Technical Report

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Identifying and Tracking Emerging Transportation Trends and Indicators

Final Report

Prepared For

Forecasting and Trends Office
Florida Department of Transportation

Prepared By

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The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the State of Florida Department of Transportation or the U.S. Department of Transportation.

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METRIC CONVERSION CHART

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
LENGTH				
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
AREA				
in²	square inches	645.2	square millimeters	mm²
ft²	square feet	0.093	square meters	m²
yd²	square yards	0.836	square meters	m²
ac	acres	0.405	hectares	ha
mi²	square miles	2.59	square kilometers	km²
VOLUME				
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft³	cubic feet	0.028	cubic meters	m³
yd³	cubic yards	0.765	cubic meters	m³
NOTE: Volumes greater than 1000 L shall be shown in m³				
MASS				
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or metric ton)	Mg (or t)
TEMPERATURE (exact degrees)				
°F	Fahrenheit	5 (F−32)/9 or (F−32)/1.8	Celsius	°C
ILLUMINATION				
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m²	cd/m²
FORCE and PRESSURE or STRESS				
lbf	pound force	4.45	newton	N
lbf/in²	pound force per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
LENGTH				
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
AREA				
mm²	square millimeters	0.0016	square inches	in²
m²	square meters	10.764	square feet	ft²
m²	square meters	1.195	square yards	yd²
ha	hectares	2.47	acres	ac
km²	square kilometers	0.386	square miles	mi²
VOLUME				
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m³	cubic meters	35.314	cubic feet	ft³
m³	cubic meters	1.307	cubic yards	yd³
MASS				
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or t)	mega grams (or metric ton)	1.103	short tons (2000 lb)	T
TEMPERATURE (exact degrees)				
°C	Celsius	1.8C+32	Fahrenheit	°F
ILLUMINATION				
lx	lux	0.0929	foot-candles	fc
cd/m²	candela/m²	0.2919	foot-Lamberts	fl
FORCE and PRESSURE or STRESS				
N	newton	0.225	pound force	lbf
kPa	kilopascals	0.145	pound force per square inch	lbf/in²

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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16. Abstract

This report presents a study in understanding the impacts of external trends on transportation demand. Two major efforts were carried out in this project: (1) a nationwide survey was conducted to solicit opinions from transportation professionals to evaluate the impacts of various existing and emerging trends on transportation demand, and (2) geo-tagged Tweets were collected to extract public sentiments and topics related to those trends through text mining and infographics techniques.

The survey results indicate that most of the technology-related trends were considered highly influential and highly likely to persist for the long term because they were mostly emerging trends. Many of the demographic trends showed influential impacts on Vehicle miles traveled (VMT) decrease, although these trends may be diminishing as some of the existing demographic dynamics transition to the next phase. It is worth noting that increasing awareness of environmental issues was considered as both highly influential and highly likely to continue in the next 10-20 years, which may indicate a more sustainable future in terms of mobility.

Tweets closely in alignment with emerging transportation and mobility trends (such as shared mobility, vehicle technology, built environment, user fees, telecommuting, and e-commerce) were identified. Los Angeles, Manhattan, Houston, and Chicago were among the highly visible cities discussing such trends. Being neutral overall, people carried more positive views on vehicle technology, telecommuting, and e-commerce, while being more negative on shared mobility, user fees, and built environment. Ride hailing, fuel efficiency, trip navigation, daily as well as shopping and recreational activities, gas price, tax, and product delivery were among the emergent topics.

A better understanding of these trends would allow planners and decision makers to better account for these factors in the planning process and facilitate better investment and policy decisions. The social media data-driven framework would allow real-time monitoring of transportation trends by agencies, researchers, and professionals.

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EXECUTIVE SUMMARY

The landscape of transportation, for both passenger and freight, has been changing at an unprecedented speed. The change has been driven by multiple external factors, including rapid advancement of new technologies, shifts in the economy from goods to services, evolving traveler behavior and lifestyle preferences, changing social demographics of the society, and gradual change of environmental factors. There is no doubt that these changes will reshape transportation priorities and needs over the next decades. However, how these changes will affect transportation demand in both the near term and the long term are not entirely clear.

In order to inform the planning process and provide broader insights into the changing nature of transportation demand, this study seeks to advance our understanding of the nature and extent of the influences of external factors on transportation demand and the performance of transportation systems. Two major efforts were carried out in this project to achieve the goals.

- A nationwide survey was conducted to solicit opinions from transportation professionals to evaluate the impacts of various existing and emerging trends on transportation demand.
- Geo-tagged Tweets were collected to extract public sentiments and topics related to emerging transportation trends through text mining and infographics techniques.

Trend Impact Survey

A Web-based survey was developed to help assess the significance of 18 identified trends. This qualitative assessment approach is taken considering that while we may have a relatively long-standing understanding of the impacts of the conventional economic conditions and demographic factors, these emerging trends are just arriving and probably still evolving. Given the lack of observed historical data to support statistical analysis and data analytics, this panel survey provided a qualitative assessment of the emerging trends. The survey was implemented online through FIU Qualtrics from January to March 2020. In total, 400 attempts were recorded, among which 152 complete responses were collected and used for this study.

A list of the identified trends along with the brief descriptions was presented to the respondents at the beginning of the survey, in order to provide the necessary background (with statistics obtained from reliable sources) for each trend, thus allowing the respondents to provide a more reliable assessment of the impact of the trends. These trends are categorized in three main groups: economic trends (income inequality, GDP shift from manufacturing to service, and increasing e-commerce sales), demographic trends (slow population growth, aging population, increasing race or ethnicity mix, smaller household size, delay in retiring, delay in marriage, and childbearing, urban population growth, and increasing awareness of environmental issues), and technological trends (availability of communication technologies, shared mobility, autonomous and connected vehicles, alternative fuel and electric vehicles, micromobility, and automation in jobs, and increasing international trade volume).

In the survey, the respondents were asked to rate the likely impact of each trend on passenger and freight vehicle miles traveled (VMT), as well as to assess the likely progression of the trend within the next 10-20 years. The results indicated interesting findings. Particularly, most of the technology-related trends were considered highly influential, and because they were mostly emerging trends, their impacts were likely to persist for a long term, except for micromobility and shared mobility, which were not as influential or as persistent, probably due to the constraints of micromobility (i.e., mostly focusing on short trips or first mile/last mile connections) or attitudinal barriers toward shared services. Many of the demographic trends showed influential impacts on VMT decrease, although these trends may be diminishing as some of the existing demographic dynamics transition to the next phase. It is worth noting that increasing awareness of environmental issues was considered as both highly influential and highly likely to continue in the next 10-20 years, which may indicate a more sustainable future in terms of mobility.

On the freight side, increasing e-commerce sales was highly influential in terms of both its impacts on VMT increase and the long-lasting effects. Increasing international trade volumes was also considered highly likely to lead to increasing VMT but with relatively shorter timeframe. Technologies related to freight vehicles were likely to lead to increases in freight VMT and highly likely to continue in the next couple decades.

