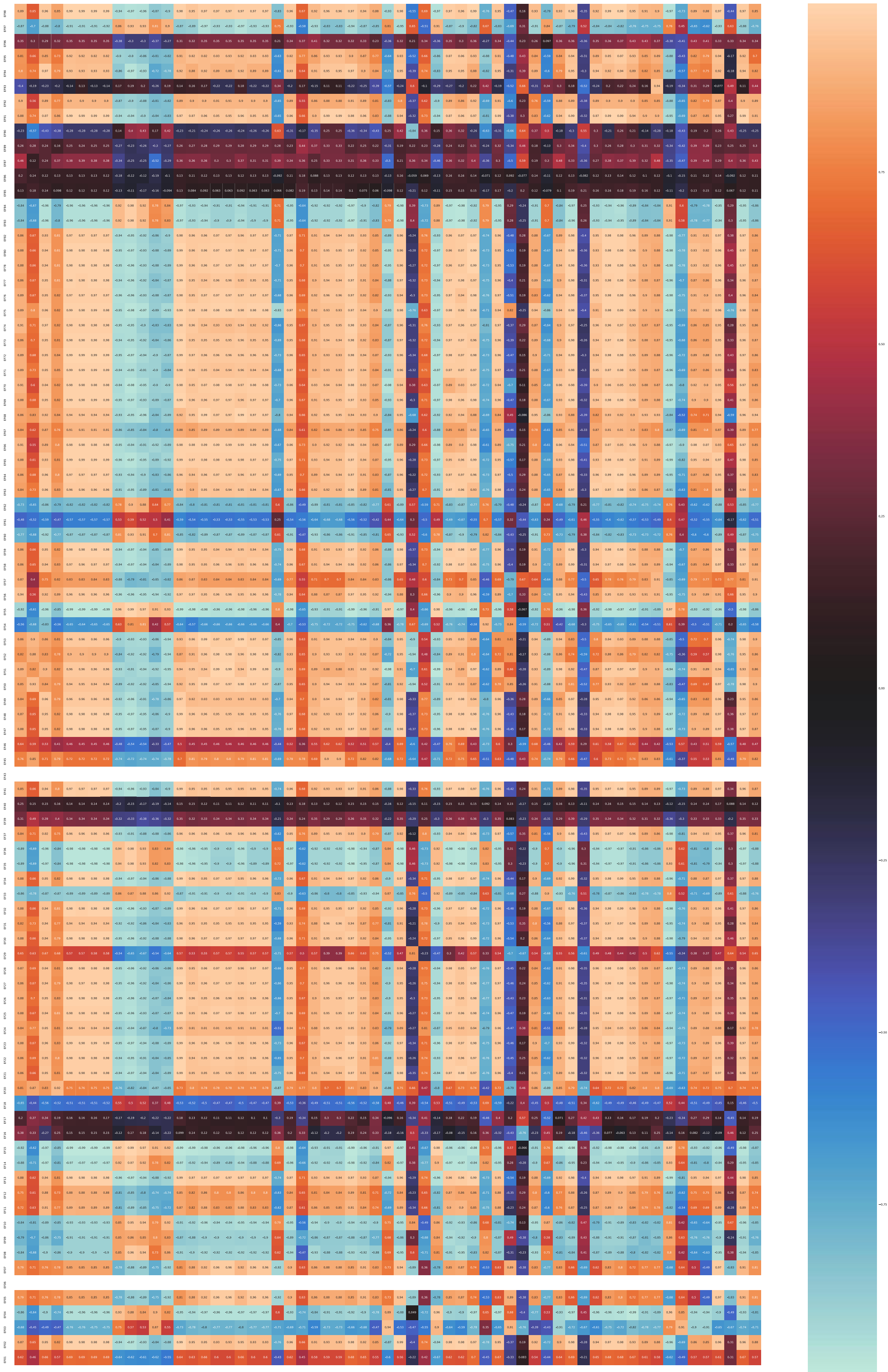


Figure 25: Heatmap of all cross-correlations

3.3.3.3 The process of selecting external factors for each mode

To select the most influential external factors for each transportation mode, both cross-correlation analysis and Granger causality analysis were performed together. To be more specific, the Granger causality analysis was performed first for each pair of external factors and performance measures to identify the external factors that had the Granger causality relationship with the performance measures of each mode. As a result, the lists of external factors with Granger causality relationships were prepared for each performance measure. Cross-correlation analysis was then performed for each pair of external factors and performance measures where a Granger causality relationship existed. The external factors were ranked based on their absolute correlation value. In the next step, for each performance measure, the top ten highly correlated external factors that have a Granger causality relationship were selected and combined. Finally, the top 10 external factors that were most frequently included in the combined list of external factors were selected for each mode. In situations where, multiple external factors had a similar number of appearances for the same mode, the external factors were further ranked based on their cross-correlation with the performance measures. Figure 26 illustrates the external factor selection process for each transportation mode.

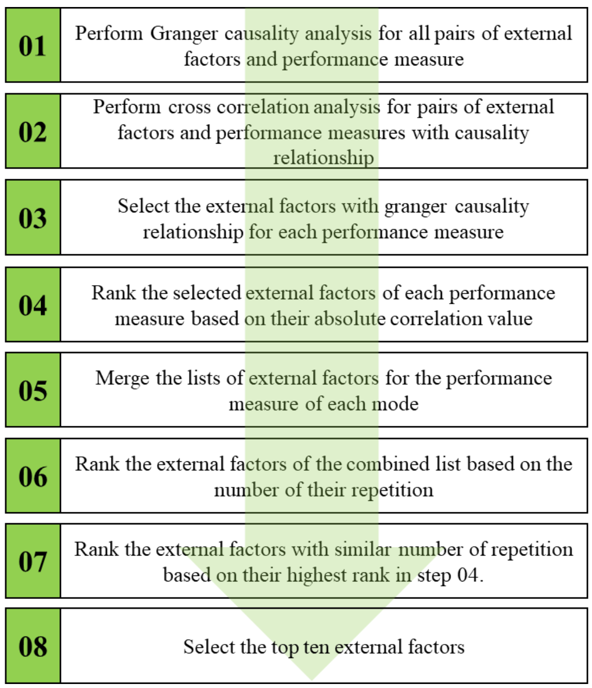


Figure 26: The selection process for factors for each mode

This selection process made it possible to identify the top 10 external factors for each transportation mode (Table 13). For each mode, the external factors are ranked from top to bottom in the tables.

Table 13: Selected external factors for each mode

	Code	External factor name		Code	External factor name
Auto	EF55	Percentage of Population in Poverty (SL)	**Transit**	EF70	GDP of FL- Construction (In Millions of Dollars) (SL)
	EF15	% Population in Poverty (NL)		EF55	Percentage of Population in Poverty (SL)
	EF68	Viability of Streams (Gas, tax, etc.) (Millions) (SL)		EF15	% Population in Poverty (NL)
	EF66	Number of Licensed Drivers (SL)		EF51	International Migration (SL)
	EF53	Net Migration (SL)		EF31	Consumer Price Index (CPI) (NL)
	EF50	FL Population Change (SL)		EF49	Alabama Population (SL)
	EF65	Number of Housing Units (SL)		EF66	Number of Licensed Drivers (SL)
	EF69	GDP- FL All Industries (In Millions of Dollars) (SL)		EF41	Number of Smartphone Users (NL)
	EF91	Highway Operations and Maintenance Decisions (Millions) (SL)		EF65	Number of Housing Units (SL)
	EF52	Domestic Migration (SL)		EF80	CPI–Rent Price Index (SL)

Table 13: Selected external factors for each mode (Continued)

	Code	External factor name		Code	External factor name
Pedestrian and Bike	EF14	Population in College (NL)	**Truck**	EF13	Number of Housing Units (NL)
	EF36	Percentage of Unemployed (NL)		EF65	Number of Housing Units (SL)
	EF35	Number of Unemployed (NL)		EF30	House Price Index (NL)
	EF59	Seniors Population (65+) (SL)		EF15	% Population in Poverty (NL)
	EF94	Fuel Taxes (SL)		EF91	Highway Operations and Maintenance Decisions (Millions) (SL)
	EF08	Rental Vacancy Rate (NL)		EF66	Number of Licensed Drivers (SL)
	EF84	Percentage of Unemployed (SL)		EF55	Percentage of Population in Poverty (SL)
	EF58	Political Party Affiliation (other) (SL)		EF32	CPI–Rent Price Index (NL)
	EF02	Population Estimate (NL)		EF37	Financial Markets (Dow Jones Avg Closing Price) (NL)
	EF83	Number of Unemployed (SL)		EF78	House Price Index (SL)

Table 13: Selected external factors for each mode (Continued)

	Code	External factor name		Code	External factor name
Rail	EF15	% Population in Poverty (NL)	**Aviation**	EF76	Personal Income (In Millions of Dollars) (SL)
	EF36	Percentage of Unemployed (NL)		EF31	Consumer Price Index (CPI) (NL)
	EF35	Number of Unemployed (NL)		EF98	Number of Tourists to Orlando (SL)
	EF10	Homeownership Rate (NL)		EF54	Population in College (SL)
	EF20	Immigration (NL)		EF04	Natural Increase - Births (NL)
	EF08	Rental Vacancy Rate (NL)		EF30	House Price Index (NL)
	EF55	Percentage of Population in Poverty (SL)		EF95	Privatization of Roads (SL)
	EF70	GDP of FL- Construction (In Millions of Dollars) (SL)		EF27	Per Capita Income (NL)
	EF29	Financial Condition Index (NL)		EF80	CPI–Rent Price Index (SL)
	EF33	CPI–Fuel Price Index (NL)		EF14	Population in College (NL)

Table 13: Selected external factors for each mode (Continued)

Mode	Code	External factor name
Seaport	EF22	GDP–All industries (NL)
	EF15	% Population in Poverty (NL)
	EF55	Percentage of Population in Poverty (SL)
	EF49	Alabama Population (SL)
	EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)
	EF24	GDP - Manufacturing (NL)
	EF51	International Migration (SL)
	EF34	Number of Employed (NL)
	EF04	Natural Increase - Births (NL)
	EF23	GDP - Construction (NL)

3.3.3.4 Normalization of the external factors

Because the data for each external factor (in FIT) is measured in different units, normalization is required to unify the scale of the data. The standardization normalization method was performed before applying factor analysis (FA). This method converts the data to a common scale with a mean of zero and unit variance. Equation (4) shows the formula for the normalization process where X^t is the value for the external factor at each time interval, while μ and σ are the average and standard deviations, respectively, of the data for the external factor in the time frame. Thus, the mean (μ) of the data over time as well as its standard deviation (σ) is calculated for each external factor. Then the scaled value of the external factor at each time interval is calculated using Equation (4).

$$\mathrm{X}^{\mathrm{t}}_{\mathrm{Scaled}} = \frac{\mathrm{X}^{\mathrm{t}} - \mu}{\sigma} \qquad \text{Equation 4}$$

3.3.3.5 Factor analysis

FA is a statistical method to describe variability among observed, correlated variables using a lower number of variables called latent factors. To be more specific, consider a case where ten external factors are selected as the most influential ones for a transportation mode. Using FA, the variation explained in these ten external factors could potentially be described by two to three unobserved variables. FA searches for such joint variations in response to unobserved latent variables. The assumption behind the theory of FA is that the information resulting from the correlation of the observed variables can be used to derive the smaller number of unobserved variables to explain variances among the observed variables. In this regard, the FA model can be interpreted as a set of regression equations between the original variables, the unobserved variables, and a set of error terms. The FA model is given by

$$\begin{aligned} X_1 &= \alpha_{11}F_1 + \alpha_{12}F_2 + \cdots + \alpha_{1m}F_m + e_1 \\ X_2 &= \alpha_{21}F_1 + \alpha_{22}F_2 + \cdots + \alpha_{2m}F_m + e_2 \\ &\dots \\ X_Q &= \alpha_{Q1}F_1 + \alpha_{Q2}F_2 + \cdots + \alpha_{Qm}F_m + e_Q \end{aligned} \qquad \text{Equation 5}$$

where X_i (i=1, …, Q) represents the original variables that are standardized with zero mean and unit variance, F_j (j=1, …, m) stands for the corresponding latent factors, and $\alpha_{ij}((i = 1, \dots, Q), (j = 1, \dots, m))$ is the factor loading related to each variable. The latent factors are uncorrelated common factors, each with zero mean and unit variance. Furthermore, e_i is the specific factor that is considered to be independently and identically distributed with zero mean.

Each latent factor describes a portion of the variance of the original data. In this regard, the squared factor loading represents the portion of the variation in the observed variable, which is described by the latent factor. Therefore, the total variance explained by each latent factor is the sum of the squared factor loading of that latent factor. The ratio of the total variance explained to the number of observed variables gives the proportional variance explained by each latent factor. (Note that the observed variables are standardized to have zero mean and unit variance; thus, the number of variables equals the total variance.)

To decide the number of latent factors that can represent the Q observed variables, first, the FA is performed to get the Q number of latent factors to ensure that the variance among the observed variables is described by the latent factors. Then, in the second step, a lower number of latent factors is extracted based on the first step results. The decision about when to stop obtaining factors depends on when there is only minimal "random" variability left. Multiple approaches have been proposed in the literature to determine the number of latent factors. Variance explained criteria is one of the proposed criteria where researchers simply use the rule of keeping enough latent factors to account for at least 90% of the variation. Therefore, the top n latent factors that cumulatively can describe at least 90% of the variation will be extracted. Another strategy is called the Kaiser criterion. In this strategy, all latent factors with eigenvalues below 1.0 will be dropped. Also, latent factors could be selected based on their individual explained variance. In this case, any factors with an overall 10% individual explanation of the variation will be kept.

The latent factors are unobserved variables that can describe the variance of observed data. Thus, it is essential to understand which observed variables can be best explained by which latent factor. In other words, we need to identify which observed variables are loaded on each latent factor. Factor rotation is used to minimize the number of individual observed variables that have a high loading on the same latent factor. The objective of the rotation strategy is to obtain a more straightforward structure where each observed variable is exclusively loaded on one of the latent factors. Therefore, rotation enhances the interpretability of the results by clarifying which observed variables are dominating each latent factor. Various rotation strategies have been proposed in the literature. The varimax and Promax rotation methods are two common types of rotation strategies. Varimax rotation rotates the factor loading matrix to maximize the sum of the variance of squared loadings while preserving the orthogonality of the loading matrix. The ProMax rotation is used for oblique rotation. This rotation method builds upon varimax rotation but ultimately allows factors to become correlated.

In this study, the observed variables are the top 10 external factors selected for each mode. The data for these external factors were standardized with zero mean and unit variance. Then FA was carried out to find the unobserved latent factors. Variance explained criteria were used to determine the number of latent factors to extract. In this study, the top n latent factors, which cumulatively can describe at least 95% of the variation, were obtained. For example, Table 14 displays the results of the FA for the auto mode. The results show that the first two latent factors cover more than 95 percent of the cumulative variation; thus, the first two latent factors were selected for the auto mode.

Table 14: Factor analysis results (eigenvalues and variance) for the auto mode

	EV	Proportional Variance	Cumulative Variance
1	8.35	0.83	0.83
2	1.51	0.15	0.98
3	0.09	0.01	0.99
4	0.03	0.00	1.00
5	0.01	0.00	1.00
6	0.01	0.00	1.00
7	0.00	0.00	1.00
8	0.00	0.00	1.00
9	0.00	0.00	1.00
10	0.00	0.00	1.00

The latent factors are dimensions of the observed variables (which are the external factors in this study). After the latent factors were identified, the external factors loaded on each dimension were explored to investigate the implication of the dimensions of the transportation mode. In order to improve the interpretability of the grouped external factors for each dimension, the factor loadings were extracted and rotated using the Promax rotation method. From there, the squared value of the loadings was calculated and scaled to have a unit sum. Finally, the most relevant dimension for each external factor was identified based on the value of the scaled squared factor loading. Table 15 shows this process using the auto mode as an example. The highlighted cells on the right-hand side of the table show the external factors selected for each dimension. That is, EF55, EF15, EF66, EF65, EF69, and EF91 were selected for the first latent factor (or dimension), while EF68, EF53, and EF50 were selected for the second latent factor (or dimension). Please refer to Appendix E for the details of factor analysis results for other transportation modes.

Table 15: Factor analysis results (factor loadings) for the auto mode

	EF	External Factors	Factor Loading				Squared Factor Loading (Scaled to Unity)			
			1	2	3	4	1	2	3	4
Auto	EF55	Percentage of Population in Poverty (SL)	-0.9073	-0.1298			**0.14**	0.00		
	EF15	% Population in Poverty (NL)	-0.8986	-0.1419			**0.14**	0.01		
	EF68	Viability of Streams (Gas, tax, etc.) (Millions) (SL)	0.4101	0.6623			0.03	**0.12**		
	EF66	Number of Licensed Drivers (SL)	1.1492	-0.2791			**0.23**	0.02		
	EF53	Net Migration (SL)	0.0685	0.9520			0.00	**0.24**		
	EF50	FL Population Change (SL)	-0.0829	1.0463			0.00	**0.29**		
	EF65	Number of Housing Units (SL)	0.9993	-0.0016			**0.17**	0.00		
	EF69	GDP- FL All Industries (In Millions of Dollars) (SL)	0.9435	0.0755			**0.15**	0.00		
	EF91	Highway Operations and Maintenance Decisions (Millions) (SL)	0.8831	0.1225			**0.13**	0.00		
	EF52	Domestic Migration (SL)	-0.1194	1.0683			0.00	**0.31**		
		Explained Variance	5.81406	3.71636	0	0				

Tables 16–22 provide a list of the external factors for each analyzed mode. The external factors are grouped by dimension. Factors listed under each dimension are correlated. In many cases, the relationship between the factors is apparent. In the literature and in practice, once the external factors that are correlated under each dimension have been identified, each dimension needs to

be named by combining the meaning of the grouped factors and based on the interaction with end users (i.e., how end users interpret the combined meaning of factors; (Naderpajouh et al. 2016). When factors are all closely aligned, this task is very intuitive. In some cases, one or more correlating factors may not have an apparent connection to the other factors, which may make the naming process more difficult. The project team has attempted to come up with a name for each dimension under each of the analyzed modes. As noted, these names are rarely a perfect fit, but help in differentiating between dimensions and modes and in describing and applying the index.

Table 16 shows the external factors for each dimension of the auto mode. Based on the implication of the grouped external factors, the meaning of each dimension is determined. For example, the external factors grouped under the first latent factor are commonly related to the community's economic status. Poverty factors represent the population with poor financial conditions. The number of licensed drivers and the number of housing units represents the ability of the community to afford two essential categories of living costs (house and car). The last two factors (GDP and highway operations) also represent the community wealth available to spend on development. On the other hand, factors grouped under the second category are mostly related to population change. For example, migration factors contribute to the change in the population, while the state's tax revenue reflects the change in the population as well.

Table 16: Subdimension interpretation of the auto mode

<table>
<tr><th colspan="3">Auto</th></tr>
<tr><td colspan="2">Factors in the first dimension</td><td rowspan="2"></td></tr>
<tr><td>Code</td><td>EF Name</td></tr>
<tr><td>EF55</td><td>Percentage of Population in Poverty (SL)</td><td rowspan="6">Economic status of Florida</td></tr>
<tr><td>EF15</td><td>% Population in Poverty (NL)</td></tr>
<tr><td>EF66</td><td>Number of Licensed Drivers (SL)</td></tr>
<tr><td>EF65</td><td>Number of Housing Units (SL)</td></tr>
<tr><td>EF69</td><td>GDP- FL All Industries (In Millions of Dollars) (SL)</td></tr>
<tr><td>EF91</td><td>Highway Operations and Maintenance Decisions (Millions) (SL)</td></tr>
<tr><td colspan="2">Factors in the second dimension</td><td rowspan="2"></td></tr>
<tr><td>Code</td><td>EF Name</td></tr>
<tr><td>EF68</td><td>Viability of Streams (Gas, tax, etc.) (Millions) (SL)</td><td rowspan="4">Population change in Florida</td></tr>
<tr><td>EF53</td><td>Net Migration (SL)</td></tr>
<tr><td>EF50</td><td>FL Population Change (SL)</td></tr>
<tr><td>EF52</td><td>Domestic Migration (SL)</td></tr>
</table>

In the next subsection, the results of the FA for other modes are presented. The factors contributing to each dimension of the mode and the interpretations of the dimensions are presented. More detailed results of the FA for each mode, including the eigenvalues, explained variances, and factor loadings, are presented in Appendix E.

3.3.3.6 Dimensions of other transportation modes

Pedestrian and bike. A single dimension was found for the pedestrian and bike mode. Table 17 shows how the latent factor for the pedestrian and bike mode was interpreted. Based on the group of external factors found for this mode, the latent factor was determined to be related to vulnerable populations since the grouped external factors are mostly related to the unemployed and senior populations who represent economically vulnerable populations. Specifically, EF36, EF35, EF84, and EF83 being directly related to unemployment at both the national and state levels. Also, EF14 and EF59 are correlated with unemployment because a high underemployment rate is often considered as one of the consequences of the aging society (Akanni and Čepar 2015) and often leads to a high retirement rate and higher educational enrollment (Schmidt 2018). On the other hand, high tax rates (EF94) can discourage work, saving, investment, and innovation, leading to less growth (Vartia 2008) and making people more financially vulnerable. Finally, higher vacancy rates (EF08) imply less demand for housing units and represent higher unemployment, less GDP, and less individual income (Painter and Redfearn 2002; Pashardes and Savva 2009).

Table 17: Dimension interpretation of the pedestrian and bike mode

Pedestrian and Bike		
Factors in the first dimension		
Code	EF Name	
EF14	Population in College (NL)	Vulnerable populations
EF36	Percentage of Unemployed (NL)	
EF35	Number of Unemployed (NL)	
EF59	Seniors Population (65+) (SL)	
EF94	Fuel Taxes (SL)	
EF08	Rental Vacancy Rate (NL)	
EF84	Percentage of Unemployed (SL)	
EF58	Political Party Affiliation (other) (SL)	
EF02	Population Estimate (NL)	
EF83	Number of Unemployed (SL)	

Truck. As a result of the FA, a single dimension was found for the truck mode (Table 18). Considering the external factors, this dimension was interpreted as housing demand. In this regard, EF13 and EF65 are the number of housing units, which reflect the availability of housing units at both state and national levels. Moreover, EF30, EF32, and EF78 are all related to housing expenses, which are good indicators of supply with respect to demand for housing (Gasparėnienė et al. 2016). In addition, an increase in the need for housing units is associated with people’s positive economic outlook and higher expectations for financial gains in the future (Li 2015; Painter and Redfearn 2002). In this regard, the remaining external factors are associated with individuals’ economic conditions and thus represent overall housing demand as well. Specifically, while EF15 and EF55 are directly related to people’s poverty level and economic condition, EF66 connects to the community’s financial situation because increasing licensed drivers means the community is more able to afford automobiles. Finally, EF37 measures the stock performance of the 30 largest companies listed on stock exchanges in the United States. In other words, EF37 represents an overall economic growth rate. Because the economic growth rate is correlated to the overall income rate of the people (Stone 2017), EF37 may be related to the housing demand.

Table 18: Dimension interpretation of the truck mode

Truck		
Factors in the first dimension		
Code	EF Name	
EF13	Number of Housing Units (NL)	Housing demand
EF65	Number of Housing Units (SL)	
EF30	House Price Index (NL)	
EF15	% Population in Poverty (NL)	
EF91	Highway Operations and Maintenance Decisions (Millions) (SL)	
EF66	Number of Licensed Drivers (SL)	
EF55	Percentage of Population in Poverty (SL)	
EF32	CPI–Rent Price Index (NL)	
EF37	Financial Markets (Dow Jones Avg Closing Price) (NL)	
EF78	House Price Index (SL)	

Transit. Table 19 presents how the dimensions of the transit mode are interpreted. In this regard, the first dimension includes EF70 and EF65, which represent the community wealth spent on housing sector development. These factors imply existing demand for the housing sector, which is correlated with higher individual income rates and expectations for better financial gains in the future (Li 2015; Painter and Redfearn 2002). Furthermore, EF55, EF66, and EF41 indicate a community's financial condition since EF55 is directly related to the poverty level, and EF66 and EF41 represent the ability of the community to afford more expensive commodities such as automobiles and smartphones. Finally, EF31 and EF80 are related to the living costs of the community because they include consumer price indexes. Considering these three groups of factors, the first dimension is held to represent the economic condition of Florida residents. On the other hand, the second latent factor is called international migration. International migration usually happens when workers seek better economic conditions in foreign countries with better job opportunities (Castelli 2018). In other words, they are moving out from countries where the financial situation is worse than the destination country (the U.S. in this case). These international workers are not considered permanent residents of the host country, at least not in the early years of their entry. Moreover, foreign workers are usually poorer than native workers due to their worse economic backgrounds and lower earning rates compared to their native-born counterparts (Blau and Kahn 2015). Therefore, increasing international migration increases the low-income group of a community (Blau and Kahn 2015). Moreover, due to their poor economic condition, they are likely to be considered as a population living in poverty during their limited residency period. Thus, the two factors in the second dimension of the transit mode were interpreted as representing international migration.

Table 19: Dimension interpretation of the transit mode

Transit		
Factors in the first dimension		
Code	EF Name	
EF70	GDP of FL- Construction (In Millions of Dollars) (SL)	Economic condition of Florida residents
EF55	Percentage of Population in Poverty (SL)	
EF31	Consumer Price Index (CPI) (NL)	
EF49	Alabama Population (SL)	
EF66	Number of Licensed Drivers (SL)	
EF41	Number of Smartphone Users (NL)	
EF65	Number of Housing Units (SL)	
EF80	CPI–Rent Price Index (SL)	
Factors in the second dimension		
Code	EF Name	
EF15	% Population in Poverty (NL)	International migration
EF51	International Migration (SL)	

Rail. The interpretation of the dimensions of the rail transportation mode is presented in Table 20. Based on the external factors contributing to the first dimension, it represents unemployment because it includes employment factors (EF35 and EF36) and poverty factors (EF15 and EF55), which increase by unemployment. The second dimension contains factors indicating living expenses, including housing expenses (EF10 and EF08) and fuel price expenses, in its group of correlated external factors. Finally, the third dimension is interpreted as covering national economic attractiveness since emigrants are likely to choose a country with robust and promising financial conditions when leaving their own countries.

Table 20: Dimension interpretation of the rail mode

Rail		
Factors in the first dimension		
Code	EF Name	
EF15	% Population in Poverty (NL)	Unemployment
EF36	Percentage of Unemployed (NL)	
EF35	Number of Unemployed (NL)	
EF55	Percentage of Population in Poverty (SL)	
EF70	GDP of FL- Construction (In Millions of Dollars) (SL)	
Factors in the second dimension		
Code	EF Name	
EF10	Homeownership Rate (NL)	Living expenses
EF08	Rental Vacancy Rate (NL)	
EF33	CPI–Fuel Price Index (NL)	
Factors in the third dimension		
Code	EF Name	
EF20	Immigration (NL)	National Economic Attractiveness
EF29	Financial Condition Index (NL)	

Seaport. As a result of FA, two dimensions were found for the seaport mode (Table 21). The first dimension is interpreted as representing economic well-being as it includes four GDP-related external factors (EF22, EF72, EF24, and EF23) and one economic-related factor (EF34). Moreover, similar to the second dimension of the transit mode, the second dimension of the seaport mode is also interpreted as covering international migration since it includes external factors related to international migration and poverty.

Table 21: Dimension interpretation of the seaport mode

Seaport		
Factors shown up in the first dimension		
Code	EF Name	
EF22	GDP–All industries (NL)	Economic well-being
EF49	Alabama Population (SL)	
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)	
EF24	GDP - Manufacturing (NL)	
EF34	Number of Employed (NL)	
EF04	Natural Increase - Births (NL)	
EF23	GDP - Construction (NL)	
Factors shown up in the second dimension		
Code	EF Name	
EF51	International Migration (SL)	International migration
EF15	% Population in Poverty (NL)	
EF55	Percentage of Population in Poverty (SL)	

Aviation. Two dimensions were found for the aviation mode as a result of the FA (Table 22). The first dimension of the aviation transportation mode includes EF76 and EF27, which are directly related to people’s income levels. At the same time, EF98 is associated with the income of a community since tourism improves economic growth (Adnan Hye and Ali Khan 2013) and economic growth is associated with personal income (Stone 2017). On the other hand, EF31, EF30, and EF80 are correlated with the expenditures of the people in the community. Considering these two groups of factors along with their relationship, the first dimension is interpreted as spending power. The second dimension includes factors related to the population in college. A substantial increase in the college population, especially in cities where the majority of the population are college students, may increase the need for road infrastructure (Dill and Voros 2007; Eren and Uz 2020). State agencies may work with the private sector to provide the required infrastructure to meet increasing travel demand, and they are unlikely to be considered taxpayers. Privatization of roads can be taken into consideration in the form of public-private-partnership contracts to attract funding from the private sector so that state agencies can secure any required financing.

Table 22: Dimension interpretation of the aviation mode

Aviation		
Factors in the first dimension		
Code	EF Name	
EF76	Personal Income (In Millions of Dollars) (SL)	Spending power
EF31	Consumer Price Index (CPI) (NL)	
EF98	Number of Tourists to Orlando (SL)	
EF04	Natural Increase - Births (NL)	
EF30	House Price Index (NL)	
EF27	Per Capita Income (NL)	
EF80	CPI–Rent Price Index (SL)	
Factors in the second dimension		
Code	EF Name	
EF54	Population in College (SL)	Population in college
EF95	Privatization of Roads (SL)	
EF14	Population in College (NL)	

3.3.4 Step 04: Weighting processes

3.3.4.1 FIT weighting mechanism

Five levels of a weighting process are considered to acknowledge the natural impact of the external factors as well as decision maker preferences. In other words, transportation planners have the opportunity to customize the composite index based on their objectives and areas of interest. Figure 27 shows the various categories of weights that can be applied to the different levels of the composite index. While two of the weighting sets are applied to the corresponding indicators based on their importance in explaining variance, the other three weighting sets can be specified by the decision makers at different levels. The five weighting sets specified in Figure 27 are explained in detail in the following subsections.

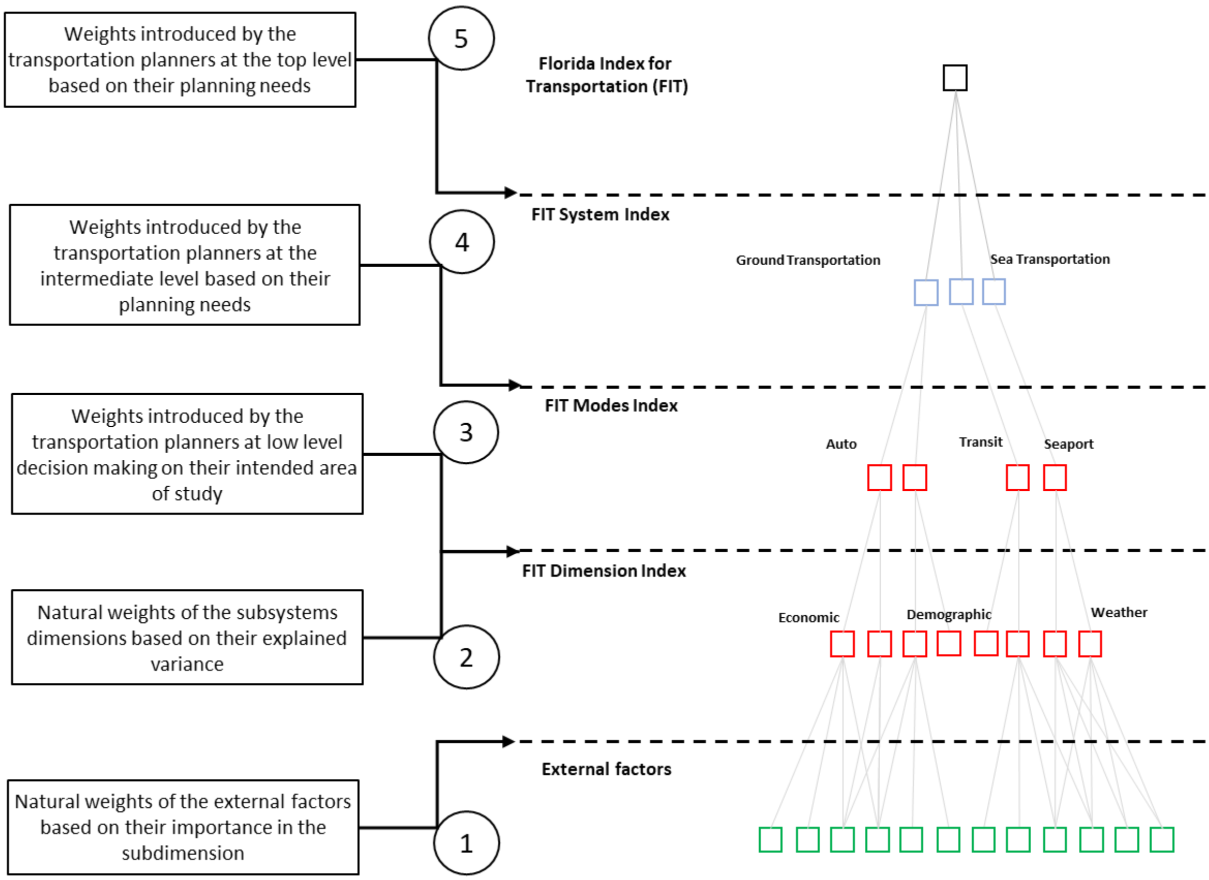


Figure 27: Weighting mechanism of the external factors

Weighting set 01 with reference to Figure 27. A single set of weights is applied to the external factors at the base level for aggregation to FIT dimensions. These weights are calculated for each external factor based on the results of the FA. As a result of FA, the loading of each external factor for each dimension is calculated. The factor loading represents the extent to which each external factor represents each dimension. According to the handbook on constructing the composite index, each external factor's weight is calculated based on the squared factor loading value (i.e., with higher weights for the factors better representing the latent factor; (Joint Research Centre-European Commission 2008). For example, the scaled squared factor loadings of the auto mode dimensions are presented in Table 23. These values are used to calculate the weight for each external factor. In this regard, the squared factor loadings are scaled to unity to be considered as their corresponding weights for calculating their latent factors. While all of the grouped factors collectively determine each dimension, the factors with higher weights (e.g., EF66 Number of Licensed Drivers (SL) for Dimension one [Economic status in Florida] and EF 52 Domestic Migration (SL) for Dimension two [Population Change in Florida]) are more important for determining the meaning of each dimension.

Table 23: External factors' weights for the auto mode

Dimension	External factor	Scaled squared factor loading	Weight
1	EF55	0.14	0.1465
	EF15	0.14	0.1437
	EF66	0.23	0.2350
	EF65	0.17	0.1777
	EF69	0.15	0.1584
	EF91	0.13	0.1388
2	EF68	0.12	0.1225
	EF53	0.24	0.2531
	EF50	0.29	0.3057
	EF52	0.31	0.3187

The weights for the external factors in each dimension for the other modes are presented in Table 24. The weights for each dimension are scaled to unity.

Table 24: Aggregation weights of the external factors at the base level

Pedestrian and Bike			Transit			Truck		
Dimension	**External factor**	**Weight**	**Dimension**	**External factor**	**Weight**	**Dimension**	**External factor**	**Weight**
Economic stagnation	EF14	0.101	Economic condition of Florida residents	EF70	0.112	Economic status of the community	EF13	0.102
	EF36	0.102		EF55	0.085		EF65	0.102
	EF35	0.102		EF31	0.174		EF30	0.102
	EF59	0.101		EF49	0.105		EF15	0.100
	EF94	0.098		EF66	0.156		EF91	0.096
	EF08	0.090		EF41	0.106		EF66	0.094
	EF84	0.102		EF65	0.127		EF55	0.100
	EF58	0.099		EF80	0.136		EF32	0.102
	EF02	0.102	International migration	EF15	0.092		EF37	0.098
	EF83	0.102		EF51	0.908		EF78	0.102

Table 24 (Continued): Aggregation weights of the external factors at the base level

Aviation			Rail			Seaport		
Dimension	**External factor**	**Weight**	**Dimension**	**External factor**	**Weight**	**Dimension**	**External factor**	**Weight**
Spending power	EF76	0.168	Economic condition	EF15	0.202	National GDP per capita	EF22	0.156
	EF31	0.092		EF36	0.155		EF49	0.123
	EF98	0.095		EF35	0.155		EF72	0.108
	EF04	0.138		EF55	0.209		EF24	0.221
	EF30	0.187		EF70	0.280		EF34	0.114
	EF27	0.141	Living expenses	EF10	0.567		EF04	0.171
	EF80	0.179		EF08	0.219		EF23	0.108
Population in college	EF54	0.519		EF33	0.214	International migration	EF15	0.141
	EF95	0.376	National Economic Attractivenes	EF20	0.424		EF55	0.140
	EF14	0.105		EF29	0.576		EF51	0.719

Weights at the dimension level

Weighting set 02 with reference to Figure 27. The first set of weights at the dimension level is calculated based on the importance of the latent factor (dimension) in explaining the variance of the data. In this regard, the proportional explained variance for each dimension is considered its weight. As described previously, the explained variance for each latent factor is the sum of the squared factor loading for each latent factor (before scaling to unity). Moreover, the proportional explained variance is calculated by dividing the total explained variance of each latent factor by the number of observed variables. The calculated proportional variance is then scaled to unity to be considered the weight for the latent factors. Table 25 contains the weighting set 02 for each mode.

Table 25: Dimension weights of the modes

Mode	Dimension	Weight
Auto	1	0.61
	2	0.39
Pedestrian and Bike	1	1.00
Rail	1	0.50
	2	0.29
	3	0.20
Transit	1	0.83
	2	0.17
Truck	1	1.00
Aviation	1	0.77
	2	0.23
Seaport	1	0.77
	2	0.23

Weighting set 03 with reference to Figure 27. Different contexts for policy and decision making translate to different levels of importance for each dimension. To accommodate these varied decision making needs, the second set of weights is designed to reflect the decision makers' inputs to determine each subsystem's dimension's importance. In this regard, the decision makers who are in charge of the planning for a single transportation mode can give different weights to each dimension based on their preferences. For example, "economic status of Florida" and "population change in Florida" are two auto mode dimensions. Decision makers focused on the auto mode can weigh the demographic dimension more heavily than the economic dimension or vice versa.

Since in this level, two sets of weights should be applied to the indicators (i.e., the dimension level), the two sets of weights will be multiplied by each other and scaled to unity to be used for weighting purposes. This process is demonstrated in Table 26.

Table 26: Example for the aggregation of weights at the same level

Dimension	**Weights calculated based on explained variance**	**Weights introduced by the decision maker**	**Preliminary weight**	**Scaled weight**
LF1	W1	W3	W1*W3 = W5	W5/(W5+W6)
LF2	W2	W4	W2*W4=W6	W6/(W5+W6)

Weights at the mode level

Weighting set 04 with reference to Figure 27. The decision makers can specify the single set of weights at the mode level at the intermediate level to reflect their different priorities for each mode based on their planning needs. Thus, these individuals who are making plans relevant to their transportation systems (i.e., either ground transportation, air transportation, or sea transportation) can weigh the different modes. For example, intermediate planners may want to focus more on the transit mode than the auto mode.

Weights at the transportation system level

Weighting set 05 with reference to Figure 27. Decision makers again control the final weighting set designed for FIT at the high level of transportation planning. Using this weighting set, planners can weight different transportation systems based on their focus areas.

3.3.4.2 FPI weighting mechanism

FPI allows transportation planners to vary the weight of its components at three levels based on their planning contexts. In the first weighting set (i.e., weighting set 01 in Figure 28), transportation planners can assign relative weights to mobility-related performance measures and safety-related performance measures at the FPI base level (i.e., α level in Figure 28). Weighting set 02 (Figure 28) enables transportation planners to assign different weights to transportation modes based on the importance of different modes for planning. Finally, transportation planners can specify weighting set 03 (Figure 28) to customize FPI results at the γ level. In this regard, they can assign different weights to transportation systems (i.e., ground, sea, and air) based on the significance of each system within their decision making problem. Unlike FIT, all weighting sets in FPI need to be determined by transportation planners, and no statistical analysis is required to determine weights for its components.

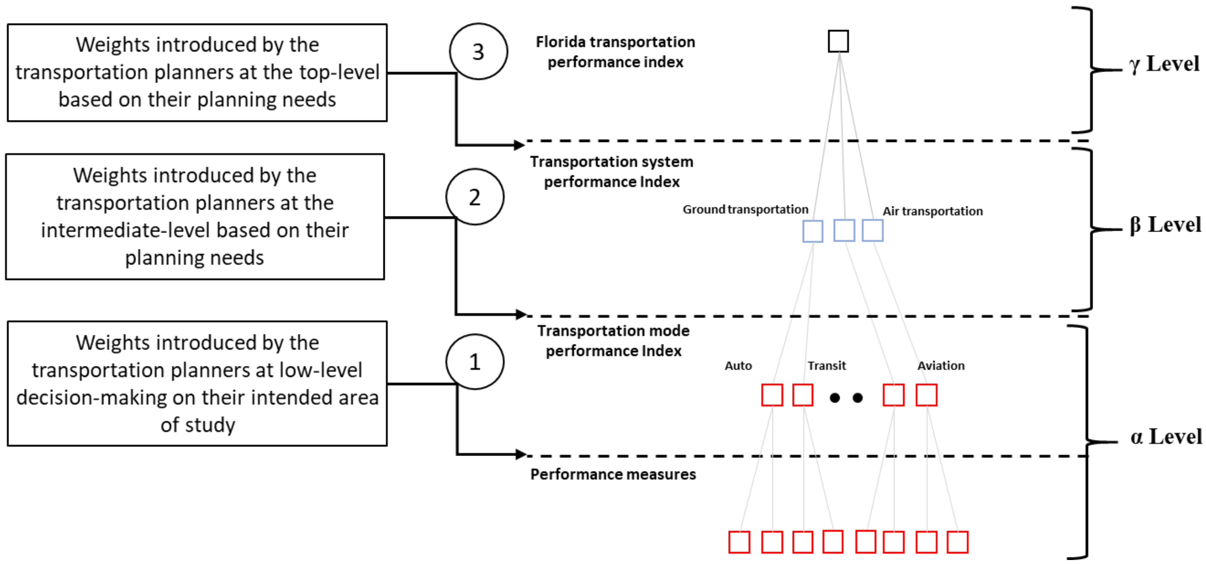


Figure 28: FPI weighting mechanism

3.3.5 Step 05: Aggregation of the indicators

In the aggregation phase, the indicators from the different levels will be aggregated to construct the composite indexes at each level. Additive aggregation methods and geometric aggregation methods are two common types of aggregation strategies used in the literature. Selecting the proper aggregation method is essential to obtain a meaningful composite index. Which aggregation strategy is chosen depends on the quality of the underlying individual indicators and their units of measurement (Joint Research Centre-European Commission 2008).

Specifically, additive aggregation methods are desirable when the underlying variables are preferentially independent (Gan et al. 2017). In other words, the two indicators can be linearly added when no synergy or conflict exists among different indicators, and thus, their contribution can be joined to yield a total value. This criterion could not be applied to the transportation dimensions or modes since they could be ranked differently across various scenarios. Also, additive aggregation methods are considered fully compensatory, which implies the possibility of offsetting a disadvantage with one criterion through an advantage with another criterion (Gan et al. 2017). Meanwhile, geometric aggregation methods can reduce compensability among the dimensions. Therefore, the geometric aggregation method was used to construct FIT and FPI. Equation (6) shows the weighted geometric aggregation strategy formula where X_i represents underlying indicators and w_i corresponding weights.

$$CI = \left(\prod_{i=1}^{n} X_i^{w_i}\right)^{1/\sum_{i=1}^{n} w_i} \qquad \text{Equation 6}$$

3.3.5.1 FIT aggregation

The mechanism of the effect of external factors. FIT is designed to help indicate the need for investment in the Florida transportation industry. In this regard, the effect of the selected external factors needs to be studied in terms of its impact on the need for investment in transportation infrastructure. As shown in Figure 29, external factors can affect transportation infrastructure's operation through either the supply or demand sides. For example, population growth would have an increasing effect on the demand side of transportation demand. On the other hand, extreme environmental conditions would deteriorate the physical condition of infrastructures and affect the supply side of the transportation infrastructure. Ultimately, suppose an external factor has an increasing effect on the demand side. In that case, it means that there should be more investment in the transportation infrastructure to keep up with the public's transportation demand adequately. Similarly, suppose an external factor has a negative impact on the supply side. In that case, it means that existing infrastructure has enough capacity to handle the current demand, and less budget should be allocated to transportation infrastructure projects.

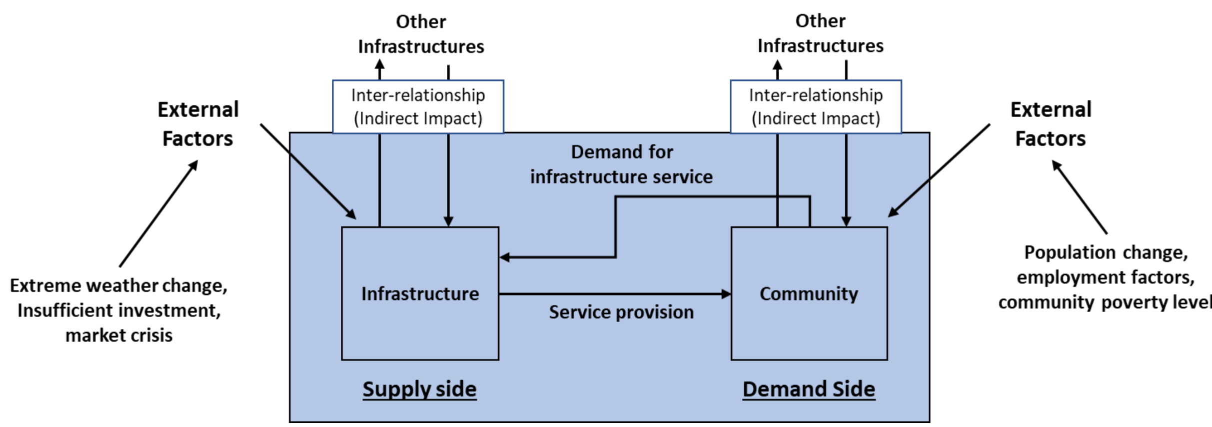


Figure 29: Mechanism of the effect of external factors (Adopted from Choi [2015])

Following the mechanism (Figure 29), the influential external factors identified for each mode are investigated in terms of their impact on either the transportation industry's demand or supply side. The results are presented in Table 27. The information gathered in the definition phase for each mode was used to support the arguments made for each external factor's impact. To ensure that an increase in each factor has a consistent meaning (i.e., of a growing need for investment in transportation), we either used external factors or took their inverse based on their impact (as identified in Table 27).