Tweet Data Analysis

Social media platforms (SMPs) generate spontaneous expressions of public opinion at large. Social signals from messages posted on social networking sites record users' daily activities and create large amounts of data that can be used for traffic and transportation analysis. SMPs hold the potential to provide large-scale data with detailed temporal and spatial information that could help transportation agencies to understand travelers' mobility patterns and travel behavior. The novelty of this study was in the demonstration of the capability of large-scale social media data using natural language processing techniques to capture emerging transportation trends and mobility indicators. We explored emerging travel trends in North America using data obtained from Twitter for around 20 days from Dec 16, 2019 to Jan 4, 2020. The main purpose is to understand public opinion and identify emerging transportation trends based on social media interactions with enriched space and time information. We focused on the following tasks:

- Identify spatiotemporal characteristics of relevant social media interactions on shared mobility, vehicle technology, built environment, user fees, e-commerce, and telecommuting, which can give an understanding about the spatial and

temporal distribution of the relevant tweets describing the emerging transportation trends;
- Measure public sentiments and perceptions on emerging transportation trends through natural language processing such as sentiment analysis, which can allow the classification of tweets based on sentiment scores (highly positive, positive, neutral, negative, and highly negative);
- Explore spatiotemporal differences of user sentiments by classifying sentiment scores on transportation and mobility indicators, which can make sense about the spatial and temporal distribution of tweets concerning their sentiment direction;
- Extract emerging transportation topics and user concerns from social media interactions through Latent Dirichlet Allocation (LDA), which is a machine learning approach to identify the patterns of the filtered relevant tweets to recognize the emerging transportation trends.

Data analytics captured spatiotemporal differences in social media user interactions and concerns about the six main categories as well as topics of discussions formed through such interactions. Los Angeles, Manhattan, Houston, and Chicago were among the highly visible cities discussing such trends. Key observations from sentiment analysis indicated that being neutral overall, people carried more positive views on vehicle technology, telecommuting and e-commerce, while being more negative on shared mobility, user fees, and built environment.

Topic modeling analysis identified 17 topics related to transportation trends. Ride hailing, fuel efficiency, trip navigation, daily as well as shopping and recreational activities, gas price, tax, and product delivery were among the topics. Specifically, people primarily discussed ride hailing and employment opportunities as part of shared mobility. On vehicle technology, interactions mainly included topics on fuel efficiency and trip navigations. Regular activities on a day-to-day basis were among the built environment topics in addition to shopping and recreational activities. Under the user fees category, people were more concerned about gas price, tax, and expressways along with their probable frustration towards lane blocks while driving. On telecommuting, people talked more about the holiday season and healthcare activities. Customer services related to item delivery was among the predominant topics on e-commerce. Such topics and associated words provide better insights on how to identify and connect to social media users based on their topics of interest and the use of specific keywords that can maximize influence. The above-listed topics and information can help transportation planners and policymakers systematically make better and more timely decisions while facing future transportation demand for emerging technology. This will lead to a step forward in understanding the need for a modern transportation system to reduce dependency on fossil fuel, controlling climate changes, and reducing traffic jams and accidents while increasing the reliability of the transportation system.

The social media data-driven framework would allow real-time monitoring of transportation trends by agencies, researchers, and professionals. Potential applications of the work may include: (i) identify spatial diversity of public mobility needs and concerns through social media channels; (ii) develop new policies that would satisfy the diverse needs at different locations; (iii) leverage SMPs to promote user interests on emerging trends based on similar word clustering; (iv) design and implement more efficient strategies to improve and influence public interest and satisfaction. While data biases may exist in such an approach, large-scale observations would help to predict patterns with heightened statistical power.

This study represents an effort to evaluate the potential influence and relative importance of various trends that might impact transportation demand in the next decades. A better understanding of these trends would allow planners and decision-makers to incorporate these factors into the planning process and facilitate better investment and policy decisions. The findings of this study may also help improve demand forecasting efforts and lead to better practices anticipating shifts in demand and transportation needs.

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1 INTRODUCTION

The landscape of transportation, for both passenger and freight, has been changing at an unprecedented speed. The change has been driven by multiple external factors, including rapid advancement of new technologies, shifts in the economy from goods to services, evolving traveler behavior and lifestyle preferences, changing social demographics of the society, and gradual change of environmental factors. After many decades of steady growth, the use of private vehicles in the United States in terms of per capita vehicle miles traveled (VMT) has been in decline since 2005 (Sivak 2014; Sivak 2013; Kuhnimhof, Zumkeller and Chlond 2013). Besides changes in economic activities, the decline may be attributed to a number of factors, including the emergence of alternative mobility options and advanced vehicle technologies, shifts in sociodemographics along with personal preferences and lifestyles, and changes in the urban form of American cities, among other factors. Similarly, the freight industry has also transformed, driven by advanced logistics, increasingly complicated supply chains, globalization, policy and regulations, and technology innovations (NASEM 2013; NCFRP 2011).

There is no doubt that these changes will reshape transportation priorities and needs over the next decades. However, how these changes will affect transportation demand in both the near term and the long term are not entirely clear. There are two sources of uncertainty involved. The first lies in the trend itself, whether it represents a long-lasting force or only a temporary phenomenon, or if it might change its course as situations evolve. The second stems from the uncertainty as well as complexity of the interplays among the driving forces behind the trends. For example, behavioral shifts and personal preferences may be influenced by changing urban forms, which in turn could be guided by policies in land development and infrastructure investments. It is often the combination of multiple forces that drives the demand and determines the final possible outcomes.

Transportation planning agencies are charged with making transportation investments that often have long-lasting effects on the traveling public and the society as a whole. A good understanding of these trends and their driving forces, as well as the potential interactions among the drivers and their impacts, will allow the agencies and the decision makers to become proactive to changes rather than reactive. The ability to account for the impacts of external factors will also benefit post-deployment studies that evaluate the effectiveness of transportation management and operation strategies. Accordingly, the Florida Department of Transportation (FDOT), which is charged to oversee the state's transportation system, to develop long-range transportation plans, and to recommend infrastructure investment and policy decisions, is seeking to advance through this project a better understanding of the external factors and trends that influence transportation demand. A better understanding of the contributions of these factors, trends, and interrelationships will help FDOT improve the accuracy of demand forecasting, provide better understanding of future uncertainty, and lead to better practices in tracking external factors and trends to anticipate shifts in demand and transportation needs.

The goal of this project is to advance our understanding on the nature and extent of the influences of external factors on transportation demand and the performance of transportation systems. This project will inform the planning process and provide broader insights into the changing nature of transportation demand. The specific objectives of this project are to:

- Identify external factors and trends that influence the demand for the transportation systems, including highway, transit and freight;
- Evaluate the impact and significance of these factors on transportation demand, including their reliability at explaining the variability in demand; and
- Identify indicators that should be monitored to detect major trends and recommend an approach to track them periodically.

In order to inform the planning process and provide broader insights into the changing nature of transportation demand, this study seeks to advance our understanding on the nature and extent of the influences of external factors on transportation demand and the performance of transportation systems. Two major efforts were carried out in this project to achieve the goals.

1. A nationwide survey was conducted to solicit opinions from transportation professionals to evaluate the impacts of various existing and emerging trends on transportation demand.
2. Geo-tagged Tweets were collected to extract public sentiments and topics related to emerging transportation trends through text mining and infographics techniques.

This report presents the study effort including a comprehensive review of existing and emerging trends, the survey design and implementation process, Tweet data collection and processing methods, the analysis results and conclusions.

2 LITERATURE REVIEW

The literature has discussed five general dimensions of external factors that have influence on transportation demand: economic growth, demographic trends, behavior shifts, policy implementation, and technology advancement. Figure 2-1 lists some example indicators under each of these factors.

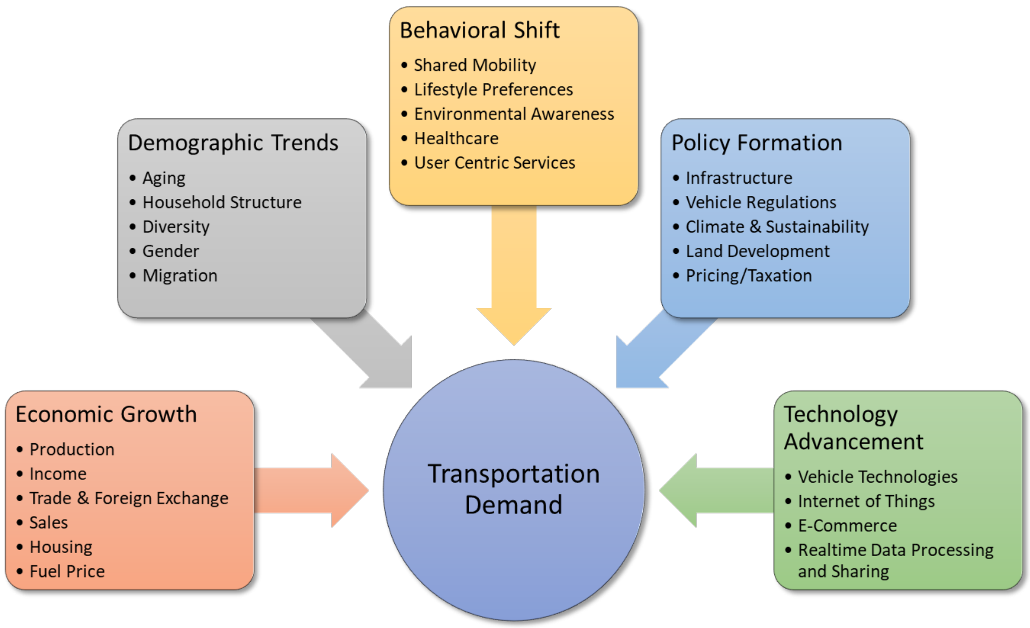


Figure 2-1 Major dimensions of driving forces that influence travel demand

2.1 External Factors

2.1.1 Economic Growth

Economic activities and demographic characteristics not only determine the overall volume of people and goods to be moved from one place to another, but also the types and modes of trips and freight to be carried by our transportation systems. Employment rate and personal income have been recognized as the exogenous drivers of transportation demand (Brownstone and Golob 2009; Rentziou et al. 2012). Income, through its effect on car ownership, purchase of new homes, and the availability of funds for leisure trips, also has an indirect impact on travel demand. However, economic activity may no longer be as a strong driver as in the past due to changes in sociodemographics, workforces, adoption of technology, differential growth between economic sectors, and growing disparity in personal wealth (Circella et al., 2016).

Gross domestic production (GDP) remains a critical measure of the national output of freight (NCFRP 2011). Globalization and the increased economic efficiency and prosperity also resulted in increasing demand for goods. The strong U.S. dollar in recent years also resulted in reduced export activities and an overall reduction in international shipping, which is one of the leading causes of change on freight demand (American Group 2016). Another critical economic factor affecting transportation demand is fuel price. Recent research findings (e.g., Hakimelahi et al. 2016; Odeck and Johansen 2016; Lin and Prince 2013) indicated that the magnitude of the impact of fuel prices on travel demand varied with the timeframe that was considered. Similar findings were found on freight demand (Gately 1990; West et. al 2011; De Borger and Mulalic 2012; Winebrake et al. 2015), although a recent study of Winebrake et al. (2015) showed that fuel price elasticities have shifted from elastic to inelastic over time.

2.1.2 Demographic Trends

Socio-demographics have direct impacts on travel demand. NCHRP report 750 (2014) identified eight key trends, including slow population growth, aging population, structural changes in population by ethnicity, older and more diverse workforce, blurring of city and suburb, slow growth in households, increasing users of communication technologies, and salience of environmental concerns. Some of these trends share common drivers, such as aging population, longer life span, lifestyle choices of younger generations (residing in parental home, delaying marriage and childbearing, and urban lifestyle preference, etc.), and immigration. These socio-demographic trends may result in declining VMT per capita, decreased auto ownership, increases in carpooling, increases in non-motorized trips. While other forces may lead to contradicting effects, such as the use of transit, which may decrease with age, but will increase as Hispanics and Millennials become a larger portion of the population.

2.1.3 Behavior and Attitudes

User behavior governs the choice-making process, captures user preferences and attitudes toward transportation alternatives, and reflects societal trends. The shift of travelers' needs, preferences, and perceptions on shared mobility, lifestyle choices, environmental awareness, and user centric services will drive the priorities of transportation system. Shared mobility is growing and sprouting to meet the needs of travelers, which resulted in the reduction of vehicle use, vehicle ownership, VMT, and public transit (Shaheen et al. 2015). The public's environmental attitude, assessment, and knowledge also affect their travel behavior and demand (Tse 2019). A survey conducted by the American Public Transportation Association (APTA) (2013) showed that one third of the respondents' transportation decisions were impacted by environmental concerns. However, the degree of such impact is still not clear. Among the different generations, younger generations (e.g., millennials) are more environmentally conscious and prefer living in urban setting with extensive transit options (Lorenzoni and Pidgeon 2006, Hine and Scott 2000; Metz 2012; van Dender and Clever 2013; Berger et al. 2013).

2.1.4 Policy and Regulations

Public policies regarding infrastructure investment, vehicle regulations, environmental issues, land development, and pricing/taxation also play critical roles in shaping the transportation systems from the supply side and consequently influence the demand. The environmental and social costs of congestion have led to the implementation of Transportation Demand Management (TDM) policies, which promote more efficient use of transportation resources (Habibian and Kermanshah 2011; Litman 2003; Litman 2006). They in turn affect the car usage, traffic congestion, travel time variability, travel cost as well as long-term transportation system performance (Habibian and Kermanshah 2011; Cervero and Kockelman 2012; Bricka 2015).

Policies on land development also have a direct impact on the land use patterns and the availability and accessibility of alternative transportation options (Metz 2012, Van Dender and Clever 2013). Another recent change in policies places an increasing focus on safety (e.g., passage of the FAST Act), which is expected to improve the flow of logistics by investing in badly needed repairs and expanding infrastructure capacity at bottlenecks along routes. In addition, revisions to the hours of service and the upcoming requirement of electronic logging devices are two examples of regulations impacting the freight demand. These revisions directly affect productivity in the freight industry by managing the hours that truck drivers may work during a time when driver availability is already an issue (American Group 2016).

2.1.5 Technology

Technology has long been the driving force to the advancements in the society, and the emerging technologies in vehicles, mobility services, e-commerce, and information and communications, etc., are expected to revolutionize the transportation industry and impact safety, mobility, reliability and environmental measures. Many research studies have shown significant impacts of telecommuting and e-commerce on mobility patterns and freight demand (Mokhtarian 2009; Mans et al. 2012; Zhang et al. 2007; Weltevreden 2007; Mokhtarian 2004; Wilson et al. 2015). Real-time information on current network performance and travel options is increasingly influencing travelers' decisions before and during their travel. Precise, timely, personalized, and multi-modal real-time information through smartphones, in-vehicle displays, and fixed and virtual signs enables travelers and carriers to plan for and adjust their route, mode, and departure time choices. Other technological advancements that are about to reshape the transportation industry include the electric and shared vehicles (ACES) vehicles. These technologies are expected to dramatically change future travel demand (Malokin et al. 2015). How exactly these technologies may pan out and influence demand depends on many other factors, such as the demographic trends, behavioral shifts and policy implementation. Part of the complexity lies in the unknowns and uncertainties of the interactions among these driving forces.