Table 27: The impact of external factors on the need for investment in the transportation industry

Mode	EF	EF Name	Demand / Supply	Impact	Justification
Auto	**EF55**	Percentage of Population in Poverty (SL)	Demand	Reverse	People in poverty tend to use less-expensive transportation modes, including transit and bike. Thus the demand for these modes will be increased by increasing poverty, while other modes, including auto, aviation, rail, and seaport, will experience less demand (FHWA 2014).
	EF15	% Population in Poverty (NL)	Demand	Reverse	People in poverty tend to use less-expensive transportation modes, including transit and bike. Thus the demand for these modes will be increased by increasing poverty, while other modes, including auto, aviation, rail, and seaport, will experience less demand (FHWA 2014).
	EF68	Viability of Streams (Gas, Tax, Etc. in Millions of Dollars; SL)	Demand	Reverse	Fuel prices harm transportation demand because they increase the transportation cost. Therefore, the increase in fuel costs is recognized as an incentive for people to use public transportation (Taylor and Fink 2013).

Table 27: The impact of external factors on the need for investment in the transportation industry (continued)

Mode	EF	EF Name	Demand / Supply	Impact	Justification
Auto	**EF66**	Number of Licensed Drivers (SL)	Demand	Normal	The number of drivers is associated with higher demand for auto and truck transportation modes because it means people tend to use their personal vehicles. Therefore, it has a negative effect on the demand for the transit mode.
	EF53	Net Migration (SL)	Demand	Normal	Population increase in any form, including migration and birth, results in higher demand for transportation (Wardman 2006).
	EF50	Florida Population Change (SL)	Demand	Normal	Population increase in any form, including migration and birth, results in higher demand for transportation (Wardman 2006).
	EF65	Number of Housing Units (SL)	Demand	Normal	Increasing the number of housing units means more investment is required for transportation systems because new housing units require accessibility. Moreover, due to the increasing demand for the new housing units, the transportation demand will also increase since the new housing units will have new residents.
	EF69	GDP—Florida, All Industries (in Millions of Dollars; SL)	Demand	Normal	Generally, economic growth is known as a driver for transportation demand; moreover, enhancing transportation has a strong role in economic growth too (Wardman 2006).
	EF91	Highway Operations and Maintenance Decisions (in Millions of Dollars; SL)	Supply	Reverse	Investments in transportation assets and improving them has a positive impact on the supply side of the transportation industry. Such decisions help to catch up with growing infrastructure need. As such, an inverse of this factor was taken for consistency with other external factors directly implying infrastructure need.
	EF52	Domestic Migration (SL)	Demand	Normal	Population increase in any form, including migration and birth, results in higher demand for transportation (Wardman 2006).
Aviation	**EF76**	Personal Income (in Millions of Dollars; SL)	Demand	Normal	Generally, improving the financial condition of people increases the demand for transportation since they have more budget to spend on transportation, travel, car ownership, and so on (FHWA 2014).
	EF31	Consumer Price Index (CPI) (NL)	Demand	Reverse	A consumer price index measures the changes in the price of the market basket of consumer goods and services. Transportation is one of the items in the market basket of consumer services. Increasing consumer costs for other categories reduces their budget for transportation purposes.
	EF98	Number of Tourists to Orlando (SL)	Demand	Normal	Tourism increases travel demand because visitors use multiple transportation modes for their trips.
	EF54	Population in College (SL)	Demand	Normal	Education drives transportation because it increases school trips. Moreover, educated people are likely to find high-income jobs, which also increases their budget for transportation expenditures. Furthermore, college students have the highest rate of bicycle usage (Dill and Voros 2007; Eren and Uz 2020).
	EF04	Natural Increase—Births (NL)	Demand	Normal	Population increase in any form, including migration and birth, results in higher demand for transportation (Wardman 2006).
	EF30	House Price Index (NL)	Demand	Normal	Housing prices are associated with factors such as GDP, population, the inflation rate, and construction costs. Among them, the community drives the demand for houses and per capita GDP, which are the most important factors. These two factors also increase the demand for transportation as well (Égert and Mihaljek 2007; Pashardes and Savva 2009).
	EF95	Privatization of Roads (SL)	Supply	Reverse	Privatization is one way to provide infrastructure for community by bringing private resources. As a result, it can have a positive impact on the supply side of the transportation industry. Thus, an inverse was taken for this factor.
	EF27	Per Capita Income (NL)	Demand	Normal	Generally, improving the financial condition of people increases the demand for transportation since they have more budget to spend on transportation, travel, car ownership, and so on (FHWA 2014).
	EF80	CPI—Rent Price Index (SL)	Demand	Normal	Housing prices are associated with factors such as GDP, population, the inflation rate, and construction costs. Among them, the community drives the demand for houses and per capita GDP, which are the most important factors. These two factors also increase the demand for transportation as well (Égert and Mihaljek 2007; Pashardes and Savva 2009),
	EF14	Population in College (NL)	Demand	Normal	Education drives transportation because it increases school trips. Moreover, educated people are likely to find high-income jobs, which also increase their budget for transportation expenditures. Furthermore, college students have the highest rate of bicycle usage (Dill and Voros 2007; Eren and Uz 2020).

Table 27: The impact of external factors on the need for investment in the transportation industry (continued)

Mode	EF	EF Name	Demand / Supply	Impact	Justification
Pedestrian and Bike	**EF14**	Population in College (NL)	Demand	Normal	Education drives transportation because it increases school trips. Moreover, educated people are likely to find high-income jobs, which also increase their budget for transportation expenditures. Furthermore, college students have the highest rate of bicycle usage (Dill and Voros 2007; Eren and Uz 2020).
	EF36	Percentage of Unemployed (NL)	Demand	Reverse	The employment rate impacts the number of transit work trips because it increases the number of work-related trips. Moreover, it increases people's personal incomes and improves their financial conditions, which also increases the demand for transportation (FHWA 2014).
	EF35	Number of Unemployed (NL)	Demand	Reverse	The employment rate impacts the number of transit work trips because it increases the number of work-related trips. Moreover, it increases people's personal incomes and improves their financial conditions, which also increases the demand for transportation (FHWA 2014).
	EF59	Seniors Population (65+; SL)	Demand	Normal	The senior population is encouraged to walk regularly for their well-being. Moreover, seniors are less likely to drive due to age related eyesight and cognitive impairment. Therefore, this factor increases the demand for the pedestrian and bike modes.
	EF94	Fuel Taxes (SL)	Demand	Normal	Fuel prices harm transportation demand because they increase the transportation cost. Therefore, the increase in fuel costs is recognized as an incentive for people to use public transportation (Taylor and Fink 2013).
	EF08	Rental Vacancy Rate (NL)	Demand	Reverse	Increasing vacancy rate means fewer residents and thus less travel demand.
	EF84	Percentage of Unemployed (SL)	Demand	Reverse	The employment rate impacts the number of transit work trips because it increases the number of work-related trips. Moreover, it increases people's personal incomes and improves their financial conditions, which also increases the demand for transportation (FHWA 2014).
	EF58	Political Party Affiliation (Other) (SL)	Supply	Reverse	Democratic-leaning communities are more likely to support public expenditures on transportation subsidies.
	EF02	Population Estimate (NL)	Demand	Normal	Population increase in any form, including migration and birth, results in higher demand for transportation (Wardman 2006).
	EF83	Number of Unemployed (SL)	Demand	Reverse	The employment rate impacts the number of transit work trips because it increases the number of work-related trips. Moreover, it increases people's personal incomes and improves their financial conditions, which also increases the demand for transportation (FHWA 2014).
Rail	**EF15**	% Population in Poverty (NL)	Demand	Reverse	People in poverty tend to use less-expensive transportation modes, including transit and bike. Thus the demand for these modes will be increased by increasing poverty, while other modes, including auto, aviation, rail, and seaport, will experience less demand (FHWA 2014).
	EF36	Percentage of Unemployed (NL)	Demand	Reverse	The employment rate impacts the number of transit work trips because it increases the number of work-related trips. Moreover, it increases people's personal incomes and improves their financial conditions, which also increases the demand for transportation (FHWA 2014).
	EF35	Number of Unemployed (NL)	Demand	Reverse	The employment rate impacts the number of transit work trips because it increases the number of work-related trips. Moreover, it increases people's personal incomes and improves their financial conditions, which also increases the demand for transportation (FHWA 2014).
	EF10	Homeownership Rate (NL)	Demand	Normal	Higher homeownership is associated with higher income, higher education, less inequality in income, reasonable house prices, and an affordable general cost of living. These factors are also associated with higher transportation needs
	EF20	Immigration (NL)	Demand	Normal	Population increase in any form, including migration and birth, results in higher demand for transportation (Wardman 2006).
	EF08	Rental Vacancy Rate (NL)	Demand	Reverse	Increasing vacancy rate means fewer residents and thus less travel demand.
	EF55	Percentage of Population in Poverty (SL)	Demand	Reverse	People in poverty tend to use less-expensive transportation modes, including transit and bike. Thus the demand for these modes will be increased by increasing poverty, while other modes, including auto, aviation, rail, and seaport, will experience less demand (FHWA 2014).
	EF70	GDP of Florida—Construction (in Millions of Dollars; SL)	Demand	Normal	Generally, economic growth is known as a driver for transportation demand; moreover, enhancing transportation has a strong role in economic growth too (Wardman 2006).

Table 27: The impact of external factors on the need for investment in the transportation industry (continued)

Mode	EF	EF Name	Demand / Supply	Impact	Justification
Rail	**EF29**	Financial Condition Index (NL)	Demand	Normal	The Chicago Fed's National Financial Conditions Index (NFCI) provides a comprehensive weekly update on U.S. financial conditions in money markets, debt and equity markets, and the traditional and shadow banking systems. Positive values of the NFCI indicate economic conditions that are tighter than average, while negative values indicate financial conditions that are looser than average. A better-condition index increases demand for transportation in general.
	EF33	CPI—Fuel Price Index (NL)	Demand	Reverse	Fuel prices harm transportation demand because they increase the transportation cost. Therefore, the increase in fuel costs is recognized as an incentive for people to use public transportation (Taylor and Fink 2013).
Seaport	**EF22**	GDP—All Industries (NL)	Demand	Normal	Generally, economic growth is known as a driver for transportation demand; moreover, enhancing transportation has a strong role in economic growth too (Wardman 2006).
	EF15	% Population in Poverty (NL)	Demand	Reverse	People in poverty tend to use less-expensive transportation modes, including transit and bike. Thus the demand for these modes will be increased by increasing poverty, while other modes, including auto, aviation, rail, and seaport, will experience less demand (FHWA 2014).
	EF55	Percentage of Population in Poverty (SL)	Demand	Reverse	People in poverty tend to use less-expensive transportation modes, including transit and bike. Thus the demand for these modes will be increased by increasing poverty, while other modes, including auto, aviation, rail, and seaport, will experience less demand (FHWA 2014).
	EF49	Alabama Population (SL)	Demand	Normal	Population increase in any form, including migration and birth, results in higher demand for transportation (Wardman 2006).
	EF72	GDP of Florida—Real Estate (in Millions of Dollars; SL)	Demand	Normal	Generally, economic growth is known as a driver for transportation demand; moreover, enhancing transportation has a strong role in economic growth too (Wardman 2006).
	EF24	GDP—Manufacturing (NL)	Demand	Normal	Generally, economic growth is known as a driver for transportation demand; moreover, enhancing transportation has a strong role in economic growth too (Wardman 2006).
	EF51	International Migration (SL)	Demand	Normal	Population increase in any form, including migration and birth, results in higher demand for transportation (Wardman 2006).
	EF34	Number of Employed (NL)	Demand	Normal	The employment rate impacts the number of transit work trips because it increases the number of work-related trips. Moreover, it increases people's personal incomes and improves their financial conditions, which also increases the demand for transportation (FHWA 2014).
	EF04	Natural Increase—Births (NL)	Demand	Normal	Population increase in any form, including migration and birth, results in higher demand for transportation (Wardman 2006).
	EF23	GDP—Construction (NL)	Demand	Normal	Generally, economic growth is known as a driver for transportation demand; moreover, enhancing transportation has a strong role in economic growth too (Wardman 2006).
Transit	**EF70**	GDP of Florida—Construction (in Millions of Dollars; SL)	Demand	Normal	Generally, economic growth is known as a driver for transportation demand; moreover, enhancing transportation has a strong role in economic growth too (Wardman 2006).
	EF55	Percentage of Population in Poverty (SL)	Demand	Normal	People in poverty tend to use less-expensive transportation modes, including transit and bike. Thus the demand for these modes will be increased by increasing poverty, while other modes, including auto, aviation, rail, and seaport, will experience less demand (FHWA 2014).
	EF15	% Population in Poverty (NL)	Demand	Normal	People in poverty tend to use less-expensive transportation modes, including transit and bike. Thus the demand for these modes will be increased by increasing poverty, while other modes, including auto, aviation, rail, and seaport, will experience less demand (FHWA 2014).
	EF51	International Migration (SL)	Demand	Normal	Population increase in any form, including migration and birth, results in higher demand for transportation (Wardman 2006).
	EF31	CPI (NL)	Demand	Reverse	A consumer price index measures the changes in the price of the market basket of consumer goods and services. Transportation is one of the items in the market basket of consumer services. Increasing consumer costs reduces their budget for transportation purposes.
	EF49	Alabama Population (SL)	Demand	Normal	Population increase in any form, including migration and birth, results in higher demand for transportation (Wardman 2006).
	EF66	Number of Licensed Drivers (SL)	Demand	Reverse	The number of drivers is associated with a higher demand for auto and truck transportation modes because it means that people tend to use their vehicles. Therefore, it has a negative effect on demand for the transit mode.

Table 27: The impact of external factors on the need for investment in the transportation industry (continued)

Mode	EF	EF Name	Demand / Supply	Impact	Justification
Transit	**EF41**	Number of Smartphone Users (NL)	Demand	Normal	Smartphones facilitate transportation by providing maps, navigation, trip plans, and so on.
	EF65	Number of Housing Units (SL)	Demand	Normal	An increasing number of housing units means more investment is required for the transportation systems because the new housing units require accessibility. Moreover, due to the growing demand for the new housing units, the transportation demand will also increase since the new housing units will have new residents.
	EF80	CPI—Rent Price Index (SL)	Demand	Normal	Housing prices are associated with factors such as GDP, population, the inflation rate, and construction costs. Among them, the community drives the demand for houses and per capita GDP, which are the most important factors. These two factors also increase the demand for transportation as well (Égert and Mihaljek 2007; Pashardes and Savva 2009).
Truck	**EF13**	Number of Housing Units (NL)	Demand	Normal	An increasing number of housing units means more investment is required for the transportation systems because the new housing units require accessibility. Moreover, due to the growing demand for the new housing units, the transportation demand will also increase since the new housing units will have new residents.
	EF65	Number of Housing Units (SL)	Demand	Normal	An increasing number of housing units means more investment is required for the transportation systems because the new housing units require accessibility. Moreover, due to the growing demand for the new housing units, the transportation demand will also increase since the new housing units will have new residents.
	EF30	House Price Index (NL)	Demand	Normal	Housing prices are associated with factors such as GDP, population, the inflation rate, and construction costs. Among them, the community drives the demand for houses and per capita GDP, which are the most important factors. These two factors also increase the demand for transportation as well (Égert and Mihaljek 2007; Pashardes and Savva 2009).
	EF15	% Population in Poverty (NL)	Demand	Reverse	People in poverty tend to use less-expensive transportation modes, including transit and bike. Thus the demand for these modes will be increased by increasing poverty, while other modes, including auto, aviation, rail, and seaport, will experience less demand (FHWA 2014).
	EF91	Highway Operations and Maintenance Decisions (in Millions of Dollars; SL)	Supply	Reverse	Investments in transportation assets and improving them has a positive impact on the supply side of the transportation industry. Thus, less investment is required after such investments
	EF66	Number of Licensed Drivers (SL)	Demand	Normal	The number of drivers is associated with a higher demand for auto and truck transportation modes because it means that people tend to use their vehicles. Therefore, it hurts the need for the transit mode.
	EF55	Percentage of Population in Poverty (SL)	Demand	Reverse	People in poverty tend to use less-expensive transportation modes, including transit and bike. Thus the demand for these modes will be increased by increasing poverty, while other modes, including auto, aviation, rail, and seaport, will experience less demand (FHWA 2014).
	EF32	CPI—Rent Price Index (NL)	Demand	Normal	Housing prices are associated with factors such as GDP, population, the inflation rate, and construction costs. Among them, the community drives the demand for houses and per capita GDP, which are the most important factors. These two factors also increase the demand for transportation as well (Égert and Mihaljek 2007; Pashardes and Savva 2009).
	EF37	Financial Markets (Dow Jones Avg Closing Price; NL)	Demand	Normal	The right economic conditions and positive trends in market performance results in transportation demands because they are associated with GDP and ultimately personal income.
	EF78	House Price Index (SL)	Demand	Normal	Housing prices are associated with factors such as GDP, population, the inflation rate, and construction costs. Among them, the community drives the demand for houses and per capita GDP, which are the most important factors. These two factors also increase the demand for transportation as well (Égert and Mihaljek 2007; Pashardes and Savva 2009).

Note: NL: national-level, SL: state-level, CPI: consumer price index, GDP: gross domestic product, MSA: metropolitan statistical area

Once the external factors' data is adjusted based on Table 27, the geometric aggregation method will be used to aggregate them and construct higher-level indexes. The results will be presented in Section 2.3.6.1.

3.3.5.2 FPI aggregation

Similar to external factors composition in the FIT base level, the performance measures at the FPI base level should be adjusted to ensure that an increase in each performance measure has a consistent meaning. In this regard, we evaluated each performance measure with respect to the performance of the transportation supply system. If an increase in the performance measure means better conditions of the transportation system, the performance measure's data itself was used in the construction of the FPI without adjustment. On the other hand, if an increase in the performance measure represents worse conditions of the transportation system, the inverse of that indicator was used to develop the FPI. Table 28 presents how each performance measure was used in FPI development. It should be noted that FPI contains some performance measures for which data are not consistently available (i.e., missing data points). Thus 58 performance measures are considered and listed in this table (instead of 67).

Table 28: Interpretation of performance measures with respect to transportation supply system performance

Code	PM Name	Impact	Code	PM Name	Impact
PM01	Safety Belt Use	Normal	PM31	Rate of Fatalities	Reverse
PM02	Bicycle Fatalities	Reverse	PM32	Passenger Trips	Normal
PM03	Pedestrian Fatalities	Reverse	PM33	Revenue Miles (Millions)	Normal
PM04	Motorcyclist Fatalities	Reverse	PM34	Revenue Miles Between Failures	Normal
PM05	Vehicle Miles Traveled (Million) (Daily)	Normal	PM35	Weekday Span of Service (Hours)	Normal
PM06	Vehicle Miles Traveled (Million) (Peak Hours)	Normal	PM36	Passenger Trips per Revenue Mile	Normal
PM07	Person Miles Traveled (Millions) (Daily)	Normal	PM39	% Pedestrian Facility Coverage (Total Statewide urban)	Normal
PM08	Person Miles Traveled (Millions) (Peak Hour)	Normal	PM41	% Bicycle Facility Coverage (Total State Urban)	Normal
PM09	Percentage of Travel Meeting LOS Criteria (Daily)	Normal	PM42	Passenger Enplanements	Normal
PM10	Percentage of Travel Meeting LOS Criteria (Peak Hour)	Normal	PM43	Gate Departure Delay	Reverse
PM11	Percentage of Miles Meeting LOS Criteria (Peak Hour)	Normal	PM44	Tonnage	Normal
PM13	Travel Time Reliability (On Time Arrival) (Daily)	Normal	PM49	Passengers	Normal
PM14	Travel Time Reliability on Freeways: On-Time Arrival (Peak hour)	Normal	PM50	Rail On-Time Arrival	Normal

Table 28: Interpretation of performance measures with respect to transportation supply system performance (continued)

Code	PM Name	Impact	Code	PM Name	Impact
PM15	Travel Time Reliability (PLANNING TIME INDEX) (Daily)	Normal	PM51	Tonnage	Normal
PM16	Travel Time Reliability on Freeways: PLANNING TIME INDEX (Peak hour)	Normal	PM52	Twenty-Foot Equivalent Units	Normal
PM17	Vehicle Hours of Delay, Thousands (Peak hour)	Reverse	PM53	Value of Freight	Normal
PM18	Vehicle Hours of Delay, Thousands (Daily)	Reverse	PM54	Seaport Passengers	Normal
PM19	Vehicle Hours of Delay, Thousands (Yearly)	Reverse	PM55	Truck Miles Traveled (Millions)	Normal
PM20	Person Hours of Delay, Thousands (Peak hour)	Reverse	PM56	Combination Truck Miles Traveled (Millions)	Normal
PM21	Person Hours of Delay, Thousands (Daily)	Reverse	PM57	Combination Truck Ton Miles Traveled (Billion Ton Miles)	Normal
PM22	Person Hours of Delay, Thousands (Yearly)	Reverse	PM58	Combination Truck Tonnage	Normal
PM23	Average Travel Speed	Normal	PM60	Truck Travel Time Reliability (Peak Hour or Peak Period)	Normal
PM24	Percentage of Travel Heavily Congested (Peak hour)	Reverse	PM61	Travel Time Reliability: On-time Arrival (Daily)	Normal
PM25	Percentage of Travel Heavily Congested (Daily)	Reverse	PM62	Combination Truck Planning Time Index (Peak Hour or Peak Period)	Normal
PM26	Percentage of Miles Heavily Congested	Reverse	PM63	Combination Truck Planning Time Index (Daily)	Normal
PM27	Hours Heavily Congested (Daily)	Reverse	PM64	Combination Truck Hours of Delay, Vehicle Hours (Thousands) (Daily)	Reverse
PM28	Hours Heavily Congested (Yearly)	Reverse	PM65	Combination Truck Average Travel Speed	Normal
PM29	Vehicles Per Lane Mile	Normal	PM66	Combination Truck Cost of Delay	Reverse
PM30	Number of Fatalities	Reverse	PM67	Combination Truck Empty Backhaul Tonnage	Reverse

Once the performance measure's data is adjusted based on Table 28, the geometric aggregation method will be used to aggregate them and construct higher-level indexes. The results will be presented in Section.

3.3.6 Composite index results

3.3.6.1 FIT results

Figure 30 shows FIT and its sub indicators at each level. In this figure, all the weights specified by the decision makers are assumed to be equal. In other words, only the weights resulting from the explained variance of the indicators were used to develop the index. However, FIT is designed to be customizable based on the transportation planners' decision making needs. Decision makers may have different priorities for the choices they need to make depending on the different planning levels. For example, transportation planners may be interested in prioritizing transportation systems for limited funding at the top decision making level. At the intermediate level (i.e., β level in Figure 30), transportation planners may prefer weighting a single transportation mode over others according to their relevant planning divisions. At the base level (i.e., α level in Figure 30), for instance, auto transportation planners may need to focus on only one of the auto dimensions. In this regard, decision makers can focus on their areas of interest by specifying their desired weights to the transportation dimensions, modes, or systems and customize the FIT based on their needs. Detailed figures for all FIT levels all presented in Appendix F.

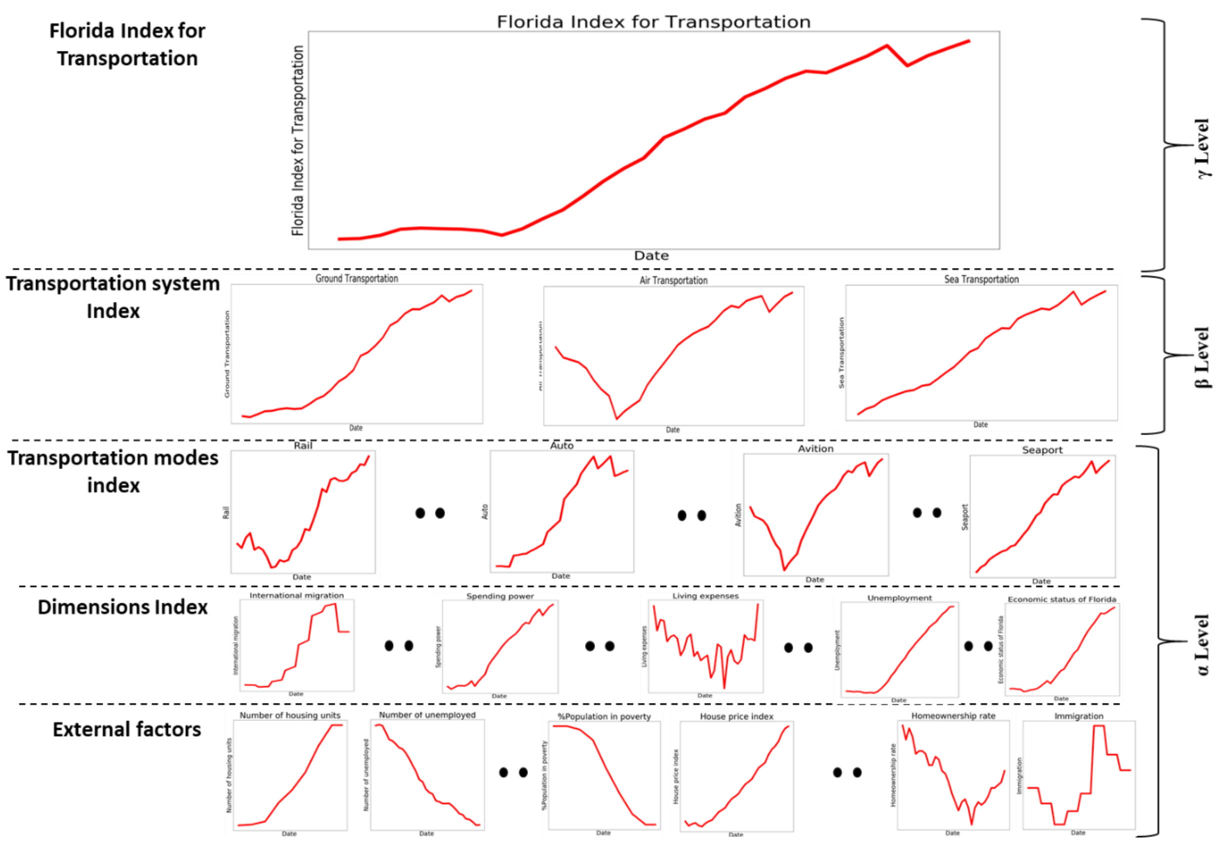


Figure 30: Florida Index for Transportation

3.3.6.2 FPI results

Figure 31 displays the FPI and its sub indicators at each level. Similar to the FIT, in this section, we assumed equal weights to develop the FPI. However, transportation planners can adjust the weights at the performance measures level (α level in Figure 31), mode level (α level in Figure

31), and system level (β level in Figure 31) to customize the FPI according to their planning problem.

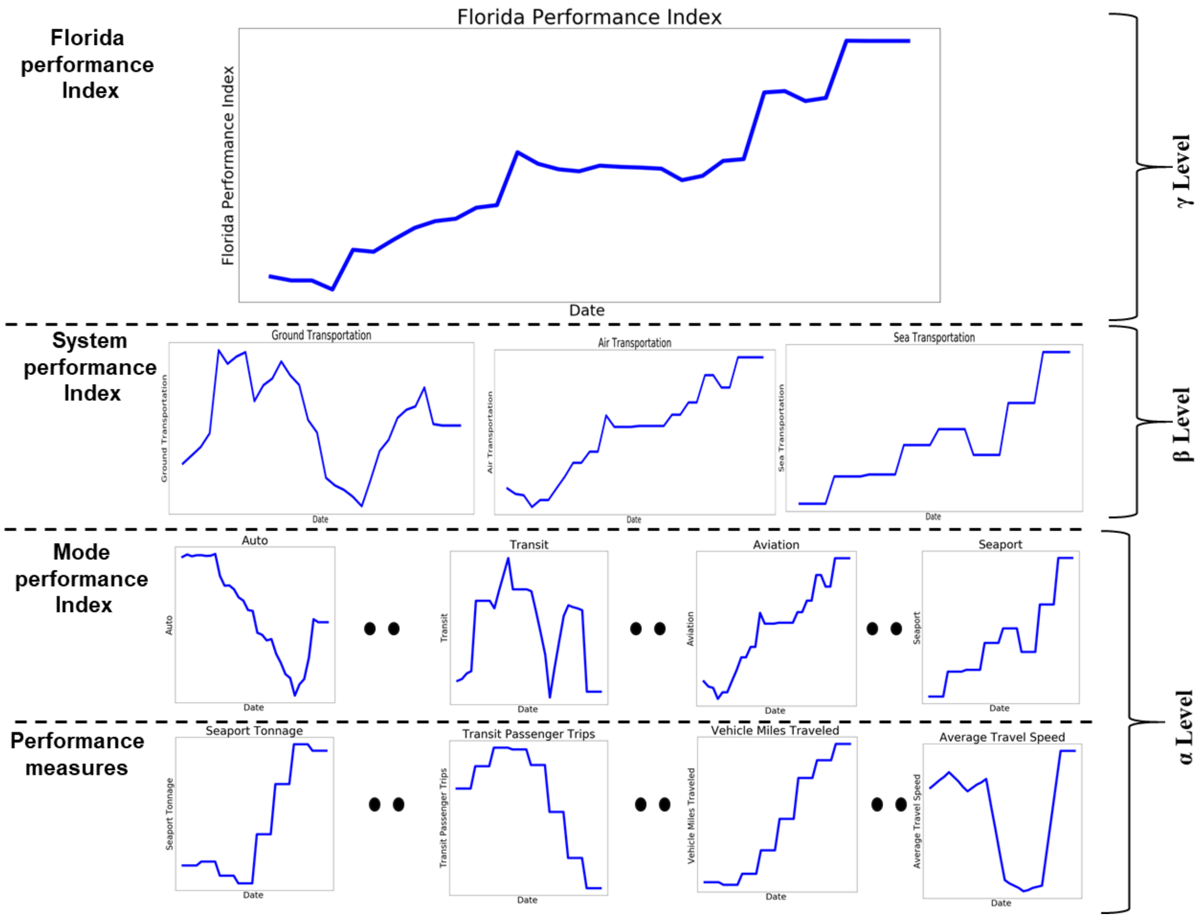


Figure 31: Florida Performance Index (FPI)

3.4 FIT Applications

3.4.1 Application of the FIT in decision making

As explained previously, FIT trends represent the transportation needs while the FPI trends indicate transportation capacity. The combination of FIT and FPI trends can support decision making at two levels: mode and system levels[1]. To be more specific, transportation planners can refer to the appropriate level of FIT and FPI (i.e., mode or system) based on decision making problems of interest. Then, once the appropriate level is identified, corresponding FIT and FPI trends are investigated to understand (i) how external factors have affected travel demand or infrastructure need and (ii) how well the current transportation system has accommodated such demand. A faster increase in FIT than FPI (i.e., in terms of the slope of the trends of FIT and FPI) indicates that the current and previous planning effort may not be enough to keep up with travel demand growth as a result of external factors, thereby urging transportation planners to investigate the underlying reasons and develop proper plans to address such behavior. On the contrary, similar FIT and FPI trends (i.e., in terms of the slope of the trend lines) or a higher

[1] Please refer to Appendix G for more details regarding the significance of external factors for decision making at various planning levels

slope of FPI than FIT imply that current infrastructure systems may either meet or sufficiently accommodate changing travel demand. For example, consider the hypothetical example depicted in Figure 32. The figure shows FIT and FPI results for the transit mode. According to the figure, FIT shows an increasing trend while FPI trends are negative. The trends imply that more resources are required to meet the increasing transportation demand.

Since the FIT and FPI allow decision makers to customize the weights of each index's components based on the planning contexts, user preference, and the nature of the decision making problem, they can be used for a broad range of decision making problems.

Figure 32: FIT application for decision making in a hypothetical example

3.4.2 Application of the FIT in understanding the changing nature of transportation systems

This section provides some applications of the FIT to show how it can serve transportation planners and aid them in interpreting the changing nature of the transportation system. The FIT assists transportation planners in two ways: (i) studying abnormal changes in FIT trends and (ii) investigating changes in the FIT components.

3.4.2.1 Studying unexpected trends in the FIT

Transportation planners might be interested in studying abnormal changes in FIT. In other words, transportation decision makers can track and understand the root causes for unexpected jumps and drops in FIT trends. Consider, for example, the third quarter of 2012 until the third quarter of 2013. This period is marked in Figure 33 using two green dashed lines. As shown in the figure, there is a sudden drop in the FIT caused by the air transportation system.

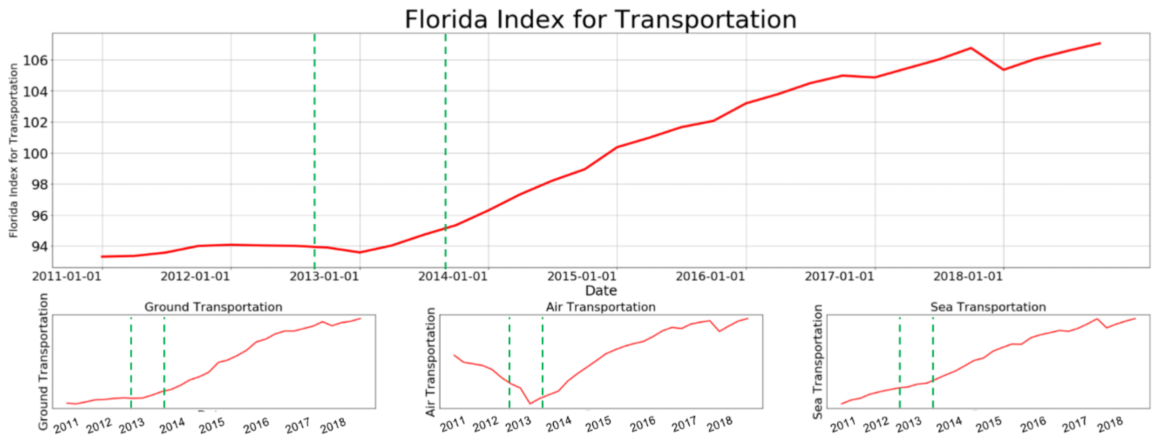


Figure 33. Example application of the Florida Index for Transportation

To track this behavior, the composite indexes for the subsequent levels of FIT are further analyzed. Because the air transportation system has only one transportation mode, the composite index for the aviation mode and its dimensions are the cause of this particular change (Figure 34). The aviation mode has two FIT dimensions: spending power and population in college (Figure 34). As shown in Figure 34, the first sharp drop in the air transportation system is primarily attributed to the second dimension, representing the population in college, while the subsequent increase is attributed to the first dimension (i.e., spending power). Since, in this chapter, the weights do not reflect the decision makers' inputs, only the weights resulting from the explained variance are considered when constructing the aviation composite index. These weights are 0.77 for the first dimension and 0.23 for the second dimension. Therefore, the first dimension has a considerably higher impact on the aviation composite index.

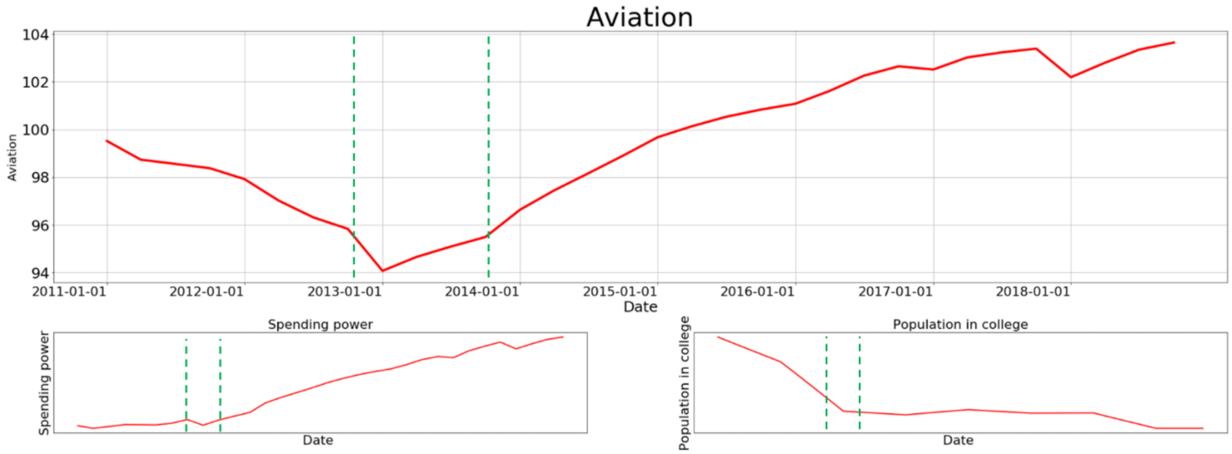


Figure 34. Example application of the Florida Index for Transportation: Aviation subsystems

The origins of the dimensions' behaviors can be tracked down to the level of the external factors. Figures 35 and 36 present the dimension-level composite index for the aviation transportation mode. The results for the first dimension of the aviation transportation mode (Figure 35) reveal that five out of the seven external factors (EF76, EF98, EF30, EF27, and EF80) have an increasing trend. This rising trend in the majority of the external factors results in an overall growing trend in the dimension. However, the steep positive slope of the dimension after the drop primarily results from the increase in the positive slope in EF76, "Personal Income (in

Millions of Dollars)"; EF30, "House Price Index (national level [NL])"; EF27, "Per Capita Income (NL); and EF80, "CPI—Rent Price Index (state level [SL])."
Moreover, the results for the second dimension also show that the decreasing trend results from the decrease in all of the underlying external factors: EF54, "Population in College (SL)"; EF14, "Population in College (NL)"; and EF95, "Privatization of Roads."

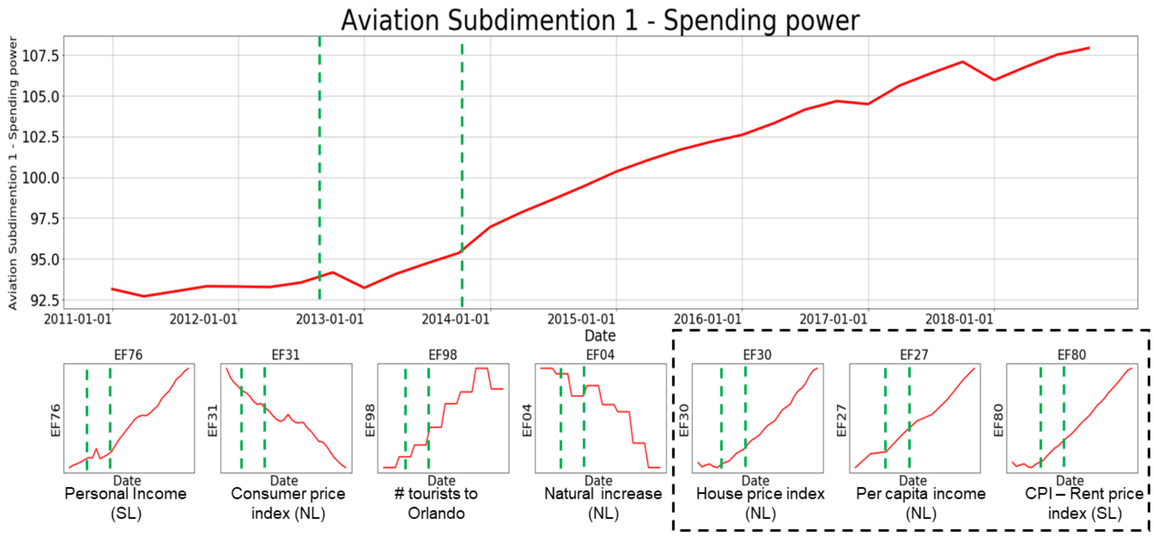


Figure 35. Example application of the Florida Index for Transportation: External factors for the aviation subsystem 01

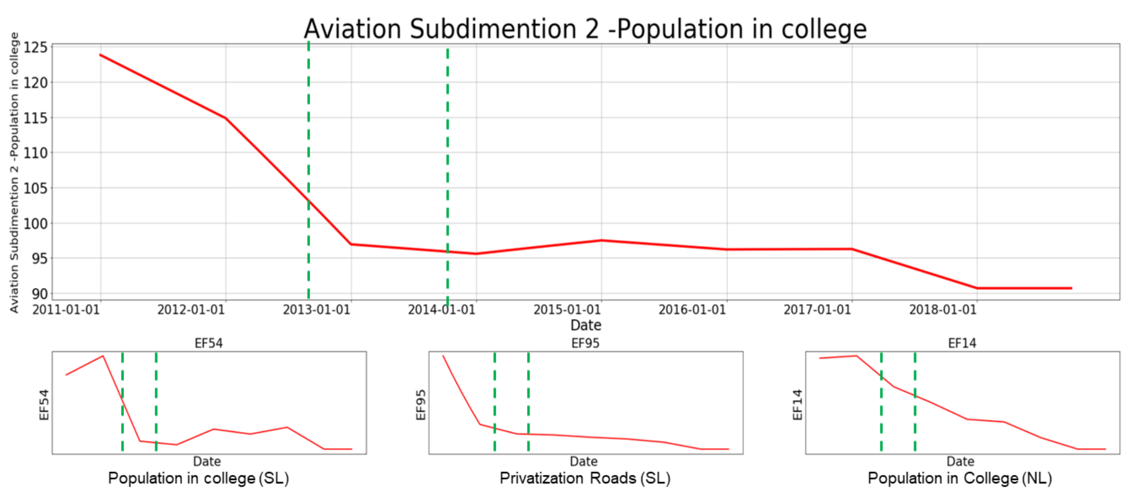


Figure 36. Example application of the Florida Index for Transportation: External factors for the aviation subsystem 02

3.4.2.2 Studying new compositions in the FIT

Transportation agencies normally track a fixed list of external factors such as travel demand and economic growth over time (e.g., through a web-based dashboard called "Vital Signs," developed by the Metropolitan Transportation Commission in California). However, due to the changing nature of transportation systems, the list of influential external factors may change. FIT is capable of updating the most influential external factors of a system in different time frames.

To be more specific, the composition of FIT at different levels varies depending on the input data. As such, changing the time frame of the analysis alters the input data, thus resulting in a change in the analysis results (i.e., selection of external factors to construct FIT). In this context, developing the FIT with different time frames helps decision makers understand the changing nature of transportation systems in two ways.

First, transportation planners can identify which external factors emerge as influential in a new time frame. Developing FIT for two separate time frames can result in two different external factors compositions at the FIT base level. For example, the fuel tax factor might show up as an important external factor for the auto mode in a time frame even though this factor was not identified to be important in previous time frames. Research on the changes of influential external factors may help planners identify a potential past disruptive event and make plans accordingly.

Secondly, changes in the composition of FIT (i.e., the lists of important external factors for modes) may alter the number and implication of transportation dimensions. By developing the FIT in different time frames, transportation planners can study which dimensions remain consistent across different time frames (i.e., remaining important) and which dimensions will emerge in different time frames. By tracking changes in the dimensions (i.e., FIT Dimension Index at the α level), planners understand the implications of changes in the lists of influential external factors at a high level rather than trying to understand the micro-level phenomena. Such information facilitates developing informed and timely decision making in response to changes in transportation. For example, an increasing number of economic-related external factors in the composition of the FIT implies an increasing impact of external economic conditions on transportation performance. Transportation planners may develop appropriate plans to cope with the changing economic conditions and mitigate their adverse effects on transportation systems.

The application of the FIT in understanding the changing behavior of the Florida transportation system using studying new compositions in the FIT will be demonstrated in the next chapter.

CHAPTER IV: DEMONSTRATION OF FIT APPLICATION

This section aims to demonstrate two major functions of FIT: (Function i) improving FDOT's planning process and (Function ii) facilitating the understanding of the Florida transportation system's changing nature.

To validate the former function of the FIT (i.e., Function i), the FSU team demonstrated the application of the FIT for decision making and policy-making to FDOT planners. In this regard, two demonstration sessions were organized where the FSU team presented the FIT and its applications in transportation planning. The first meeting was focused on the validation of the overall FIT approach (the structure and how FIT can support decision making), while the second meeting aimed to understand the usability (i.e., implementability) of FIT (i.e., whether FIT can be directly implementable for transportation planning). Based on the feedback acquired from these meetings, two sample scenarios are designed to explain the FIT application in decision making for future guidance.

To demonstrate the latter function (i.e., Function ii), the FSU team developed the FIT for four different time frames to investigate the impact of a possible disruptive event on transportation through FIT (i.e., by seeking for changes in the composition of FIT at the base and dimension levels). Monitoring changes in the composition of FIT enables decision makers to detect the varying impact of external factors (i.e., either gaining or losing significance for transportation performance). Also, studying changes in the FIT dimensions helps decision makers to interpret the impact of changes in the list of the important external factors (i.e., at the base level) by looking at their underlying causes, which informs the development of strategies and plans in response to such changes.

4.1 FIT application in decision making purposes

In this section, the application of the FIT for decision making purposes is explained. The section is divided into two parts. The first part describes the methodology that was used to demonstrate the FIT application to FDOT planners. In the second part, the capability of the FIT in facilitating decision making is explained using two decision making scenarios.

4.1.1 Demonstration methodology

To demonstrate the application of the FIT for decision making purposes, two virtual demonstration sessions were organized. FDOT transportation planners were invited to the meetings to learn about the FIT and its applications in decision making. Table 29 provides detailed information regarding each meeting.

The first meeting was focused on the validation of the overall FIT approach. This meeting can be broken into two main sections. In the first section, the FSU team described the Florida transportation system as a system-of-systems (SoS) concept along with the structure, development process, and application of FIT. The FSU team then presented the FIT trends at different levels while explaining its possible application for planning. The followings are key takeaways from the first session:

Table 29: Demonstration sessions information

Session	Date	Objective	Participant office	Participant role
First meeting	January 19^{th}, 2021	To validate the overall FIT approach	FDOT Trends & Emerging Transportation Office	Manager, Trends & Emerging Transportation
			FDOT Trends & Emerging Transportation Office	Mobility Measures Program Coordinator
Second meeting	February 9^{th}, 2021	To understand the FIT application in transportation planning efforts	State Seaport Program	State Seaport Program Coordinator
			FDOT Transit Office	Transit Planning Coordinator
			FDOT Transit Office	Planning Administrator
			FDOT Transit Office	Transit Planner

1) FDOT planners asked the team regarding applying the tool in practice and what resources are required for implementation. The team responded that the tool can be presented in a dashboard format that facilitates transportation planners' monitoring and tracking the transportation demand and investment needs (i.e., by looking at FIT trends) and compares them with current infrastructure performance trajectories.