2.2 Emerging Trends

This section summarizes the specific trends that can impact future demand for passenger travel and freight transportation. These trends are organized into the same 5 categories as the external factors.

2.2.1 Economic Growth

2.2.1.1 Economic Growth and Passenger Travel Demand

Personal income, an indicator of economic growth, has long been recognized as a factor in driving passenger travel demand. However, in the past two decades, the steady increase in personal income is not associated with an increase in per capita VMT of the same magnitude (Garceau et al. 2014). As seen in Figure 2-2, the slope of VMT per capita curve follows the curve of average personal income consistently since 1970 until approximately 1996, when VMT per capita began to level off while the trajectory of average personal income continued to rise (Circella et al. 2016).

Circella et al. (2016) identified several potential causes for the disassociation of economic growth and passenger travel demand in the last 20 years:

- Income growth mostly in the higher income groups
- Economic shift from manufacturing to the service industry
- Stabilized rates of female employment and auto ownership

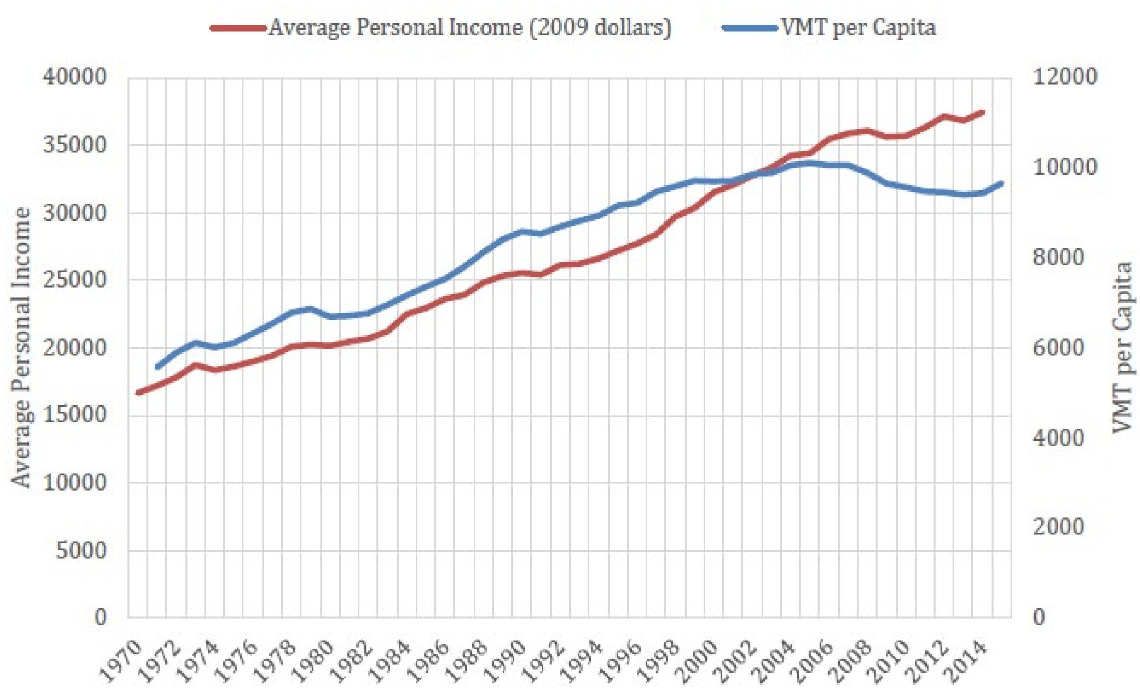


Figure 2-2 Average personal income vs. VMT per capita (source: Circella et al., 2016)

Research findings (Holtzclaw et al. 2002; Salon et al. 2012; Bento et al. 2005; Boarnet et al. 2011) suggest that VMT per capita increases as incomes rise at lower income levels, but VMT tends to level out once households have reached the median income level. Income increase at the lower income groups is expected to be accompanied with an increase in VMT per capita. However, as Figure 2-3 shows, the income levels of the two lowest quantiles have been largely stagnant since 2000 as compared to the upper three groups. Thus, the average income increase seen during this period is mostly distributed to the upper income groups that are not associated with significant VMT increase, contributing to the disassociation of average personal income and VMT per capita seen in Figure 2-2.

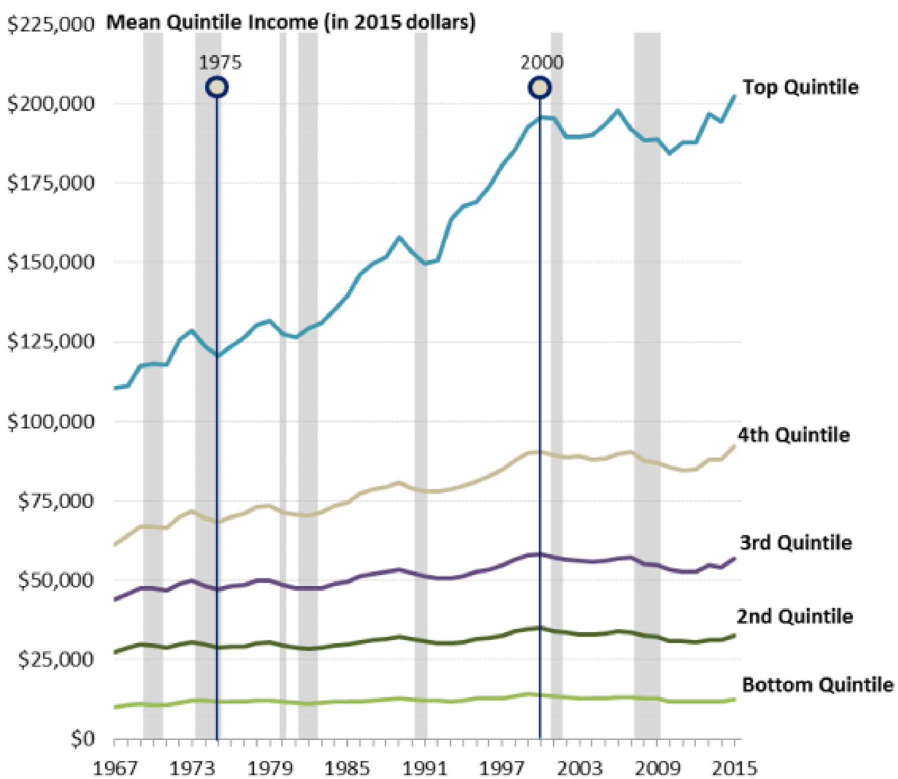


Figure 2-3 Mean quintile household income, 1967–2015 (source: Donovan et al. 2016)

Fletcher et al. (2005) noted that low-income households tend to have less access to vehicles and depend more on alternative modes for transportation. Prioritizing efficiency and reliability among all modes is important for the low-income population. If the income levels of the lower quantiles do not increase, the State of Florida can expect to see an increase in demand for public transit and facilities for non-motorized modes (Florida State University 2018).

The second potential cause for the disassociation of economic growth and passenger travel demand is the differential growth in various sectors of the U.S. economy. The manufacturing industry's percent share of GDP had continuously fallen since 1980 while that of the service industry continued to rise (see Figure 2-4). The manufacturing industry is traditionally associated with a higher demand for personal travel (i.e., labors) and freight movement than the service industry. Thus, the shift of economic orientation from manufacturing to services might have contributed to the disassociation of economic growth and VMT.