2) FDOT planners asked the team whether the tool is helpful for regional-level planning. The team responded although the FIT is developed for state-level decision making in this project, the proposed framework is flexible enough to be applied for regional-level decision making.

3) FDOT planners asked the team whether FIT can facilitate cross-modal planning. The team responded FIT can support decision making related to cross-modal planning. In this regard, the FIT system-level index that aggregates various transportation modes can be used to compare the trends at different modes with adjustment of the weights for each mode in order to reflect the context of relevant budget allocation and policy-making problems.

4) FDOT planners asked the team how the information is combined into one composite index. The team explained the statistical analyses performed to find the most influential external factors for each mode and to group them under multiple dimensions. Also, the team added that the external factors grouped under the same dimension are statistically highly correlated with one another, and these dimension indexes were then aggregated using the geometric aggregation method to construct higher-level indexes.

5) FDOT planners commented that FIT can be potentially useful in budget allocation decision making problems. For example, decision makers may adjust the FIT and FPI components' weights for analysis of the transit mode and compare their trends. By comparing the FIT and FPI trends, the transportation planners can evaluate whether current transit plans can effectively address transit demands. If the past performance improvement is not enough to keep up with growing demand (i.e., as indicated by FIT), the transportation planners can track down and investigate which transportation performance indicator(s) requires more attention and resources to meet the transportation demands.

The second section was dedicated to addressing the participants' questions regarding FIT and its applications. Like the first meeting, the second meeting consists of two main sections. During the first section, the FSU team introduced the FIT structure and its application. During the latter section, the FSU team received the participants' feedback regarding the implementability of the FIT within FDOT's current decision making effort. The followings are some of the key takeaways from the second session:

1) FDOT Transit Office offers several tools to support transit agencies to address their mobility and safety issues. With that, FIT can help transit planners with planning efforts. For example, planners can compare transit performance measures such as transit ridership trends with the relevant FIT trends. Such comparison helps transit planners evaluate how sensitive transit performance is to external factors (FIT) and how external factors drive the transit performance more significantly. Transit planners can develop corresponding plans to mitigate and manage external factors' impact based on this knowledge.

2) FDOT Seaport Planning Office is not involved with details of seaport operations. However, the office supports seaport-related infrastructure projects that provide public benefits. These include capacity-related projects, accessibility-related projects, etc. FIT seaport external factors and dimensions may help planners identify and prioritize proper projects for funding. For example, a high number of population- and manufacturing-related external factors may imply the need for expanding seaport capacities to cope with the growing demand.

3) Most transportation modes contain a single category of performance measures (i.e., mobility). Increasing the number of performance measures and diversifying them help identify more relative influential external factors and improve FIT results. Moreover, this addition to the performance measures enables FIT to cover more diverse planning problems as decision makers will be able to give different weights and priorities to various performance measures in different planning problems.

4.1.2 FIT application examples

Based on input from FDOT planners, two sample scenarios were developed to elaborate on the possible application of FIT in transportation planning. The first example scenario is related to highway safety planning, and the second scenario focuses on cross-modal budget allocation. Specifically, we assume that decision makers choose the auto mode (i.e., α level) and the ground transportation system (β level) within the FIT hierarchy in the first and second planning scenarios, respectively.

4.1.2.1 Example scenario 01: Highway safety planning

In this scenario, a transportation planner is assumed to be interested in investigating and tracking how the Florida state highway system has been performed in response to safety demand. The goal is to understand whether more resources are required to meet desired safety performance levels considering the impact of external factors on highway safety. Specifically, it is assumed that the planner focuses on private vehicle safety, which is part of the auto transportation mode. To use FIT, the transportation planner needs to refer to an appropriate model level based on the decision making problem. Since the decision making problem is related to private vehicles' safety, the FIT auto mode should be investigated.

As shown in Figure 37, the auto mode contains two dimensions: "economic status of Florida" and "population change in Florida." Meanwhile, FPI includes two categories of performance measures (mobility and safety). Note that FIT and FPI can be customized to reflect the context of decision making problems by varying weights of their component indicators. Since this example is focused on highway safety, the user may give higher weights to the safety dimension of the FPI index with respect to the mobility dimension. On the other hand, the user may give higher weight to the "population change in Florida" dimension since transportation users' safety is more related to demographic factors. After deciding each component's weights, the transportation planner customizes the FIT and FPI accordingly. The used weights are provided in Table 30. Based on the weights, FIT and FPI will be drawn as shown in Figure 37. Note that the weights are determined by the FSU team for the purpose of plotting FIT and FPI.

Table 30: Example 01 - Defined weights for each component of FIT and FPI

FIT dimensions		**FPI dimensions**	
Economic Status of Florida	Population change in Florida	Mobility	Safety
0.2	0.9	0.2	0.9

FPI shows a decreasing trend in FPI until January of 2017. Then, the auto mode's performance has improved. As for FIT, both auto mode dimensions, *economic status of Florida* and *population change in Florida* show increasing trends from 2011 to 2018. Comparing the slope of FIT and FPI trends (+0.58 vs. +0.33) implies that the current planning efforts are in the right direction (i.e., increasing planning effort to accommodate an increase in safety demand as a result of external factors). Still, more resources may be considered to keep up with growing safety demand (i.e., based on the FIT trend). To further investigate which specific aspects of the auto mode require more attention, the transportation planner can further trace the roots of changes in FIT and FPI and take actions accordingly.

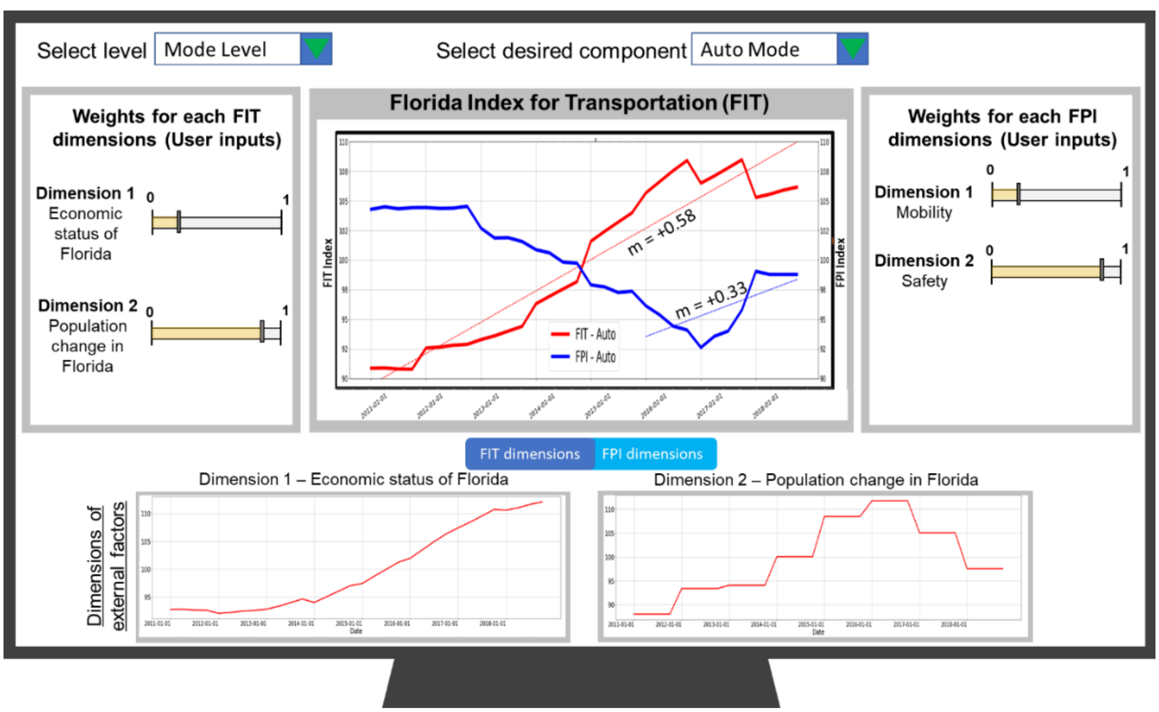


Figure 37: Decision making sample scenario 01

4.1.2.2 Example scenario 02: Cross-mode budget allocation

In this planning scenario, a transportation planner is interested in monitoring and investigating the trends in ground transportation performance with respect to travel demand for budget allocation across various surface transportation modes while considering the impact of external factors. To be more specific, the planner believes that the promotion of public transit systems helps to improve the overall mobility of the transportation system via decreasing the number of private vehicles and thus reducing traffic congestions. As such, the planner intends to use this budget to primarily promote public transportation modes. Like Scenario 1, an appropriate level in FIT and FPI needs to be identified; the FIT system level (β level) is selected since this planning problem requires monitoring performance and demand trends across several ground modes. Note that the ground transportation system consists of auto, rail, transit, and pedestrian and bike within the FIT hierarchy (β level in Figure 27). Reflecting the planning context (i.e., promoting public transportation modes), the transportation planner may give higher weights to public transportation modes (i.e., transit and rail). Table 31 shows the weights used in this planning scenario. As the result of adjusting the weights, FIT and FPI trends will be updated. Based on the weights of the planner, FIT and FPI will be calculated and compared (Figures 38 and 39). All ground transportation modes show increasing trends in FIT, indicating increasing demand for all ground transportation modes (Figure 38). Meanwhile, according to FPI, rail and truck modes show increasing trends while auto, transit, and pedestrian modes show decreasing trends, which may require the planner’s attention. To be more specific, despite some fluctuations, an overall increasing trend is found in FPI results. In more recent years, the performance of the ground transportation system has been improved. However, comparing FIT’s and FPI’s slopes (+0.5 vs. +0.23) implies that more resources are required to keep the growing trends and address the increasing demand caused by external factors.

Table 31: Example 02 - Defined weights for each component of FIT and FPI

FIT components		FPI components	
Auto	0.1	Auto	0.1
Transit	0.9	Transit	0.9
Rail	0.9	Rail	0.9
Truck	0.2	Truck	0.2
Pedestrian and Bike	0.4	Pedestrian and Bike	0.4

Based on further investigation of the FPI trends, it can be concluded that the rail mode is in good condition (i.e., in terms of growing transportation performance). On the other hand, the transit mode does not show continuous improvement; the transit mode may not have sufficient resources to meet demand growth as a result of external factors. Therefore, since the focus of the planning problem is on promoting public transportation systems, the transportation planner should allocate more budget to the transit system.

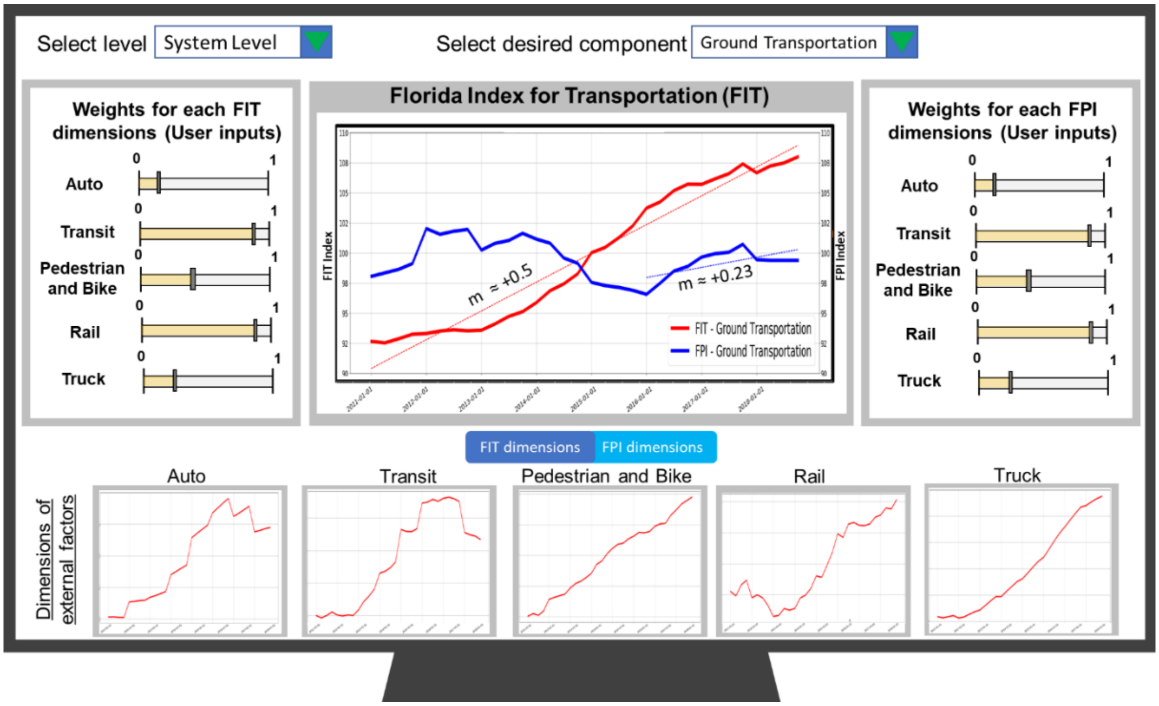


Figure 38: Decision making sample scenario 02, FIT results

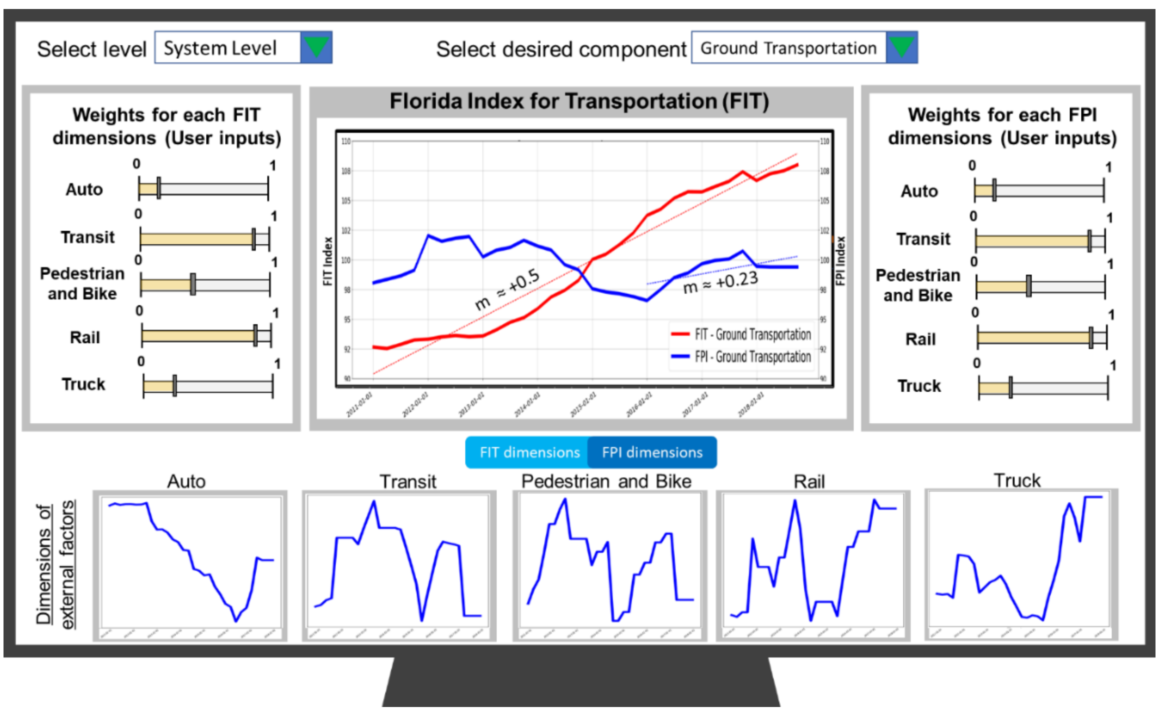


Figure 39: Decision making sample scenario 02, FPI results

4.2 FIT application in understanding the changing nature of transportation system

In this section, the capability of the FIT to track the changing nature of transportation is demonstrated. In this regard, the FIT is applied in different time frames while changes in its components are explored in two steps. In the first step, the external factors composition of the FIT is compared across various time frames to understand a possible disruptive event that cause changes in the Florida transportation system. Next, the changes in the FIT dimension level were analyzed to further understand the implication of the possible disruption from the planning perspective (i.e., by identifying the consistent and emerging dimensions in different time frames).

4.2.1 Investigating changes in the FIT external factors' composition

4.2.1.1 Methodology

Studying the changes in the external factors' composition (i.e., α level) starts with specifying the time window for analysis according to the available data. In this analysis, the time window was set to 2008–2018 since most of the performance measures and external factors data are available in this period. Four different time subframes were defined to perform the statistical analysis. These time frames are:

- 2008–2015
- 2009–2016
- 2010–2017
- 2011–2018

Each time frame contains eight years of quarterly data (i.e., 32 data points). Considering the minimum number of data points required for statistical analysis (i.e., at least 30 data points for factor analysis), eight years is the smallest time span that can be selected for each time frame. Therefore, it is not possible to add the 2012–2018 time frame to the analysis. Moreover, eight years seems to be enough time for recovering from a disruptive event. For instance, the air transportation system recovered in about two years after the 2007–2009 market crisis (Pearce 2012). As another example, housing prices recovered to their pre-market crisis levels after almost eight years (Young 2020).

The external factors and performance measures that contain missing data are dropped from the analysis to create a consistent set of data for all four statistical analyses. As a result, 78 external factors and 55 performance measures were selected for the final analysis.

In the next step, statistical analysis was performed for each time frame to rank external factors based on their influence on the performance measures of each transportation mode. In particular, this analysis focuses on having some diversity in the external factors that have a causal relationship with performance measures, thereby providing more insights derived from a broad range of external factors. Therefore, Granger causality analysis was conducted for each pair of external factors and performance measures. The external factors are then ranked based on the number of repetitions of causality relationships in descending order. To select the influential external factors, the variable "N" is defined as the number of the tenth-ranked external factor's Granger causality relationships with the performance measures. All the external factors with Granger causality relationships greater than or equal to "N" are reported as the influential external factors in the subsequent analyses. Depending on the number of external factors having "N" number of relationships, the total number of influential external factors varies across different transportation modes. In other words, at least 10 external factors are reported as influential external factors for each mode. Then, the changes in the external factors composition for each mode will be analyzed to investigate changes. Figure 40 illustrates this analysis procedure.

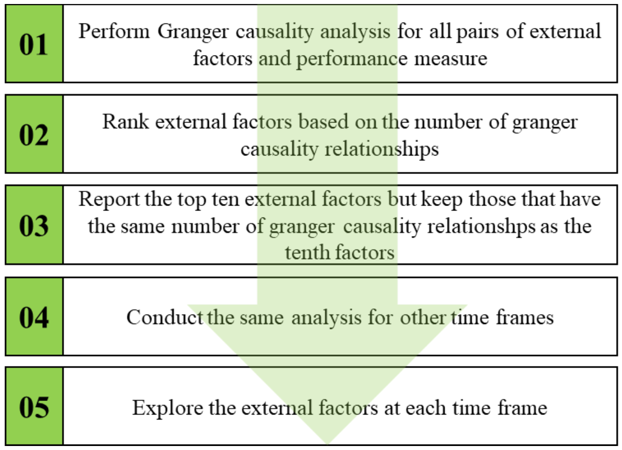


Figure 40: The analysis procedure for investigating changes in the FIT external factors' composition at the FIT base level

Figure 41 shows the time frames used for the statistical analysis. Please note that comparing influential external factors for one-time frame with the ones for its subsequent time frame enables investigating the impact of a disruptive event on transportation systems. To be more specific, if we compare the results of two subsequent time frames, the variance stems from the difference between the first year of the former time frame and the last year of its subsequent time frame. As mentioned before, eight years are assumed to be long enough for transportation systems to recover from any disruptive events; the impact of any disruptive events on transportation will be dissipated within eight years and transportation systems recover their normal causal relationships with external factors. As such, if a disruptive event occurs in the first year of one time frame and consequently affects transportation systems to be more sensitive to certain types of external factors, such an impact can be observed and explored by comparing its list of external factors with the one for its subsequent time frame. For example, the starting year of the second time frame is 2009, which is one year after the first year of its preceding time frame (i.e., 2008). Similarly, the last year of this time frame (i.e., 2016) is one year after the ending year of the first time frame (i.e., 2015). The difference between the first two time frames in terms of the covered years is 2008 and 2016 (marked as "a" and "b" in Figure 41, respectively). Therefore, changes in the statistical analysis results in these time frames arise from these two years. If the result shows a significant change or abnormal patterns in the list of the important external factors, it is a sign that a disruptive event may happen in 2008.

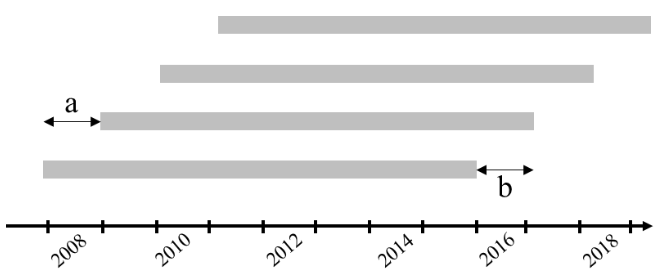


Figure 41: Time frames for first statistical analysis

In order to facilitate studying the external factors composition, the factors were categorized into six groups (i.e., demographic, housing, economic, income, employment, and others; Table 32). In each time frame, the number of external factors under each category will be counted. Finally, the external factors composition changes will be studied by analyzing changes in external factor categories across different time frames.

Table 32: Categorization of external factors

Demographic factors	Housing factors
Population Estimate (NL)	Rental Vacancy Rate (NL)
Population Change (NL)	Homeowner Vacancy Rate (NL)
Natural Increase - Births (NL)	Homeownership Rate (NL)
International Migration (NL)	Total Building Permits (NL)
Domestic Migration (NL)	Single Family (SF) Permits (NL)
Net Migration (NL)	Number of Housing Units (NL)
Population in College (NL)	House Price Index (NL)
Racial/ethnic composition (NL)	CPI - Rent Price Index (NL)
Immigration (NL)	Rental Vacancy Rate (SL)
Aging Populations (NL)	Homeowner Vacancy Rate (SL)
Florida Population (SL)	Homeownership Rate (SL)
Georgia Population (SL)	Total Building Permits (SL)
Alabama Population (SL)	Single Family (SF) Permits (SL)
FL Population Change (SL)	Number of Housing Units (SL)
International Migration (SL)	House Price Index (SL)
Domestic Migration (SL)	CPI - Rent Price Index (SL)
Net Migration (SL)	**Income, Poverty factors**
Population in College (SL)	% Population in Poverty (NL)
Seniors Population(65+) (SL)	Per Capita Income (NL)
Economic Factors	Personal Income (NL)
GDP - All industries (NL)	Percentage of Population in Poverty (SL)
GDP - Construction (NL)	Per Capita Income (SL)
GDP - Manufacturing (NL)	Personal Income (In Millions of Dollars) (SL)
GDP - Real Estate (NL)	**Environmental**
GDP - Transportation (NL)	Total Precipitation (NL)
Financial Condition Index (NL)	Average Temperature (NL)
Consumer Price Index (CPI) (NL)	Total Precipitation (SL)
CPI - Fuel Price Index (NL)	Average Temperature (SL)
Financial Markets (Dow Jones Avg Closing Price) (NL)	Number of Hurricane Strikes + tropical storms (SL)
GDP- FL All Industries (In Millions of Dollars) (SL)	Sea Level Rise* (SL)
GDP of FL- Construction (In Millions of Dollars) (SL)	Weather related inland flooding* (SL)
GDP of FL- Manufacturing (In Millions of Dollars) (SL)	**Other**
GDP of FL-Real Estate (In Millions of Dollars) (SL)	VMT (NL)
GDP of FL- Retail Trade (In Millions of Dollars) (SL)	Political Party Affiliation - Democratic (NL)
GDP of FL- Transportation (In Millions of Dollars) (SL)	Political Party Affiliation - Republican (NL)
Economic Condition Index (SL)	Political Party Affiliation - Independent (NL)
Average CPI for all MSAs (SL)	Emerging Industries *tech, aerospace (NL)
CPI - Fuel Price Index (SL)	Number of Smartphone Users (NL)
Employment Factors	Number of Mobile Internet Users (NL)
Number of Employed (NL)	Hours of Service (HOS) Rules (Driving Limit Without Breaks) (NL)
Number of Unemployed (NL)	Subsidies for Renewable Fuels (Millions) (NL)
Percentage of Unemployed (NL)	Level of Highway Funding (NL)
Number of Employed (SL)	Investments and Incentives for Alternative Fuel Infrastructure and Vehicles (NL)
Number of Unemployed (SL)	Political Party Affiliation (republican) (SL)
Percentage of Unemployed (SL)	Political Party Affiliation (democrat) (SL)
	Political Party Affiliation (other) (SL)
	Number of Licensed Drivers* (SL)
	Tourism* (SL)
	Viability of Streams (Gas, tax, etc.) (Millions) (SL)
	Electric Vehicle Sales (SL)
	Highway Operations and Maintenance Decisions (Millions) (SL)
	Level of Highway Funding (Payments into Highway Trust Fund) (SL)
	Florida Total Amount of Highway Trust Fund Money (Allocations) (SL)
	Fuel Taxes (SL)
	Privatization of Roads (SL)
	Number of Launches at Kennedy Space Center (SL)
	International Trade Through Miami-Dade (Billions) (SL)
	Number of Tourists to Orlando (SL)

NL: National level, SL: State level, GDP: gross domestic product, CPI: consumer price index

4.2.1.2 Results

In this section, the analysis results for each mode are provided. For each mode, two figures are presented. The first figure (i.e., Figures 42, 44, 46, 48, 50, 52, and 54) presents the distribution of all the influential external factors for each time frame. The second figure (i.e., Figures 43, 45, 47, 49, 51, 53, and 55) presents the distribution of new external factors emerging at each time frame compared to its previous time frame. The 2008–2015 time frame cannot be compared to any prior time frame as it is the first time frame available for analysis based on the data availability. Therefore, the second figure of each mode only demonstrates the emerging factors in the three subsequent time frames.

Pedestrian and bike*:* Figure 42 shows the distribution of all the influential external factors that emerged at different time frames for pedestrian and bike modes for different categories. Figure 43 presents the distribution of new influential external factors that emerged at different time frames. As shown in the figures, most new factors emerged within the 2010–2017 time frame; economic factors, which consist of GDP-related factors, are the major new factors. This result indicates that a disruptive event affects the pedestrian and bike mode in a way that becomes more sensitive to the economy.

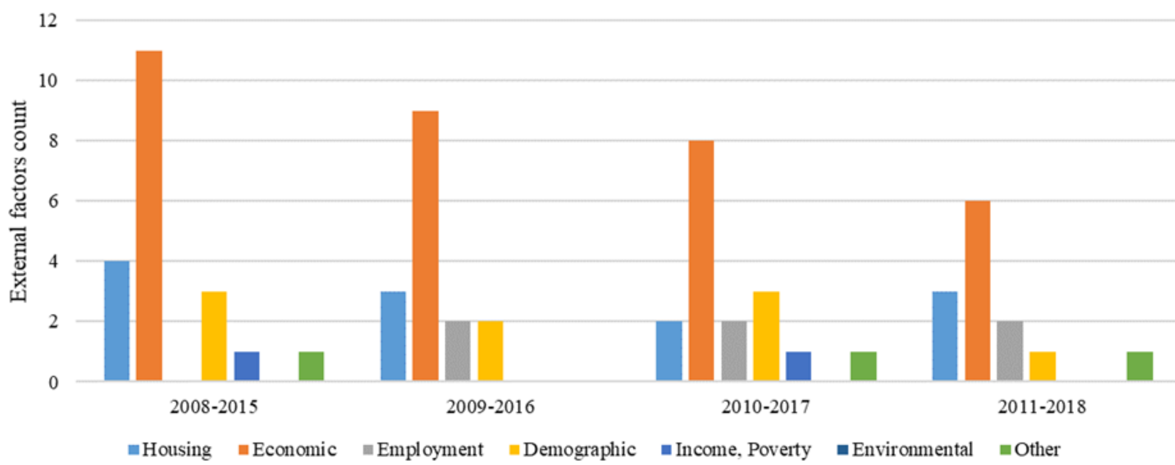


Figure 42: Distribution of all external factors for different categories at each time frame (pedestrian and bike mode)

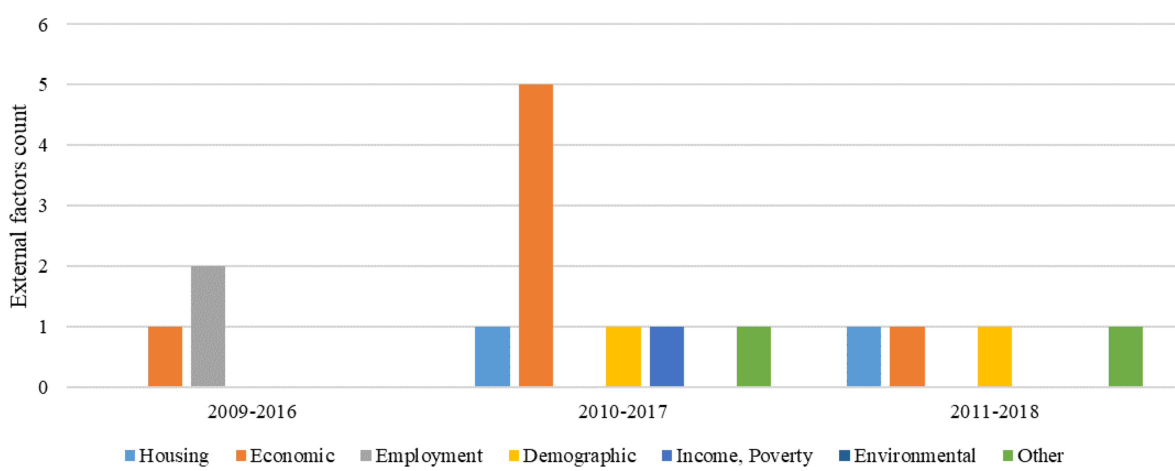


Figure 43: Distribution of new external factors for different categories at each time frame (pedestrian and bike mode)

Auto: Figure 44 presents the distribution of all influential external factors for each time frame, while Figure 45 shows the distribution of the new external factors that arise at each time frame for different categories. According to the figure, the number of the new external factors decreases as the analysis time frame moves closer to the present time. Housing factors, employment-related factors, and economic factors, which consist of GDP-related factors, account for the majority of the new factors. The results show that a disruptive event might occur in 2008 or before and had affected the auto mode to be sensitive to economic, housing, and employment-related factors until 2010.

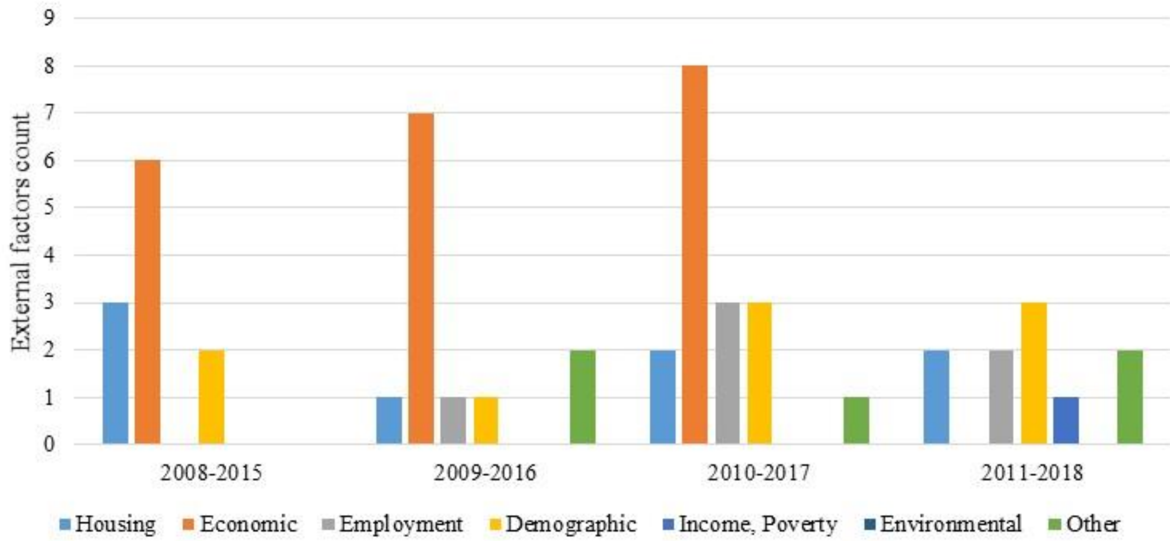


Figure 44: Distribution of all external factors for different categories at each time frame (auto mode)

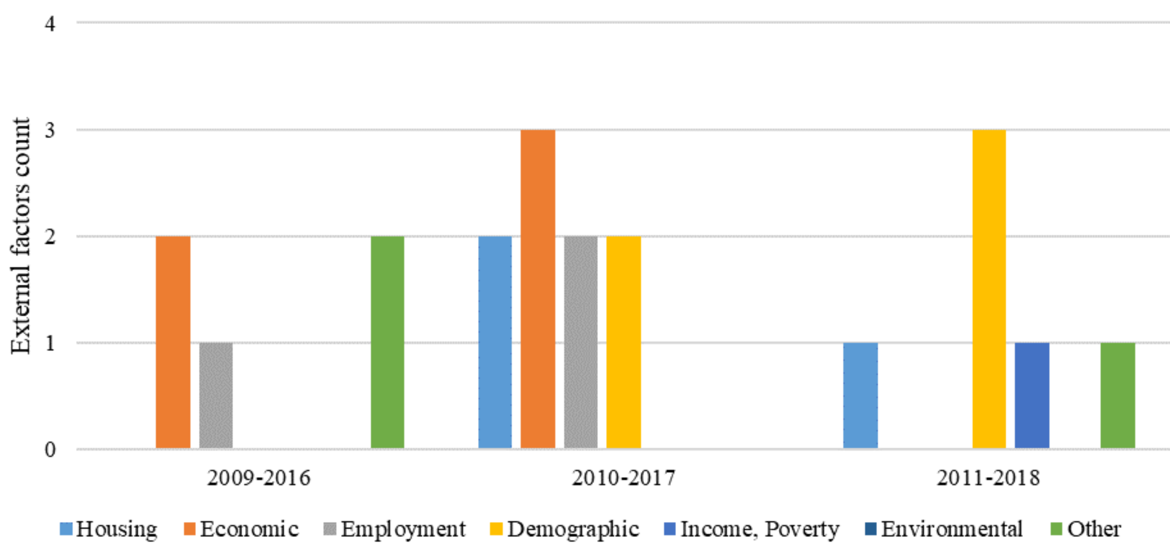


Figure 45: Distribution of new external factors for different categories at each time frame (auto mode)

Transit: Figures 46 and 47 present the distribution of all external factors and new external factors selected at different time frames for the transit mode. According to Figure 47, most new factors emerge within the 2010–2017 time frame. The lower number of new factors within the 2011–2018 time frame implies that most of the new factors emerging within the previous time frame continue to arise within the subsequent time frame. Demographic, economic, and housing-related factors form the emerging factors in the 2010–2017 time frame. This result indicates that the transit mode has become more sensitive to demographic, economic, and housing-related factors due to some external disruptive events.

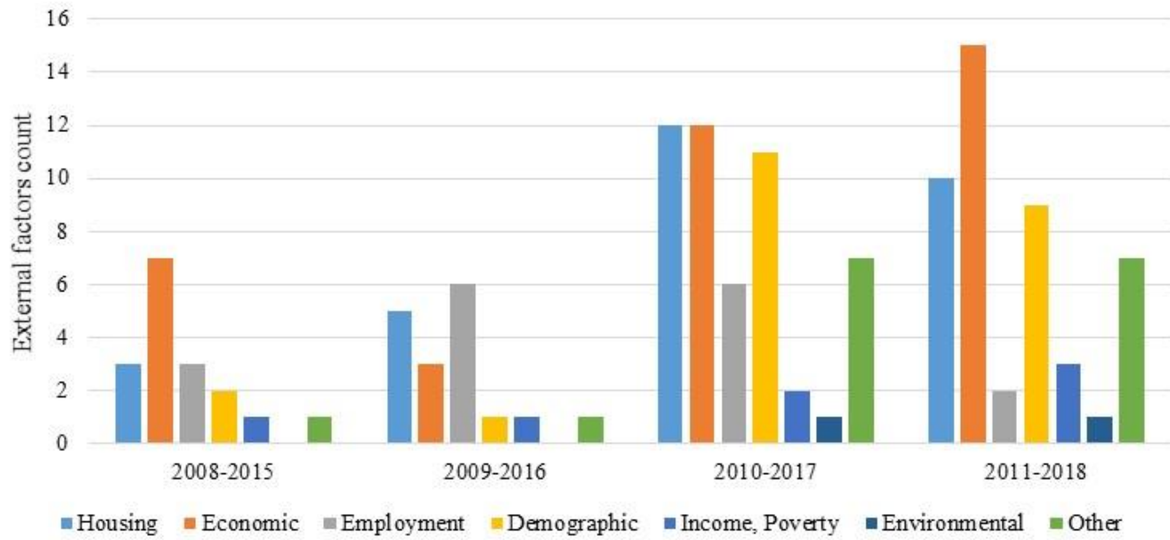


Figure 46: Distribution of all external factors for different categories at each time frame (transit mode)

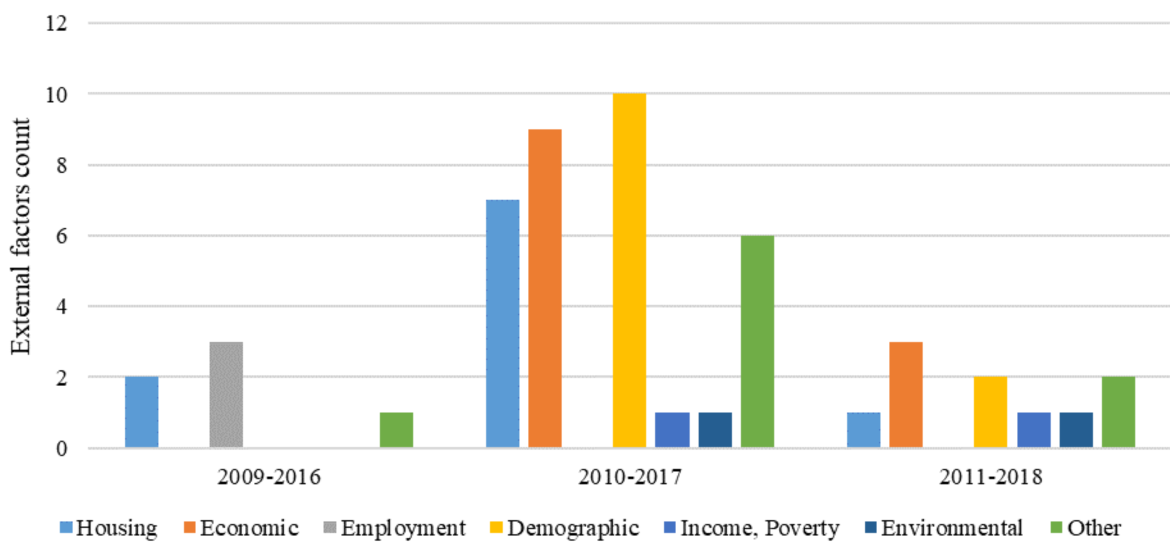


Figure 47: Distribution of new external factors for different categories at each time frame (transit mode)

***Aviation**:* Figure 48 depicts the distribution of all influential external factors for each category in different time frames, while Figure 49 presents the composition of new factors. According to Figure 49, environmental factors are the major new factors emerging during the 2008-2015 time frame; Housing factors, economic factors, and employment factors comprise the majority of the factors arising in the subsequent time frames. The results imply that a disruptive event affected the aviation mode in a way that becomes more sensitive to environmental, housing, and economic and employment factors.

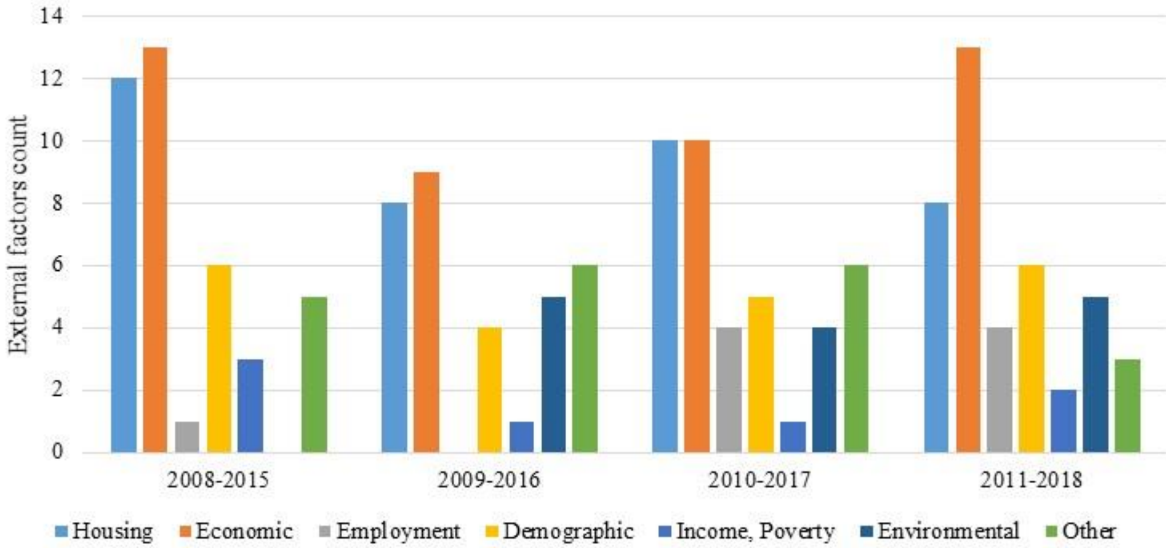


Figure 48: Distribution of all external factors for different categories at each time frame (aviation mode)

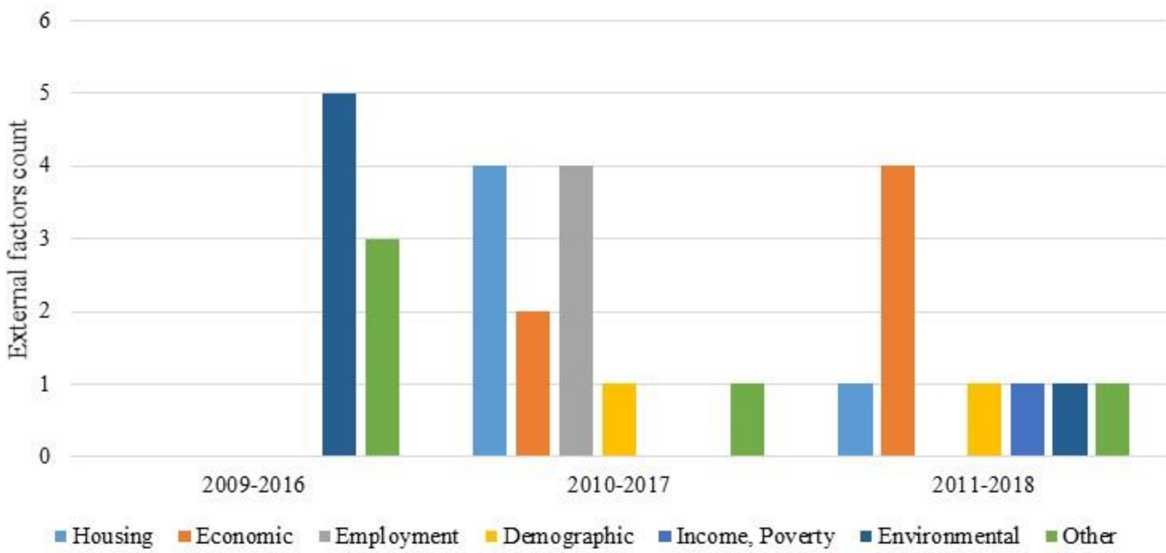


Figure 49: Distribution of new external factors for different categories at each time frame (aviation mode)

Rail: Figures 50 and 51 present the distribution of all external factors and new external factors selected for each category at different time frames for the rail mode. According to Figure 51, most new external factors emerge within the 2009–2016 and 2010-2017 time frames. These new factors continue to arise within the 2011–2018 time frame. While housing factors and demographic factors are the dominant new factors within the 2009–2016 time frame, economic and environmental factors arise within the 2010–2017 time frame. The results suggest that a disruptive event might affect the rail mode significantly, and more sensitive to economic, environmental, and demographic factors became important for rail mode planning.

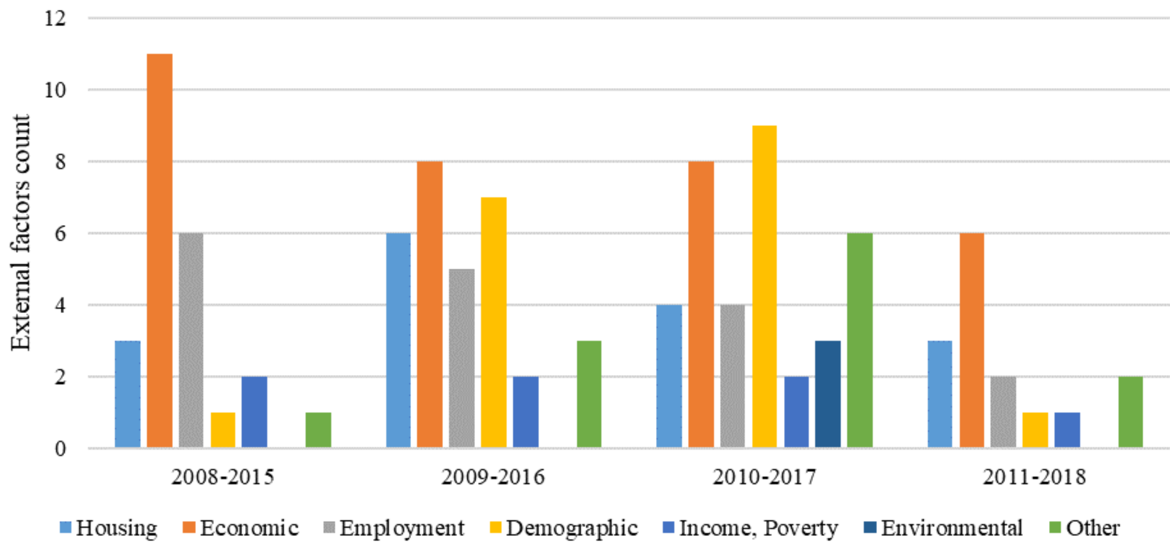


Figure 50: Distribution of all external factors for different categories at each time frame (rail mode)

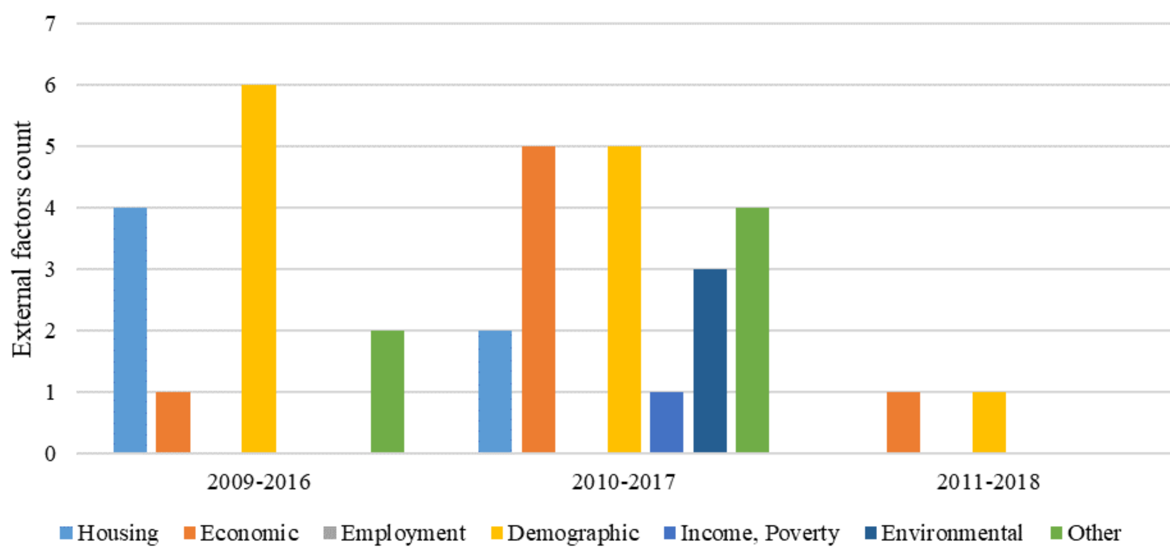


Figure 51: Distribution of new external factors for different categories at each time frame (rail mode)

Seaport: Figure 52 depicts the distribution of all influential external factors during each time frame. Figure 53 presents the distribution of new influential external factors that emerged at different time frames for each category. According to Figure 53, most of the new factors arise within the 2010–2017 time frame. The low number of new factors within the 2011–2018 time frame implies that the 2010–2017 time frame's factors continue to arise within the subsequent time frame. Housing, economic, and employment factors comprise most of the new factors in this time frame. The results indicate that a disruptive event impacted the seaport mode, which made it more sensitive to housing, economic, and employment factors.

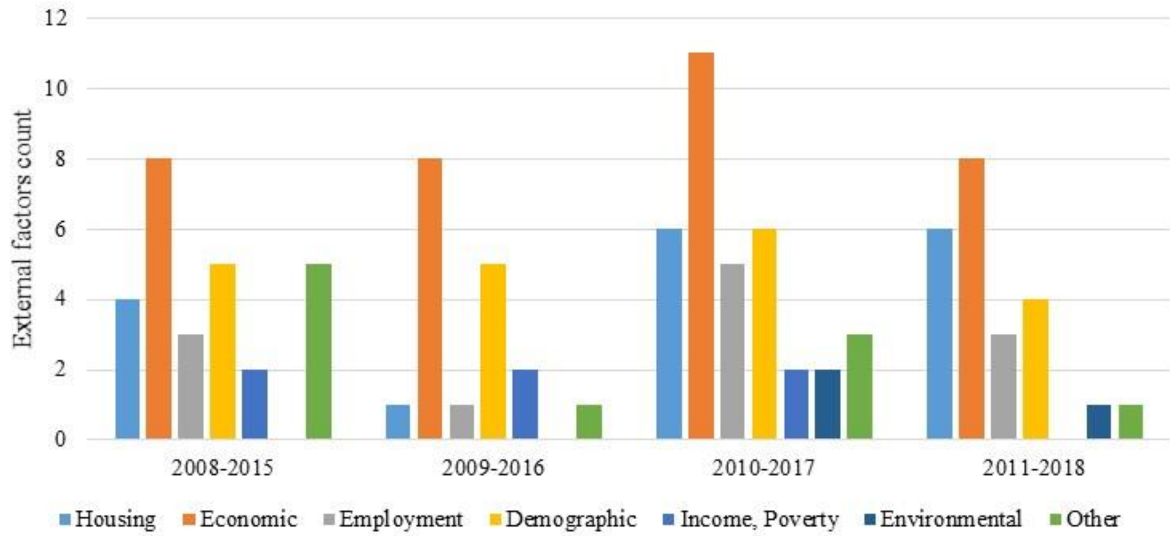


Figure 52: Distribution of all external factors for different categories at each time frame (seaport mode)

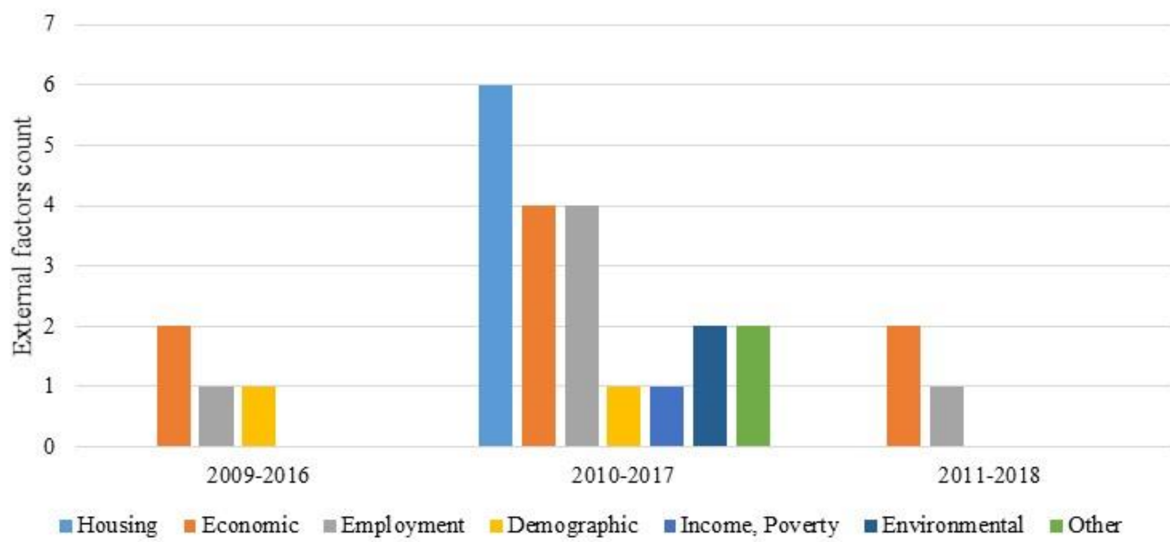


Figure 53: Distribution of new external factors for different categories at each time frame (seaport mode)

Truck*:* Figures 54 and 55 present the distribution of all external factors and new external factors selected at different time frames for each category. According to Figure 55, new external factors in the truck factors mostly emerge within the 2009–2016 time frame. The external factors within this time frame continue to arise within the subsequent time frames considering the lower number of new external factors in the 2010–2017 and 2011–2018 time frames. Housing and economic factors form most of the new external factors within the 2009–2016 time frame. The results suggest that a disruptive event might occur to affect the truck mode to be more sensitive to housing and economic factors.

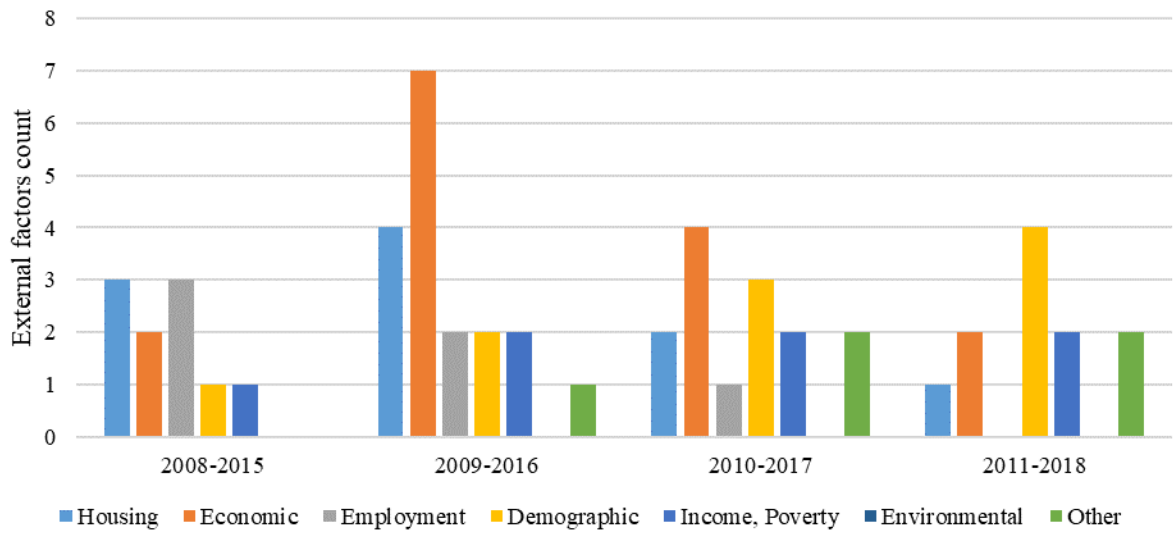


Figure 54: Distribution of all external factors for different categories at each time frame (truck mode)

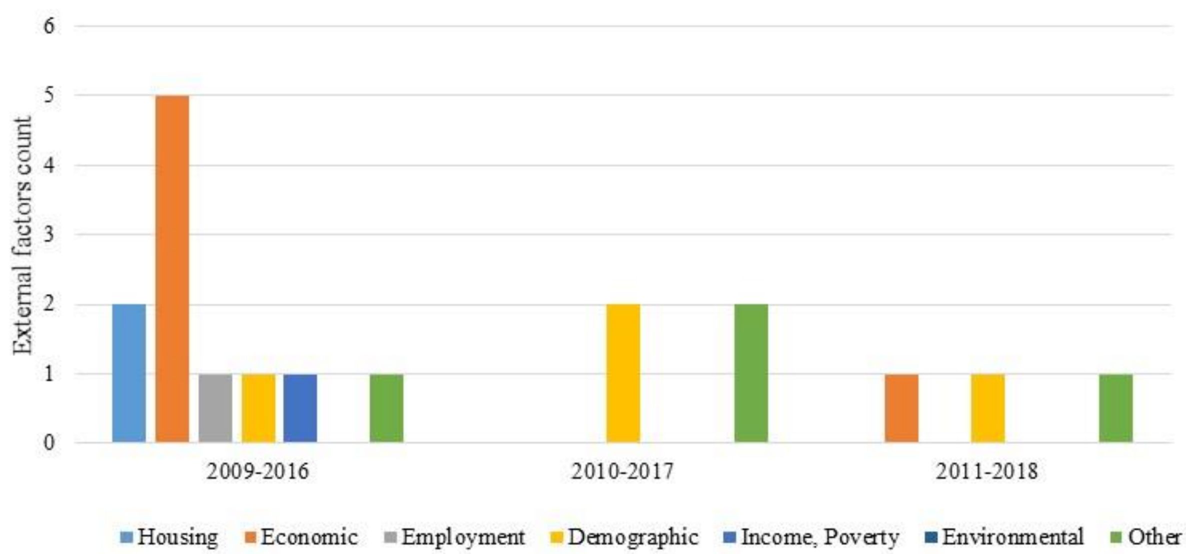


Figure 55: Distribution of new external factors for different categories at each time frame (truck mode)

4.2.1.3 Implications

Economic factors, housing factors, and employment factors are the most frequent external factors that emerge across different time frames in the Florida transportation system. As explained in Table 32, economic factors mostly consist of factors related to GDP and financial conditions. Housing factors are related to housing demand and housing-related costs, while employment factors are national and state-level employment rates. GDP is highly associated with transportation demand since higher GDP generally means more products and services are produced and transported (Wardman 2006). Moreover, as GDP increases, it also leads to more business trips made by service-related industries (Wardman 2006). Employment is a significant determinant for transportation demand as employment rates impact the number of commuters and thus the traffic volumes on roadways; previous studies show that the employment level in central business districts is highly correlated with work trips (Taylor and Fink 2013). The housing sectors also play a significant role in transportation demand. To be more specific, the geographical locations of residential developments impacts the transportation choices of people (i.e., mode choices of residents). Depending on how far away households are located from the core area of their city, they may make either more vehicle trips or not. Also, the housing category is also very related to people's transportation behavior because their residences often reflect their economic situations. For example, low-income people living in affordable housing units have limited access to personal automobiles, resulting in higher demand for transit services (Howell et al. 2018; Taylor and Fink 2013).

Most of the new external factors arise within the 2009–2016 and 2010–2017 time frames. As explained in the beginning of this section, by subtracting these time frames from their previous time frames, we can identify their differences and realize which year(s) caused the emergence of external factors as a result of a disruptive event. With that, we found a significant difference in the lists of influential external factors between the 2009–2016 time frame and 2010–2017 time frames. If we assume that there is no significant event that happened in 2017 or later, this result implies that a disruptive event might happen before or in 2009 and had affected Florida transportation systems until possibly 2010. Reviewing the categories of the new external factors emerging during these periods, the team found that economic, employment, and housing factors groups account for a significant portion of the emerging external factors. Based on these findings, the team inferred that the 2007-2009 market crisis might be the disruptive event that affected the Florida transportation system.

On the national economic scale, the housing crisis significantly affected the U.S. economy. For instance, the U.S. GDP dropped by about 4% as of early 2009, which was the most significant decline since the Second World War (Ritchie et al. 2010). Another major aspect of the recession was the record-high levels of the national unemployment rate. The U.S. unemployment level increased from 5% in December 2007 to 10% in late 2009. Moreover, the U.S. median household income was estimated to decline by about 4.2% during the recession, which in turn impacted American households' spending power (Thakuriah and Mallon-Keita 2014). Finally, the housing market was also severely impacted. In this regard, substantial drops in housing prices and homeownership rates were reported during the recession. For example, In the 2008–2010 period, the national homeownership rates dropped from their peak of 69% to 66%, and homeownership vacancy increased from a long-term average of about 1.7% to about 2.6%. (Lee and Painter 2013).

Overall, the housing crisis impacted the transportation system significantly. Prior research shows that air passenger and air cargo demand decreased during the recession while the air transportation costs are increased due to an increase in fuel prices. These resulted in a lower cost efficiency of air transportation operations (Voltes-Dorta and Pagliari 2012). Moreover, a survey conducted by the American Public Transportation Association in March 2010 revealed that 90% of transit agencies reported a decrease in their revenue, and the cumulative projected shortfall among participating transit agencies was almost $2 billion (American Public Transportation Association 2011). The housing crisis also impacted the auto mode. Due to the low median household income, household expenditure on car ownership declined significantly during the recession. Higher car-ownership costs forced households to delay purchasing new or used cars, thereby leading to increases in holding time for cars (Thakuriah and Mallon-Keita 2014).

Also, Moschovou et al. (2018) examined the economic recession's impact on the passenger and freight road transport system. In their analysis, the authors investigated potential relationships between transport performance and socioeconomic factors. The authors claimed that two socioeconomic factors (GDP and the employment rate) significantly affect transportation passenger and freight demands during and after the recession.

4.2.2 Investigating changes in FIT dimensions in different time frames

4.2.2.1 Methodology

In order to investigate changes in the FIT dimensions, the analysis time frames should be specified in the first step. Similar to the previous section, the entire time frame was set from 2008 to 2018. Four time subframes were further identified as below.

- 2008–2018
- 2009 - 2018
- 2010–2018
- 2011– 2018

Figure 56 shows the time frames selected for the statistical analysis in this section. The first year of any time frame is one year after the starting year of its preceding time frame. Moreover, the last year of all of the time frames is fixed to 2018. In other words, the years 2008, 2009, and 2010 are the differences between one time frame and its subsequent one (marked as "a," "b," and "c" in Figure 56). This selection of time frames facilitates the investigation of the impact of the disruptive event during 2008, 2009, and 2010. In other words, as we discussed in the previous section, we can further investigate the impact of the 2007–2009 market crisis on transportation modes by selecting the analysis time frames in this way.

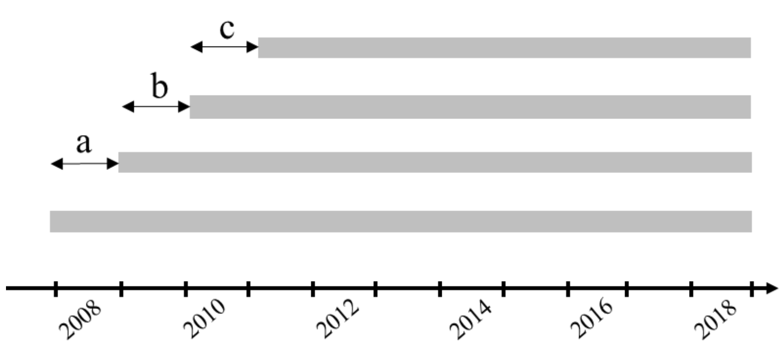


Figure 56: Time frames for the second statistical analysis

In the second step, the top ten most influential external factors for each transportation mode were identified using the same statistical analysis explained in the previous section. FIT dimensions should be determined in the next step. The factor analysis approach was employed to detect the underlying dimensions of the ten external factors. By iterating the same analysis, the dimensions for each mode were determined across different time frames. Figure 57 presents the analysis procedure for this section.

Transportation decision makers can identify and evaluate the transportation system's changes by comparing the dimensions across various time frames. In this regard, changes in FIT dimensions imply changes in the behavior of the transportation mode. For instance, an emerging dimension in the 2009–2018 time frame indicates a disruptive event that causes the transportation mode to be more sensitive to this new dimension which did not exist in the 2008–2018 time frame. On the other hand, dimensions that are repeated across all time frames mainly drive the transportation mode's behavior.

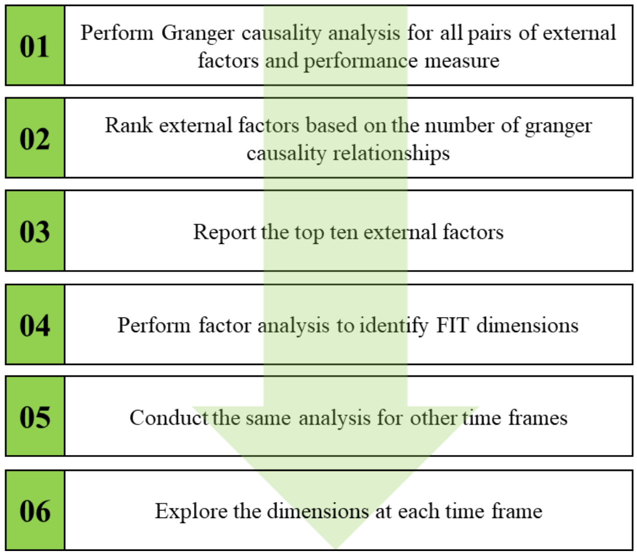


Figure 57: The analysis procedure for investigating changes in FIT dimension level

Each dimension is named based on the combined interpretation of the grouped factors. (Naderpajouh et al. 2016). In the following paragraphs, a general description for each dimension and the reasons regarding the naming of each dimension are provided.

Housing demand: The dimensions named "housing demand" contain external factors related to the number of housing units and prices. The number of housing units is available at both state and national levels. Housing price factors, including "house price index" and "rent price index," are good indicators of supply with respect to demand for housing (Gasparėnienė et al. 2016). Additionally, this dimension may also include external factors associated with individuals' economic conditions such as poverty and income level since an increase in housing demand is associated with people's positive economic outlook (Li 2015; Painter and Redfearn 2002).

Residential mobility: Residential mobility implies the households' moving to other neighborhoods or cities to improve or accommodate housing situations to financial conditions (Coulton et al. 2012). The external factors in this dimension mostly consist of housing and migration factors, including homeownership rate, vacancy rate, domestic migration, and net migration. Residential mobility rates are higher among low-income households, renters, and younger families (Coulton et al. 2012). Further, low-income households may make frequent moves because of economic or social distress.

Economic well-being: External factors grouped under this dimension are commonly related to the community's economic status. These include GDP factors, the community's financial condition (e.g., poverty level, income level, employment), living costs, and wealth of the community which are correlated with individuals' higher expectations for better financial gains in the future (Li 2015; Painter and Redfearn 2002).

Population change: The external factors grouped under this dimension are mostly related to population changes. Examples of these factors include domestic, international, and net migration, natural increase, and immigration.

Housing prices: The external factors grouped under this dimension are mostly related to housing prices. Examples of these factors include national- or state-level house price index and rent price index. Unlike the housing demand dimension, which contains a broader range of housing-related factors, housing prices primarily include price-related and economic factors. For example, the housing-demand dimension contains the number of housing permits, homeownership rates, and vacancy rates, which are not the primary factors within the housing prices dimension.

Homeownership: The external factors grouped under this dimension are related to homeownership. Examples of these external factors include national- and state-level homeownership rates, rental vacancy rates, and homeownership vacancy rates.

Climate impact: The external factors under this dimension are primarily indicators of climate changes. Examples of these factors include average temperature and total precipitation.

4.2.2.2 Results

In this section, the results for each transportation mode are presented. For each mode, four tables are presented. Each table includes dimensions and their corresponding external factors for each of the time frames.

***Pedestrian and bike**:* Tables 33 to 36 present the pedestrian mode's dimensions along with corresponding external factors for each time frame. Reviewing the external factors listed in the 2008–2018 time frame (Table 33) reveals that 60% of external factors are changed in the 2009–2018 time frame (Table 34). Similarly, 40% of external factors in the 2009–2018 time frame (Table 34) and 40% of external factors in the 2010–2018 time frame (Table 35) are changed in their subsequent time frames.

According to the dimension results, despite changes in the external factors at different time frames, the overall interpretation of the dimensions remained the same. In this regard, the first dimension was interpreted as "Economic well-being" while the second dimension was interpreted as "Economic condition." The difference between the two dimensions is that the economic well-being dimension mainly contains a broad measure of overall domestic production or GDP-related factors (i.e., an indicator of a country's economic health) whereas the economic condition dimension comprises individual economic conditions, including employment, income, and homeownership status.

Table 33: Pedestrian and bike mode dimensions from 2008 to 2018

2008-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)	1	0.375	Economic well-being
EF74	GDP of F.L. - Transportation (In Millions of Dollars) (SL)		0.16	
EF25	GDP Real Estate (NL)		0.131	
EF37	Financial Markets (Dow Jones Avg Closing Price) (NL)		0.123	
EF77	Economic Condition Index (SL)		0.112	
EF22	GDP All industries (NL)		0.099	
EF62	Homeownership Rate (SL)	2	0.423	Economic condition
EF31	Consumer Price Index (CPI) (NL)		0.279	
EF24	GDP - Manufacturing (NL)		0.167	
EF27	Per Capita Income (NL)		0.132	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 34: Pedestrian and bike mode dimensions from 2009 to 2018

2009-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF23	GDP - Construction (NL)	1	0.285	Economic well-being
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)		0.266	
EF32	CPI - Rent Price Index (NL)		0.201	
EF26	GDP - Transportation (NL)		0.135	
EF77	Economic Condition Index (SL)		0.114	
EF62	Homeownership Rate (SL)	2	0.55	Economic condition
EF24	GDP - Manufacturing (NL)		0.136	
EF84	Percentage of Unemployed (SL)		0.13	
EF35	Number of Unemployed (NL)		0.093	
EF36	Percentage of Unemployed (NL)		0.091	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 35: Pedestrian and bike mode dimensions from 2010 to 2018

2010-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF71	GDP of F.L.- Manufacturing (In Millions of Dollars) (SL)	1	0.198	Economic well-being
EF69	GDP- F.L. All Industries (In Millions of Dollars) (SL)		0.187	
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)		0.183	
EF26	GDP - Transportation (NL)		0.16	
EF74	GDP of F.L.- Transportation (In Millions of Dollars) (SL)		0.153	
EF24	GDP - Manufacturing (NL)		0.119	
EF62	Homeownership Rate (SL)	2	0.477	Economic condition
EF08	Rental Vacancy Rate (NL)		0.316	
EF35	Number of Unemployed (NL)		0.105	
EF36	Percentage of Unemployed (NL)		0.102	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 36: Pedestrian and bike mode dimensions from 2011 to 2018

2011-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF70	GDP of FL- Construction (In Millions of Dollars) (SL)	1	0.36	Economic well-being
EF71	GDP of F.L.- Manufacturing (In Millions of Dollars) (SL)		0.241	
EF24	GDP - Manufacturing (NL)		0.2	
EF31	Consumer Price Index (CPI) (NL)		0.199	
EF62	Homeownership Rate (SL)	2	0.435	Economic condition
EF08	Rental Vacancy Rate (NL)		0.218	
EF94	Fuel Taxes (SL)		0.108	
EF14	Population in College (NL)		0.08	
EF35	Number of Unemployed (NL)		0.08	
EF36	Percentage of Unemployed (NL)		0.08	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Auto: Tables 37 to 40 present the auto mode's dimensions and their corresponding external factors. In the auto mode, 40% of external factors in the 2008-2018 time frame (Table 37), 30% of external factors in the 2009-2018 time frame (Table 38), and 30% of external factors in the 2010-2018 time frame (Table 39) are changed in the subsequent time frames.

Residential mobility and economic condition are the auto mode's major dimensions across different time frames. Residential mobility is repeated in the 2008–2018 time frame (Table 37), the 2009–2018 time frame (Table 38), and the 2010–2018 time frame (Table 39). Moreover, economic condition is also repeated in all time frames. In more recent years (i.e., 2011–2018) (Table 40), the importance of housing-related factors, compared to population change-related factors, decreases since the top three external factors, which are all related to population change, form about 67% of the total weight of the dimension. Therefore, the first dimension in the last time frame was named population change in Florida instead of residential mobility.

The external factors belonging to the residential mobility dimension (i.e., migration, homeownership rate, and unemployment) are consistent with 2007-2009 recession-related factors; residential mobility may increase as a result of an economic recession. For example, in 2010, after the 2007-2009 recession, nearly one in five residents moved in one year (Stoll 2013). During this period, local movers reported recession-related reasons for their move, such as finding affordable housing or looking for work. Those who moved during the recession were more likely to be unemployed and renters. Unemployment is also related to residential mobility since unemployment affects households' income and may hinder them from paying for their current housing and force them to move to more affordable places (Stoll 2013). Finally, the change of residential mobility dimension to population change dimension in the most recent time frame (i.e., 2011–2018) (Table 40) may imply that the transportation systems gradually recovered from the recession.

Table 37: Auto mode dimensions from 2008 to 2018

2008-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF52	Domestic Migration (SL)	1	0.226	Residential mobility
EF53	Net Migration (SL)		0.198	
EF10	Homeownership Rate (NL)		0.192	
EF08	Rental Vacancy Rate (NL)		0.147	
EF60	Rental Vacancy Rate (SL)		0.142	
EF68	Viability of Streams (Gas, tax, etc.) (Millions) (SL)		0.095	
EF15	% Population in Poverty (NL)	2	1	Poverty level
EF66	Number of Licensed Drivers* (SL)	3	0.609	Economic condition
EF02	Population Estimate (NL)		0.296	
EF63	Total Building Permits (SL)		0.095	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 38: Auto mode dimensions from 2009 to 2018

2009-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF10	Homeownership Rate (NL)	1	0.275	Residential mobility
EF08	Rental Vacancy Rate (NL)		0.228	
EF02	Population Estimate (NL)		0.122	
EF35	Number of Unemployed (NL)		0.107	
EF36	Percentage of Unemployed (NL)		0.105	
EF68	Viability of Streams (Gas, tax, etc.) (Millions) (SL)		0.09	
EF73	GDP of F.L.- Retail Trade (In Millions of Dollars) (SL)		0.074	
EF66	Number of Licensed Drivers* (SL)	2	0.485	Economic condition
EF15	% Population in Poverty (NL)		0.366	
EF69	GDP- F.L. All Industries (In Millions of Dollars) (SL)		0.149	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 39: Auto mode dimensions from 2010 to 2018

2010-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF52	Domestic Migration (SL)	1	0.31	Residential mobility
EF10	Homeownership Rate (NL)		0.263	
EF08	Rental Vacancy Rate (NL)		0.173	
EF83	Number of Unemployed (SL)		0.09	
EF68	Viability of Streams (Gas, tax, etc.) (Millions) (SL)		0.088	
EF35	Number of Unemployed (NL)		0.076	
EF66	Number of Licensed Drivers* (SL)	2	0.462	Economic condition
EF15	% Population in Poverty (NL)		0.251	
EF73	GDP of F.L.- Retail Trade (In Millions of Dollars) (SL)		0.153	
EF24	GDP - Manufacturing (NL)		0.133	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 40: Auto mode dimensions from 2011 to 2018

2011-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF52	Domestic Migration (SL)	1	0.252	Population change in Florida
EF50	FL Population Change (SL)		0.233	
EF53	Net Migration (SL)		0.19	
EF10	Homeownership Rate (NL)		0.172	
EF68	Viability of Streams (Gas, tax, etc.) (Millions) (SL)		0.086	
EF08	Rental Vacancy Rate (NL)		0.068	
EF66	Number of Licensed Drivers* (SL)	2	0.408	Economic condition
EF15	% Population in Poverty (NL)		0.256	
EF84	Percentage of Unemployed (SL)		0.171	
EF83	Number of Unemployed (SL)		0.165	

L.F: Latent Factor (dimension), NL: National level, SL: State level

***Transit**:* Tables 41 to 44 present the transit mode's dimensions and their corresponding external factors for each dimension. Reviewing the external factors composition shows that 40% of external factors in the 2008-2018 time frame (Table 41), 40% of external factors in the 2009-2018 time frame (Table 42), and 90% of external factors in the 2010–2018 time frame (Table 43) are changed in the subsequent time frames.

Economic well-being and housing prices are the two dimensions for the 2008–2018 time frame (Table 41) and the 2009–2018 time frame (Table 42). The "economic well-being" dimension is dropped from the result for the 2010–2018 (Table 43) time frame, although some external factors related to the economic well-being dimension remain within the top ten factors. The factor analysis grouped all of the ten external factors into a single dimension, which is interpreted as housing prices based on their aggregated meaning (Table 43). The most recent time frame (i.e., 2011–2018) (Table 44) includes one housing dimension (i.e., housing demand) and one migration dimension. Considering the higher weight of the migration factor, the second dimension in this time frame is interpreted as migration.

The consistency of housing-related dimensions (i.e., housing prices and housing demand) implies the importance of the housing costs for transit system demands. Housing costs play an essential role in people's monthly payments, particularly low-income individuals who use public transit systems more frequently (Pashardes and Savva 2009).

Table 41: Transit mode dimensions from 2008 to 2018

2008-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF15	% Population in Poverty (NL)	1	0.267	Housing prices
EF80	CPI - Rent Price Index (SL)		0.222	
EF78	House Price Index (SL)		0.222	
EF30	House Price Index (NL)		0.149	
EF23	GDP - Construction (NL)		0.073	
EF66	Number of Licensed Drivers* (SL)		0.068	
EF31	Consumer Price Index (CPI) (NL)	2	0.523	Economic well-being
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)		0.174	
EF71	GDP of F.L.- Manufacturing (In Millions of Dollars) (SL)		0.163	
EF12	Single Family (S.F.) Permits (NL)		0.14	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 42: Transit mode dimensions from 2009 to 2018

2009-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF94	Fuel Taxes (SL)	1	0.297	Economic well-being
EF35	Number of Unemployed (NL)		0.225	
EF32	CPI - Rent Price Index (NL)		0.2	
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)		0.146	
EF23	GDP - Construction (NL)		0.132	
EF33	CPI - Fuel Price Index (NL)	2	0.355	Housing prices
EF15	% Population in Poverty (NL)		0.23	
EF80	CPI - Rent Price Index (SL)		0.15	
EF78	House Price Index (SL)		0.149	
EF30	House Price Index (NL)		0.116	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 43: Transit mode dimensions from 2010 to 2018

2010-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF32	CPI - Rent Price Index (NL)	1	0.105	Housing prices
EF23	GDP - Construction (NL)		0.105	
EF77	Economic Condition Index (SL)		0.104	
EF82	Number of Employed (SL)		0.104	
EF21	Aging Populations (NL)		0.103	
EF80	CPI - Rent Price Index (SL)		0.097	
EF78	House Price Index (SL)		0.097	
EF31	Consumer Price Index (CPI) (NL)		0.097	
EF30	House Price Index (NL)		0.097	
EF94	Fuel Taxes (SL)		0.091	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 44: Transit mode dimensions from 2011 to 2018

2011-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF66	Number of Licensed Drivers* (SL)	1	0.142	Housing demand
EF22	GDP - All industries (NL)	1	0.142	
EF76	Personal Income (In Millions of Dollars) (SL)		0.138	
EF82	Number of Employed (SL)		0.126	
EF64	Single Family (S.F.) Permits (SL)		0.124	
EF13	Number of Housing Units (NL)		0.118	
EF70	GDP of F.L.- Construction (In Millions of Dollars) (SL)		0.107	
EF49	Alabama Population (SL)		0.104	
EF51	International Migration (SL)	2	0.913	Migration
EF15	% Population in Poverty (NL)		0.087	

L.F: Latent Factor (dimension), NL: National level, SL: State level

***Aviation**:* Tables 45 to 48 present the aviation mode's dimensions and corresponding dimensions. Reviewing external factors reveals that 60% of external factors in the 2008-2018 time frame (Table 45) are changed in the 2009-2018 time frame (Table 46). Similarly, 40% of external factors in the 2009–2018 time frame and 60% of external factors in the 2010- 2018 time frame (Table 47) are changed in the subsequent time frames.

The dimension results indicate that economic well-being and housing demand are the two major dimensions of the aviation mode that are most frequently repeated across time frames. In this regard, the economic well-being dimension is repeated in all four tables, and the housing demand dimension is repeated in three of the four tables (i.e., Table 45, Table 47, and Table 48). Although the housing demand dimension is not found based on the result of the factor analysis for the 2009–2018 (Table 46) time frame, some of the factors related to housing demand, such as "number of housing units," "total building permits," and "single-family permits," exist within the top ten external factors.

Interestingly, a new dimension called "climate impact on transportation," which consists of climate-related factors (i.e., average temperature and total precipitation) emerged within the 2010–2018 time frame (Table 46) and remained within the subsequent time frame (2011–2018) (Table 48). Aviation mode is one of the transportation modes sensitive to climate stressors (Rowan et al. 2013). For example, heavy rain can flood runways, lower the crosswind takeoff, and cause landing limits for aircraft. Similarly, thunderstorms can lead to flight delays or cancellations, and hail can cause significant damage to aircraft, hangars, and buildings (Rowan et al. 2013).

Table 45: Aviation mode dimensions from 2008 to 2018

2008-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF73	GDP of F.L.- Retail Trade (In Millions of Dollars) (SL)	1	0.19	Economic well-being
EF25	GDP - Real Estate (NL)		0.17	
EF77	Economic Condition Index (SL)		0.15	
EF22	GDP - All industries (NL)		0.15	
EF12	Single Family (S.F.) Permits (NL)		0.15	
EF58	Political Party Affiliation (other) (SL)		0.1	
EF21	Aging Populations (NL)		0.1	
EF62	Homeownership Rate (SL)	2	0.58	Housing demand
EF08	Rental Vacancy Rate (NL)		0.24	
EF02	Population Estimate (NL)		0.17	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 46: Aviation mode dimensions from 2009 to 2018

2009-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF22	GDP - All industries (NL)	1	0.104	Economic well-being
EF25	GDP - Real Estate (NL)		0.104	
EF26	GDP - Transportation (NL)		0.103	
EF74	GDP of F.L.- Transportation (In Millions of Dollars) (SL)		0.103	
EF76	Personal Income (In Millions of Dollars) (SL)		0.103	
EF02	Population Estimate (NL)		0.102	
EF34	Number of Employed (NL)		0.102	
EF13	Number of Housing Units (NL)		0.102	
EF11	Total Building Permits (NL)		0.092	
EF12	Single Family (S.F.) Permits (NL)		0.085	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 47: Aviation mode dimensions from 2010 to 2018

2010-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF69	GDP- F.L. All Industries (In Millions of Dollars) (SL)	1	0.173	Economic well-being
EF13	Number of Housing Units (NL)		0.173	
EF74	GDP of F.L.- Transportation (In Millions of Dollars) (SL)		0.155	
EF34	Number of Employed (NL)		0.141	
EF73	GDP of F.L.- Retail Trade (In Millions of Dollars) (SL)		0.14	
EF02	Population Estimate (NL)		0.114	
EF14	Population in College (NL)		0.104	
EF11	Total Building Permits (NL)	2	0.617	Housing demand
EF12	Single Family (S.F.) Permits (NL)		0.383	
EF40	Average Temperature (NL)	3	1	Climate impact on transportation

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 48: Aviation mode dimensions from 2011 to 2018

2011-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF27	Per Capita Income (NL)	1	0.179	Economic well-being
EF25	GDP - Real Estate (NL)		0.172	
EF24	GDP - Manufacturing (NL)		0.169	
EF74	GDP of F.L.- Transportation (In Millions of Dollars) (SL)		0.164	
EF31	Consumer Price Index (CPI) (NL)		0.163	
EF58	Political Party Affiliation (other) (SL)		0.153	
EF40	Average Temperature (NL)	2	0.561	Climate impact on transportation
EF85	Total Precipitation (SL)		0.439	
EF12	Single Family (S.F.) Permits (NL)	3	0.638	Housing demand
EF14	Population in College (NL)		0.362	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Rail*:* Tables 49 to 52 present each rail mode's dimensions and their corresponding external factors. Comparing external factors composition shows that 40% of external factors in the 2008-2018 time frame (Table 49), 50% of external factors in the 2009–2018 (Table 50) time frame, and 30% of external factors in the 2010- 2018 time frame (Table 51) are changed within subsequent time frames.

The dimension results show that at least four dimensions were reported for the rail mode over different time frames. For instance, within the 2010–2018 time frame (Table 51), six different dimensions were reported for the rail mode. However, in some cases, only one external factor is included under a dimension. For example, fuel price dimension in the 2008–2018 time frame (Table 49), privatization of roads dimension in the 2009–2018 time frame (Table 50), homeownership dimension in the 2010–2018 time frame (Table 51), and fuel prices dimension in the 2011–2018 time frame (Table 52) include a single external factor. Although names were suggested to such dimensions based on their constituent external factor, a single external factor is not enough to interpret its relevant dimension with high confidence. In order to resolve this issue, the factor analysis should be conducted using a higher number of external factors (and observations) to investigate the external factors that will be additionally included under these otherwise single-factor dimensions. However, due to the limited data availability of performance measures (i.e., available only from 2008 to 2018), such analysis was not possible in this project. Reviewing other rail mode dimensions suggests that homeownership, economic well-being, and population change are the major rail mode dimensions that are repeated throughout different time frames.

Table 49: Rail mode dimensions from 2008 to 2018

2008-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF10	Homeownership Rate (NL)	1	0.319	Homeownership
EF62	Homeownership Rate (SL)		0.296	
EF08	Rental Vacancy Rate (NL)		0.243	
EF25	GDP - Real Estate (NL)		0.141	
EF03	Population Change (NL)	2	0.374	Population change
EF04	Natural Increase - Births (NL)		0.338	
EF07	Net Migration (NL)		0.288	
EF15	% Population in Poverty (NL)	3	0.664	Economic well-being
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)		0.336	
EF33	CPI - Fuel Price Index (NL)	4	1	Fuel price

L.F: Latent Factor (dimension), NL: National level, SL: State level, CPI: consumer price index

Table 50: Rail mode dimensions from 2009 to 2018

2009-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF15	% Population in Poverty (NL)	1	0.333	Economic well-being
EF23	GDP - Construction (NL)		0.248	
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)		0.24	
EF25	GDP - Real Estate (NL)		0.18	
EF05	International Migration (NL)	2	0.693	Population change
EF10	Homeownership Rate (NL)		0.203	
EF08	Rental Vacancy Rate (NL)		0.104	
EF29	Financial Condition Index (NL)	3	0.849	Economic conditions
EF62	Homeownership Rate (SL)		0.151	
EF95	Privatization of Roads (SL)	4	1	Privatization of Roads (SL)

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 51: Rail mode dimensions from 2010 to 2018

2010-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF76	Personal Income (In Millions of Dollars) (SL)	1	0.359	Economic well-being
EF25	GDP Real Estate (NL)		0.322	
EF15	% Population in Poverty (NL)		0.319	
EF04	Natural Increase - Births (NL)	2	0.553	Population change
EF03	Population Change (NL)		0.447	
EF16	Political Party Affiliation - Democratic (NL)	3	1	Political affiliation
EF62	Homeownership Rate (SL)	4	1	Homeownership
EF10	Homeownership Rate (NL)	5	0.674	Residential mobility
EF07	Net Migration (NL)		0.326	
EF08	Rental Vacancy Rate (NL)	6	1	Rental housing

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 52: Rail mode dimensions from 2011 to 2018

2011-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF76	Personal Income (In Millions of Dollars) (SL)	1	0.283	Unemployment
EF25	GDP Real Estate (NL)		0.255	
EF15	% Population in Poverty (NL)		0.212	
EF36	Percentage of Unemployed (NL)		0.126	
EF35	Number of Unemployed (NL)		0.124	
EF62	Homeownership Rate (SL)	2	0.411	Homeownership
EF10	Homeownership Rate (NL)		0.395	
EF08	Rental Vacancy Rate (NL)		0.194	
EF33	CPI - Fuel Price Index (NL)	3	1	Fuel price
EF16	Political Party Affiliation - Democratic (NL)	4	1	Political affiliation

L.F: Latent Factor (dimension), NL: National level, SL: State level, CPI: consumer price index

Seaport*:* Tables 53 to 56 present the seaport mode's dimensions and other corresponding external factors. The external factors composition shows considerable variations in different time frames. In this regard, 60% of external factors in the 2008–2018 (Table 53) time frame, 60% of external factors in the 2009–2018 (Table 54) time frame, and 30% of external factors in the 2010–2018 (Table 55) time frame are changed in the subsequent time frames.

The dimension results imply that economic well-being is the major dimension of the seaport mode, repeated in all time frames. In addition to economic well-being, climate-related external factors emerged from the 2009–2018 time frame (Table 54). These climate-related external factors construct climate-related dimensions, including "climate impact on rental preference" in the 2009 - 2018 time frame and "climate impact on travel demand" in the 2010–2018 time frame (Table 55) and the 2011–2018 (Table 56) time frames. The first climate-related dimension (i.e., climate impact on travel demand) consists of "average temperature" and "vehicle miles traveled" external factors. Climate-related factors, including temperature and precipitation, may impact maintenance operations (Rowan et al. 2013). For example, road pavements are sensitive to extreme heat events and large swings in daily temperatures. The second climate-related dimension consists of "total precipitation" and "rent price index" external factors. Prior research suggests that unfavorable climate conditions may reduce housing prices (Butsic et al. 2011). Thus, this dimension is named as "climate impact on rental preferences." Finally, climate factors are also essential from the perspective of seaport transportation mode. In fact, port services are sensitive to extreme temperatures and heavy rains (Rowan et al. 2013). The emergence of climate-related dimensions in seaport and aviation transportation modes highlights the significance of sufficient understanding of climate impacts for the designing, planning, and managing of infrastructure to withstand extreme weather events (Rowan et al. 2013).

Table 53: Seaport mode dimensions from 2008 to 2018

2008-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF69	GDP- F.L. All Industries (In Millions of Dollars) (SL)	1	0.135	Economic Well-being
EF73	GDP of F.L.- Retail Trade (In Millions of Dollars) (SL)		0.127	
EF77	Economic Condition Index (SL)		0.12	
EF22	GDP - All industries (NL)		0.114	
EF37	Financial Markets (Dow Jones Avg Closing Price) (NL)		0.112	
EF27	Per Capita Income (NL)		0.108	
EF21	Aging Populations (NL)		0.103	
EF13	Number of Housing Units (NL)		0.093	
EF31	Consumer Price Index (CPI) (NL)		0.09	
EF29	Financial Condition Index (NL)	2	1	Financial conditions

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 54: Seaport mode dimensions from 2009 to 2018

2009-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF31	Consumer Price Index (CPI) (NL)	1	0.179	Economic Well-being
EF24	GDP - Manufacturing (NL)		0.173	
EF27	Per Capita Income (NL)		0.167	
EF22	GDP - All industries (NL)		0.163	
EF77	Economic Condition Index (SL)		0.159	
EF82	Number of Employed (SL)		0.159	
EF86	Average Temperature (SL)	2	0.539	Climate
EF40	Average Temperature (NL)		0.461	
EF39	Total Precipitation (NL)	3	0.537	Climate impact on rental preference
EF32	CPI - Rent Price Index (NL)		0.463	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 55: Seaport mode dimensions from 2010 to 2018

2010-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF32	CPI - Rent Price Index (NL)	1	0.128	Economic Well-being
EF22	GDP - All industries (NL)		0.127	
EF73	GDP of F.L.- Retail Trade (In Millions of Dollars) (SL)		0.126	
EF26	GDP - Transportation (NL)		0.125	
EF37	Financial Markets (Dow Jones Avg Closing Price) (NL)		0.125	
EF74	GDP of F.L.- Transportation (In Millions of Dollars) (SL)		0.125	
EF24	GDP - Manufacturing (NL)		0.122	
EF49	Alabama Population (SL)		0.121	
EF86	Average Temperature (SL)	2	0.561	Climate impact on travel demand
EF01	VMT (NL)		0.439	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 56: Seaport mode dimensions from 2011 to 2018

2011-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF32	CPI - Rent Price Index (NL)	1	0.172	Economic Well-being
EF23	GDP - Construction (NL)		0.171	
EF22	GDP - All industries (NL)		0.169	
EF26	GDP - Transportation (NL)		0.165	
EF74	GDP of F.L.- Transportation (In Millions of Dollars) (SL)		0.164	
EF71	GDP of F.L.- Manufacturing (In Millions of Dollars) (SL)		0.159	
EF39	Total Precipitation (NL)	2	0.792	Climate impact on travel demand
EF01	VMT (NL)		0.208	
EF24	GDP - Manufacturing (NL)	3	1	Manufacturing GDP
EF49	Alabama Population (SL)	4	1	Alabama population

L.F: Latent Factor (dimension), NL: National level, SL: State level

Truck: Tables 57 to 60 present the truck mode's dimensions and their corresponding external factors. Reviewing the external factors in different time frames shows considerable variations. For example, 60% of the external factors in the 2008–2018 time frame (Table 57), 50% of external factors in the 2009–2018 time frame (Table 58), and 20% of the external factors in the 2010–2018 (Table 59) time frame are changed in the subsequent time frames.