In addition, the rapid increase in the employment of women seen before 2000 has leveled off in the last 10 years (see Figure 2-5). Thus, female participation in the labor force no longer contributes to the increase of auto ownership and VMT per capita at the same level as in the past.

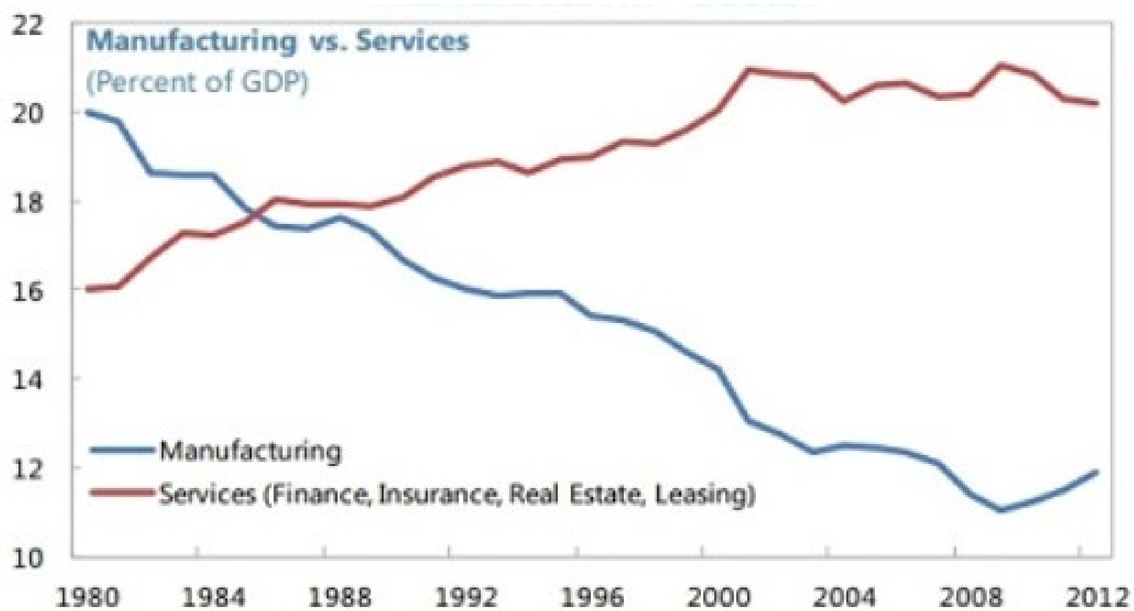


Figure 2-4 Percent GDP of manufacturing vs. services, 1980–2012 (source: Wall Street Journal 2014)

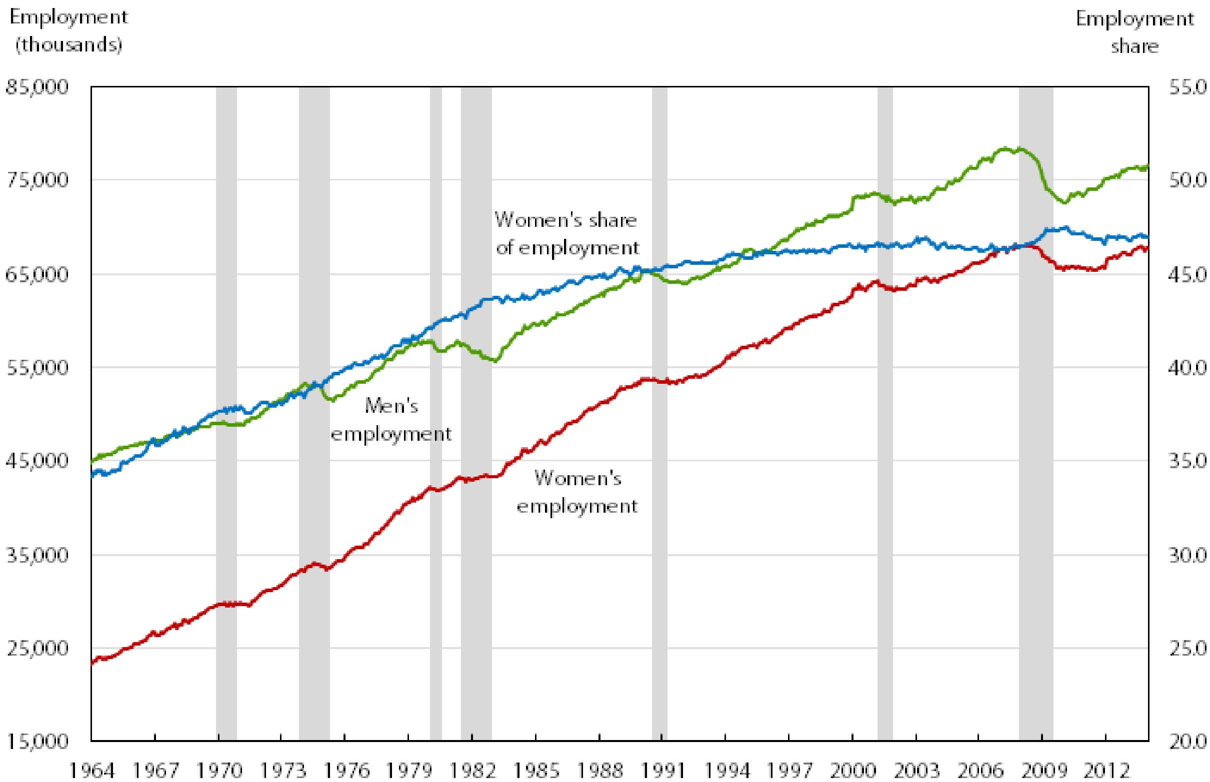


Figure 2-5 Civilian employment of men and women, in thousands, and women's share of employment, seasonally adjusted, 1964–2013 (source: BLS 2014)

2.2.1.2 Economic Growth and Freight Transportation

Unlike passenger travel demand, the demand for freight transportation is by itself an indication of the economy and in general no dissociation has been observed between the trends of economic growth and activities of freight transportation. Figure 2-6 shows that the demand for freight as measured by the Bureau of Transportation Statistics' (BTS 2017) Freight Transportation Service Index (TSI) had tracked the growth of GDP consistently, except during the period of economic recession that started in 2006 and ended in 2009, in which freight TSI reduced by a larger level than GDP. Since 2009, Freight TSI had rebounded back from the recession and has been tracking the GDP curve closely since 2012.

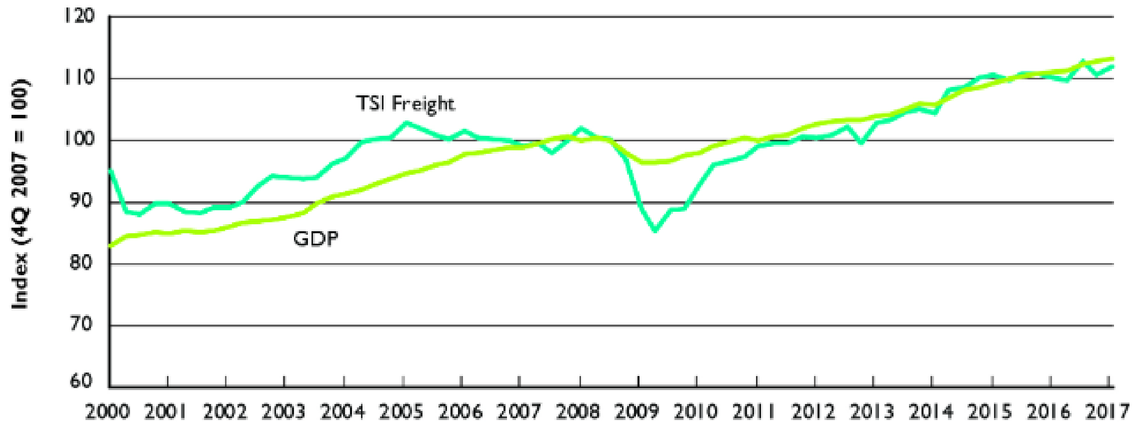


Figure 2-6 Real quarterly gross domestic product and freight transportation services index, 2000 Q1 to 2017 Q1 (source: BTS 2018)

The rise of e-commerce and its supply chain logistics with associated delivery services has reshaped freight operation (ATRI 2019). Figure 2-7 shows that US e-commerce retail sales have increased annually since 1999.