The dimension results indicate that economic well-being is the truck mode's major dimension repeated over different time frames. Housing prices is the second dimension of the truck mode found in the earlier time frames (i.e., 2008-2018 (Table 57) and 2009–2018 (Table 58)). However, this dimension is removed in more recent time frames (i.e., 2010–2018 (Table 59) and 2011–2018 (Table 60)). That is, the impact of housing-related factors on truck transportation mode was more significant during 2008 and 2009 than later. The emergence of recession-related factors (i.e., housing prices) implies the significant impact of the 2007–2009 market crisis on the truck transportation mode. Moreover, the drop of this dimension in more recent time frames implies that the overall transportation systems, including truck mode, started to recover after the recession period (Pearce 2012).

Table 57: Truck mode dimensions from 2008 to 2018

2008-2018				
EF	EF Name	L.F.	Weight	L.F. Name
EF02	Population Estimate (NL)	1	0.226	Economic well-being
EF58	Political Party Affiliation (other) (SL)		0.194	
EF77	Economic Condition Index (SL)		0.154	
EF73	GDP of F.L.- Retail Trade (In Millions of Dollars) (SL)		0.131	
EF68	Viability of Streams (Gas, tax, etc.) (Millions) (SL)		0.118	
EF69	GDP- F.L. All Industries (In Millions of Dollars) (SL)		0.104	
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)		0.072	
EF80	CPI - Rent Price Index (SL)	2	0.368	Housing prices
EF78	House Price Index (SL)		0.368	
EF30	House Price Index (NL)		0.264	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 58: Truck mode dimensions from 2009 to 2018

2009-2018				
EF	EF Name	L.F.	Weight	LF Name
EF47	Florida Population (SL)	1	0.185	Economic well-being
EF82	Number of Employed (SL)		0.176	
EF76	Personal Income (In Millions of Dollars) (SL)		0.175	
EF32	CPI - Rent Price Index (NL)		0.132	
EF34	Number of Employed (NL)		0.127	
EF69	GDP- FL All Industries (In Millions of Dollars) (SL)		0.122	
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)		0.081	
EF15	% Population in Poverty (NL)	2	0.376	Housing prices
EF80	CPI - Rent Price Index (SL)		0.312	
EF78	House Price Index (SL)		0.311	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 59: Truck mode dimensions from 2010 to 2018

2010-2018				
EF	EF Name	LF	Weight	LF Name
EF23	GDP - Construction (NL)	1	0.104	Economic well-being
EF32	CPI - Rent Price Index (NL)		0.104	
EF13	Number of Housing Units (NL)		0.103	
EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)		0.103	
EF47	Florida Population (SL)		0.102	
EF76	Personal Income (In Millions of Dollars) (SL)		0.102	
EF48	Georgia Population (SL)		0.101	
EF02	Population Estimate (NL)		0.098	
EF15	% Population in Poverty (NL)		0.097	
EF66	Number of Licensed Drivers* (SL)		0.086	

L.F: Latent Factor (dimension), NL: National level, SL: State level

Table 60: Truck mode dimensions from 2011 to 2018

2011-2018				
EF	EF Name	LF	Weight	LF Name
EF23	GDP - Construction (NL)	1	0.103	Economic well-being
EF47	Florida Population (SL)		0.103	
EF48	Georgia Population (SL)		0.103	
EF32	CPI - Rent Price Index (NL)		0.103	
EF21	Aging Populations (NL)		0.102	
EF15	% Population in Poverty (NL)		0.101	
EF76	Personal Income (In Millions of Dollars) (SL)		0.101	
EF02	Population Estimate (NL)		0.101	
EF98	Number of Tourists to Orlando (SL)		0.094	
EF66	Number of Licensed Drivers* (SL)		0.087	

L.F: Latent Factor (dimension), NL: National level, SL: State level

4.2.2.3 Summary

The key findings of investigating changes in FIT dimensions in different time frames include:

1- Comparing the changes in FIT dimensions with the ones in the influential external factors indicate that transportation dimensions are more stable than the influential external factors. For example, no changes were observed in the pedestrian and bike mode dimensions (Tables 33-36), and one difference was found in the auto mode's dimensions (Tables 37-40) and truck mode's dimensions (Tables 57 - 60). However, five, six, and six new external factors emerged at different time frames, on average, for the pedestrian (Figure 43), auto (Figure 45), and truck (Figure 55) modes, respectively.

2- The impact of the 2007-2009 market crisis was found to be more visible in auto, transit, and truck modes. In this regard, the "residential mobility" dimension, which is a recession-related dimension, arises for the auto mode within the time frames closer to the market crisis (i.e., 2008-2018 and 2009-2018). This dimension was then replaced by the population change dimension in the later time frames (i.e., 2011-2018). Similarly, the truck mode contains housing-related dimensions (i.e., housing prices) in the early time frames (i.e., 2008-2018 and 2009-2018). This dimension is dropped in the more recent time frame (i.e., 2011-2018). These results may indicate the gradual recovery of the transportation systems after the market crisis.

3- Climate-related factors arise in recent time frames (i.e., 2010-2018 and 2011-2018) for the seaport and aviation transportation modes. This implies that transportation planners should pay close attention to climate-related stressors for the design, maintenance, and operations of aviation and seaport mode to withstand extreme weather events.

CHAPTER V: CONCLUSIONS

Transportation systems are constantly changing due to the impact of various external factors on their complex structures comprising heterogeneous distributed systems. Understanding these changes in transportation environments and their root causes is essential for effective planning. To be more specific, transportation planners can benefit from such knowledge because it helps them more effectively and efficiently allocate resources in response to any changes caused by potential disruptive events. Therefore, it is necessary to track and monitor numerous external factors to analyze their impact on transportation systems. However, the huge volume of information related to external factors that need to be considered in any relevant analysis makes it challenging to carry out such work. In this project, the FSU research team has adopted a system of systems (SoS) school of thought to understand and interpret the changing nature of transportation and facilitate decision making at various planning levels.

In the first step, the FSU research team conducted an extensive literature review to identify possible external factors affecting all travel modes of the Florida transportation system along with their relevant performance measures and to understand the use of these factors in state, regional, and local transportation planning. An expert survey was also conducted to augment the understanding of the external factors and identify additional external factors that were not captured during the literature review. The findings and recommendations from the review of external factors associated with all transportation modes can be summarized as follows.

- Although there are some studies on evaluating external factors on the performance of a single transportation mode (e.g., transit and highway), limited studies were found on the evaluation of external factors on a multimodal transportation system.
- Even in the existing studies on external factors, only a few transportation performance measures are used, such as highway travel time index, planning time index, and congested hours.
- In addition to typical economic, employment, population, and housing factors, the State of Florida should track a few external factors relevant to it, including climate, weather-related events, and international trade and commerce.
- There is a trade-off between the number of performance measures and the complexity of data collection and analysis. Thus, performance measures should be selected properly for each mode considering the data availability and relevance.
- Performance measures of emerging transportation modes, such as shared mobility, bikesharing, or e-scooters, should be selected and monitored regularly.
- Travel demand is the only external factor that is consistently evaluated by state DOTs.
- State DOTs have yet to start systematically evaluating the performance or effects of emerging modes of transportation or how external factors affect them.
- Contextual factors, such as the urban context (urban vs. rural), can determine which factors are relevant and which metrics are most informative.

- Local and regional agencies are examining emerging mobility modes but have yet to incorporate them into their key performance measures.

- Equity is an important concern for emerging mobility plans.

- Several cities have created emerging mobility plans that can be a component of a long-range transportation plan or serve as a standalone document.

In the second step, an SoS framework for Florida transportation was developed to facilitate the understanding of the changing nature of the Florida transportation system. The Florida Index for Transportation (FIT) was developed as the tool for streamlining the abundant information related to external factors required for monitoring, analyzing a broad range of external factors, and facilitate the development of data-drive and -informed decision making in transportation planning. The findings regarding the FIT development can be summarized as follows:

- The hierarchical structure of FIT as a composite index makes it appropriate to manage the overwhelming amount of information that needs to be considered for decision making at each level. Moreover, FIT is customizable and can accommodate the various decision making needs of transportation planners at different levels of the system. Multiple weighting mechanisms have been designed to help decision makers focus on their areas of interest.

- FIT helps transportation planners recognize and understand changing conditions in the transportation SoS. In this regard, transportation planners can develop FIT for different time frames and study any resultant changes since changing the time frame of the analysis might then alter the trends, the composition of the selected external factors, and the importance of the external factors at the base level of FIT. Studying such changes provides valuable information for decision makers regarding whether a disruptive occurred and affected the transportation system in the past, how the transportation system has been changed as a result of that event, and what actions need to be taken.

In the last step, the FIT application in (i) improving FDOT's planning process and (ii) facilitating the understanding of the changing nature of the Florida transportation system was demonstrated.

In order to demonstrate the application of the FIT in transportation planning, the FSU team organized two virtual demonstration sessions with FDOT planners. During these online sessions, the FSU team presented FIT and its transportation planning applications to FDOT decision makers. The first meeting was focused on the validation of the overall FIT approach (the structure and how FIT can support decision making), while the second meeting aimed to assess the usability (implementability) of FIT (i.e., whether FIT can be directly implementable for transportation planning). The following are some of the key takeaways from the first meeting:

1) The FIT can be presented in a dashboard format that can be used by transportation planners to monitor transportation demands and compare them with infrastructure performance.

2) FIT can facilitate cross-modal decision making problems. In this regard, transportation planners can use the FIT system-level index that aggregates various transportation modes

to compare the trends at different modes and customize the FIT for budget allocation and policy-making purposes.

3) Although FIT is developed for state-level decision making, the proposed framework is flexible enough to be applied to local-level decision making.

4) FIT can be helpful in budget allocation decision making problems. In this regard, the decision makers may compare the FIT and FPI trends and evaluate whether current existing plans can effectively address transportation demands.

The following are some of the key takeaways from the second meeting:

1) FIT can help transit planners with long-term planning efforts. For example, planners can evaluate how transit ridership trends would fit FIT trends for long-term planning.

2) FIT seaport external factors and dimensions may help planners to identify proper projects for funding. For example, a high number of population and manufacturing-related external factors imply the need to expand seaport capacities to cope with the increasing demand.

5) Increasing the number and types of performance measures helps identify more relative influential external factors, improves FIT results, and enables FIT to cover more diverse planning problems

To demonstrate the FIT application in facilitating the understanding of the changing nature of the Florida transportation system, the FSU team investigated the changes in the FIT external factors compositions and in FIT dimensions. In this regard, the FIT was developed for four time frames based on the data availability. In the second step, changes in the influential external factors and FIT dimensions for each transportation mode at each time frame were investigated. The following are major conclusions from the analyses.

1) Economic factors, housing factors, and employment factors are the most repetitive external factors emerging in different transportation modes across different time frames. Economic factors mostly consist of GDP and financial conditions factors. Housing factors are related to housing demand and housing-related costs, while employment factors are related to national and state-level employment rates.

2) Most of the new external factors arise within the 2009–2016 and 2010–2017 time frames. Considering the categorization of the new external factors (i.e., economic factors, employment factors, and housing factors), we discussed the 2008 Housing Crisis as one of the major disruptive events that caused most transportation modes to be subjected to economic conditions between 2007 and 2010.

3) Transportation dimensions were found to be more stable than the influential external factors. In other words, less variation was observed in transportation mode dimensions compared to the composition of influential external factors. Therefore, in most cases, the interpretation of the transportation dimensions remains consistent across the different time frames. For example, no changes were observed in the pedestrian and bike mode

dimensions (Tables 33-36), while only one change was observed in the auto mode's dimensions (Tables 37-40) and truck mode's dimensions (Tables 57 - 60). However, more changes were observed in the comparison of FIT external factors across subsequent time frames. For example, five, six, and six new external factors emerged at different time frames, on average, for the pedestrian (Figure 43), auto (Figure 45), and truck (Figure 55) modes, respectively.

The proposed approach is compatible with the current planning practices (e.g., reporting performance measures to support planning) and implementable to better understand externa factors. However, the current analysis has some limitations. For example, performance measures data were only available at the yearly frequency. The limited number of data points for the statistical analysis affects its ability to search for more reliable casual relationships between performance measures and external factors. Moreover, data for the majority of the performance measures was only available after 2008. This limits the statistical analysis in examining the market crisis, which started in 2007, or any disruptive events that occurred before 2008. Considering such limitations, a more advanced statistical analysis is required to further investigate transportation dimensions' inter-relationship across different time frames. Analytical methodologies, such as longitudinal structural equation modeling, can be used to further examine the interrelationship between constructs across different time frames.

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APPENDIX A: FLORIDA INDEX FOR TRANSPORTATION SURVEY QUESTIONAIRE

Transportation consists of a network of systems including auto, truck, transit, bicycle and pedestrian, and rail. Each of these systems is impacted by a wide range of dynamic factors (such as population change, environmental hazards, etc.), which can make it difficult to anticipate and react to future changes.

Monitoring the effect of these factors on transportation is complex and can make planning and spending decisions difficult. Consequently, identifying accurate indicators of how the transportation system is changing is vital to helping planners make decisions on infrastructure investments.

To help the Florida Department of Transportation bring clarity and simplicity to this process, a team of researchers from Florida State University is developing a composite measure to track the impact of numerous factors on the transportation system in order to guide future decision making.

As an important input in identifying which factors should be included in this measure, the research team is surveying transportation planning experts to uncover best practices in transportation evaluation.

Transportation Goals

The Florida Transportation Plan (FTP) is the single overarching statewide plan guiding Florida's transportation future. The FTP sets a 50-year vision as well as a 25-year set of policies to ensure state resources will be strategically used to achieve goals in seven areas. These goals currently include:

1. **Safety and security for residents, visitors, and businesses:** Florida strives for a transportation system that is fatality free and limits vulnerability to natural disaster, cargo theft, terrorism, and cyberattacks.

2. **Agile, Resilient, and quality transportation infrastructure:** Florida strives for a transportation system that is in good condition across every mode and every level of geography. This includes infrastructure capable of adapting to new technologies and user-needs and resilient enough to withstand extreme weather events.

3. **Efficient and reliable mobility for people and freight:** Florida strives for a mobility system that performs without unnecessary delay on all modes due to bottlenecks, crashes, and regulatory activities such as permitting, payment, or customs.

4. **More transportation choices for people and freight:** Florida strives to provide residents and visitors with the freedom to choose between several high-quality transportation modes, including passenger rail, bus, shared vehicles, bicycles, and walking.

5. **Transportation solutions that support global economic competitiveness:** Florida strives for a transportation system that supports economic competitiveness by connecting people to jobs, and connecting businesses to their suppliers, customers, and partners.

6. **Transportation solutions that support quality places to live, learn, work, and play:** Florida strives for a transportation system that supports and prioritizes vibrant places through context-sensitive investments.

7. **Transportation solutions that enhance environmental and energy conservation:** Florida strives to preserve and enhance Florida's unique environment through system infrastructure investments to preserve wildlife habitat, reduce energy consumption, and reduce greenhouse gas emissions.

What best describes the organization you are employed by?

- Federal transportation agency
- State government Department of Transportation
- Regional organization (TPO, MPO, Regional planning councils) Local Government
- Private Sector
- University or other educational unit
- Other: _______________

How many years of experience do you have in transportation planning? __________

What is the highest level of education you have attained?

- Less than High School degree or equivalent
- High School degree or equivalent
- Some College
- College degree
- Technical degree
- Graduate degree or above

Please rank the following transportation goal areas in order of their importance to the future of transportation.

- Safety and security for residents, visitors, and businesses
- Agile, Resilient, and quality transportation infrastructure
- Efficient and reliable mobility for people and freight
- More transportation choices for people and freight
- Transportation solutions that support economic competitiveness
- Transportation solutions that support quality places to live, learn, work, and play
- Transportation solutions that enhance environmental and energy conservation

Do you and/or your agency believe there are additional key goal areas important to the future of transportation that were not mentioned in the previous question? Please elaborate if so:

Identifying External Factors

The performance of the transportation system is impacted by a host of interconnected factors. To help identify which factors should be monitored to evaluate the transportation system, please rate the level of impact the following factors have on each of the goals areas listed above.

Please rate the level of impact the following factors have on the each of the seven transportation goals listed above? (0 = No Impact; 5 = Extreme Impacts)

	Safety and Security	Agile, Resilient, Quality Infrastructure	Efficient and Reliable Mobility	More Transportation Choices	Economic Competitiveness	Quality Places	Environmental and Energy
Demographic Factors							
Population Growth							
# of Licensed Drivers							
Suburbanization							
Immigration							
Aging Populations							
Tourism							
Traffic Safety							
Economic Factors							
Economic Growth (GDP)							
Unemployment							
Fuel Costs							
Financial Markets							
Housing Markets							
Freight transport							
Emerging Industries (Tech, Aerospace)							
Viability of Revenue Streams (gas tax, etc.)							
Environmental Factors							
Development/Open land conversion							
Sea Level Rise							
Weather related inland flooding							
Coastal flooding and hurricane related storm surge							
Air Quality							

	Safety and Security	Agile, Resilient, Quality Infrastructure	Efficient and Reliable Mobility	More Transportation Choices	Economic Competitiveness	Quality Places	Environmental and Energy
Climate-Change based natural hazards (intensifying hurricanes, tornadoes, etc.)							
Technological Factors							
Autonomous Vehicles							
Connected Vehicles							
Electric Vehicles							
Shared Vehicles							
E-commerce							
Cyber Security							
Emerging modes of personal transportation (e-bikes, e-scouters)							

Incorporating External Factors into the Planning Process

At which phase(s) of the planning process do you/your agency evaluate the following factors to assess your communities' transportation system? (check all that apply)

	Not Evaluated	Trends Analysis	Long-Range Planning	Policy and Plan Development	Implementation and Construction	Operations and Maintenance
Demographic Factors						
Population Growth		✓		✓		
# of Licensed Drivers	✓					
Suburbanization						
Immigration						
Aging Populations						
Tourism						
Traffic Safety						
Economic Factors						

	Not Evaluated	Trends Analysis	Long-Range Planning	Policy and Plan Development	Implementation and Construction	Operations and Maintenance
Economic Growth (GDP)		✓		✓		
Unemployment						
Fuel Costs						
Financial Markets						
Housing Markets						
Freight transport						
Emerging Industries (Tech, Aerospace)						
Viability of Revenue Streams (gas tax, etc.)						
Environmental Factors						
Development/Open land conversion						
Sea Level Rise						
Weather related inland flooding						
Coastal flooding and hurricane related storm surge						
Air Quality						
Climate-Change based natural hazards (intensifying hurricanes, tornadoes, etc.)						
Technological Factors						
Autonomous Vehicles						
Connected Vehicles						
Electric Vehicles						
Shared Vehicles						
E-commerce						
Cyber Security						
Emerging modes of personal transportation (e-bikes, e-scouters)						

Measuring External Factors

Agencies monitor external factors for the purposes of understanding emerging trends in transportation. Part of this project will be to determine the best evaluation metrics to monitor external factors and their impacts on the transportation system. Please list the metric(s) you/your agency uses to measure the following factors.

Does your agency monitor the following factors when evaluating your communities' transportation system?

Demographic Factors

- Population Growth: Yes or No?
  - (If Yes)
    - What metric(s) does your agency use to measure that factor? __________
    - What data source does your agency use to monitor that metric? ______________
- # of Licensed Drivers:
- Suburbanization:
- Immigration:
- Aging Populations:
- Tourism:
- Traffic Safety:

Economic Factors

- Economic Growth (GDP):
- Unemployment:
- Fuel Costs:
- Financial Markets:
- Housing Markets:
- Freight transport:
- Emerging Industries (Tech, Aerospace):
- Viability of Revenue Streams (gas tax, etc.):

Environmental Factors

- Development/Open land conversion:
- Sea Level Rise:
- Weather related inland flooding:
- Coastal flooding and hurricane related storm surge:
- Air Quality:
- Climate-Change based natural hazards (intensifying hurricanes, tornadoes, etc.:

Technological Factors

- Autonomous Vehicles:
- Connected Vehicles:
- Electric Vehicles:
- Shared Vehicles:
- E-commerce:
- Cyber Security:

- Emerging modes of personal transportation (e-bikes, e-scouters):

The factors included above were identified as being used by state level transportation agencies for the use of monitoring trends in transportation. Does your agency use any additional factors to measure the performance of the transportation system?

- Yes
- No

(If Yes)

a) What additional factors does your agency measure? ___________________
b) What metric does your agency use to measure that factor? ___________________
c) What data source does your agency use to monitor that metric? ___________________

APPENDIX B: FOLLOW-UP INTERVIEW QUESTIONS

1. Which external factors does your agency evaluate to measure the performance of the transportation system?
    a. Which ones have the greatest impact?
2. In what phase of the planning process do you incorporate these factors?
3. How are those external factors measured?
4. Do you look at factors regarding emerging modes of transportation? What factors?
5. What are the sources of data that you use to measure those factors?

APPENDIX C: PRELIMINARY SURVEY RESULTS

Respondents rated a set of external factors on a scale of 0 to 5 (5 being the greatest impact) for their expected impact to the future transportation system. Table C-1 displays the average scores for each factor.

Table C-1: Average expected impact of external factors on the future of the transportation system (0 = no impact; 5 = extreme impacts)

Population Factors		Economic Factors	
Factor	**Average Score**	**Factor**	**Average Score**
Suburbanization	3.64	Viability of Revenue Streams	3.89
Population Growth	3.58	Economic Growth	3.52
Traffic Safety	3.18	Freight Transport	3.31
Tourism	2.97	Emerging Industries	2.89
# of Licensed Drivers	2.84	Housing Markets	2.82
Aging Population	2.46	Unemployment	2.78
Immigration	2.01	Fuel Cost	2.77
		Financial Markets	2.34
Environmental Factors		**Technological Factors**	
Factor	**Average Score**	**Factor**	**Average Score**
Climate Change	3.79	Autonomous Vehicles	3.82
Weather Related Inland Flooding	3.53	Share Vehicles	3.75
Coastal Flooding/Hurricane Storm Surge	3.48	Electric Vehicles	3.14
Development/Open Land Conversion	3.41	Connected Vehicles	2.92
Sea Level Rise	3.34		
Air Quality	3.13		
Financial Markets	2.86		

Table C-2: Average expected impact of external factors on the goals of the Florida transportation plan (0 = no impact; 5 = extreme impacts)

Demographic Factors							
	Goal 1: Safety and Security	**Goal 2: Agile, Resilient, Quality Infrastructure**	**Goal 3: Efficient and Reliable Mobility**	**Goal 4: More Transportation Choices**	**Goal 5: Economic Competitiveness**	**Goal 6: Quality Places**	**Goal 7: Environmental and Energy Conservation**
Population Growth	3.4	3.53	3.93	3.5	3.14	3.07	4.46
# of Licensed Drivers	3.5	2.69	3.54	2.43	2.07	2.5	3.21
Suburbanization	3	4.14	4.29	3.71	2.64	3.36	4.36
Immigration	2.23	1.85	2	2	2.31	1.69	2
Aging Population	3.4	1.8	3.07	3.73	2.2	1.8	1.2
Tourism	2.69	2.36	3.36	3.29	3.67	2.79	2.57
Traffic Safety	4.43	3.43	3.64	3.07	2.71	3.29	1.71
Economic Factors							
	Goal 1: Safety and Security	**Goal 2: Agile, Resilient, Quality Infrastructure**	**Goal 3: Efficient and Reliable Mobility**	**Goal 4: More Transportation Choices**	**Goal 5: Economic Competitiveness**	**Goal 6: Quality Places**	**Goal 7: Environmental and Energy Conservation**
Economic Growth	3.33	3.58	3.83	3.42	4.46	3.17	2.75
Unemployment	2.36	2.09	3	3	3.85	2.73	2.18
Fuel Cost	1.82	2.17	2.55	3.42	3.83	2	3.42
Financial Markets	1.64	2	2.17	2.45	3.46	2.5	2
Housing Markets	2	2.25	2.58	3.33	3.62	3.25	2.67
Freight Transport	3.42	4	3.77	2.42	4.15	2.33	2.92
Emerging Industries	2.91	2.83	2.75	2.92	3.69	2.42	2.64
Viability of Revenue Streams	3.69	4.07	4	3.92	4.21	3.62	3.69
Environmental Factors							
	Goal 1: Safety and Security	**Goal 2: Agile, Resilient, Quality Infrastructure**	**Goal 3: Efficient and Reliable Mobility**	**Goal 4: More Transportation Choices**	**Goal 5: Economic Competitiveness**	**Goal 6: Quality Places**	**Goal 7: Environmental and Energy Conservation**
Development/Open Land Conversion	2.38	3.15	3.08	3.38	3.08	4	4.31
Sea Level Rise	3.31	4	3.23	2.31	3.23	3.54	3.77
Weather Related Inland Flooding	3.69	3.85	3.85	2.46	3.69	3.62	3.54
Financial Markets	1.82	2.27	2.27	2.64	2.91	2.27	1.82

Table C-2: Average expected impact of external factors on the goals of the Florida transportation plan (0 = no impact; 5 = extreme impacts) (continued)

	Goal 1: Safety and Security	**Goal 2: Agile, Resilient, Quality Infrastructure**	**Goal 3: Efficient and Reliable Mobility**	**Goal 4: More Transportation Choices**	**Goal 5: Economic Competitiveness**	**Goal 6: Quality Places**	**Goal 7: Environmental and Energy Conservation**
Coastal Flooding/Hurricane Storm Surge	3.69	4.15	3.62	2.69	3.15	3.46	3.62
Air Quality	2.38	2.23	2.46	2.92	3.31	4.46	4.15
Climate Change	3.92	4.38	3.92	2.69	3.77	3.92	3.92
Technological Factors							
	Goal 1: Safety and Security	**Goal 2: Agile, Resilient, Quality Infrastructure**	**Goal 3: Efficient and Reliable Mobility**	**Goal 4: More Transportation Choices**	**Goal 5: Economic Competitiveness**	**Goal 6: Quality Places**	**Goal 7: Environmental and Energy Conservation**
Autonomous Vehicles	4.23	3.31	4.38	4	3.46	3.62	3.77
Connected Vehicles	2.54	2.62	3.38	2.77	4.08	2.31	2.77
Electric Vehicles	4.57	2.42	3.54	2.67	3.92	2.67	1.92
Shared Vehicles	4.08	3.23	3.85	4.15	3.54	3.69	3.69

APPENDIX D: EXTERNAL FACTORS AND PERFORMANCE MEASURES DATA

D1 - External factors (national level)

Travel Demand

EF01 - Average Daily Traffic Volume

This factor captures the hourly traffic count, which is reported by each state. For this external factor, the monthly and annual raw data was gathered from the Federal Highway Administration Travel Monitoring Analysis System (TMAS). The quarterly data was calculated by summing up the monthly data.

Data Source Link:	https://www.fhwa.dot.gov/policyinformation/travel_monitoring/tvt.cfm
Original Data Coverage:	Monthly/Annually from 2005 to 2019

Demographics and Housing

EF02 - Population Estimates

This external factor captures the number of people living in an area at a specific time of every year, which is usually on July 1. The annual data for this external factor was collected from U.S. Census Bureau data repository. The quarterly data was then imputed by using linear interpolation.

Data Source Link:	https://data.census.gov/cedsci/table?q=B01003%3A%20TOTAL%20POPULATION&t=Total%20population&tid=ACSDT1Y2019.B01003&hidePreview=false
Original Data Coverage:	Annually from 2005 to 2019

EF03 - Population Change

This external factor captures the annual growth of the population. The annual data for this external factor was collected from the U.S. Census Bureau data repository. The quarterly data was then imputed by equally dividing the annual data into four quarters.

Data Source Link:	https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-total.html
Original Data Coverage:	Annually from 2011 to 2019

EF04 - Natural Increase - Births

Births minus death. The annual data for this external factor was collected from U.S. Census Bureau data repository. The census dataset called "Population, Population Change, and Estimated Components of Population Change: April 1, 2010 to July 1, 2019 (NST-EST2019-alldata)" was used to gather the data for this factor. The quarterly data was then imputed by equally dividing the annual data into four quarters.

Data Source Link:	https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-total.html
Original Data Coverage:	Annually from 2011 to 2019

EF05 - International Migration

International migration captures any change of residence across the borders of the United States. The annual data for this external factor was collected from U.S. Census Bureau data repository. The census dataset called "Population, Population Change, and Estimated Components of

Population Change: April 1, 2010 to July 1, 2019 (NST-EST2019-alldata)" was used to gather the data for this factor. The quarterly data was then imputed by equally dividing the annual data into four quarters.

Data Source Link: https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-total.html

Original Data Coverage: Annually from 2011 to 2019

EF06 - Domestic Migration

Domestic migration captures the move where the origin and destination are within the borders of the United States. The annual data for this external factor was collected from U.S. Census Bureau data repository. The census dataset called "Population, Population Change, and Estimated Components of Population Change: April 1, 2010 to July 1, 2019 (NST-EST2019-alldata)" was used to gather the data for this factor. The quarterly data was then imputed by equally dividing the annual data into four quarters.

Data Source Link: https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-total.html

Original Data Coverage: Annually from 2011 to 2019

EF07 - Net Migration

Net migration is calculated based on the net domestic migration and net international migration. The annual data for this external factor was collected from U.S. Census Bureau data repository. The census dataset called "Population, Population Change, and Estimated Components of Population Change: April 1, 2010 to July 1, 2019 (NST-EST2019-alldata)" was used to gather the data for this factor. The quarterly data was then imputed by equally dividing the annual data into four quarters.

Data Source Link: https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-total.html

Original Data Coverage: Annually from 2011 to 2019

EF08 - Rental Vacancy Rate

Rental vacancy rate indicates the proportion of the rental inventory, which is vacant for rent. The quarterly data for this external factor was collected from U.S. Census Bureau data repository. The annual data was then imputed by calculating the average value of the quarters within one year.

Data Source Link: https://www.census.gov/housing/hvs/data/histtabs.html

Original Data Coverage: Quarterly from 2005 to 2019

EF09 - Homeowner Vacancy Rate

Homeowner vacancy rate indicates the proportion of the homeowner housing inventory, which is vacant for sale. The quarterly data for this external factor was collected from U.S. Census Bureau data repository. The annual data was then imputed by calculating the average value of the quarters within one year.

Data Source Link: https://www.census.gov/housing/hvs/data/histtabs.html

Original Data Coverage: Quarterly from 2005 to 2019

EF10 - Homeownership rate

Homeownership rate indicates the proportion of households that are owners. The quarterly data for this external factor was collected from U.S. Census Bureau data repository. The annual data was then imputed by calculating the average value of the quarters within one year.

Data Source Link: https://www.census.gov/housing/hvs/data/histtabs.html
Original Data Coverage: Quarterly from 2005 to 2019

EF11 - Total Building Permits

This external factor indicates the approval given by a local jurisdiction to proceed on a construction project. The monthly and annual data for this external factor was collected from U.S. Census Bureau data repository. The quarterly data was then calculated by summing up the monthly data only.

Data Source Link: https://www.census.gov/construction/bps/
Original Data Coverage: Monthly/Annually from 2005 to 2019

EF12 - Single Family Permits

The one-unit structure category is a single-family home. The monthly and annual data for this external factor was collected from U.S. Census Bureau data repository. The quarterly data was then calculated by summing up the monthly data only.

Data Source Link: https://www.census.gov/construction/bps/
Original Data Coverage: Monthly/Annually from 2005 to 2019

EF13 - Number of Housing Units

This external factor captures all housing units including occupied and vacant houses. The annual data for this external factor was collected from U.S. Census Bureau data repository. The quarterly data was then calculated by linearly interpolating the annual data.

Data Source Link: https://data.census.gov/cedsci/table?q=B25024&hidePreview=false&tid=ACSDT1Y2018.B25024&vintage=2018
Original Data Coverage: Annually from 2005 to 2019

EF14 - Population in College

The sum of the total number of people either in undergraduate colleges or graduate or professional school is used for this external factor. The annual data for this external factor was collected from U.S. Census Bureau data repository. The quarterly data was then imputed by linear interpolation of the annual data into four quarters.

Data Source Link: https://data.census.gov/cedsci/table?q=s1401&tid=ACSST1Y2018.S1401
Original Data Coverage: Annually from 2005 to 2018

EF15 - Percentage of Population in Poverty (National)

The population whose income falls below a certain poverty threshold, declared by the Office of Management and Budget (OMB). The annual data for this external factor was collected from U.S. Census Bureau data repository. The quarterly data was then imputed by linear interpolation of the annual data into four quarters.

Data Source Link: https://data.census.gov/cedsci/table?q=s1701&tid=ACSST1Y2018.S1701
Original Data Coverage: Annually from 2005 to 2018

EF16 - EF17–EF18 –Political Party Affiliation

Political Party Affiliation indicates the portion of the people who are either Democratic, Republican, or independent. Based on this, three different percentages for each month are collected from the Gallup website. The quarterly and annual data for this factor were calculated by averaging the monthly data.

Data Source Link: https://news.gallup.com/poll/15370/party-affiliation.aspx
Original Data Coverage: Monthly from 2005 to 2019

EF19 - Racial/Ethnic Composition

The annual population of different races is gathered from the census data repository. The quarterly population is then imputed by linearly interpolating the annual data.

Data Source Link: https://data.census.gov/cedsci/table?q=black&tid=ACSDT1Y2018.B02001&t=Black%20or%20African%20American&vintage=2018
Original Data Coverage: Annually from 2010 to 2019

EF20 - Immigration

The number of people who have obtained lawful permanent resident status was considered for this external factor. The annual data for this external factor was collected from the Homeland Security website. The quarterly data was then imputed by equally dividing the annual data into four quarters.

Data Source Link: https://www.dhs.gov/immigration-statistics/yearbook/2018
Original Data Coverage: Annually from 2005 to 2018

EF21 - Aging Populations

The aging population is defined as adults ages 65 years or older. The annual data for this external factor was collected from U.S. Census Bureau data repository. The quarterly data was then imputed by linear interpolation of the annual data into four quarters.

Data Source Link: https://data.census.gov/cedsci/table?q=s0103&tid=ACSST1Y2018.S0103
Original Data Coverage: Annually from 2005 to 2019

Economic, Employment and Price

EF22 - GDP All Industries (Billions)

GDP All Industries refers to the total monetary and market value of all the finished products in a country in a specific period. Original data was found with the annual and quarterly frequency. An important note is that for all GDP data, including the national level and the state-level GDP data, the seasonally adjusted data is downloaded from the sources since the unadjusted quarterly data was not available.

Data Source Link: https://apps.bea.gov/histdata/histChildLevels.cfm?HMI=8
Original Data Coverage: Annual and Quarterly 2005 to 2019

EF23 - GDP Construction (Billions)

GDP All Industries refers to the total monetary and market value of all the finished products related to construction in a country in a specific period. Original data was found with the annual and quarterly frequency.

Data Source Link: https://apps.bea.gov/histdata/histChildLevels.cfm?HMI=8
Original Data Coverage: Annual and Quarterly 2005 to 2019

EF24 - GDP Manufacturing (Billions)

GDP All Industries refers to the total monetary and market value of all the finished products related to manufacturing in a country in a specific period. Original data was found with the annual and quarterly frequency.

Data Source Link: https://apps.bea.gov/histdata/histChildLevels.cfm?HMI=8

Original Data Coverage: Annual and Quarterly 2005 to 2019

EF25 - GDP Real Estate (Billions)

GDP All Industries refers to the total monetary and market value of all the finished products related to real estate in a country in a specific period. Original data was found with the annual and quarterly frequency.

Data Source Link: https://apps.bea.gov/histdata/histChildLevels.cfm?HMI=8

Original Data Coverage: Annual and Quarterly 2005 to 2019

EF26 - GDP Transportation (Billions)

GDP All Industries refers to the total monetary and market value of all the finished products related to transportation in a country in a specific period. Original data was found with the annual and quarterly frequency.

Data Source Link: https://apps.bea.gov/histdata/histChildLevels.cfm?HMI=8

Original Data Coverage: Annual and Quarterly 2005 to 2019

EF27 - Per Capita Income

Per capita income measures the average income earned per person in a given area in a specified year. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link: https://fred.stlouisfed.org/series/A792RC0A052NBEA

Original Data Coverage: Annually from 2005 to 2019

EF28 - Personal Income

Personal income is an individual's total earnings from wages, investment enterprises, and other ventures. Original data was found with a quarterly frequency. To get the annual value, the average of the four quarters was used.

Data Source Link: https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=survey

Original Data Coverage: Quarterly 2005 to 2019

EF29 - Financial Condition Index

The Chicago Fed's National Financial Conditions Index (NFCI) was used for this factor. This index updates U.S. financial conditions. Original data was found with a quarterly and annual frequency.

Data Source Link: https://fred.stlouisfed.org/series/ANFCI#0

Original Data Coverage: Annual / Quarterly 2005 to 2019

EF30 - House Price Index

The house price index measures the percentage of change in the prices of housing. Original data was found with a quarterly frequency. To get the annual value, the average of the four quarters was used.

Data Source Link: https://fred.stlouisfed.org/series/USSTHPI

Original Data Coverage: Quarterly 2005 to 2019

EF31 - Consumer Price Index (CPI)

Consumer price index is a measure of the average change in the price for goods and services paid by urban consumers in a time frame. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://fred.stlouisfed.org/series/CPIAUCSL

Original Data Coverage: Monthly 2005 to 2019

EF32 - CPI -Rent Price Index

Consumer price index for all urban consumers based on the rent of primary residence. Original data was found with a monthly frequency. To get the annual value, the average of the twelve

Data Source Link: https://fred.stlouisfed.org/series/CUUR0000SEHA

Original Data Coverage: Monthly 2005 to 2019

months was used. To get the quarterly value, the average of the three months was used.

EF33 - CPI–Fuel Price Index

Consumer price index for all urban consumers based on gasoline (all types) in the United States. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://fred.stlouisfed.org/series/CUUR0000SETB01

Original Data Coverage: Monthly 2005 to 2019

EF34 - Number of Employed (in Thousands)

Number of employed refers to the number of people engaged in productive activities. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://data.bls.gov/timeseries/LNS12000000

Original Data Coverage: Monthly 2005 to 2019

EF35 - Number of Unemployed (in thousands)

Number of unemployed refers to the number of people that are not engaged in productive activities. They are not employees nor self-employed. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://fred.stlouisfed.org/series/UNEMPLOY

Original Data Coverage: Monthly 2005 to 2019

EF36 - Percentage of Unemployed (Unemployment Rate)

The unemployment rate is defined as the percentage of unemployed workers in the total labor force. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://data.bls.gov/timeseries/LNS14000000

Original Data Coverage: Monthly 2005 to 2019

EF37 - Financial Markets (Dow Jones Average Closing Price)

The Dow Jones Industrial Average (DJIA) is an index that tracks 30 large, publicly-owned blue chip companies trading on the New York Stock Exchange (NYSE) and the NASDAQ. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link: https://www.macrotrends.net/1358/dow-jones-industrial-average-last-10-years

Original Data Coverage: Annual 2005 to 2019

EF38 - Direct Employment by Aerospace and Defense Sector

Direct employment by aerospace and defense sector classification was used for this factor. The data was gathered from the "2017 U.S. aerospace and defense sector export and labor market study" report. Original data was found with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was used to fill the missing values.

Data Source Link: https://www2.deloitte.com/content/dam/Deloitte/us/Documents/manufacturing/us-2017-us-A&D-exports-and-labor-market-study.pdf figure 15

Original Data Coverage: Annual 2011 to 2016

Weather and Climate

EF39 - Total Monthly Precipitation (inches)

Precipitation includes rain, snow, sleet, ice pellets dew, frost, and hail. Fog and mist are not precipitation but suspensions. Original data was found with a monthly frequency. To get the annual value, the sum of the twelve months was used. To get the quarterly value, the sum of the data for three months was used.

Data Source Link: https://www.ncdc.noaa.gov/cag/national/time-series/110/tavg/all/12/2012-2019?base_prd=true&begbaseyear=1901&endbaseyear=2000

Original Data Coverage: Monthly 2005-2019

EF40 - Average Temperature

Average temperature is given in Fahrenheit. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://www.ncdc.noaa.gov/cag/national/time-series/110/tavg/all/12/2012-2019?base_prd=true&begbaseyear=1901&endbaseyear=2000

Original Data Coverage: Monthly 2005-2019

Emerging Technologies

EF41 - Number of Smart Phone Users

Number of Smart phone users refers to the number of people that own a smart phone. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link: https://www.statista.com/statistics/201182/forecast-of-smartphone-users-in-the-us/

https://internetinnovation.org/general/research-peek-of-the-week-smartphone-users-in-the-us-expected-to-reach-over-270-million-by-2020/

Original Data Coverage: Annual 2010-2019

EF42 - Number of Mobile Internet Users (millions)

The data shows the number of mobile internet users in the United States. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values. This factor is removed from the statistical analysis since the number of observations is too small.

Data Source Link: https://www.statista.com/statistics/275591/number-of-mobile-internet-user-in-usa/

Original Data Coverage: Annual 2017-2019

Regulations and Policies

EF43 - Hours of Service (HOS) Rules(Driving Limit Without Breaks)

The total allowed hours of service driving without a break. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values. This factor is removed from the statistical analysis since there is no variations in the data.

Data Source Link: https://www.govinfo.gov/content/pkg/FR-2011-12-27/pdf/2011-32696.pdf
https://en.wikipedia.org/wiki/Hours_of_service

Original Data Coverage: Annual 2005-2019

EF44 - Subsidies for Renewable Fuels (millions)

Subsidies for renewable fuels are federal financial interventions and subsidies. Original data was found with a frequency of every three years. To get the quarterly value, equal distribution of the yearly value was used to fill the missing values. This factor is eliminated from the statistical analysis since the number of data observations is too small.

Data Source Link: https://www.eia.gov/analysis/requests/subsidy/

Original Data Coverage: every three years 2010-2016

EF45 - Level of Highway Funding

The highway trust fund highway account receipts attributable to the states and federal aid appointments and allocations from the United States. Original data was found with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was used to fill the missing values.

Data Source Link: https://www.fhwa.dot.gov/policy/ohim/hs05/pdf/fe221.pdf
https://www.fhwa.dot.gov/policyinformation/statistics/2015/pdf/fe221b.pdf
https://www.fhwa.dot.gov/policyinformation/statistics/2016/pdf/fe221.pdf
https://www.fhwa.dot.gov/policyinformation/statistics/2017/pdf/fe221.pdf

https://www.fhwa.dot.gov/policyinformation/statistics/2018/pdf/fe221.pdf

Original Data Coverage: Annual 2005-2018

EF 46 - Investments & Incentives for Alternative Fuel Infra. & Vehicles

Transportation section energy consumption in terms of electricity retail sales was used as a proxy for this external factor.

Data Source Link: https://www.eia.gov/state/seds/sep_use/tra/pdf/use_tra_US.pdf

Original Data Coverage: Annual 2005-2018

D2 - External factors (state level)

Population, Demographics, and Housing

EF47 - Florida Population

This external factor captures the number of people living in Florida at a specific time. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link: https://data.census.gov/cedsci/table?q=florida%20population&g=0400000US12,01,13&tid=ACSDT1Y2016.B01003&vintage=2018&hidePreview=true
https://www.census.gov/data/tables/time-series/demo/popest/intercensal-2000-2010-state.html

Original Data Coverage: Annual 2005-2019

EF48 - Georgia Population

This external factor captures the number of people living in Georgia at a specific time. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link: https://data.census.gov/cedsci/table?q=florida%20population&g=0400000US12,01,13&tid=ACSDT1Y2016.B01003&vintage=2018&hidePreview=true
https://www.census.gov/data/tables/time-series/demo/popest/intercensal-2000-2010-state.html

Original Data Coverage: Annual 2005-2019

EF49 - Alabama Population

This external factor captures the number of people living in Alabama at a specific time. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link: https://data.census.gov/cedsci/table?q=florida%20population&g=0400000US12,01,13&tid=ACSDT1Y2016.B01003&vintage=2018&hidePreview=true
https://www.census.gov/data/tables/time-series/demo/popest/intercensal-2000-2010-state.html

Original Data Coverage: Annual 2005-2019

EF50 - Florida Change Population

This external factor captures the annual growth of the population in Florida. Original data was found with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was used to fill the missing values. The census dataset called "Population, Population Change, and Estimated Components of Population Change: April 1, 2010 to July 1, 2019 (NST-EST2019-alldata)" was used to gather the data for this factor.

Data Source Link: https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-total.html

Original Data Coverage: Annually from 2011 to 2019

EF51 - International Migration (Florida)

International migration refers to people migrating from outside of the country into Florida. Original data was found with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was assumed to fill the missing values. The census dataset called "Population, Population Change, and Estimated Components of Population Change: April 1, 2010 to July 1, 2019 (NST-EST2019-alldata)" was used to gather the data for this factor.

Data Source Link: https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-total.html

Original Data Coverage: Annually from 2011 to 2019

EF52 - Domestic Migration (Florida)

Domestic migration refers to people migrating from any other state in the United States into Florida. Original data was found with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was used to fill the missing values. The census dataset called "Population, Population Change, and Estimated Components of Population Change: April 1, 2010 to July 1, 2019 (NST-EST2019-alldata)" was used to gather the data for this factor.