Figure 2-7 U.S. retail sale, 1999–2017 (Adapted from: ATRI, 2019)

The logistic model of e-commerce retailers such as Amazon involves establishment of distribution centers throughout the US. Merchandises are sourced from suppliers and shipped to the distribution centers first. Upon receiving an order, if stock is available, the order is shipped from the closest distribution center to the consumer, often via a sorting center. The segment from the last center to the delivery destination is called the Last Mile delivery. The Last Mile deliveries may be contracted to US Postal Service or courier services like UPS or FedEx. Because e-commers offer on-time delivery guarantee, express deliveries from suppliers to the distribution centers are often made with trucks that have not been loaded to their full capacities (i.e., Less-Than-Truckload). Such a logistic model inevitably increases the number of freight trucks on highways and last mile deliveries on urban streets (ATRI 2019). Thus, estimates and forecasts of quarterly and annual e-commerce sales volumes together with the number and locations of distribution centers can offer information as to how freight movements in the region can change in the future.

For a state with significant international trade activities, the capacity and efficiency of the state's freight transportation systems can significantly impact the state's economic growth. With more than 58,000 companies involved in exporting, Florida accounts for 20 percent of all U.S. exporters in 2016, the second highest in the U.S. after California (Enterprise Florida 2018). Understanding the commodities and trading origins and destinations is a critical step in evaluating a trade state's freight systems (FDOT 2013). Tables 2-1 to 2-2 and Figure 2-8 are sourced from the *International Business Highlights* published by Enterprise Florida (2018). Information in these tables and figure can help transportation agencies make decisions as to which aspects of the freight systems need to be improved for most trade revenue.

Table 2-1 Florida Top 5 Merchandise Export Destinations and Commodities

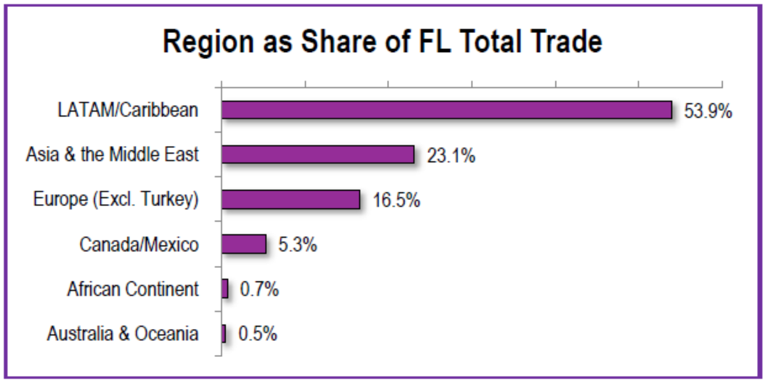
Top Merchandise Export Destinations $US Millions, 2018		**Top Merchandise Export Commodities $US Millions, 2018**	
Brazil	$14,698.0	Civilian Aircraft Engines & Parts	$8,996.4
Colombia	$4,444.5	Telecommunications Equipment	$4,644.6
Chile	$3,987.1	Passenger Motor Cars & Vehicles	$3,611.4
Dominican Republic	$3,239.1	Computers and Components	$3,065.2
Argentina	$3,211.7	Gold	$2,014.7
All Other Countries	$43,922.3	All Other	$51 ,170.5
Total	**$73,502.8**	Total	$73,502.8

Note: Sourced from Enterprise Florida (2018)

Table 2-2 Florida Top 5 Merchandise Import Origins and Commodities

Top Merchandise Import Destinations $US Millions, 2018		**Top Merchandise Import Commodities $US Millions, 2018**	
China	$10,762.3	Motor Cars & Vehicles	$11,386.1
Japan	$7,108.0	Oil (not crude)	$2,821.5
Brazil	$5,707.7	Telecommunications Equipment	$2,621.2
Mexico	$4,919.0	Gold	$2,240.4
Chile	$3,925.6	Refined Copper and Alloys	$1,903.7
All Other Countries	$47,606.6	All Other	$59,056.3
Total	$80,029.2	Total	$80,029.2

Note: Sourced from Enterprise Florida (2018)



Note: LATAM= Latin America.

Figure 2-8 Florida trade partners by region of the world (source: Enterprise Florida, 2018)

Table 2-3 presents a summary of economic trends, potential indicators and expected impacts.

Table 2-3 Summary of Emerging Trends in Economic Growth

Trends	Indicators	Impacts
Income growth mostly in the higher income groups	Personal income, household income by quantiles	Income inequality can lead to reduced VMT per capita, but greater need for improved public transits
Economic shift from manufacturing to the service industry	Employment by industries, GDP by industries	Higher proportion of manufacturing employment can lead to higher VMT per capita than service employment.
Stabilized rates of female employment and auto ownership	Civilian labor force by gender and age, auto ownership rate	Increased female employment increases VMT per capita and auto ownership.
Increased e-commerce sales	Retail e-commerce sale, number and locations of distribution and fulfillment centers	Increased online shopping activities increase Less-Than-Truckload delivery trips to distribution centers and Last Mile delivery trips from the centers to the consumers.
Increased international trade volumes	Value of total trade (import vs. export), top merchandise imports and exports	Increased trade volumes increase the demand for freight transportation and the associated cost for facility maintenance.

2.2.2 Demographics

In NCHRP Report 750 (NCHRP 2014), several demographic trends that have impacts on US passenger travel demand were discussed:

1. Slow population growth
2. Aging population
3. Changes in population distribution by race/ethnicity
4. Change in workforce composition
5. Smaller household size and family structure

The U.S. Census Bureau forecasted that U.S. population will grows from 310 million in 2010 to just over 400 million by 2051 (U.S. Census 2013). It is estimated that most of the population growth will be attributed to immigrants and their descendants. At this rate, the population is growing slower than the decades before 2000. Population aging is also evident as the Baby Boomers generation becomes older. Overall, although total VMT will increase as population slowly grow, per capita VMT will decrease as the older age groups retire from the workforce.

It is noted that the State of Florida has not experienced slow population growth like the U.S. in general. Florida became the third largest state in 2015 and continues to grow approximately twice as fast as the U.S. (Williams et al. 2018). However, Boomers' numbers grew at a higher rate in Florida than in the rest of the U.S. due to migration from other states (Smith 2015).

The effect on passenger travel of more immigrants with greater race and ethnicity mix in the future population is increased use of public transit. Per capita VMT may also increase due to automobile use by some of the immigrants and their descendants. It is also expected that the workforce in the next two decades will be older and more diverse in terms of genders and ethnicity mix. For the State of Florida, Williams et al. (2018) reported that migration accounted for 86% of population growth in the state from 2011 through 2015. The effect of this diverse workforce on personal travel is increase in car-pooling, use of public transit, and reduced per capita VMT.