Data Source Link: https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-total.html

Original Data Coverage: Annually from 2011 to 2019

EF53 - Net Migration (Florida)

This factor compares residents moving into a state to those moving out in a time period. Original data was found with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was assumed to fill the missing values. The census dataset called "Population, Population Change, and Estimated Components of Population Change: April 1, 2010 to July 1, 2019 (NST-EST2019-alldata)" was used to gather the data for this factor.

Data Source Link: https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-total.html

Original Data Coverage: Annually from 2011 to 2019

EF54 - Population in College (Florida)

This external factor is the total number of people either in undergraduate colleges or graduate or professional school. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link: https://data.census.gov/cedsci/table?q=florida%20s1401&g=0400000US12&tid=ACSST1Y2018.S1401

Original Data Coverage: Annually from 2010 to 2018

EF55 - Percentage of Population in Poverty (Florida)

This external factor captures the population whose income falls below a certain poverty threshold, declared by the Office of Management and Budget (OMB). Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link: https://data.census.gov/cedsci/table?q=florida%20s1701&g=0400000US12&tid=ACSST1Y2018.S1701

Original Data Coverage: Annually from 2010 to 2018

EF56–EF57–EF58 - Political Party Affiliation (Florida)

Political Party Affiliation indicates the portion of the people who are either Democratic, Republican or other. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link: https://dos.myflorida.com/elections/data-statistics/voter-registration-statistics/voter-registration-reportsxlsx/voter-registration-by-party-affiliation/

Original Data Coverage: Annually from 2005 to 2019

EF59 - Seniors Population (65+) (Florida)

This external factor is the number of senior citizens in Florida at a certain point in time. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link: https://data.census.gov/cedsci/table?q=65&g=0400000US12&tid=ACSST1Y2018.S0103&vintage=2010&hidePreview=true

Original Data Coverage: Annually from 2010 to 2018

EF60 - Rental Vacancy Rate (Florida)

Rental vacancy rate indicates the proportion of the rental inventory in Florida, which is vacant for rent. Original data was found with a quarterly frequency. Average value of the quarterly data is used for the annual data.

Data Source Link: https://www.census.gov/housing/hvs/data/rates.html

Original Data Coverage: Quarterly 2005-2019

EF61 - Homeowner Vacancy Rate (Florida)

Homeowner vacancy rate indicates the proportion of the homeowner housing inventory, which is vacant for sale. Original data was found with a quarterly frequency. The average value of the quarterly data is used for the annual data.

Data Source Link: https://www.census.gov/housing/hvs/data/rates.html

Original Data Coverage: Quarterly 2005-2019

EF62 - Homeownership Rate (Florida)

The proportion of households in Florida that are owners. Original data was found with a quarterly frequency. The average value of the quarterly data is used for the annual data.

Data Source Link: https://www.census.gov/housing/hvs/data/rates.html

Original Data Coverage: Quarterly 2005-2019

EF63 - Total Building Permits (Florida)

This external factor indicates the approval given by a local jurisdiction to proceed on a construction project. Original data was found with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was used to fill the missing values.
Data Source Link: https://www.census.gov/construction/bps/stateannual.html
Original Data Coverage: Annually from 2005 to 2019

EF64 - Single Family (S.F.) Permits (Florida)
The one-unit structure category is a single-family home. Original data was found with a yearly frequency. The equal distribution of the yearly value was assumed to fill the missing values to get the quarterly value.
Data Source Link: https://www.census.gov/construction/bps/stateannual.html
Original Data Coverage: Annually from 2005 to 2019

EF65 - Number of Housing Units (Florida)
This external factor captures all housing units of Florida. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.
Data Source Link: https://data.census.gov/cedsci/table?q=florida%20DP04&g=0400000US12&tid=ACSDP5Y2017.DP04
Original Data Coverage: Annually from 2010 to 2019

EF66 - Number of Licensed Drivers (Florida)
This external factor refers to the total number of licensed drivers in Florida. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.
Data Source Link: https://www.flhsmv.gov/pdf/driver-vehiclereports/drivers.pdf
Original Data Coverage: Annually from 2005 to 2019

EF67 - Number of tourists to Florida (Millions) [Florida]
Tourism data is the number of tourists to Florida from other states in the United States, Canada, and other countries. Original data was found with a quarterly frequency. To get the yearly value, the four quarters of each year were summed up.
Data Source Link: https://www.visitflorida.org/resources/research/
Original Data Coverage: Quarterly 2009-2019

EF68–Gas Tax Revenue
This factor captures the revenue acquired from the fuel tax.
Data Source Link:
Original Data Coverage: Quarterly 2009-2019

Economic, Employment and Price
EF69 - GDP All Industries (Billions) [Florida]
GDP All Industries refers to the total monetary and market value of all the finished products in Florida in a specific period. Original data was found with an annual and quarterly frequency.
Data Source Link: https://fred.stlouisfed.org/series/FLNQGSP
https://apps.bea.gov/regional/histdata/

Original Data Coverage: Annual and Quarterly 2005-2018

EF70 - GDP Construction (Billions) [Florida]

GDP All Industries refers to the total monetary and market value of all the finished products related to construction in Florida in a specific period. Original data was found with an annual and quarterly frequency.

Data Source Link: https://fred.stlouisfed.org/series/FLCONSTNQGSP https://apps.bea.gov/regional/histdata/

Original Data Coverage: Annual and Quarterly 2005-2018

EF71 - GDP Manufacturing (Billions) [Florida]

GDP All Industries refers to the total monetary and market value of all the finished products related to manufacturing in Florida in a specific period. Original data was found with an annual and quarterly frequency.

Data Source Link: https://fred.stlouisfed.org/series/FLMANNQGSP https://apps.bea.gov/regional/histdata/

Original Data Coverage: Annual and Quarterly 2005-2018

EF72 - GDP Real Estate (Billions) [Florida]

GDP All Industries refers to the total monetary and market value of all the finished products related to real estate in Florida in a specific period. Original data was found with an annual and quarterly frequency.

Data Source Link: https://apps.bea.gov/regional/histdata/

Original Data Coverage: Annual and Quarterly 2005-2018

EF73 - GDP Retail Trade (Billions) [Florida]

GDP All Industries refers to the total monetary and market value of all the finished products related to retail and trade in Florida in a specific period. Original data was found with an annual and quarterly frequency.

Data Source Link: https://apps.bea.gov/regional/histdata/

Original Data Coverage: Annual and Quarterly 2005-2018

EF74 - GDP Transportation (Billions) [Florida]

GDP All Industries refers to the total monetary and market value of all the finished products related to transportation in Florida in a specific period. Original data was found with an annual and quarterly frequency.

Data Source Link: https://apps.bea.gov/regional/histdata/

Original Data Coverage: Annual and Quarterly 2005-2018

EF75 - Per Capita Income (Florida)

Per capita income measures the average income earned per person in a given area in a specified year. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link: https://www.deptofnumbers.com/income/florida/#percap

Original Data Coverage: Annual 2005-2017

EF76 - Personal Income (Florida)

Personal income indicates Floridians' total earnings from wages, investment enterprises, and other ventures. Original data was found with a quarterly frequency. To get the annual value, the average of the four quarters was used.

Data Source Link: https://fred.stlouisfed.org/series/FLOTOT
Original Data Coverage: Quarterly 2005-2019

EF77 - Coincident Economic Activity Index (Florida)

The economic activity index measures average economic growth in the metropolitan area. For this factor, the quarterly and annual data was directly gathered from the source.

Data Source Link: https://fred.stlouisfed.org/series/FLPHCI
Original Data Coverage: Annual / Quarterly 2005-2019

EF78 - House Price Index (Florida)

The house price index measures the percentage change in housing prices. For this factor, the quarterly and annual data was directly gathered from the source.

Data Source Link: https://fred.stlouisfed.org/series/FLSTHPI
Original Data Coverage: Annual / Quarterly 2005-2019

EF79 - Average CPI for all MSAs (Florida)

This factor represents the consumer price index for all urban consumers. This factor was removed from the analysis due to a lack of enough data.

Data Source Link:
Original Data Coverage:

EF80 - CPI–Rent Price Index (Florida)

Consumer price index for all urban consumers based on the rent of primary residence. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://fred.stlouisfed.org/series/FLSTHPI
Original Data Coverage: Quarterly 1/2005-10/2019

EF81 - CPI–Fuel Price Index (Florida)

This factor represents the consumer price index for all urban consumers based on the fuel price. This factor was removed from the analysis due to a lack of enough data.

Data Source Link:
Original Data Coverage:

EF82 - Number of Employed (In Thousands) [Florida]

This external factor refers to the number of people engaged in productive activities. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://data.bls.gov/timeseries/LASST120000000000005?amp%253bdata_tool=XGtable&output_view=data&include_graphs=true
Original Data Coverage: Monthly 2005-2019

EF83- Number of Unemployed (in thousands) [Florida]

This external factor refers to the number of people that are not engaged in productive activities. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://data.bls.gov/timeseries/LASST120000000000005?amp%253bdata_tool=XGtable&output_view=data&include_graphs=true

Original Data Coverage: Monthly 2005-2019

EF84 - Percentage of Unemployed (Florida)

The unemployment rate is defined as the percentage of unemployed workers in the total labor force. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://data.bls.gov/timeseries/LASST120000000000005?amp%253bdata_tool=XGtable&output_view=data&include_graphs=true

Original Data Coverage: Monthly 2005-2019

Weather and Climate

EF85 - Total Precipitation (inches) [Florida]

This external factor refers to the monthly precipitation. Precipitation includes rain, snow, sleet, ice pellets dew, frost, and hail. Fog and mist are not precipitation but suspensions. Original data was found with a monthly frequency. To get the annual value, the sum of the twelve months was used. To get the quarterly value, the sum of the three months was used.

Data Source Link: https://www.ncdc.noaa.gov/cag/statewide/time-series/8/tavg/all/12/2000-2019?base_prd=true&begbaseyear=1901&endbaseyear=2020

Original Data Coverage: Monthly 2005-2019

EF86 - Average Temperature (Florida)

This external factor refers to the average temperature given in Fahrenheit. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://www.ncdc.noaa.gov/cag/statewide/time-series/8/tavg/all/1/2012-2019?base_prd=true&begbaseyear=1901&endbaseyear=2000

Original Data Coverage: Monthly 2005-2019

EF87 - Number of Hurricane Strikes (Florida)

This external factor refers to the number of Hurricane Strikes in Florida. Original data was found with a monthly frequency. To get the annual value, the average of the twelve months was used. To get the quarterly value, the average of the three months was used.

Data Source Link: https://coast.noaa.gov/hurricanes/

Original Data Coverage: Yearly 2005-2019

EF88 - Sea Level Change in Florida's Coastal Borders (Florida)

This external factor refers to sea level change in inches in Florida's coastal borders. Original data was found with a yearly frequency. To get the quarterly value, the equal division of the year value was used.

Data Source Link: https://sealevelrise.org/states/florida/
Original Data Coverage: Yearly 2005-2016

EF89 - Weather related inland flooding - FIMA (- NFIP Redacted Claims Data (Florida)
This external factor refers to the number of claims on flooding related to weather. Original data was found with a monthly frequency. To get the annual value, the sum of the twelve months was used. To get the quarterly value, the sum of the three months was used.
Data Source Link: https://www.fema.gov/openfema-data-page/fima-nfip-redacted-claims

Original Data Coverage: Monthly 2005-2019

Regulations and Policies
EF90 - Transportation Electric Vehicle Retail Sales [Florida]
This external factor represents the total sales of electric vehicles in Florida. The original data was collected monthly; the quarterly and annual data were calculated by summing the monthly data.
Data Source Link: https://autoalliance.org/energy-environment/advanced-technology-vehicle-sales-dashboard/
Original Data Coverage: Monthly 2011-2018

EF91 - Highway Operations and Maintenance Decisions (millions) [Florida]
This external factor shows the amount of dollars in millions related to highway operations and maintenance. Original data was found with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was used to fill the missing values.
Data Source Link: https://fdotewp1.dot.state.fl.us/fmsupportapps/Documents/pra/ProgramAndResourcePlanHistory.pdf
Original Data Coverage: Annual 2005-2019

EF92 - Level of Highway Funding (Payments into Highway Trust Fund) [Florida]
This external value shows payments into the Highway Trust Fund. Original data was found with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was used to fill the missing values.

Data Source Link: https://www.fhwa.dot.gov/policyinformation/statistics/2015/fe221b.cfm
Original Data Coverage: Annual 2005-2019

EF93 - Florida Total Amount of Highway Trust Fund Money (Allocations)
Federal highway trust fund allocations from the highway account into Florida. Original data was found with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was assumed to fill the missing values.

Data Source Link: https://www.fhwa.dot.gov/policyinformation/statistics/2015/fe221b.cfm
Original Data Coverage: Annual 2005-2019

EF 94 - Fuel Taxes (cents per gallon) [Florida]

This external factor is the state tax imposed on fuels in cents per gallon. Original data was found with a yearly frequency. The same annual value is assumed for all quarters of the year.

Data Source Link:	2005: http://edr.state.fl.us/Content/local-government/data/data-a-to-z/2005LOFTrates.pdf 2006:http://edr.state.fl.us/Content/local-government/data/data-a-to-z/2006LOFTrates.pdf 2007:http://edr.state.fl.us/Content/local-government/data/data-a-to-z/2007LOFTrates.pdf 2008:http://edr.state.fl.us/Content/local-government/data/data-a-to-z/2008LOFTrates.pdf 2009:http://edr.state.fl.us/Content/local-government/data/data-a-to-z/2009LOFTrates.pdf 2010:http://edr.state.fl.us/Content/local-government/data/data-a-to-z/2010LOFTrates.pdf 2011:http://edr.state.fl.us/Content/local-government/data/data-a-to-z/2011LOFTrates.pdf 2012:http://edr.state.fl.us/Content/local-government/data/county-municipal/2012LOFTrates.pdf 2013:http://edr.state.fl.us/content/local-government/data/county-municipal/2013LOFTrates.pdf 2014:http://edr.state.fl.us/Content/local-government/data/county-municipal/2014LOFTrates.pdf 2015:http://www.edr.state.fl.us/Content/local-government/data/county-municipal/2015LOFTrates.pdf 2016:http://edr.state.fl.us/content/local-government/data/county-municipal/2016LOFTrates.pdf 2017:http://edr.state.fl.us/content/local-government/data/county-municipal/2017LOFTrates.pdf 2018:http://edr.state.fl.us/Content/local-government/data/county-municipal/2018LOFTrates.pdf
Original Data Coverage:	Annual 2005-2018

EF95–Privatization of Roads (Florida)

This external factor is measured using the toll road value of the center lines miles. Original data was found with a yearly frequency. To get the quarterly value, linear interpolation was used to fill the missing values.

Data Source Link:	2006: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/20068cae283a20fd4028bc75a74f5429834b.pdf?sfvrsn=b536859_0 2007: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/200702c960ab03c54fa59bcea4b0d0d91849.pdf?sfvrsn=a50c2f47_0 2008:https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/20083b57c2cc49f545469db6ec7c03662fea.pdf?sfvrsn=9ea28760_0

2009:https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/20091703d60e0aaa43f3b3259a81b369fc1d.pdf?sfvrsn=87a995e0_0
2010:https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/20100ea50e09fff84f8d9ad2b7860fd88a5f.pdf?sfvrsn=465d41db_0
2011: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/20110461af56a5d1493c828813fffd39cfe2.pdf?sfvrsn=b2b0e688_0
2012:https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/20132a0bd3057a5341c5a6571745ad9144f8.pdf?sfvrsn=47589238_0
2013:https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/20132a0bd3057a5341c5a6571745ad9144f8.pdf?sfvrsn=47589238_0
2014:https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/20149832b0dfbd8741d1813fdc33add7a649.pdf?sfvrsn=f9b5f147_
2015:https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/20154340d6a16a0a41c88d5dddc1b327b88d.pdf?sfvrsn=f44a97e4_0
2016:https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/2016ef355ac8d53a4144bc69639493e33ffc.pdf?sfvrsn=590f1b70_0
2017:https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/2017a153a8a9b38b43439068a2c11159020b.pdf?sfvrsn=b0d8ebe1_0
2018:https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/statistics/mileage-rpts/nhs2018.pdf?sfvrsn=be5d0ca3_2

Original Data Coverage:	Annual 2006-2018

EF96 - Number of Launches at Kennedy Space Center (Florida)
This external factor measures the number of launches done by The John F. Kennedy Space Center, located in Merritt Island, Florida. Original data was found with a monthly frequency. To get the annual value, the sum of the twelve months was used. To get the quarterly value, the sum of the three months was used.

Data Source Link:	https://www.nasa.gov/centers/kennedy/about/annual_rpt/annual_rpt-index.html
Original Data Coverage:	Monthly 2005-2019

EF97 - International Trade Through Miami-Dade (Billions) [Florida]
This external factor shows international trade through Miami-Dade, which is calculated by subtracting Miami-Dade's imports from its exports to get the net balance. Original data was found

with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was used to fill the missing values.

Data Source Link: https://www.miamidade.gov/business/international-imports-exports.asp

Original Data Coverage: Annual 2012-2018

EF98 - Number of Tourists to Orlando

This external factor represents the number of tourists that visited Orlando during a certain period of time. Original data was found with a yearly frequency. To get the quarterly value, equal distribution of the yearly value was used to fill the missing values.

Data Source Link: http://f.tlcollect.com/fr2/512/73754/pres_CBRE_Orlando_Tourism_short.pdf

Original Data Coverage: yearly 2005-2019

D3 - Performance measures

Safety Measures

PM01 - Safety Belt Use

This measure captures the percentage of drivers who use the safety belt through annual surveys. The measure is reported annually. The annual data are converted to quarterly data via linear

Data Source Link: https://www.flhsmv.gov/resources/crash-citation-reports/

Original Data Coverage: Annually from 2009 to 2019

interpolation.

PM02 - Bicyclist Fatalities

This measure captures the total number of bicyclist fatalities on all of Florida's roadways. This measure is reported annually. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://www.flhsmv.gov/resources/crash-citation-reports/

Original Data Coverage: Annually from 2005 to 2018

PM03 - Pedestrian Fatalities

This measure captures the total number of pedestrian fatalities on all of Florida's public roads. This measure is reported annually. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://www.flhsmv.gov/resources/crash-citation-reports/

Original Data Coverage: Annually from 2005 to 2018

PM04 - Motorcyclist Fatalities

This measure captures the total number of motorcyclist and their passengers' fatalities on all of Florida's roadways. This measure is reported annually. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://www.flhsmv.gov/resources/crash-citation-reports/

Original Data Coverage: Annually from 2005 to 2018

Auto

PM05, PM06 - Vehicle Miles Traveled (VMT)

VMT measures the amount of travel for all vehicles in Florida over a given period of time. The annual data is obtained from the FDOT Transportation Data and Analytics Office. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2006 to 2018

PM07, PM08 - Person Miles Traveled

Person Miles Traveled (PMT) indicates the miles each person travels in a vehicle. This measure is reported in peak hours and daily. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM09, PM10 - Percentage of Travel Meeting Level of Service Targets

This measure is calculated based on the following formula.

$$\frac{\sum(\text{VMT during Peak Performance} \geq \text{Acceptable LOS Target Threshold})}{\sum(\text{VMT})} \times 100$$

The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM11 - Percentage of Miles Meeting Level of Service Targets

This measure is calculated based on the following formula.

$$\frac{\sum(\text{Segment Length during Peak Performance} \geq \text{Acceptable LOS Target Threshold})}{\sum(\text{Segment Length})} \times 100$$

The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM12 - % non-Single Occupancy Vehicle Travel

This measure captures the travel via carpool, can, public transportation, walking, commuter rail. This factor was removed from the analysis as it not included in the FDOT sourcebook anymore.

PM13, PM14 - Travel Time Reliability: On-Time Arrival

According to the FDOT sourcebook, this measure is defined based on the percentage of trips traveling at greater than or equal to 5 mph below the peak hour's posted speed limit. The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM15, PM16 - Travel Time Reliability: Planning Time Index

This measure represents the additional time that should be accounted for to ensure on-time arrival at 95 percent of the time. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM17, PM18, PM19 - Vehicle Hours of Delay

This measure represents the amount of delay that a traveler experiences as the result of congestion. The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM20, PM21, PM22 - Person Hours of Delay

The following formula is used for calculating this measure.

$$\sum (\text{Daily or Peak Travel Time} - \text{Travel Time at LOS B}) \times \text{Vehicle Volume} \times \text{Average Vehicle Occupancy}$$

The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM23 - Average Travel Speed

This measure captures the average of all hourly travel speed. The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM24, PM25 - Percentage of Travel Heavily Congested

The following formula is used for calculating this measure.

$$\frac{\sum (\text{VMT during Peak Performance at defined LOS thresholds})}{\sum \text{VMT}} \times 100$$

The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM26 - Percentage of Miles Heavily Congested

The following formula is used for calculating this measure.

$$\frac{\sum(\text{Segment Length during Peak Performance at defined LOS thresholds})}{\sum \text{Segment Length}} \times 100$$

The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM27, PM28 - Hours Heavily Congested

Hours Heavily Congested accounts for the duration of congestion. This is the average number of hours in a day that are heavily congested in Florida. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM29 - Vehicles Per Lane Mile

Vehicles per Lane Mile is a measure of average density on the roadway.

$$\frac{\sum(\frac{\text{Volume}}{\text{Number of Lanes}} \times (\text{Lane Miles}))}{\sum \text{Lane Miles}}$$

The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM30–Number of fatalities

This measure captures the total number of fatalities on all of Florida's public roads. This measure is reported annually. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://www.flhsmv.gov/resources/crash-citation-reports/

Original Data Coverage: Annually from 2005 to 2018

PM31–Rate of fatalities

This measure captures the total number of fatalities on all of Florida's public roads per 100 million vehicle miles traveled. This measure is reported annually. Linear interpolation was used to get the quarterly data.

Data Source Link: https://www.flhsmv.gov/resources/crash-citation-reports/

Original Data Coverage: Annually from 2005 to 2018

Transit

PM32 - Transit Passenger Trips

This measure captures the number of passengers boarding on transit vehicles annually. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2005 to 2018

PM33 - Transit Revenue Miles

This measure captures the annual miles of a transit vehicle travel while being in active service. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2007 to 2018

PM34 - Transit Revenue Miles Between Failures

This measure indicates how the delays caused by a problem with the equipment are frequent. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2006 to 2018

PM35 - Transit Weekday of Span of Service.

This measure represents the number of hours that transit service is available on a weekday. The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2005 to 2018

PM36 - Transit Passenger Trips Per Revenue Mile

This measure is an indicator of the service's effectiveness, which is impacted by the demand and supply levels.

$$\frac{\sum \text{Annual Transit Passenger Trips}}{\sum \text{Annual Transit Revenue Miles}}$$

The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2006 to 2018

PM37 - Job Accessibility–Transit

This measure is an indicator of the number of jobs which are accessible by a maximum of 30 minutes travel. This measure is removed from the analysis because of a lack of data points.

PM38 - Transit Subsidies

This measure indicates the total federal subsidies paid to the transit services. This measure was removed from the analysis due to a lack of data.

Pedestrian / Bike

PM39 - Percentage of Pedestrian Facility Coverage
The following formula is used to calculate this measure.

$$\frac{\sum \text{Pedestrian Facility Miles in Urban Areas}}{\sum \text{Centerline Miles in Urban Areas}} \times 100$$

The annual data is obtained from the FDOT sourcebook. The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf
Data Coverage: Annually from 2011 to 2018

PM40, PM41 - Percentage of Bicycle Facility Coverage
The following formula is used to calculate this measure.

$$\frac{\sum \text{Miles of Bicycle Facilities}}{\sum \text{Centerline Miles in Urban Areas}} \times 100$$

The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf
Data Coverage: Annually from 2011 to 2018

Aviation

PM42 - Passenger Enplanements
Aviation passenger boardings are the total number of revenue passengers who board an aircraft at a Florida airport. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf
Data Coverage: Annually from 2007 to 2018

PM43 - Gate Departure Delay
This measure reflects the ratio of flights departed with less than 15 minutes of delay to the total departure. The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf
Data Coverage: Annually from 2007 to 2018

PM44 - Aviation Tonnage
This measure represents the weight of all air cargo handled at Florida airports. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf
Data Coverage: Annually from 2007 to 2018

PM45 - Aviation Value of Freight
The following formula is used to calculate this measure.

$$\sum Tonnage \times Average\ Value\ per\ Ton$$

The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2012 to 2018

PM46–Aircraft operations:

This measure was removed from the analysis due to lack of data.

PM47–Operating Cost per Passenger:

This measure was removed from the analysis due to lack of data.

Rail

PM48 - Rail Tonnage

This measure represents the weight of all cargo carried by rail from or to Florida. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2006 to 2017

PM49 - Rail Passenger

This measure captures the total annual rail passengers in Florida. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2007 to 2018

PM50 - Passenger Rail On-Time Arrival

This measure reflects the ratio of trains arrived within a specified threshold time frame of their scheduled arrival. The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2007 to 2018

Seaport

PM51 - Seaport Tonnage

This measure represents the weight of all waterborne tons of cargo handled at Florida's public seaports. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2007 to 2018

PM52 - Seaport Twenty-Foot Equivalent Units

Twenty-Foot Equivalent Unit (TEU) represents the cargo capacity of a standard intermodal container. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2007 to 2018

PM53 - Seaport Value of Freight

This measure represents the monetary value of international cargo handled at public seaports of Florida. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2006 to 2018

PM54 - Seaport Passenger

This measure captures the passengers embarking and disembarking cruise ships at Florida seaports. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2007 to 2018

Truck

PM55 - Truck Miles Traveled

The following formula is used to calculate this measure.

$$\sum (\text{Segment Length} \times \text{Volume} \times \%\text{ of Trucks})$$

The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM56 - Combination Truck Miles Traveled

The following formula is used to calculate this measure.

$$\sum (\text{Segment Length} \times \text{Volume} \times \text{Combination Truck Factor})$$

The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM57 - Combination Truck Ton Miles Traveled

This measure indicates a unit of freight transportation measurement equivalent to transporting a ton of freight for a distance of one mile. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf
Data Coverage: Annually from 2008 to 2018

PM58 - Combination Truck Tonnage

Combination Truck Tonnage refers to freight weight handled by combination trucks on the State Highway System of Florida. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf
Data Coverage: Annually from 2008 to 2018

PM59 - Combination Truck Value of Freight

This measure indicates the value of truck freight in dollar amount. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf
Data Coverage: Annually from 2012 to 2018

PM60, PM61 - Combination Truck On-Time Arrival

According to the FDOT sourcebook, this measure is defined based on the percentage of combination truck miles traveled at greater than or equal to 5 mph below the peak hour's posted speed limit. The annual data is obtained from the FDOT sourcebook. The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf
Data Coverage: Annually from 2008 to 2018

PM62, PM63 - Combination Truck Planning Time Index

This measure represents the additional time that should be accounted for to ensure on-time arrival at 95 percent of the time. The annual data is obtained from the FDOT sourcebook. The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf
Data Coverage: Annually from 2008 to 2018

PM64 - Combination Truck Hours of Delay

This measure represents the amount of delay that a traveler experiences as the result of congestion. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf
Data Coverage: Annually from 2008 to 2018

PM65 - Combination Truck Average Travel Speed

This measure captures the average of all hourly travel speed. The annual data is available on the FDOT sourcebook. The annual data is converted to quarterly data via linear interpolation.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM66 - Combination Truck Cost of Delay

The following formula is used to calculate this measure.

$$\sum (Combination\ Truck\ Hours\ of\ Delay) \times\ Average\ Marginal\ Cost\ of\ Labor\ per\ Hour$$

The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

PM67 - Truck Empty Backhaul Tonnage

This measure represents the available capacity that is not used by the trucks. The annual data is obtained from the FDOT sourcebook. The annual data is converted to quarterly data by dividing the annual data by four for each quarter.

Data Source Link: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/fto/sourcebook/2019sourcebook.pdf

Data Coverage: Annually from 2008 to 2018

APPENDIX E: FACTORS ANALYSIS RESULTS

In this section, the results of factor analysis are presented for each mode. In this regard, two tables are displayed for each mode. The first table contained the eigenvalues and explained variance for each mode. The highlighted latent factors are selected for each mode. The second table presents the factor loadings and the process of grouping the external factors under each dimension. Please note that the proportional variance shown in the second table are scaled to unity sum.

Pedestrian and Bike: Table E-1 shows the results of the factors analysis for the pedestrian and bike external factors. As the first latent factor covers more than 95 percent of the cumulative variance, only one latent factor was selected, and all of the external factors were grouped under the first latent factor. Table E-2 provide the information regarding factor loading for the pedestrian mode.

Table E- 1: Factor analysis results for the pedestrian and bike mode

	EV	Proportional Variance	Cumulative Variance
1	9.76	0.98	0.98
2	0.14	0.01	0.99
3	0.05	0.00	0.99
4	0.03	0.00	1.00
5	0.01	0.00	1.00
6	0.01	0.00	1.00
7	0.00	0.00	1.00
8	0.00	0.00	1.00
9	0.00	0.00	1.00
10	0.00	0.00	1.00

Table E- 2: Factor loading for the pedestrian and bike mode

Mode	EF	External Factors	Factor Loading				Squared Factor Loading (Scaled to Unity)			
			1	2	3	4	1	2	3	4
Pedestrian and Bike	EF14	Population in College (NL)	0.99				0.10			
	EF36	Percentage of Unemployed (NL)	1.00				0.10			
	EF35	Number of Unemployed (NL)	1.00				0.10			
	EF59	Seniors Population (65+) (SL)	-0.99				0.10			
	EF94	Fuel Taxes (SL)	-0.98				0.10			
	EF08	Rental Vacancy Rate (NL)	0.93				0.09			
	EF84	Percentage of Unemployed (SL)	1.00				0.10			
	EF58	Political Party Affiliation (other) (SL)	-0.98				0.10			
	EF02	Population Estimate (NL)	-0.99				0.10			
	EF83	Number of Unemployed (SL)	1.00				0.10			
		Explained Variance	9.73	0.00	0.00	0.00				
		Proportional Variance	1.00	0.00	0.00	0.00				

Truck: Similar to the pedestrian and bike mode, the first latent factor of the truck mode external factors also covers more than 95 percent of cumulative variance. Thus, only one latent factor was selected. Table E-3 and E-3 present the eigenvalue and factor loading results for the truck mode, respectively.

Table E- 3: Factor analysis results for the truck mode

	EV	Proportional Variance	Cumulative Variance
1	9.78	0.98	0.98
2	0.10	0.01	0.99
3	0.08	0.01	0.99
4	0.03	0.00	1.00
5	0.01	0.00	1.00
6	0.00	0.00	1.00
7	0.00	0.00	1.00
8	0.00	0.00	1.00
9	0.00	0.00	1.00
10	0.00	0.00	1.00

Table E- 4: Factor loading for the truck mode

Mode	EF	External Factors	Factor Loading				Squared Factor Loading (Scaled to Unity)			
			1	2	3	4	1	2	3	4
Truck	EF13	Number of Housing Units (NL)	1.00				0.10			
	EF65	Number of Housing Units (SL)	1.00				0.10			
	EF30	House Price Index (NL)	1.00				0.10			
	EF15	% Population in Poverty (NL)	-0.99				0.10			
	EF91	Highway Operations and Maintenance Decisions (Millions) (SL)	0.97				0.10			
	EF66	Number of Licensed Drivers (SL)	0.96				0.09			
	EF55	Percentage of Population in Poverty (SL)	-0.99				0.10			
	EF32	CPI–Rent Price Index (NL)	1.00				0.10			
	EF37	Financial Markets (Dow Jones Avg Closing Price) (NL)	0.98				0.10			
	EF78	House Price Index (SL)	1.00				0.10			
		Explained Variance	9.75	0	0	0				
		Proportional Variance	1.00	0	0	0				

Transit: Table E-5 shows the results of the factor analysis for the transit mode external factors. Since the first two latent factors cover more than 95 percent of the variance of the data, two dimensions was selected for the transit mode. Table E-6 shows the corresponding factor loadings.

Table E- 5: Factor analysis results for the transit mode

	EV	Proportional Variance	Cumulative Variance
1	9.34	0.93	0.93
2	0.35	0.03	0.97
3	0.27	0.03	0.99
4	0.02	0.00	1.00
5	0.01	0.00	1.00
6	0.00	0.00	1.00
7	0.00	0.00	1.00
8	0.00	0.00	1.00
9	0.00	0.00	1.00
10	0.00	0.00	1.00

Table E- 6: Factor loading for the transit mode

	EF	External Factors	Factor Loading				Squared Factor Loading (Scaled to Unity)			
			1	2	3	4	1	2	3	4
Transit	EF70	GDP of FL- Construction (In Millions of Dollars) (SL)	0.84	0.14			**0.10**	0.01		
	EF55	Percentage of Population in Poverty (SL)	-0.73	-0.32			**0.08**	0.07		
	EF15	% Population in Poverty (NL)	-0.72	-0.32			0.08	**0.08**		
	EF51	International Migration (SL)	-0.03	1.02			0.00	**0.76**		
	EF31	Consumer Price Index (CPI) (NL)	1.04	-0.09			**0.16**	0.01		
	EF49	Alabama Population (SL)	0.81	0.17			**0.10**	0.02		
	EF66	Number of Licensed Drivers (SL)	0.99	-0.04			**0.14**	0.00		
	EF41	Number of Smartphone Users (NL)	0.81	0.20			**0.10**	0.03		
	EF65	Number of Housing Units (SL)	0.89	0.13			**0.12**	0.01		
	EF80	CPI–Rent Price Index (SL)	0.92	0.10			**0.13**	0.01		
		Explained Variance	6.78	1.37	0	0				
		Proportional Variance	0.83	0.17	0	0				

Rail: Tables E-7 and E-8 presents the eigenvalue and factor loading results of the factor analysis for the rail transportation mode. The results show that the first three latent factors cover more than 95 percent of the variance of the data. Thus, three latent factors were selected for the rail mode.

Table E- 7: Factor analysis results for the rail mode

	EV	Proportional Variance	Cumulative Variance
1	7.66	0.76	0.76
2	1.42	0.13	0.90
3	0.55	0.05	0.95
4	0.18	0.01	0.96
5	0.11	0.01	0.97
6	0.04	0.00	0.97
7	0.02	0.00	0.97
8	0.01	0.00	0.97
9	0.00	0.00	0.97
10	0.00	0.00	0.97

Table E- 8: Factor loading for the rail mode

	EF	External Factors	Factor Loading				Squared Factor Loading (Scaled to Unity)			
			1	2	3	4	1	2	3	4
Rail	EF15	% Population in Poverty (NL)	0.88	0.08	-0.09		**0.19**	0.00	0.01	
	EF36	Percentage of Unemployed (NL)	0.78	0.34	0.16		**0.15**	0.05	0.02	
	EF35	Number of Unemployed (NL)	0.77	0.35	0.16		**0.15**	0.05	0.02	
	EF10	Homeownership Rate (NL)	-0.11	1.07	-0.01		0.00	**0.48**	0.00	
	EF20	Immigration (NL)	-0.14	-0.23	0.76		0.00	0.02	**0.36**	
	EF08	Rental Vacancy Rate (NL)	0.43	0.67	0.20		0.05	**0.19**	0.02	
	EF55	Percentage of Population in Poverty (SL)	0.90	0.06	-0.10		**0.20**	0.00	0.01	
	EF70	GDP of FL- Construction (In Millions of Dollars) (SL)	-1.04	0.23	0.20		**0.26**	0.02	0.02	
	EF29	Financial Condition Index (NL)	0.03	0.12	0.89		0.00	0.01	**0.48**	
	EF33	CPI–Fuel Price Index (NL)	0.10	0.66	-0.34		0.00	**0.18**	0.07	
		Explained Variance	4.11	2.39	1.64	0				
		Proportional Variance	0.50	0.29	0.20	0				

Seaport: Table E-9 and E-10 contain the results of eigenvalues and factor loading for the seaport transportation mode. According to the results, the top two latent factors were extracted as they account for more than 95 percent of the variance among the data.

Table E- 9: Factor analysis results for the seaport mode

	EV	Proportional Variance	Cumulative Variance
1	9.42	0.94	0.94
2	0.41	0.04	0.98
3	0.11	0.01	0.99
4	0.04	0.00	0.99
5	0.02	0.00	0.99
6	0.01	0.00	0.99
7	0.00	0.00	0.99
8	0.00	0.00	0.99
9	0.00	0.00	0.99
10	0.00	0.00	0.99

Table E- 10: Factor loading for the seaport mode

	EF	External Factors	Factor Loading				Squared Factor Loading (Scaled to Unity)			
			1	2	3	4	1	2	3	4
Seaport	EF22	GDP–All industries (NL)	0.92	0.10			**0.14**	0.01		
	EF15	% Population in Poverty (NL)	-0.58	-0.46			0.06	**0.12**		
	EF55	Percentage of Population in Poverty (SL)	-0.58	-0.46			0.06	**0.12**		
	EF49	Alabama Population (SL)	0.82	0.18			**0.11**	0.02		
	EF72	GDP of FL-Real Estate (In Millions of Dollars) (SL)	0.77	0.27			**0.10**	0.04		
	EF24	GDP - Manufacturing (NL)	1.10	-0.14			**0.20**	0.01		
	EF51	International Migration (SL)	-0.09	1.05			0.00	**0.61**		
	EF34	Number of Employed (NL)	0.79	0.25			**0.10**	0.03		
	EF04	Natural Increase - Births (NL)	-0.96	0.01			**0.15**	0.00		
	EF23	GDP - Construction (NL)	0.77	0.27			**0.10**	0.04		
		Explained Variance	6.13	1.79	0	0				
		Proportional Variance	0.77	0.23	0	0				

Aviation: Tables E-11 and E-12 contain the results of the factor analysis for the seaport transportation mode. According to the results, the top two latent factors were extracted as they account for more than 95 percent of the variance among the data.

Table E- 11: Factor analysis results for the aviation mode

	EV	Proportional Variance	Cumulative Variance
1	8.80	0.88	0.88
2	0.73	0.07	0.95
3	0.22	0.02	0.97
4	0.17	0.02	0.99
5	0.06	0.01	1.00
6	0.01	0.00	1.00
7	0.01	0.00	1.00
8	0.00	0.00	1.00
9	0.00	0.00	1.00
10	0.00	0.00	1.00

Table E- 12: Factor loading for the aviation mode

	EF	External Factors	Factor Loading				Squared Factor Loading (Scaled to Unity)			
			1	2	3	4	1	2	3	4
Aviation	EF76	Personal Income (In Millions of Dollars) (SL)	1.01	0.01			**0.16**	0.00		
	EF31	Consumer Price Index (CPI) (NL)	0.74	-0.30			**0.09**	0.05		
	EF98	Number of Tourists to Orlando (SL)	0.76	-0.22			**0.09**	0.02		
	EF54	Population in College (SL)	0.08	0.96			0.00	**0.48**		
	EF04	Natural Increase - Births (NL)	-0.91	0.05			**0.13**	0.00		
	EF30	House Price Index (NL)	1.06	0.08			**0.17**	0.00		
	EF95	Privatization of Roads (SL)	0.08	-0.82			0.00	**0.35**		
	EF27	Per Capita Income (NL)	0.92	-0.10			**0.13**	0.00		
	EF80	CPI–Rent Price Index (SL)	1.04	0.05			**0.17**	0.00		
	EF14	Population in College (NL)	-0.62	0.43			0.06	**0.10**		
		Explained Variance	6.42	1.94	0.00	0.00				
		Proportional Variance	0.77	0.23	0.00	0.00				

APPENDIX F: FIT RESULTS

In this section, the results for various levels of FIT are presented. In this regard, first, the SoS level composite index is presented, followed by system composite indexes. Then the mode level and dimension level composite indexes are depicted. For comparison purposes, the FPI results at the SoS level, system-level, and mode level are also presented.