The trend on small household size and family structure is driven in part by the Millennials' (i.e., individuals born from 1981 to 1997) lifestyle choice in delaying childbearing (NCHRP 2014). Most of such small households will have both the male and female household heads in the labor force. Thus, shares of car-pooling and public transit use can potentially increase. Table 2-4 presents a summary of demographic trends, potential indicators, and expected impacts.

Table 2-4 Summary of Emerging Trends in Demographics

Trends	Indicators	Impacts
Slow population growth	Annual population	Total VMT will increase, but VMT per capita will decrease.
Aging population	Population by age	Population aging reduces VMT per capita and increases need for public transits.
Changes in population distribution by race/ ethnicity	Population by race and Hispanic origin, numbers of migration and immigration	Foreign-born workers tend to use public transit at double the rate of native-born workers.
Smaller household size and family structure	Households by type, size, race, and Hispanic origin of householder	Small households may reduce overall auto-ownership, VMT per capita, and increase car-pooling.

2.2.3 Behavioral and Attitudes

Circella et al. (2016) observed that trends in behavior and attitudes toward personal trip-making vary by generation groups as each group possesses distinct lifestyle and household formation preferences that can determine how members of the group make travel decisions. The following four major generation groups represent dominant trip makers of the transportation systems currently and in the near future:

1. Baby Boomers—Born 1946–1964.
2. Generation X—Born 1965–1980.
3. Generation Y (Millennials)—Born 1981–1996.
4. Generation Z – Born 1997 ~

The Baby Boomers represent a large population group in the US (see Figure 2-9). It was estimated that the Boomers will push the share of age group 65+ to 19% of the US population by 2030 (Vincent and Velkoff 2010). According to data from the Bureau of Labor Statistics, many in the age group of 65 to 69 continue to work rather than retiring by age 65 (NCHRP 2014). The proportion of labor forces above age 55 has also increased since 1996 and it is to increase further by 2026 (BLS 2017).

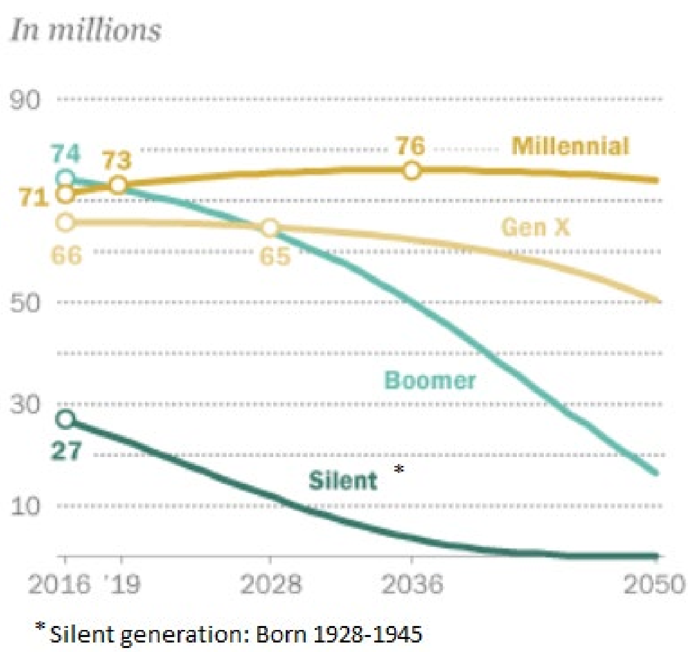


Figure 2-9 Projected population by generation (source: Pew Research Center, 2018)

For the State of Florida, Smith (2015) suggested that Boomer population grew at a higher rate in Florida than in the rest of the U.S. due to migration from other states. It was projected that Baby Boomers will make up 25% of the state's population by 2020 and 22% by 2030 (Figure 2-10).

Year	Florida			United States		
	Boomer Population	Total Population	Percent Of Total	Boomer Population	Total Population	Percent Of Total
1950	291	2,771	10.5	16,164	150,697	10.7
1960	1,467	4,952	29.6	55,786	179,323	31.1
1970	2,322	7,789	34.2	77,307	205,052	37.7
1980	3,034	9,746	31.1	79,569	226,546	35.1
1990	3,921	12,938	30.3	80,619	248,791	32.4
2000	4,555	15,982	28.5	82,826	281,422	29.4
2010	5,079	18,801	27.0	81,489	308,746	26.4
2020	5,302	21,185	25.0	75,560	333,896	22.6
2030	5,174	23,785	21.8	63,828	358,471	17.8
2040	4,057	25,970	15.6	44,255	380,016	11.6
2050	1,823	27,934	6.5	17,979	399,803	4.5

Figure 2-10 Baby Boomers and Total Population, Florida and the United States, 1950-2050
Note: Data sourced from Smith (2015)

During their prime, the Boomers favored auto as the mode of transportation and suburban communities for residence. Lee et al. (2014) suggest that Boomers living in the suburbs are unlikely to move away in large numbers. The 2010 Census data also showed that 9 out of 10 older adults still live in the same communities where their children were brought up (Farber et al. 2011). As some of them are transitioning into retirement, the number of commuting trips made by this group is reduced. However, with the increased life expectancy and available financial resources, those in retirement are expected to make increased number of discretionary trips. For the State of Florida, by 2030 Boomer population (i.e., age 66-84) is projected to be over 20% of total population. For those Boomers that continue to live in auto-oriented suburbs and small towns in rural areas, there will be increased need for the State to provide them means to access services and shops and to maintain social connectivity with friends and support networks (Steiner et al. 2018). New technologies such as shared mobility and Automated Vehicles (AV) offer a promising solution to this challenge to Florida's transportation systems.

Compared to Boomers and Millennials, Generation X is a smaller population group. Kamga (2015) suggest that members of Generation X drive less than their parents at the same age. Generation X also makes more trips by biking or walking than the previous generation (McDonald, 2015). The internet technologies came to maturity during the time when Generation X is at their prime (i.e., 1990s), thus the Generation X is the first generation that has widely adopted telecommuting (Mans et al., 2012) and online shopping, both of which can potentially reduce VMT (Salomon and Mokhtarian, 2008). It was once estimated that roughly 70-72 percent of Generation X entered parenthood

(McDonald, 2015). Before their children leave home, many of the Generation X are currently adding VMT to the systems for chauffeuring the children.

The Millennials is currently outnumbering the Boomers in the US population as the largest adult group (See Figure 2-9). It was observed that Millennials have the tendencies of owning fewer cars, driving less, and using non-motorized modes more often than the two other older generations (Blumenberg et al., 2012; Kuhnimhof et al., 2012). These unique travel behavioral traits may be attributed to this generation's lifestyle preferences in delayed marriage and childbearing age, urban residences, and adoption of new technologies (McDonald, 2015). Overall these traits can lead to increased use of shared mobility and non-motorize modes. The effect on VMT depends on how many shared mobility trips are made. However, Circella et al. (2016) noted that it is still unclear if these behaviors will last once most of the millennials get married and have children.

According to the US Census Bureau, the number of Generation Z (i.e., age 21 and younger) in 2018 is approximately 90.5 million, which accounts for 27.7% of the total population, making this generation group the largest of the US population (US Census, 2018). This generation is born after the Internet became the dominant form of communication. Since currently only the oldest members of this group reach adulthood, not much can be speculated about the potential travel behavior patterns of the members of this generation. Circella et al. (2016) note the possibility that the behavior of the older members of this cohort will resemble that of younger millennials.