SoS-level composite index

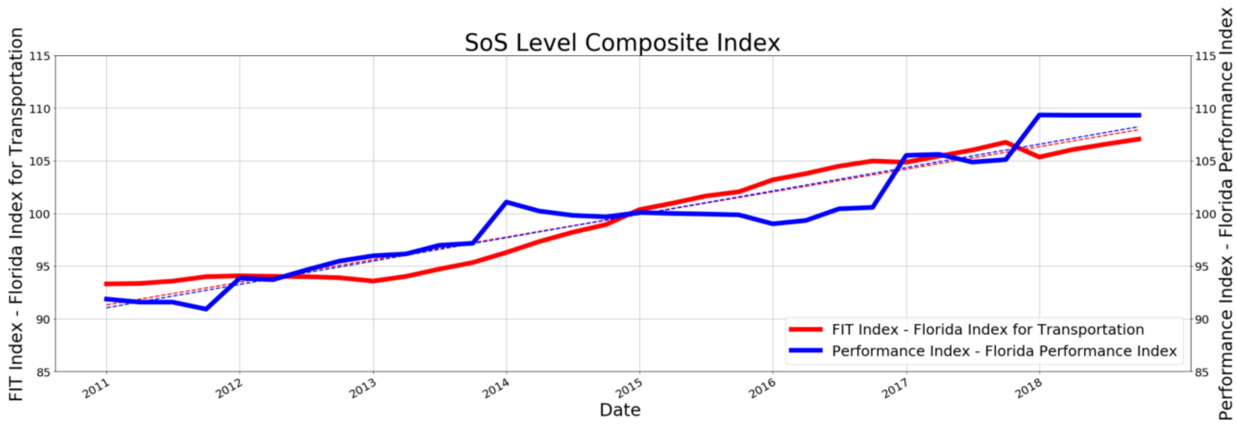

Figure F- 1: SoS level composite index

System-level composite index

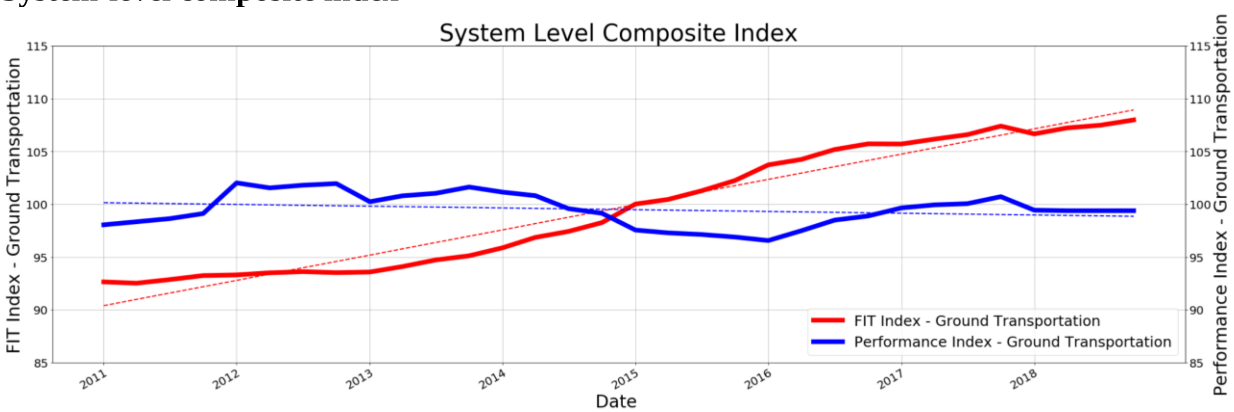

Figure F- 2: Ground transportation system composite index

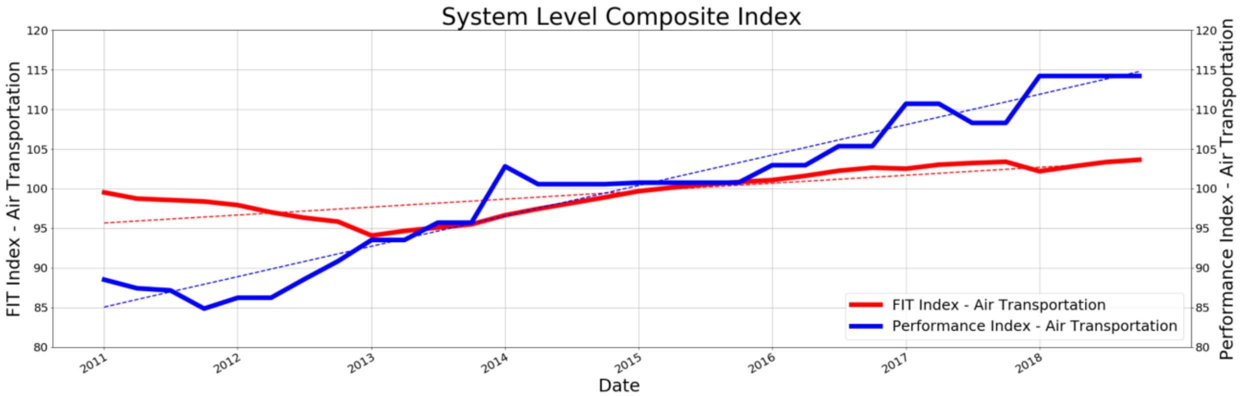

Figure F- 3: Air transportation system composite index

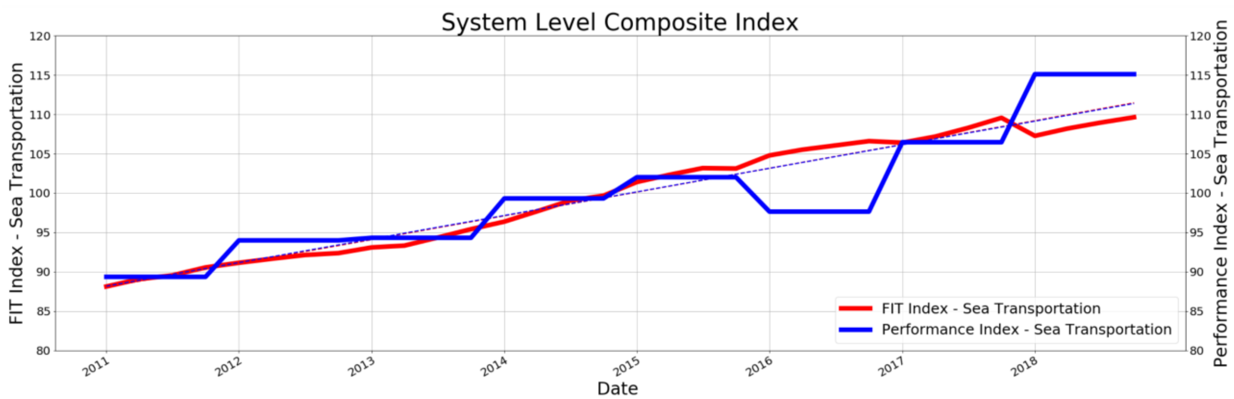

Figure F- 4: Sea transportation composite index

Mode-level composite index:

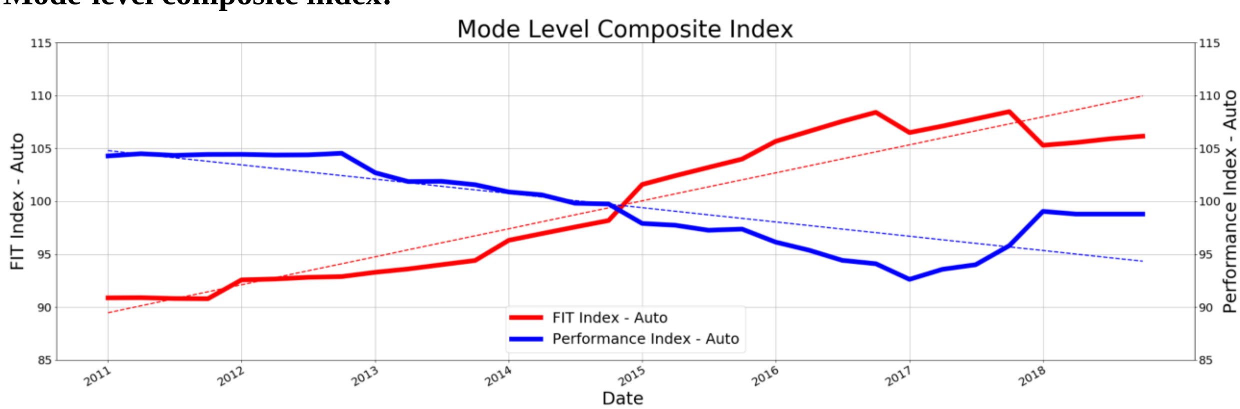

Figure F- 5: Auto mode composite index

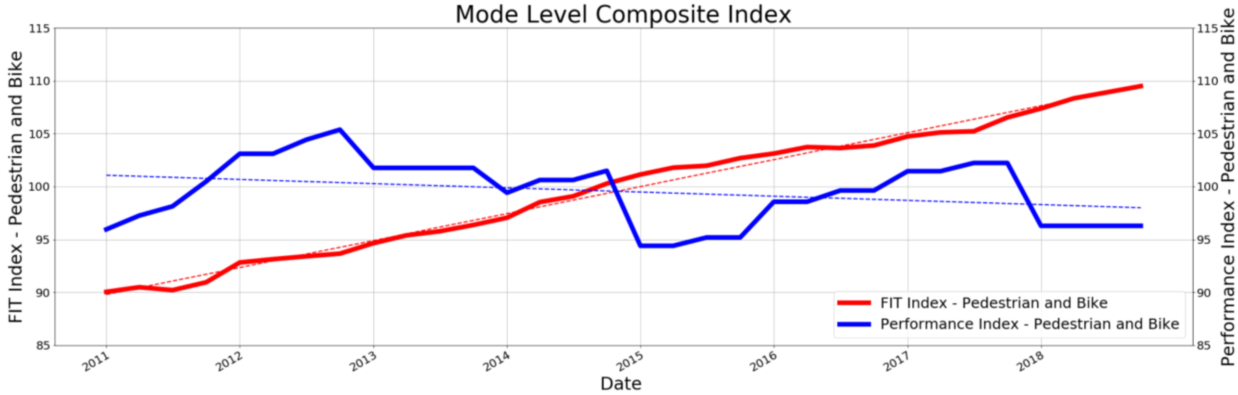

Figure F- 6: Pedestrian and bike mode composite index

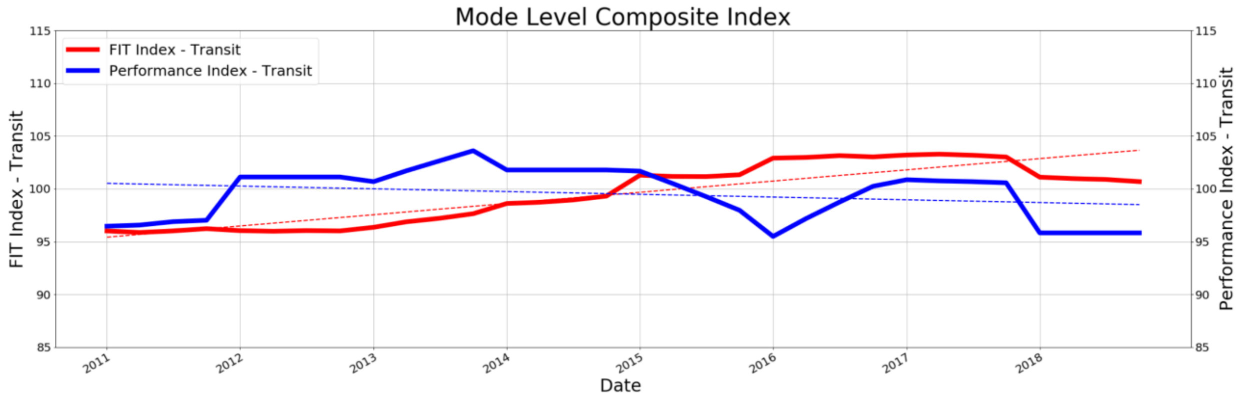

Figure F- 7: Transit mode composite index

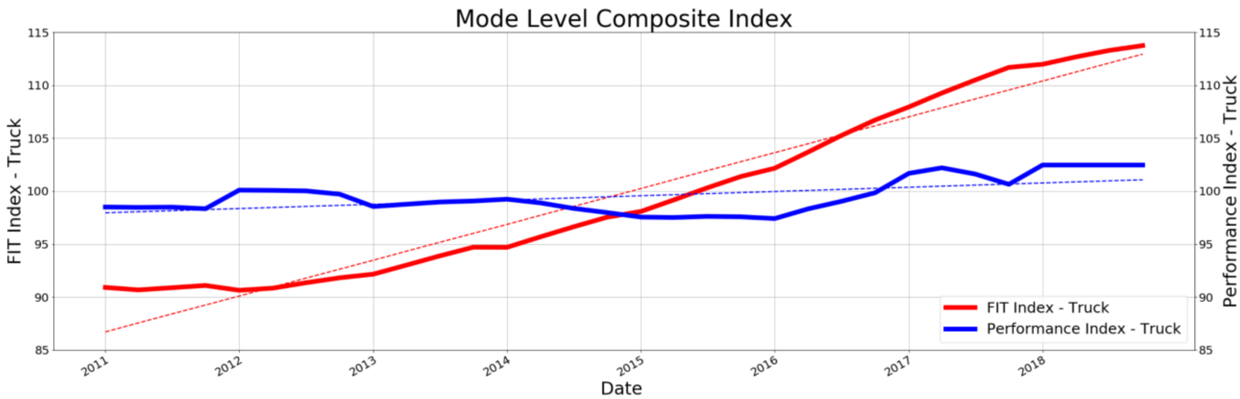

Figure F- 8: Truck mode composite index

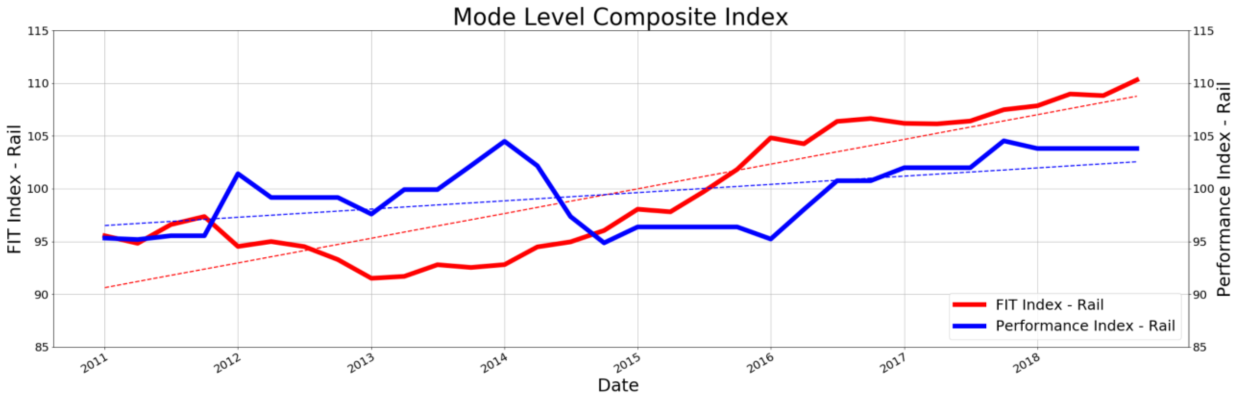

Figure F- 9: Rail mode composite index

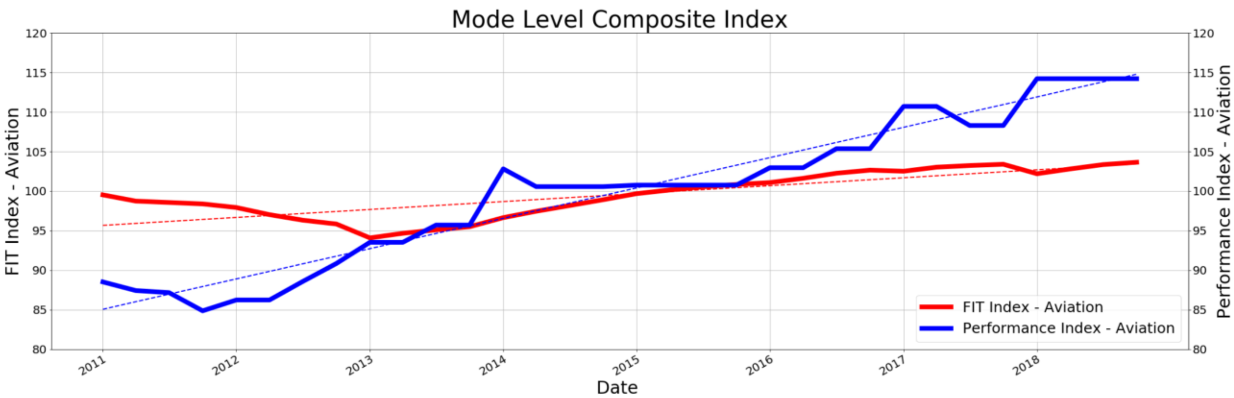

Figure F- 10: Aviation mode composite index

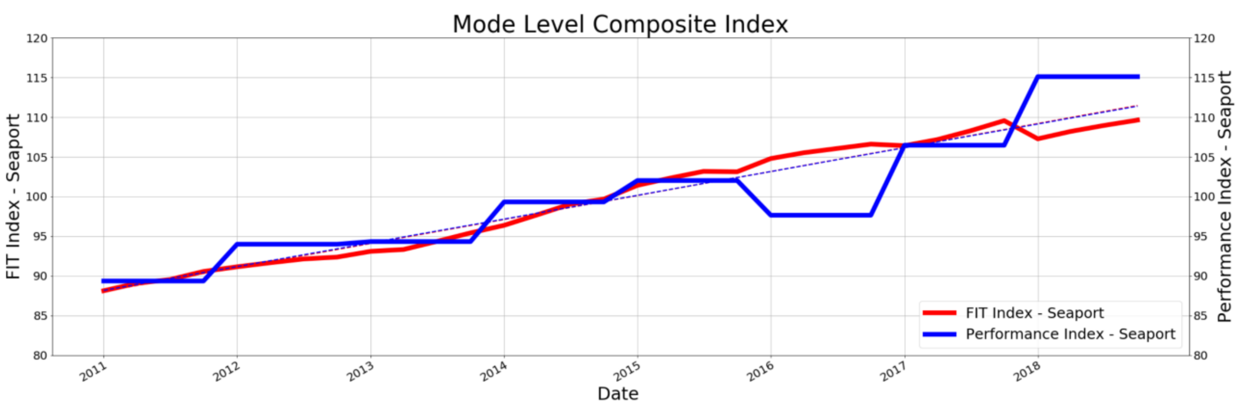

Figure F- 11: Seaport mode composite index

Dimension-level composite index

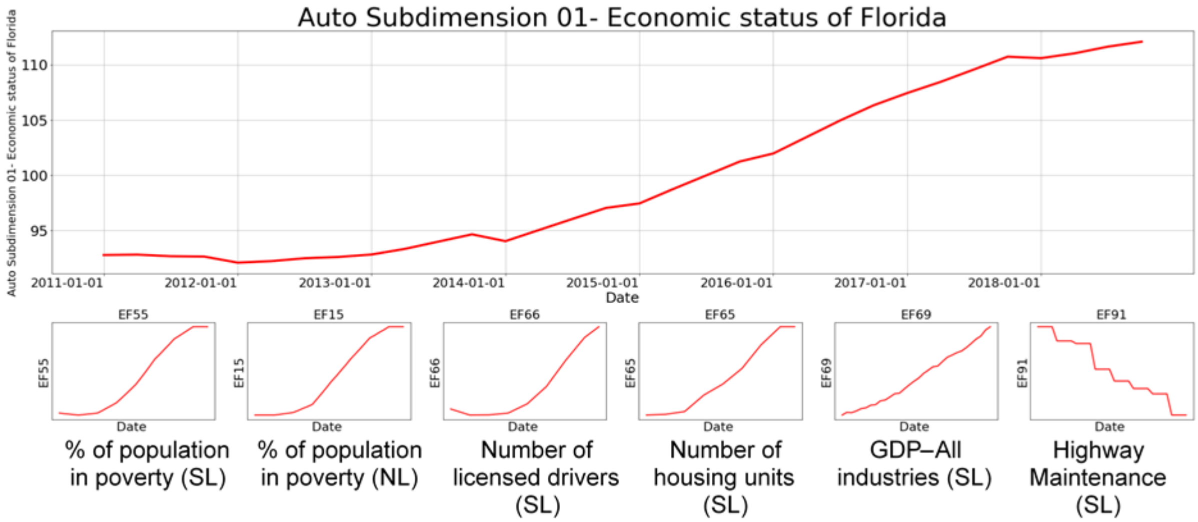

Figure F- 12: Auto subdimension 01 composite index

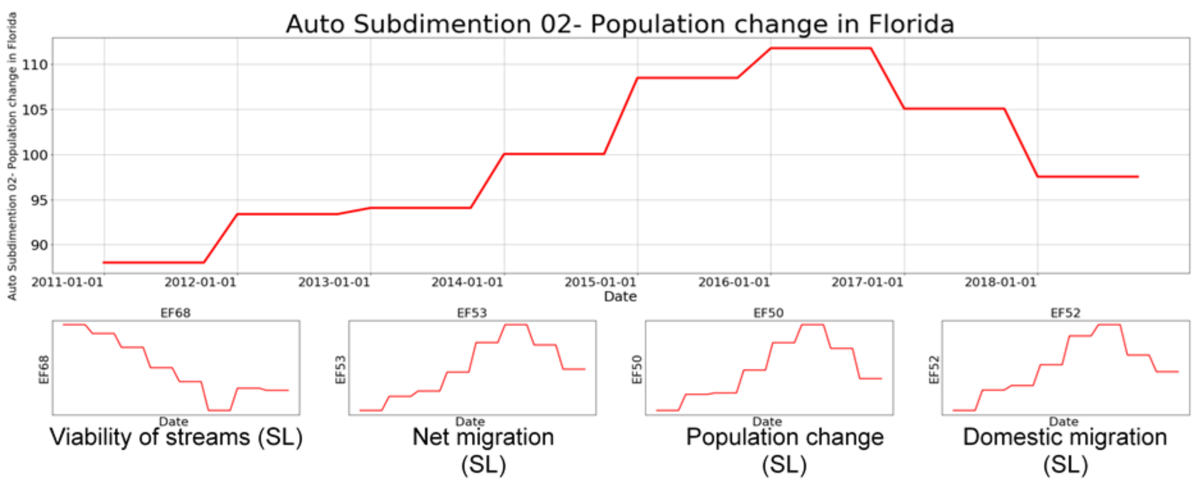

Figure F- 13: Auto subdimension 02 composite index

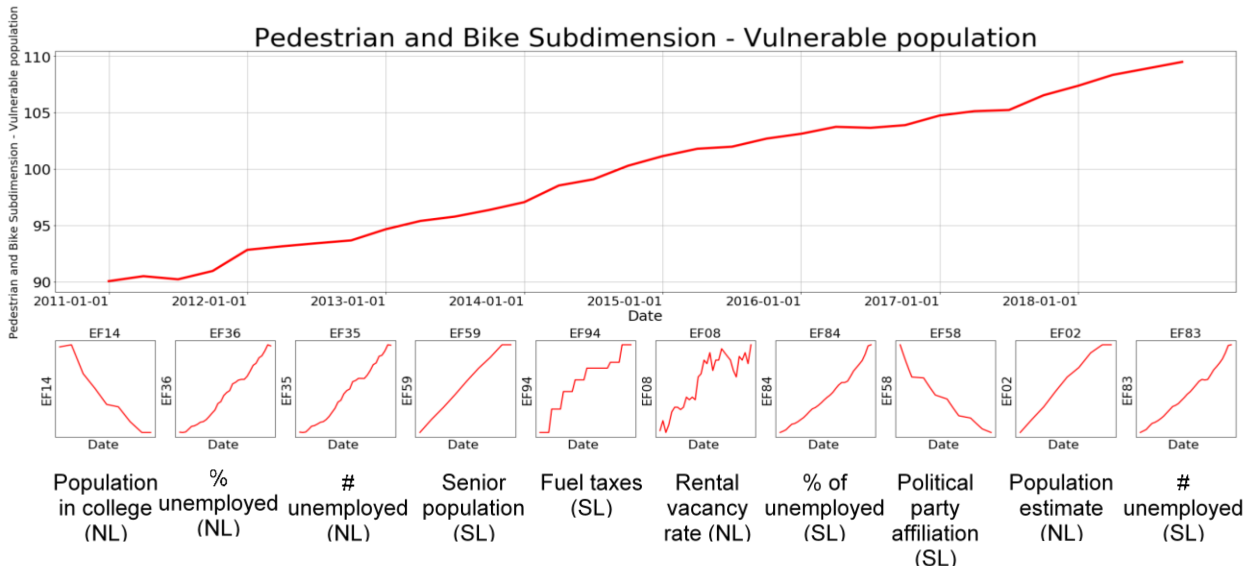

Figure F- 14: Pedestrian and bike subdimension composite index

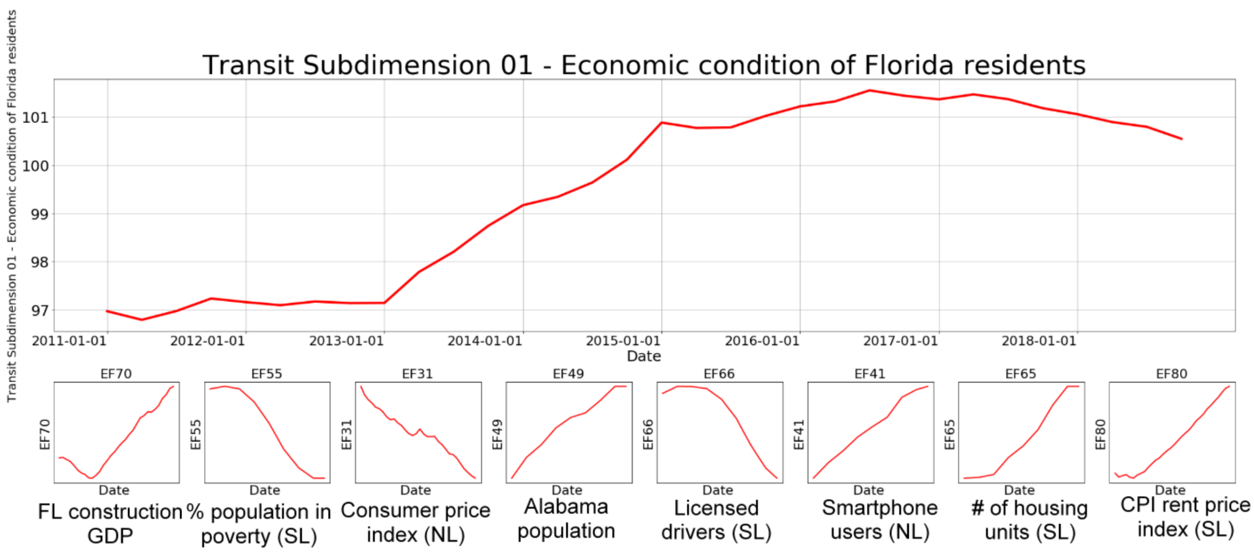

Figure F- 15: Transit subdimension 01 composite index

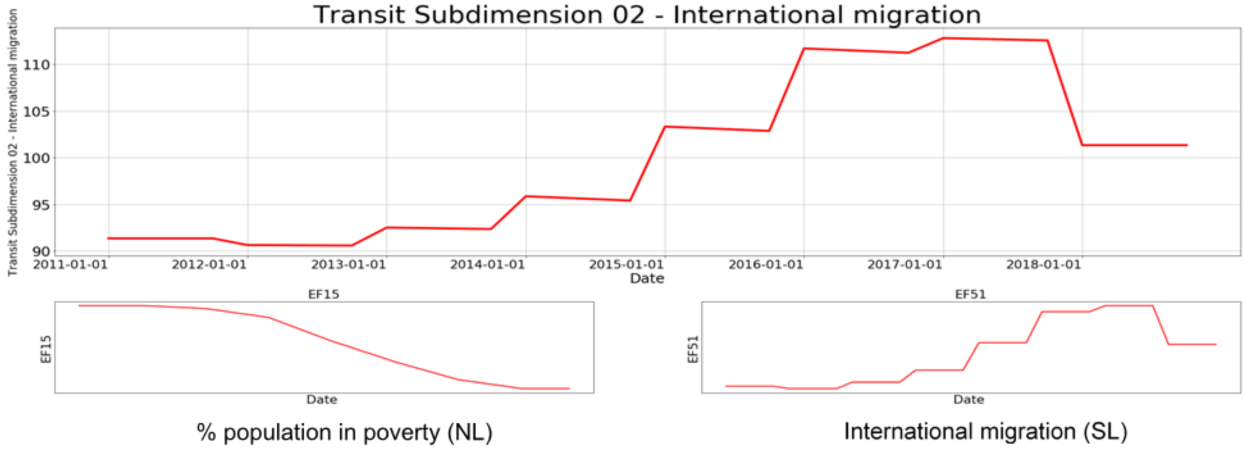

Figure F- 16: Transit subdimension 02 composite index

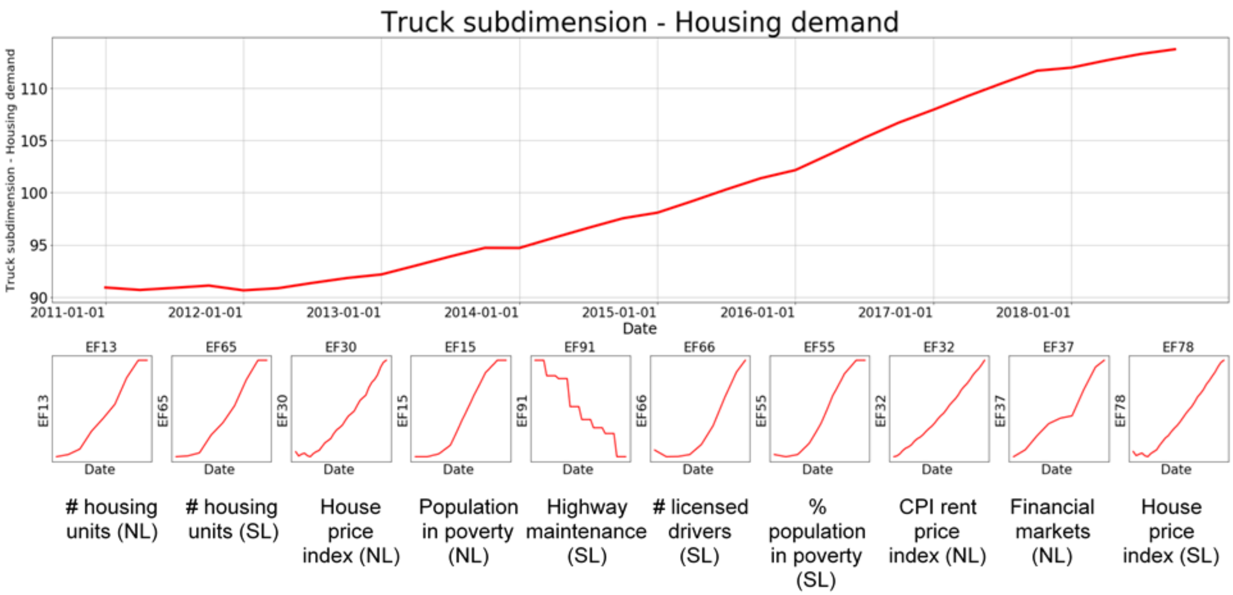

Figure F- 17: Truck subdimension composite index

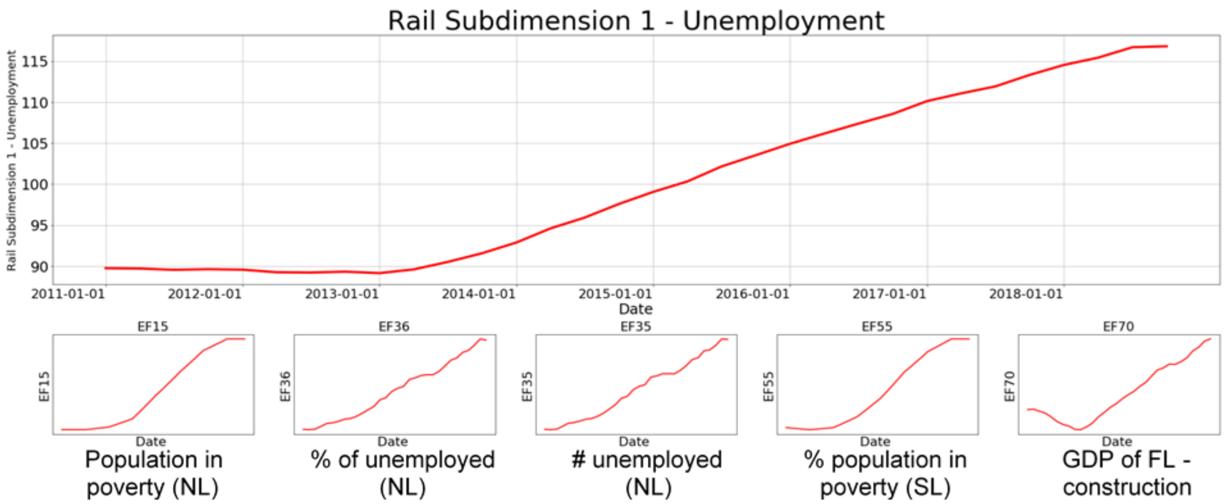

Figure F- 18: Rail subdimension 01 composite index

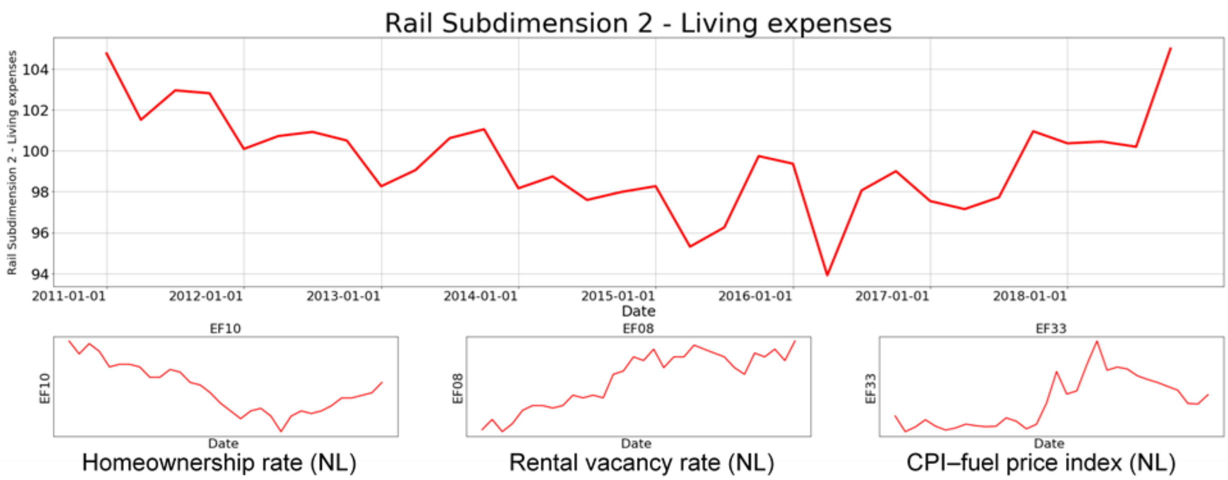

Figure F- 19: Rail subdimension 02 composite index

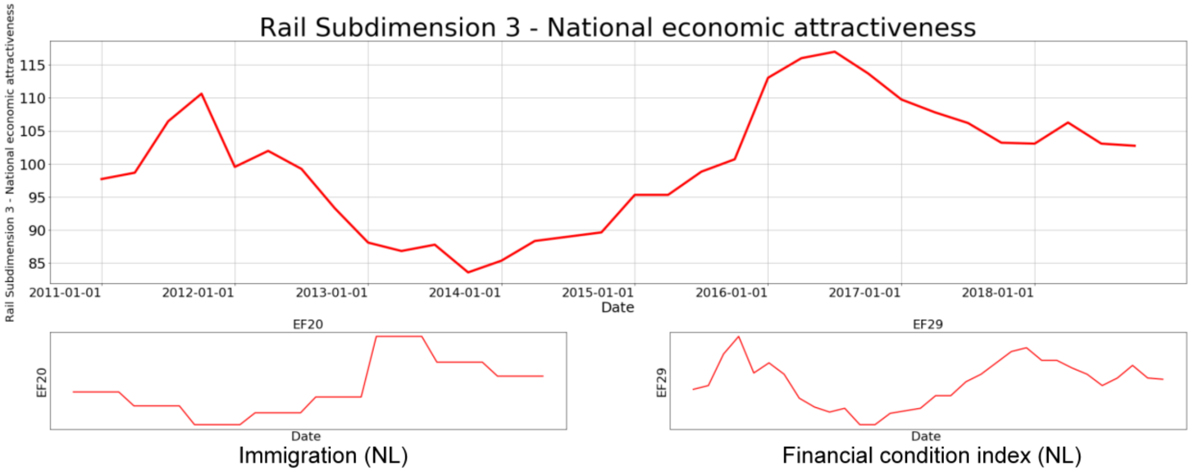

Figure F- 20: Rail subdimension 03 composite index

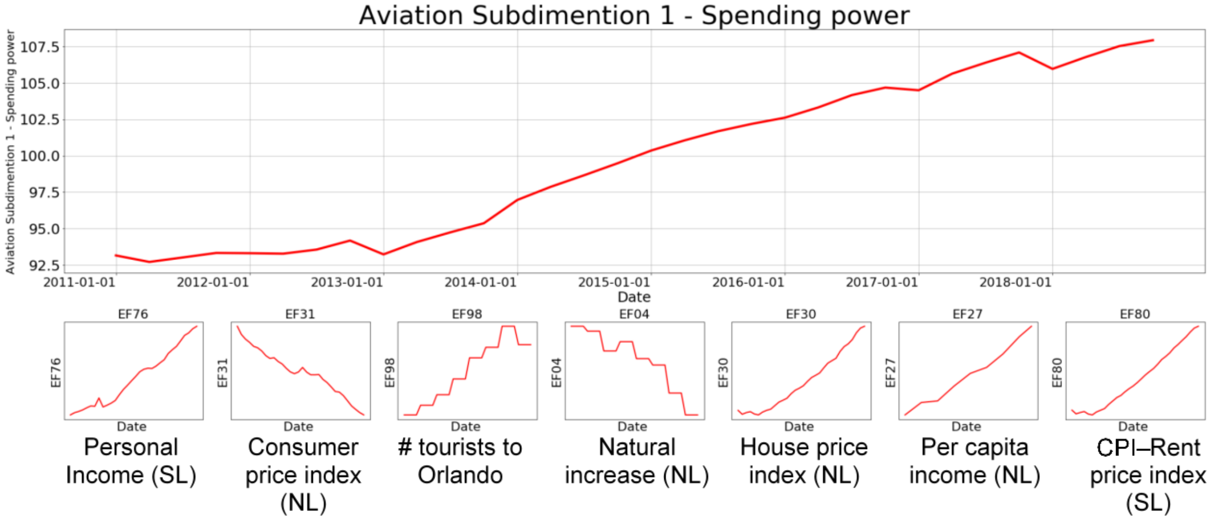

Figure F- 21: Aviation subdimension 01 composite index

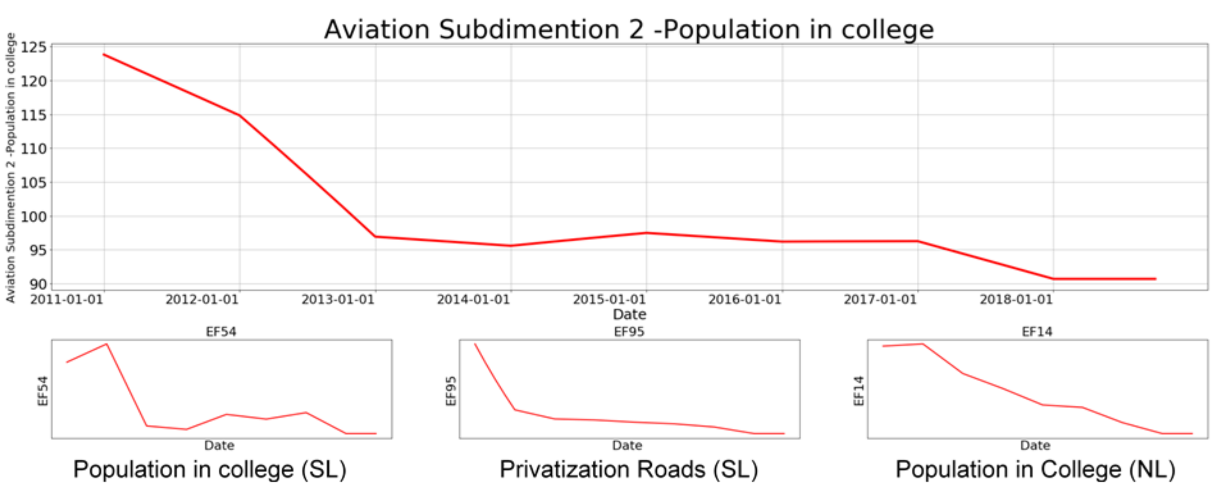

Figure F- 22: Aviation subdimension 02 composite index

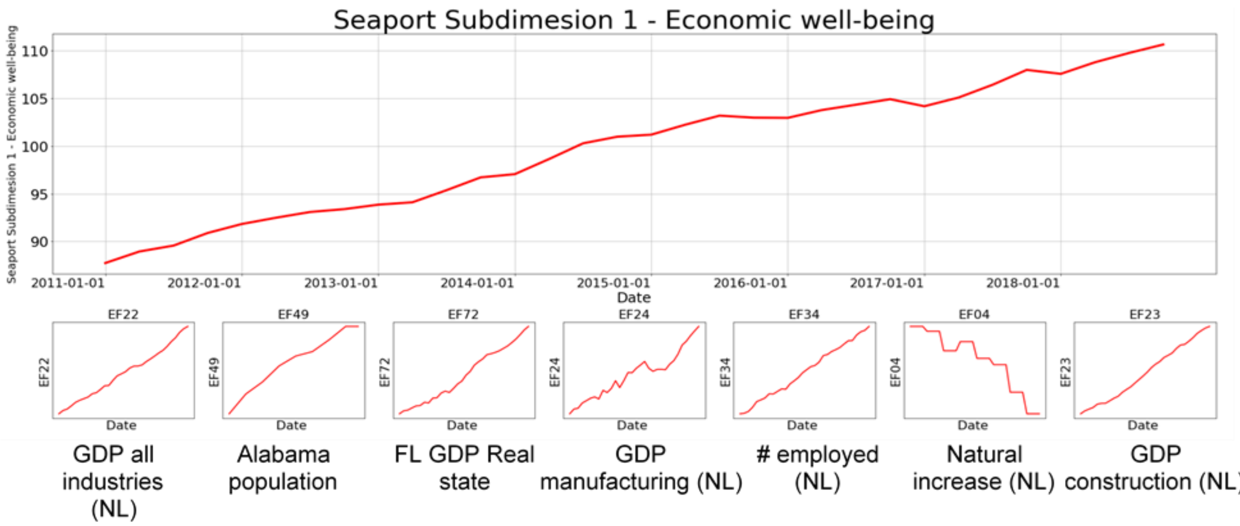

Figure F- 23: Seaport subdimension 01 composite index

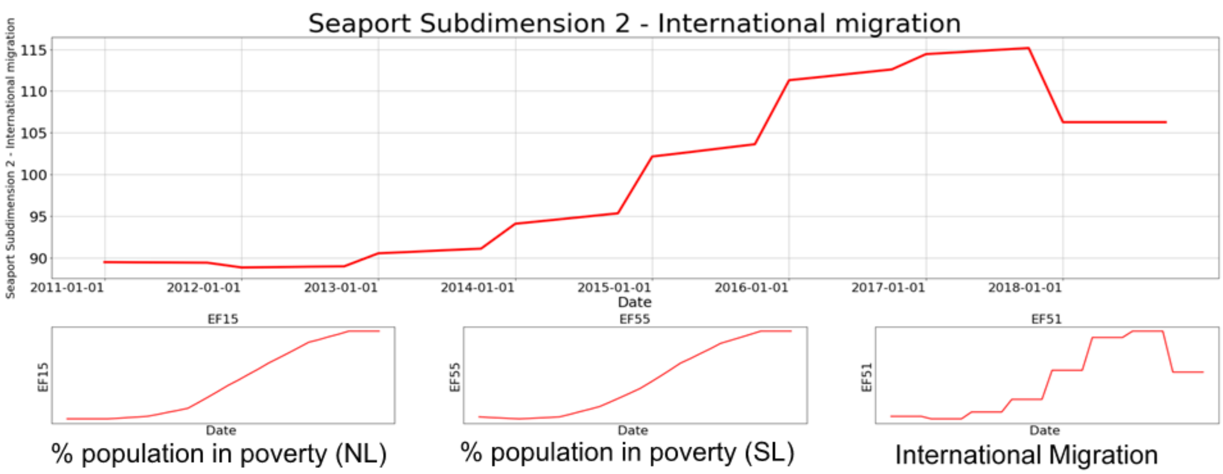

Figure F- 24: Seaport subdimension 02 composite index

APPENDIX G: STATE OF THE ART OF ANALYSIS IN THE EXTERNAL FACTORS FOR TRANSPORTATION PLANNING

The number of external factors that should be considered for decision making purposes varies based on the planning problem. For some of these planning problems, decision makers may consider only a few external factors while primarily evaluating internal factors to reach conclusions. For example, pavement maintenance may not require considering many external factors but mostly internal factors such as pavement condition. On the other hand, other decision making problems (e.g., the statewide adoption of connected autonomous vehicles) entail considering various external factors in addition to internal factors due to their significant consequences. In this regard, the FSU team conducted a literature review on the decision making process in transportation planning to understand how the external factors are utilized for decision making purposes in various transportation planning levels.

In this section, we performed a literature review on the decision making processes in transportation planning to understand (i) the varying levels of engagement of internal and external factors for different types of transportation planning and (ii) the utilization of external factors to make decisions (i.e., how external factors are captured and used to support decision making processes).

Factors that are important for different levels of transportation planning

In order to make effective plans, decision makers need to properly consider the effective factors. According to Dadashova et al. (2018), these factors can be categorized as either internal or external factors depending on whether decision makers have control or not. External factors are simply any considerations that are beyond the control of the decision makers but that still influence the system, while internal factors, which are mostly related to the capacity of transportation systems, are the ones that are under the control of decision makers.

For the literature review, we have further categorized the external factors into three main categories: social, environmental, and economic. Social factors are related to the utility of transportation stakeholders (e.g., the users of a transportation mode). Travel demand is an example of this type of external social factor. Environmental factors are associated with natural environments that can impact the operation of transportation systems. Weather conditions and natural hazards are examples of this type of external factor. Economic factors are related to the national or regional economy affecting the operation of transportation systems. These factors may include gross domestic product and gas fuel prices.

Three types of internal factors are used for the literature review: technical, operational and managerial. Technical factors are broadly defined as the technical and physical properties of transportation systems, such as the structure of a transportation network or the physical condition of transportation assets. Operational factors are associated with the status quo of transportation systems. Examples of operational factors include travel time and cost. Managerial factors are related to the management preference and resource constraints on decisions (e.g., a budget and other resource availability).

The impact of transportation plans varies depending on their scope and the geographic areas that are influenced by them. Depending on the nature of transportation plans, decision makers may consider varying levels of internal and external factors in planning. For instance, the maintenance planning of road pavements for specific roadways may not entail complicated tasks outside of traditional treatments. As such, road maintenance decisions are made based on the measurement of some physical conditions of the pavements without considering a variety of external factors, such as demographic or economic conditions. On the contrary, if one plan has the potential to affect a large geographic area and involves multiple complicated tasks that will take numerous years to implement (e.g., transportation policies or multiyear transportation plans such as resilience plans), decision makers will carefully consider alternative options and make the best choice they can (i.e., by evaluating the current status of transportation systems [an internal factor] and predicting future conditions by weighing influential factors [external factors]).

We categorized transportation planning problems into three levels (i.e., the low, intermediate, and high levels of decision making) based on the scope and consequences of the decisions involved in planning. To be more specific, low-level decision making is mainly related to planning for specific facilities or a small geographic area. The maintenance planning of road pavements is an example of low-level decision making. Intermediate-level decision making is planning at a network level. This type of decision making will have a broader impact on multiple elements of a network and stakeholders from a larger geographic area. Based on the literature review, most intermediate-level decision making problems are related to prioritization for limited funding. The rehabilitation planning of old transportation facilities in a network is an example of intermediate-level decision making. High-level planning likely impacts a larger geographic area. Decision making problems of this level are mostly related to policy-making issues and entail the management and planning of a portfolio of transportation projects. Technology implementation planning, resilience planning, and other long-term planning are examples of high-level decision making.

Analysis of the Literature on the Utilization of Various Factors for Transportation Planning

We have examined peer-reviewed journal and conference papers. Moreover, we have queried online databases and search engines such as ScienceDirect, Google Scholar, and the Wiley Online Library. Several keywords were used to cover a broad range of transportation planning problems. These keywords included but were not limited to *transportation planning*, *transportation policy making*, *transportation strategy planning*, *rehabilitation problem*, *transportation network*, *transportation resiliency*, *vehicle routing problem*, *travel demand management*, *berth scheduling problems*, *accessibility problem*, and *transportation budget planning*. In an effort to cover as many relevant articles as possible, we have also extended the search to include both papers that cited each reviewed article and those that were referenced in it. As a result, we have selected and reviewed 33 research papers; 28 of them were peer-reviewed journal papers, and the remaining five papers were conference papers.

We specifically developed a review protocol that reflected the objectives. This protocol categorized the information extracted from each paper with respect to (i) the engagement of internal and external factors, (ii) the utilization of these factors (i.e., how these factors were measured and processed to support decision making), and (iii) the nature of transportation planning (i.e., the goal of plans; see Table A-3). Each paper had its own decision making problem and aimed to make the best decision by utilizing varying levels of internal and external factors. Specifically, the authors of each paper acknowledged numerous factors that influence transportation planning. We captured these factors as either internal or external factors and further categorized them based on the inherent feature (the factor type in Table A-3) and a description of the factors (i.e., the factor category in Table A-3). The authors employed various measurement methods to consider notable factors in the decision making process. We recorded such measurement methods (factor measurement methods in Table A-3) along with the data collected and used in planning (i.e., factor/indicator in Table A-3). Depending on the nature of the decision making problems, the researchers applied various approaches, spanning from the analytic hierarchy process to simulation, machine learning, and optimization techniques (i.e., utilization of factors to support decision making in Table A-3). At the end, we looked into the objective and the results of each paper (goal of the decision making process and decision making problem in Table A-3) and categorized them as either low, intermediate, and high levels of decision making based on the problems (planning level in Table A-3).

Findings

The current literature has primarily focused on intermediate-level decision making problems. Compared to the other levels, it seems that researchers are more interested in intermediate-level decision making problems than high- or low-level decision making problems (26 articles for the intermediate level, six articles for the high level, and one article for the low level). Overall, the literature review corroborated the trend that the higher the level of decision making, the more external factors were considered during planning. But, most of these external factors are difficult to measure in real-world situations. As such, articles that address high-level decision making problems used lots of assumptions or pursued qualitative approaches to consider the selected external factors, while transportation planning at lower levels either directly measured internal factors or used reported values for them. In the following paragraphs, we discuss the main characteristics of each level of decision making problem and the trends for the utilization of factors in detail.

Low-level decision making problems have an impact on a small geographic area, and the consequences of the decisions are relatively small. The research papers categorized at this level revealed that the factors that contribute to the decision making process are mainly related to the technical aspects of the project that are under the control of the project manager (i.e., an internal factor). Additionally, there were many guidelines or instructions to guide planning. The maintenance planning of road pavements for a highway or debris cleanup projects are examples of scenarios with low-level decision making processes.

Within the internal factors engaged in the decision making process of this level, the technical properties of the project are the most common ones. Managerial aspects such as the available budget also play an important role as one of the constraints in planning. To measure relevant factors, field investigation and the use of planning guidelines are the most common approaches. Moreover, multicriteria decision making approaches and optimization techniques are found to process the information from the measurement of factors in order to make a final decision.

For example, Semaan and Zayed (2010) proposed a stochastic diagnostic model for decision makers to evaluate the rehabilitation planning of a subway station. The geographic extent of the study was a subway station, and the decision would not impact other transportation facilities or anywhere beyond the boundary of the surrounding area. These features qualify this planning as a low-level decision making problem. To be more specific, this paper aimed to develop a diagnosis index for decision makers that would ultimately be helpful in the rehabilitation planning of a subway station. The authors selected multiple criteria to develop the global diagnosis index. These factors included the structure of the station, concrete stairs, mechanical stairs, pipes and equipment, fire standpipes, lighting, cables, panels, and alarms. The selected criteria were mainly related to the technical aspects of the station (i.e., internal factors). Inspection reports and maintenance and repair planning reports were the sources of the data for each criterion. After measuring the factors, the authors employed a Monte Carlo simulation technique and multi-attribute utility theory to develop an index for the purposes of rehabilitation planning.

The papers reviewed for intermediate-level decision making problems mainly focused on planning at a transportation network level. The consequences of any decision impact the whole network, not just a small geographic area. Network design, network rehabilitation planning, budget planning, and route selection problems are other examples of intermediate-level decision making problems that were found in this literature review. In addition to internal factors, a different number of external factors are considered across different strands of the literature depending on the decision making problems involved. In this level of decision making, external factors' role becomes more important in planning than in the low-level problems. Table G-1 shows the lists of external and external factors found in the literature for intermediate-level decision making problems. External factors account for 37% of the total factors considered across different intermediate-level decision making problems, while no external factor was used in the reviewed paper for low-level decision making problems (Figure G-1).

Table G-1: Intermediate-level decision making factors

	Factor name	**Factor frequency**	**Percentage**
Internal	Technical properties	66	42%
	Network structure	37	24%
	Operational costs	14	9%
	Transport cost	10	6%
	Availability of resources	9	6%
	Transport time	8	5%
	Element operation	4	3%
	Transport quality	3	2%
	Project management (project cost & schedule)	3	2%
	Network robustness	2	1%
	Policies	1	1%
	Total Number of Internal Factors	**157**	**63%**
External	Factor name	Factor frequency	Percentage
	Travel demand	37	41%
	Stakeholder consideration	17	19%
	User properties	13	14%
	Risks	11	12%
	Demographic	8	9%
	Regulations	2	2%
	Natural properties	2	2%
	Spatial factors	1	1%
	Total Number of External Factors	**91**	**37%**

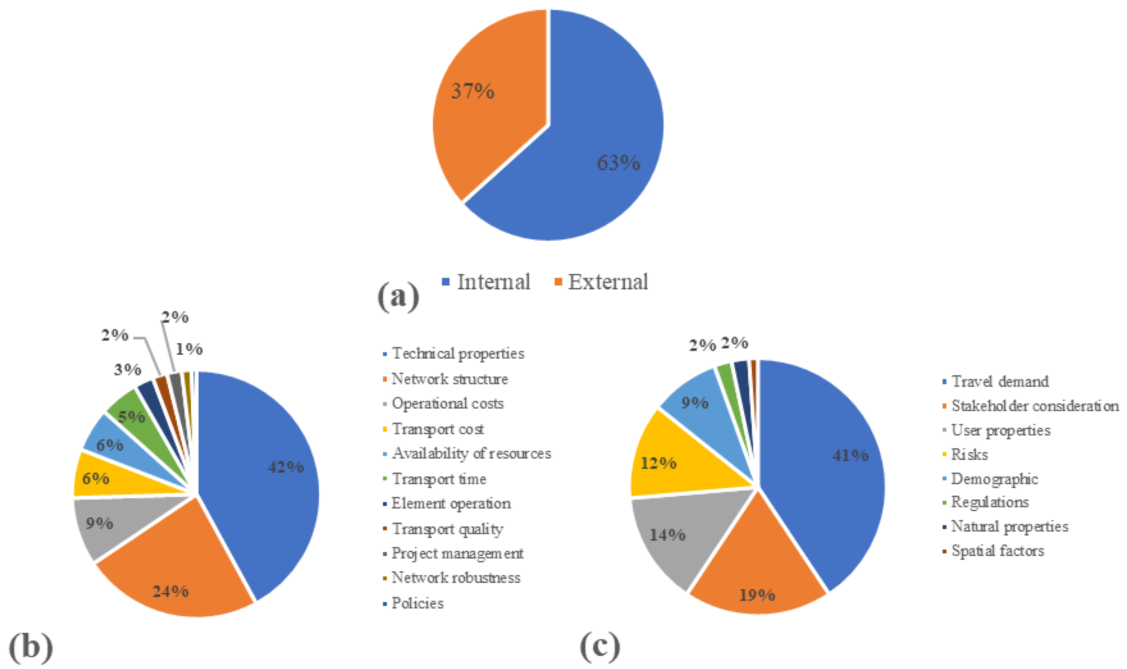

Figure G- 1: Internal and external factors for intermediate-level decision making: (a) ratio of internal and external factors, and pie charts of (b) internal factors and (c) external factors

At the intermediate-level of planning, the researchers used a variety of internal and external factors as inputs to their decision making processes. Travel demand was found to be the most common external factor. A set of origin-destination flows, the number of vehicles pass, and average daily traffic per lane are examples of travel demand. On the other hand, technical characteristics of the network (e.g., road capacity) and network characteristics (e.g., nodes and edges) were the most common internal factors.

The researchers tried to use real-world data by pulling information from surveys, reports, or online databases; however, in many cases, the authors assumed certain reasonable values as the measure of internal or external factors. This is because they used a hypothetical example as a proof of concept or did not have access to real-world data. Questionnaires and interviews were also common measurement methods, especially when the experts' opinions were required to identify factors and prioritize them depending on their importance in planning.

There were a vast range of approaches to utilizing measured internal and external factors to make the best decision. Optimization was the most common method; bilevel optimization models, linear and quadratic programming optimization models, and heuristic optimization algorithms were found in the literature. In particular, heuristic optimization algorithms were frequently found in the literature, especially when the complexity and number of input factors increase.

Orabi and El-Rayes (2012) developed a model for the rehabilitation planning of a highway network. The model tried to optimize the rehabilitation efforts for a highway network while accounting for existing financial constraints. The geographic area of the study was a network of highways, and the planning decision would impact a large area (e.g., a city). Therefore, the issue has been categorized as an intermediate-level decision making problem. In order to perform the analysis, the author considered several factors. Network structure and pavement characteristics were the main internal factors, while travel demand and travelers' vehicle operation cost were the main external factors. The authors used the reported data about a highway network within Sioux Falls, South Dakota, for external factors (i.e., average vehicle operation costs per kilometer and the number of vehicles between nodes) and network-related internal factors (e.g., road link capacity and travel distance). They also measured average travel time as a proxy for the functional performance of a highway network (an internal factor). They assumed that increasing the rehabilitation efforts for the network would enhance the overall performance of the network but at the cost of rehabilitation activities and subsequent network service disruption. The author employed a multi-objective genetic algorithm optimization method to address the trade-off between these two contradictory objectives (i.e., increasing the benefits versus minimizing the costs).

High-level decision making processes are related to transportation policymaking. National-level network reliability, national-level fund allocation, and transportation resilience planning are examples of high-level decision making problems in this category. It was found that in this level of decision making, external factors played a significant role when making final decisions; researchers tried very hard to collect information about external factors as part of the decision making process. As shown in Table G-2 and Figure G-2, almost half of the factors used across the relevant pieces of literature (i.e., 54%) are external, and the ratio of external factors to internal ones has increased by 24% from the one in the literature for intermediate-level decision making problems. Unlike the intermediate level of decision making, it was common to employ qualitative approaches to capture a variety of external factors that could not be readily quantified. Also, proxy variables were more frequently used to consider the effect of unmeasurable external factors.

Table G- 2: High-level decision making factors

	Factor name	**Factor frequency**	**Percentage**
Internal	Technical properties	13	35%
	Network structure	7	19%
	Policies	4	11%
	Availability of resources	4	11%
	Element operation	2	5%
	Labor quantity	1	3%
	Labor type	1	3%
	Manpower operation	1	3%
	Network operations	1	3%
	Organization structure	1	3%
	Transport time	1	3%
	Staff training	1	3%
	Total Number of Internal Factors	**37**	**54%**

Table G- 2 (Continued): High-level decision making factors

	Factor name	Factor frequency	Percentage
	Stakeholder consideration	6	19%
	Travel demand	5	16%
	Risks	5	16%
	Legal regulations	3	9%
	Resource rates	3	9%
	Demographic	2	6%
	Privacy issues	2	6%
External	Economic	1	3%
	Human factors	1	3%
	Industrial factors	1	3%
	Spatial factors	1	3%
	Technology development	1	3%
	Weather condition	1	3%
	Total Number of External Factors	**32**	**46%**

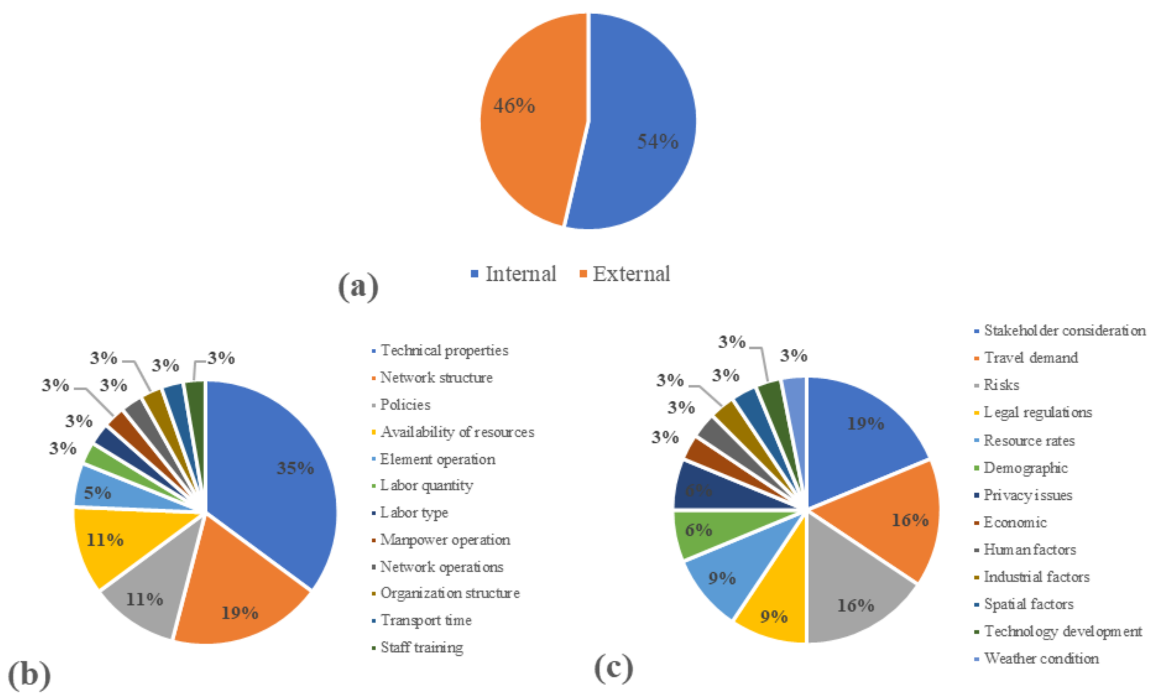

Figure G- 2: Internal and external factors for high-level decision making: (a) ratio of internal and external factors, and pie charts of (b) internal factors and (c) external factors

Like the intermediate level, diverse internal and external factors were used in high-level planning processes. As for external factors, stakeholders' consideration, travel demand, and environmental factors (e.g., risks), were frequently considered in this level of planning. These factors were measured through various methods based on the availability of data and the planning problem type. In this level of the decision making process, subject matter experts and decision makers were often used to measure external factors (e.g., the vulnerability of transportation to disruptive events). Quantitative approaches, such as optimization methods and multicriteria decision making models, were used to process the information from the factors and come to a decision.

Still, the frequency with which these qualitative approaches were used was relatively higher than the frequency seen in the lower levels of decision making problems.

Mansouri et al. (2009) proposed a risk-management-based decision analysis framework for resilience planning. The final decision could impact the national maritime infrastructure and the transportation system. Federal decision makers were involved in the decision making process. Based on these characteristics, this decision making problem was categorized as a high-level one. The researchers indicated that multiple internal and external factors affected the final decision and categorized them into four groups: natural hazards factors, organizational factors, technological factors, and human factors. Organization structure, network structure, and control system performance were the internal factors used in this study, while natural disasters, industry actions, and terrorist attacks were found as the external factors. The decision makers used the cause-and-effect diagram to evaluate the risks and their origins (i.e., by considering external factors such as natural and human-made hazards factors). Finally, decision tree analysis and options analysis were used to make the best resilience plan.

Table G- 3: Summary of literature review

Paper	Internal /External	Factor Type	Factor Category	Factor measurement methods (Generalized)	Factor/ Indicator	Utilization of factors to support decision making	Goal of the decision making process	Planning level	Decision making problem
(Cook 1984)	Internal	Technical	Technical properties	Historical data/ Field investigation	Pavement condition rate	Goal programming / Linear programming model / Lagrangean relaxation approach	To select the best maintenance planning alternative	Intermediate level	Budget planning/ Rehabilitation problem
	Internal	Technical	Network structure	Reported	Number of road sections				
	Internal	Technical	Technical properties	Reported	Length of each road section				
	Internal	Managerial	Availability of resources	Assumed as given	Budget				
(Fan and MacHemehl 2011)	Internal	Technical	Network structure	Simulation	Number of routes	Bi-level Optimization problem / The upper-level minimize total cost. The lower-level subprogram is a user self-routing optimization problem / Genetic algorithm is used to solve the bi-level optimization problem	To solve the public transportation network redesign problem while accounting for equity issues	Intermediate level	Network redesign problem
	Internal	Technical	Technical properties	Simulation	Length of routes				
	Internal	Technical	Network structure	Simulation	Number of nodes				
	Internal	Operational	Transport time	Input from the upper level management	Travel time				
	Internal	Technical	Technical properties	Input from the upper level management	Headway of the route				
	Internal	Operational	Element operation	Reported	Bus speed				
	Internal	Operational	Element operation	Reported	Bus operating costs				
	External	Social	Travel demand	Predicted demand / Network distribution	Bus transit travel demand				
	External	Social	Demographic	Input from the upper level management by defining an equity ratio	Population growth				
(Ishak et al. 2003)	External	Social	User properties	Reported	Travelers' vehicle speed	Dynamic neural networks	To optimize short-term traffic-prediction performance	Intermediate level	To optimize the short term traffic prediction to make appropriate decisions regarding congested segments of the network
	Internal	Technical	Technical properties	Reported	Lane occupancies				
	External	Social	Travel demand	Reported	Traffic volume counts				
	Internal	Technical	Network structure	Reported	Number of stations				
(Sharma et al. 2009)	External	Social	Travel demand	Predicted demand	Origin-Destination trip rates	Bi-level optimization problem/ Non dominated sorting genetic algorithm	To minimize the expected total system travel time	Intermediate level	Network design problem
	External	Social	Risks	Predicted demand	Uncertainty of demand				
	Internal	Technical	Network structure	Simulation	Network topology				

Table G-3: Summary of literature review (continued)

Paper	Internal /External	Factor Type	Factor Category	Factor measurement methods (Generalized)	Factor/ Indicator	Utilization of factors to support decision making	Goal of the decision making process	Planning level	Decision making problem
	Internal	Operational	Element operation	Assumed as given	Operational cost of transportation				
	Internal	Managerial	Availability of resources	Assumed as given	Total available budget				
	Internal	Technical	Technical properties	Simulation	Lane capacity				
	Internal	Technical	Technical properties	Assumed as given	Free-flow speed				
(Golias et al. 2010)	Internal	Technical	Technical properties	Assumed as given	Distance between the two ports	Genetic Algorithm	To maximize berth productivity by minimizing the total service time and delayed departures for all vessels / To minimize the total emissions and fuel consumption for all vessels while in transit to their next port of call	Intermediate level	The berth-scheduling problem
	External	Social	User properties	Predicted speed	Vessel speed				
	External	Social	Stakeholder consideration	Proxy variables	Customer satisfaction				
	External	Social	User properties	Predicted emission rate	Vessel emission rate				
	External	Social	User properties	Predicted	Fuel consumption / Emission rate				
	External	Social	User properties	Assumed as given	Size of the vessel				
	Internal	Technical	Network structure	Assumed as given	Number of berths				
	External	Social	Travel demand	Random generation	Number of vessels				
	External	Social	Stakeholder consideration	Reported	Preferred arrival time				
	External	Social	Stakeholder consideration	Random generation	Departure time request				
	Internal	Technical	Technical properties	Assumed as given	Number of cranes				
	Internal	Technical	Technical properties	Reported	Crane performance				
(Vromans et al. 2006)	External	Social	Travel demand	Assumed as given	Number of trains	Developing cyclic timetables with the automatic timetabling tool DONS / comparing timetables, using simulation of railway traffic which is performed with SIMONE	To find the best solutions to increase the reliability of the transportation network	High level	Network reliability
	Internal	Technical	Network structure	Predicted	The topology of the network				
	Internal	Operational	Network operations	Exponential distribution	Running time, Dwell time				
	External	Environmental	Weather condition	Proxy variables	Number of days with bad weather				
	Internal	Technical	Technical properties	Proxy variables	Reliability of the network				
(Du et al. 2017)	Internal	Technical	Network structure	Simulation	Number of depots	Bi-level programming / Fuzzy optimization / Fuzzy simulation-based heuristic algorithms	To find the optimal routing solutions with the least risk for hazardous material transportation	Intermediate level	Multi-depot vehicle routing problem for hazardous materials transportation
	External	Social	Travel demand	Assumed as given	Number of customers				
	Internal	Technical	Technical properties	Assumed as given	Capacity of depots				
	External	Social	Travel demand	Assumed as given	Demand of customers				
	External	Environmental	Risks	Proxy variables	External hazards				
	Internal	Technical	Network structure	Simulation	Network topology				
(Qu and Chen 2008)	Internal	Operational	Transport cost	Public reports/ Field investigation	Transport cost	Fuzzy AHP / Artificial Neural Network/ Multi criteria-based decision making model/ Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method	To determine the best multi-modal route alternative	Intermediate level	Route selection problem
	Internal	Operational	Transport cost	Public reports/ Field investigation	Storage cost				
	Internal	Operational	Transport cost	Public reports/ Field investigation	Load, unload cost				
	Internal	Operational	Transport time	Public reports/ Field investigation	The transport time				
	Internal	Operational	Transport time	Public reports/ Field investigation	Storage time				
	Internal	Operational	Transport time	Public reports/ Field investigation	Load, unload time				
	Internal	Operational	Transport quality	Public reports/ Field investigation	The rate of freight loss				
	Internal	Operational	Transport quality	Public reports/ Field investigation	The rate of freight defile				
	Internal	Operational	Transport quality	Interview with experts	Treat procedure efficiency				

Table G-3: Summary of literature review (continued)

Paper	Internal /External	Factor Type	Factor Category	Factor measurement methods (Generalized)	Factor/ Indicator	Utilization of factors to support decision making	Goal of the decision making process	Planning level	Decision making problem
	External	Social	Travel demand	Public reports/ Field investigation	The traffic information				
	External	Social	Stakeholder consideration	Interview with experts	The service in transfer				
	External	Social	Stakeholder consideration	Interview with experts	The social effect				
	Internal	Technical	Network structure	Assumed as given	Network Topology				
	External	Social	Risks	Interview with experts	The effect of traffic congestion				
(Yang et al. 2016)	Internal	Technical	Network structure	Simulation	Set of nodes	Tabu search/Greedy algorithm	to improve the network robustness when deciding about adding one or more air routes to the existing network	Intermediate level	Network Optimization
	Internal	Technical	Network structure	Simulation	Set of network edges				
	Internal	Technical	Network robustness	Predicted	Algebraic connectivity				
	Internal	Technical	Network robustness	Predicted	Laplacian energy				
	External	Social	Travel demand	Assumed as given	Number of the scheduled flights				
	External	Environmental	Risks	Proxy variables	Severe weather condition				
(Taylor and De Weck 2007)	Internal	Technical	Technical properties	Reported	Aircraft type	System of systems concept/ Network simulation/ Linear programming optimization	To minimize the total system cost for a single day of operation in a coupled vehicle design and network flow problem	Intermediate level	Network optimization
	Internal	Technical	Technical properties	Reported	Cargo capacity				
	Internal	Operational	Operational costs	Reported	Aircraft operating cost				
	Internal	Technical	Technical properties	Reported	Number of available aircrafts				
	Internal	Technical	Technical properties	Simulation	Set of cities as nodes				
	Internal	Technical	Technical properties	Simulation	Set of routs				
	External	Social	Travel demand	Assumed as given	Package demand between cities				
	External	Environmental	Natural properties	Assumed as given	Air density at sea level				
	External	Environmental	Natural properties	Assumed as given	Gravitational constant				
	Internal	Technical	Technical properties	Reported	Aircraft range				
	Internal	Technical	Technical properties	Reported	Aircraft cruise velocity				
	Internal	Technical	Technical properties	Reported	Aircraft wing loading				
	External	Social	Travel demand	Assumed as given	Weight of cargos to be shipped				
	Internal	Technical	Technical properties	Predicted	Aircraft weight				
(Semaan and Zayed 2010)	Internal	Technical	Technical properties	Reported	Global structure performance metrics	Criteria weighting using AHP method / multi-criteria aggregation / multi-criteria preference index probability function / Monte Carlo simulation	To diagnose the performance of subway stations and determine a stochastic Global Diagnosis Index (GDI) for future station rehabilitation planning	Low level	Subway station performance
	Internal	Technical	Technical properties	Reported	Global architecture performance metrics				
	Internal	Technical	Technical properties	Reported	Concrete stairs performance metrics				
	Internal	Technical	Technical properties	Reported	Mechanical stairs performance metrics				
	Internal	Technical	Technical properties	Reported	Ventilation system performance metrics				
	Internal	Technical	Technical properties	Reported	Pipes and mechanical equipment performance metrics				
	Internal	Technical	Technical properties	Reported	Fire stand pipes performance metrics				
	Internal	Technical	Technical properties	Reported	Lighting performance metrics				
	Internal	Technical	Technical properties	Reported	Electric wires performance metrics				
	Internal	Technical	Technical properties	Reported	Panels, transformers and breakers performance metrics				

Table G-3: Summary of literature review (continued)

Paper	Internal /External	Factor Type	Factor Category	Factor measurement methods (Generalized)	Factor/ Indicator	Utilization of factors to support decision making	Goal of the decision making process	Planning level	Decision making problem
	Internal	Technical	Technical properties	Reported	Alarm, smoke detectors performance metrics				
	Internal	Technical	Technical properties	Reported	Communication system performance metrics (telemetry)				
(Hastak and Abu-mallouh 2001)	Internal	Technical	Technical properties	Field investigation	Performance metrics related to structural factors	Four level model for station rehabilitation planning / AHP method / Integer programming optimization method	To select the most critical stations for rehabilitation process considering functional and social factors	Intermediate level	Selecting and ranking the subways stations for rehabilitation
	Internal	Technical	Technical properties	Field investigation	Performance metrics related to architectural factors				
	Internal	Technical	Technical properties	Field investigation	Performance metrics related to mechanical factors				
	Internal	Technical	Technical properties	Field investigation	Performance metrics related to electrical factors				
	Internal	Technical	Technical properties	Field investigation	Performance metrics related to communication factors				
	Internal	Technical	Technical properties	Field investigation	Performance metrics related to water condition factors				
	Internal	Technical	Technical properties	Field investigation	Performance metrics related to safety factors				
	External	Social	Travel demand	Interview with experts	Daily usage of the system				
	External	Social	Regulations	Reported	Americans with Disabilities Act (ADA) requirements				
	Internal	Managerial	Availability of resources	Assumed as given	Available funding				
	Internal	Managerial	Policies	Interview with experts	Management preference				
(Walker and Marchau 2017)	External	Social	Legal regulations	Decision maker involvement	Vehicle licensing	dynamic adaptive policymaking (DAP) method	To present a framework in order to facilitate policymaking regarding sustainability issues in a city (with a case study of automated taxis)	High level	Policymaking
	External	Social	Legal regulations	Decision maker involvement	Certification rules				
	External	Social	Legal regulations	Decision maker involvement	Third-party insurance				
	External	Social	Privacy issues	Decision maker involvement	Data privacy				
	External	Social	Privacy issues	Decision maker involvement	Electronic privacy				
	Internal	Operational	Element operation	Decision maker involvement	Level of emissions by motor vehicles				
	External	Social	Risks	Decision maker involvement	The number of road casualties				
	External	Social	Travel demand	Decision maker involvement	Level of congestion on the road network				
	External	Social	Demographic	Decision maker involvement	Consideration of demographic metrics				
	External	Economic	Economic	Decision maker involvement	Consideration of economic metrics				
	External	Environmental	Spatial factors	Decision maker involvement	Consideration of spatial factors				
	External	Social	Travel demand	Decision maker involvement	Consideration of travel demand				
	Internal	Managerial	Policies	Decision maker involvement	Consideration of policies				
	External	Social	Stakeholder consideration	Decision maker involvement	Acceptance rate by taxi operators, taxi-drivers, and travelers				
	External	Social	Technology development	Decision maker involvement	Automated taxi technology development and performance				

Table G-3: Summary of literature review (continued)

Paper	Internal /External	Factor Type	Factor Category	Factor measurement methods (Generalized)	Factor/ Indicator	Utilization of factors to support decision making	Goal of the decision making process	Planning level	Decision making problem
(Tsai et al. 2004)	Internal	Technical	Technical properties	Field investigation	Pavement performance indicators	Cost estimation based on unit costs to determine the costs / Regression models to predict the project performance / Life-Cycle cost-effectiveness analysis / What-if analysis / Network composite rating calculation	To determine the multiyear MR&R budget needs / To determine the optimum MR&R plans at the network level / Constraints: Available funding	Intermediate level	Maintenance, Rehabilitation, and Replacement (MR&R)
	Internal	Technical	Network structure	Simulation	Network topology				
	External	Social	Travel demand	Assumed as given	Traffic data				
	Internal	Technical	Technical properties	Predicted	Pavement distress				
	Internal	Technical	Technical properties	Predicted	Distress deduct value				
(Ouyang 2007)	Internal	Technical	Network structure	Simulation	Network links	Parametric approximation methodology / Policy optimization by solving an optimization problem in an iterative way	To find optimal resurfacing policies that minimize discounted life-cycle costs in the case of continuous pavement state, discrete time, and infinite horizon / Constraints: Available funding	Intermediate level	Maintenance, Rehabilitation, and Replacement (MR&R)
	Internal	Technical	Network structure	Simulation	Network Nodes				
	External	Social	Travel demand	Assumed as given	Set of origin/ destination traffic flows				
	Internal	Technical	Technical properties	Assumed as given	Deterioration rate				
	Internal	Technical	Technical properties	Assumed as given	Roughness				
	Internal	Technical	Technical properties	Assumed as given	Thickness of overlay				
	External	Social	User properties	Predicted	Vehicle operating cost				
	Internal	Technical	Transport time	Predicted	Travel time				
	Internal	Managerial	Operational costs	Assumed as given	Machine rental cost				
	Internal	Managerial	Operational costs	Assumed as given	Labor cost				
(Chan et al. 2003)	External	Social	Stakeholder consideration	Objective function	The overall objective of the central agency	Repeating genetic algorithm optimization	To identify the best fund allocation proportions for the networks such that the overall network pavement level of performance would be raised as much as possible	High level	Fund allocation
	Internal	Managerial	Policies	Objective function	A goal specified by each district or regional agency				
	Internal	Managerial	Availability of resources	Assumed as given	Available total budget				
	Internal	Technical	Technical properties	Assumed as given	Network pavement damage index				
	Internal	Operational	Availability of resources	Assumed as given	Maintenance needs budget				
	Internal	Technical	Technical properties	Assumed as given	Distress types				
	Internal	Technical	Technical properties	Assumed as given	Distress severity				
	Internal	Operational	Manpower operation	Assumed as given	Required manpower				
	Internal	Operational	Element operation	Assumed as given	Required equipment				
	External	Social	Stakeholder consideration	Objective function	Constraints and requirements of the central administration				
	Internal	Managerial	Availability of resources	Reported	Budget-maintenance strategy				
	Internal	Technical	Technical properties	Assumed as given	Length of roads				
	Internal	Technical	Network structure	Assumed as given	Total number of road segments				
	Internal	Technical	Network structure	Assumed as given	Total number of regions involved				
(Wu et al. 2014)	External	Social	Stakeholder consideration	Predicted	Route choice behavior of network users	Bilevel programming model for continues network design problem / Particle swarm optimization algorithm	To optimize the system performance within a limited budget	Intermediate level	Network design problem
	Internal	Technical	Network structure	Simulation	Network links				
	External	Environmental	Risks	Assumed as given	Link incidence variables				
	Internal	Technical	Technical properties	Assumed as given	Links capacity				
	Internal	Technical	Network structure	Assumed as given	Network vertices				

Table G-3: Summary of literature review (continued)

Paper	Internal /External	Factor Type	Factor Category	Factor measurement methods (Generalized)	Factor/ Indicator	Utilization of factors to support decision making	Goal of the decision making process	Planning level	Decision making problem
	External	Social	Travel demand	Assumed as given	Origin-Destination traffic demand				
	External	Social	Travel demand	Assumed as given	Flow on a network				
	Internal	Technical	Technical properties	Proxy variables	Network vulnerability				
	Internal	Technical	Transport time	Predicted	Link travel time				
(Orabi et al. 2009)	Internal	Managerial	Labor type	Reported	Number of crews required	Resource allocation model /Network performance loss model /Reconstruction cost model / Genetic algorithm (GA) based optimization tool	To develop a robust recovery planning model for damaged transportation networks in order to enable efficient and effective utilization of the limited reconstruction resources in the aftermath of natural disasters.	High level	Network design problem /Post-disaster reconstruction planning
	Internal	Operational	Labor quantity	Reported	Type of crews required				
	External	Environmental	Risks	Reported	Expected number of closed links by disruptive events				
	External	Social	Travel demand	Reported	The average daily traffic of the closed links				
	External	Social	Stakeholder consideration	Reported	The commitment of contractors’ resources				
	External	Social	Stakeholder consideration	Reported	Productivity rate of contractors				
	External	Economic	Resource rates	Reported	Labor rates				
	External	Economic	Resource rates	Reported	Equipment rates				
	External	Economic	Resource rates	Reported	Material costs				
	Internal	Managerial	Policies	Reported	Number of daily shifts				
	Internal	Managerial	Policies	Reported	Number of working hours				
	External	Social	Travel demand	Reported	Origin-Destination trip data				
	Internal	Technical	Transport time	Predicted	Travel time				
	External	Social	Stakeholder consideration	Proxy variables	Route preferences of travelers				
	Internal	Technical	Technical properties	Reported	The capacity of the links				
	Internal	Technical	Technical properties	Reported	The free-flow speed for each road				
(Mansouri et al. 2009)	Internal	Organizational	Staff training	Decision maker involvement	Consideration of the level of training	Cause and effect diagram / Bowties model to define the alternative resilience strategies / Decision Tree Analysis /Option Analysis	To find the best resilience strategy alternative in maritime infrastructure and transportation systems	High level	Resilience planning
	Internal	Organizational	Organization structure	Decision maker involvement	Consideration of an organization structure				
	External	Environmental	Risks	Decision maker involvement	Consideration of cybersecurity				
	Internal	Technical	Technical properties	Decision maker involvement	Consideration of computer network				
	Internal	Technical	Technical properties	Decision maker involvement	Consideration of interface performance				
	Internal	Technical	Technical properties	Decision maker involvement	Consideration of control systems performance				
	External	Environmental	Risks	Decision maker involvement	Consideration of natural disasters				
	External	Social	Industrial factors	Decision maker involvement	Consideration of industry actions				
	External	Social	Risks	Decision maker involvement	Consideration of terrorist attacks				
	External	Social	Human factors	Decision maker involvement	Consideration of human error				
(Orabi and El-Rayes 2012)	Internal	Managerial	Availability of resources	Assumed as given	Available budget	NSGA-II Multi-objective optimization Model / Cost estimating and scheduling / Network performance and road user savings module / Benefit-cost analysis	To find and prioritize the most important alternative rehabilitation planning in several projects. / Constraint: Time and budget	Intermediate level	Network rehabilitation planning
	Internal	Technical	Technical properties	Reported	Road segment capacity				
	Internal	Managerial	Project management	Reported	Rehabilitation project time				
	Internal	Managerial	Project management	Reported	Rehabilitation cost of each project				

Table G-3: Summary of literature review (continued)

Paper	Internal /External	Factor Type	Factor Category	Factor measurement methods (Generalized)	Factor/ Indicator	Utilization of factors to support decision making	Goal of the decision making process	Planning level	Decision making problem
	Internal	Technical	Technical properties	Proxy variables	Functional performance of the transportation infrastructure				
	External	Social	User properties	Reported	vehicle operating costs (VOC) per kilometer				
	Internal	Technical	Technical properties	Predicted	Travel distance				
	External	Social	Travel demand	Reported	The number of passenger-vehicle traveling between nodes				
	Internal	Technical	Technical properties	Reported	Road pavement condition index				
	Internal	Technical	Technical properties	Reported	The added capacity for each road segment				
(Wang et al. 2003)	Internal	Technical	Technical properties	Reported	Initial road condition score	Integer linear programming optimization model	To find the Pareto optimal set of best rehabilitation planning alternatives. / Constraint: Budget	Intermediate level	Network pavement maintenance and rehabilitation problem
	Internal	Technical	Technical properties	Reported	Pavement deterioration rate				
	Internal	Operational	Operational costs	Reported	Maintenance, Rehabilitation, and Replacement (MR&R) unit cost				
	External	Social	User properties	Predicted	Maintenance, Rehabilitation, and Replacement (MR&R) user-disturbance unit cost				
	Internal	Technical	Network structure	Reported	The total number of road sections				
	External	Social	Travel demand	Reported	Average daily traffic per lane				
	Internal	Technical	Technical properties	Reported	Road section length				
	Internal	Managerial	Availability of resources	Assumed as given	Available budget				
	Internal	Managerial	Project management	Reported	MR&R activity duration				
	External	Social	Regulations	Assumed as given	Minimum requirement on road condition score for each of all road sections;				
(Jakimavičius and Burinskiene 2009)	External	Social	Demographic	Reported	Population density in traffic analysis zone (TAZ)	Bogart and Ferry model with some modification in a GIS context / Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) / Simple Additive Weighting (SAW)	To find the best zones in case of a traffic situation with least disproportion of working places and inhabitants in the zone and street network density	Intermediate level	Accessibility problem
	External	Social	Demographic	Reported	The number of working places in the traffic analysis zone (TAZ)				
	Internal	Technical	Network structure	Reported	Street network density in a traffic zone				
	Internal	Technical	Network structure	Reported	Public network transport density				
	External	Social	Travel demand	Reported	The average number of daily trips in each zone				
	Internal	Technical	Network structure	Reported	street network density in a traffic zone				
	External	Social	Travel demand	Reported	Transit of trucks in peak hours %				
	Internal	Technical	Network structure	Reported	Bicycle paths network density				
	External	Social	Travel demand	Reported	Percentage of trucks in average flow				
	Internal	Technical	Network structure	Simulation	The topology of the traffic zones				
	External	Social	Demographic	Assumed as given	The number of agricultural jobs				
	External	Social	Demographic	Assumed as given	The number of mining jobs				

Table G-3: Summary of literature review (continued)

Paper	Internal /External	Factor Type	Factor Category	Factor measurement methods (Generalized)	Factor/ Indicator	Utilization of factors to support decision making	Goal of the decision making process	Planning level	Decision making problem
	External	Social	Demographic	Assumed as given	The number of retail jobs				
	External	Social	Demographic	Assumed as given	The number of service jobs				
(Ip and Wang 2011)	Internal	Technical	Network structure	Simulation	A set of cities as nodes	Linear Optimization Models / Genetic Algorithms	To find the week nodes and critical links of the network in term of resiliency and to enhance the reliance of a developing transportation network by selecting the combination of projects that maximizes network resilience or minimizes the maximum friability of hub nodes	High level	Network Resiliency
	Internal	Technical	Network structure	Simulation	A set of traffic roads as edges				
	Internal	Technical	Network structure	Simulation	Set of passageways between cities				
	Internal	Technical	Technical properties	Proxy variables	Node resilience				
	Internal	Technical	Network structure	Simulation	Railway transportation network				
	External	Social	Demographic	Reported	The population at each node				
	Internal	Technical	Technical properties	Proxy variables	Node resiliency				
	Internal	Managerial	Availability of resources	Assumed as given	Total investment				
	Internal	Technical	Technical properties	Proxy variables	Network resilience				
(Gao and Zhang 2008)	Internal	Technical	Technical properties	Reported	Road International Roughness Index (IRI)	Linear Regression Models/Robust Optimization Model to account for uncertainty in the decision making	To estimate the future budget for optimal M&R programming of a pavement OR to minimize the total cost of all the maintenance treatments in the whole planning period.	Intermediate level	Pavement maintenance budget planning problem
	Internal	Technical	Technical properties	Reported	The thickness of the surface				
	Internal	Technical	Technical properties	Reported	The thickness of the base				
	External	Social	Travel demand	Reported	Traffic load				
	Internal	Technical	Technical properties	Reported	Pavement age				
	Internal	Operational	Operational costs	Reported	M&R Treatment Unit Cost				
(Zhao et al. 2017)	Internal	Technical	Network structure	Simulation	Set of service nodes of freight transport	Load-balancing algorithm that works in a hierarchical Co-Simulation Optimization (COSMO) control approach	To find the best routing solution for freight transportation	Intermediate level	Freight routing problem
	Internal	Technical	Network structure	Simulation	A set of directed links for the freight transport				
	External	Environmental	Risks	considering congestion in the route by decreasing the route capacity	Road incidents and lane closure				
	External	Social	Travel demand	Assumed as given	Freight demand				
	External	Social	Travel demand	Reported	Passenger traffic				
	Internal	Technical	Technical properties	Assumed as given	The vehicle availability in a service link				
	Internal	Technical	Technical properties	Assumed as given	The vehicle capacity of available freight vehicles				
	Internal	Operational	Element operation	Assumed as given	The average travel cost per unit of goods on a route				
	Internal	Technical	Technical properties	Reported	Number of the lanes				
	Internal	Technical	Technical properties	Reported	Length of the lanes				
	External	Social	Stakeholder consideration	Assumed as given	Departure time				
	External	Social	Stakeholder consideration	Assumed as given	Users origin and destination				
	Internal	Technical	Technical properties	Reported	The capacity of the routes				
(Papadopoulos et al. 2019)	External	Social	Stakeholder consideration	Assumed as given	User's desired origin and destination	Non-atomic game-theoretic model	To find the best the route choice for the users(trucks) to reach the system optimum	Intermediate level	Freight routing problem
	External	Social	Stakeholder consideration	Assumed as given	User's preferred departure time				

Table G-3: Summary of literature review (continued)

Paper	Internal /External	Factor Type	Factor Category	Factor measurement methods (Generalized)	Factor/ Indicator	Utilization of factors to support decision making	Goal of the decision making process	Planning level	Decision making problem
	External	Social	Risks	Through splitting the planning horizons into non-overlapping time intervals	Traffic conditions during the day (time-varying behavior of traffic)				
	Internal	Technical	Network structure	Simulation (hypothetical network)	Network topology				
	External	Social	Travel demand	Assumed as given	Travel demand in origin destination pairs				
	External	Social	Travel demand	Assumed as given	Number of passenger vehicles				
	External	Social	Travel demand	Predicted	Number of trucks traversing in a road segment				
	External	Social	User properties	Predicted	The total cost of passenger vehicle drivers				
	External	Social	User properties	Predicted	Total truck cost (operation+ delay + fee)				
(Cho et al. 2012)	Internal	Technical	Network structure	Simulation	Set of nodes of stations, airports, and ports	Dynamic programming algorithm/ Weighted Constrained Shortest Path Problem (WCSPP) model	To find the optimal intermodal freight routing	Intermediate level	Freight routing problem
	Internal	Technical	Network structure	Simulation	Set of arcs including train links, airway links				
	External	Social	Stakeholder consideration	Assumed as given	Users arrival time				
	External	Social	Stakeholder consideration	Assumed as given	Users departure time				
	External	Social	Travel demand	Assumed as given	Quantity of cargo				
	Internal	Operational	Transport cost	Predicted	Transport cost of a transport mode on an arc				
	Internal	Operational	Transport cost	Predicted	Transport time of a transport mode on an arc				
	Internal	Operational	Operational costs	Reported	Loading cost at node				
	Internal	Operational	Operational costs	Reported	Unloading cost at node				
	Internal	Operational	Operational costs	Reported	Loading time at node				
	Internal	Operational	Operational costs	Reported	Unloading time at each node				
	External	Social	Travel demand	Assumed as given	Number of vehicles scheduled in each transportation mode				
(Hwang and Ouyang 2015)	External	Environmental	Risks	Proxy variables	Unexpected traffic accidents	Dynamic programming approach/ Deterministic shortest path heuristic	To find the optimal urban freight truck routing while considering the emission rate of the truck	Intermediate level	Freight routing problem
	External	Environmental	Risks	Proxy variables	Adverse weather conditions				
	External	Social	User properties	Predicted	Vehicle speed				
	External	Social	User properties	Predicted	Vehicle gas emission				
	External	Social	User properties	Predicted	Total transportation cost				
	Internal	Technical	Network structure	Simulation	Node sets of major intersections				
	Internal	Technical	Network structure	Simulation	Directed link sets of urban freeways and arterials				
	External	Social	Stakeholder consideration	Assumed as given	Truck origin				
	External	Social	Stakeholder consideration	Assumed as given	Truck destination				
	Internal	Technical	Technical properties	Assumed as given	Length of the link				

Table G-3: Summary of literature review (continued)

Paper	Internal /External	Factor Type	Factor Category	Factor measurement methods (Generalized)	Factor/ Indicator	Utilization of factors to support decision making	Goal of the decision making process	Planning level	Decision making problem
(Borndörfer et al. 2016)	Internal	Technical	Technical properties	Simulation as directed graphs	Train network topology	Mixed-integer nonlinear programming (MINLP) algorithm	To find a feasible route for each freight train while minimizing the expected delays and running times	Intermediate level	Freight routing problem
	External	Social	Stakeholder consideration	Assumed as given	Freight origin				
	External	Social	Stakeholder consideration	Assumed as given	Freight destination				
	External	Environmental	Risks	Proxy variables	Congestion in the network				
	External	Environmental	Risks	Predicted	Average trains delay				
	Internal	Technical	Network structure	Simulation	Set of stations as nodes				
	Internal	Technical	Network structure	Simulation	Set of tracks as links				
	Internal	Managerial	Availability of resources	Assumed as given	Number of trains on a track				
	Internal	Operational	Transport time	Predicted	Track running time				
	Internal	Technical	Technical properties	Assumed as given	Track capacity				
	External	Social	Travel demand	Reported	Freight train demand				
	Internal	Technical	Technical properties	Reported	Train type				
	External	Social	Travel demand	Assumed as given	Passenger train traffic				
	Internal	Technical	Technical properties	Assumed as given	Train speed				
(Sayarshad et al. 2012)	Internal	Technical	Network structure	Mathematical representation	The set of bike stations	Mathematical programming optimization	To find the best bike distribution among the bike stations in a bike-sharing system	Intermediate level	Bike-sharing problem
	External	Social	Travel demand	Reported	The bike demand information				
	Internal	Managerial	Availability of resources	Predicted	The number of rented bikes				
	Internal	Managerial	Availability of resources	Predicted	The number of unutilized bikes moved from a destination node to origin node				
	Internal	Managerial	Availability of resources	Predicted	The available bikes in each station				
	Internal	Operational	Transport cost	Assumed as given	The revenue per utilized bike				
	Internal	Operational	Transport cost	Assumed as given	Rental operating cost				
	Internal	Operational	Transport cost	Assumed as given	Cost of transporting an empty bike				
	Internal	Operational	Operational costs	Assumed as given	Bike maintenance cost				
(Romero et al. 2012)	Internal	Technical	Network structure	Simulation	Network topology	A bi-level mathematical programming model	To find the best public bicycle docking stations location	Intermediate level	Bike-sharing problem
	Internal	Technical	Network structure	Predicted	Number of docking stations				
	External	Social	Demographic	Reported	City population				
	External	Environmental	Spatial factors	Reported	City Area				
	Internal	Operational	Transport time	Assumed as given	Total bicycle travel time.				
	Internal	Operational	Transport cost	Assumed as given	Per-station cost.				
	External	Social	Travel demand	Predicted	Number of bike users				
(Shavarani et al. 2018)	External	Social	Travel demand	Predicted	The demand located on the edge	Mixed-integer non-linear programming model/ genetic algorithm	To find the best locations for launch/recharge stations in a drone delivery system	Intermediate level	Drone delivery problem
	Internal	Operational	Operational costs	Assumed as given	Drone procurement cost				
	Internal	Technical	Technical properties	Reported	Drone endurance				
	Internal	Technical	Network structure	Simulation	Set of the nodes of stations				
	Internal	Technical	Network structure	Simulation	Set of network edges				
	Internal	Operational	Operational costs	Assumed as given	Cost of opening a new launching station				

Table G-3: Summary of literature review (continued)

Paper	Internal /External	Factor Type	Factor Category	Factor measurement methods (Generalized)	Factor/ Indicator	Utilization of factors to support decision making	Goal of the decision making process	Planning level	Decision making problem
	Internal	Operational	Operational costs	Assumed as given	Cost of opening a new recharge station				
	Internal	Operational	Operational costs	Reported	Usage cost of drones				
	Internal	Technical	Technical properties	Predicted	Distance between facilities				
	Internal	Technical	Technical properties	Predicted	Distance between each facility and nodes				
	Internal	Technical	Technical properties	Reported	Length of edge				
	Internal	Technical	Network structure	Assumed as given	The candidate locations of facilities				
	Internal	Technical	Technical properties	Reported	The speed of the drone				
	Internal	Operational	Transport cost	Assumed as given	The cost of aerial delivery				
(Lee 2017)	External	Social	Travel demand	Random generation	Delivery package mass	Dynamic programming algorithm	To find the best drone delivery system among modular and non-modular drones	Intermediate level	Drone delivery problem
	External	Social	Travel demand	Random generation	Delivery package volume				
	External	Social	Travel demand	Random generation	Delivery distance				
	External	Social	Stakeholder consideration	Random generation	Time of the order				
	Internal	Technical	Technical properties	Predicted	Effective drone area				
	Internal	Technical	Technical properties	Assumed as given	The energy capacity of the battery				
	Internal	Technical	Technical properties	Assumed as given	The motor power of the drone				
	External	Social	Travel demand	Assumed as given	The demand of package delivery as an order matrix				
	Internal	Technical	Technical properties	Predicted	The drone modular structure				