Table 2-5 presents a summary of behavioral trends, potential indicators and expected impacts.

Table 2-5 Summary of Emerging Trends

Trends	Indicators	Impacts
Boomers delay retiring	Population by age, civilian labor force by age	Total VMT will increase.
Millennials delay marriage and childbearing; reduced household size	Marriage rate, Presence of children in the Household, households by age of householder, households by type and size	Total VMT and VMT per capita will decrease.
Millennials prefers urban lifestyle	Population by urbanized areas and age, households by urbanized area and size	The use of shared mobility and non-motorize modes will increase.

2.2.4 Policy and Regulations

US urban population growth accelerated in the last two decades. Census data indicate that many city centers grew faster than the suburbs between 2010 and 2012 (NCHRP, 2014). Behind the renaissance of American cities is the movement of Smart Growth, an approach to urban development that encourages mixture of building types and land uses, alternative transportation options, development within existing neighborhoods, and community engagement in the development process (Smart Growth America, 2019). The US Environmental Protection Agency (EPA) founded the Smart Growth Network to partner with public, private organizations, and local communities for the promotion of smart growth developments (EPA, 2019).

It was reported that Millennials showed strong residential preference for communities built with smart growth principles (BRS, 2013). Census data also show that Millennials who are delaying marriage represent a significant share of new city residents (NCHRP, 2014). These new city residents may have accounted for some of the decrease in per capita VMT, as urban residents are more likely to use other modes and shared mobility such as Uber, Lyft, ZipCars, and shared bikes that are readily available in the cities.

For freight transportation, there are policies and regulations designed to reduce highway truck crash rates such as hour of service, electronic logging device mandate, and the Compliance, Safety, and Accountability Program of the Federal Motor Carrier Safety Administration (ATRI, 2018). Collectively, the effectiveness of these measures can be monitored by truck crash rates with fatalities and injuries data.

There are also policies and regulations on commercial vehicle emissions and fuel efficiency standards (EPA, 2019) that impact freight operation costs and fuel tax revenue. These regulations essentially require the engines of the operating fleet to be updated with technologies that reduce emissions and improve fuel efficiency. The impacts of these technologies are discussed under the section Alternative Fuel and Electric Vehicles.

Table 2-6 presents a summary of policy trends, potential indicators and expected impacts.

Table 2-6 Summary of Emerging Trends

Trends	Indicators	Impacts
Smart Growth policies	Population by urbanized areas, population densities, land use mixes, proximity to transit lines, availability of sidewalks and bike paths	Total VMT will reduce. Trips by public transits and non-motorized modes will increase.
Truck crash reduction policies and regulations	Truck crash rates by fatalities and injuries	Safety regulations reduce highway truck crashes.

2.2.5 Technology

2.2.5.1 Information Communication Technologies

The rapid increase in the use of Information Communication Technologies (ICT) such as smartphones and other devices that connect to the Internet affords individuals increased opportunities to work, study, and communicate with others without making the trips across space. Technological solutions such as telecommuting can substitute for commute trips (Zhu 2012), but they can also generate additional travel as well. Choo et al. (2005) found that all telecommuters in the United States reduced annual national VMT approximately 0.8%. On the other hand, another study found that high frequency of internet and smartphone use are positively correlated with VMT, suggesting a complementary effect between the use of communication technologies and trip-making effect (Zhang et al., 2007). For example, a reduction in the number of commute trips might generate other kind of travel as the commuting trips that are eliminated by telecommuting make room for other discretionary trips. Circella et al. (2016) noted that more research is needed to fully elicit the effects of telecommuting on passenger travel behavior.

Similarly, online shopping has also dramatically increased in the past decade, but the impact of increased online shopping on travel behavior is also ambiguous. Studies have found mixed results: making an online purchase either replaced a physical shopping trip or resulted in new trips related to this purchase, such as those for exchange (Wilson et al., 2015). Regardless if a shopping trip is reduced for the online purchase, delivery of the merchandise purchased online nevertheless add additional VMT to the systems.

The use of ICT devices has largely expanded in the last decade across generations of the population. The impact of ICT on individual trip-making behavior is still unclear and more research is needed for a better understanding on how these evolving technologies will shape passenger travel choices.

2.2.5.2 Shared Mobility

Technologies for shared mobility include car-sharing (e.g., Zipcar) and ridesharing (e.g., Uber and Lyft). Car-sharing is essentially car rental services. Car-sharing services compete with traditional rental cars with enhanced accessibility and flexibility in terms of pickup time, location, and duration for lower cost. Carsharing can potentially impact vehicle ownership and mode use. It allows individuals to access a vehicle when needed without associated cost of actually owning one. Cervero and Tsai (2004) found that 30% of the car-sharing program participants indicated willingness to sell one or more of their vehicles, while other members didn't purchase a vehicle after using car-sharing services for about two years. The reduced car ownership has the potential of reducing total VMT. Without owning a vehicle, the likelihood that users of car-sharing programs will use public transits or non-motorized modes for discretionary trips may also increase.

Ridesharing (also known as ride-hailing) services such as Uber and Lyft have revolutionized traditional carpooling by allowing riders and drivers to match each other with smartphone apps in real-time. Companies that offer ridesharing services are known as Transportation Network Companies (TNC). Although ridesharing services are becoming more common in the US, information about the factors affecting their use and the potential effects of these services on travel behavior is still limited. Circella et al. (2018) conducted an online survey in 2015 to explore the factors affecting the adoption and use frequency of ridesharing services in California, and the impacts that these services have on other aspects of travel behavior. Over 2,000 respondents, including millennials and Generation X, completed the survey.

The study found the following characteristics associated with adoption of ridesharing services:

- Older millennials (between 25 and 34, in 2015) with higher educational status are more likely to use ridesharing services than other groups.
- Individuals from more central urban locations with greater land-use mix are associated with higher adoption of ridesharing.
- Individuals who make a large number of long-distance trips and those who travel more frequently by plane use ridesharing more often.
- Familiarity with ICT and other transportation service technologies positively affects the adoption of ridesharing.
- Individuals with stronger technology-embracing, pro-environment, and variety-seeking attitudes are more likely to use ridesharing services.

The survey also contains respondent-reported information on the effects that the last ridesharing trip had on their use of other modes. Analysis of the data revealed:

- Most respondents reported that the use of ridesharing reduced their use of a personal car.
- For riders from zero- or one-vehicle households, the use of ridesharing replaced some trips that would have otherwise been made by transit or active modes.
- A large proportion of millennials reduced their amount of walking and biking as a result of the use of ridesharing.
- Most non-frequent users reported that they would have driven a car, gotten a ride from someone else, or taken a taxi if ridesharing were not available.
- Frequent users reported that they are considering reducing the number of household vehicles more often than the rest of respondents in the sample.

The study results show that ridesharing has the potential of reducing auto ownership like car-sharing programs by offering individuals without cars mobility that is otherwise unattainable. Thus, overall VMT may decrease. However, ridesharing can also increase VMT by replacing some trips that would otherwise have been made by transits or non-motorized modes. It appears that the impact of ridesharing on total VMT of a region will depend on the number of ridesharing trips that occur in the region.

For example, a report from the San Francisco County Transportation Authority (SFCTA), California claims that TNC vehicles were estimated to generate over one million intra-San Francisco vehicle trips in a typical week, representing approximately 15% of all intra-SF vehicle trips (SFCTA, 2018). After accounting for the effects of increased employment, population growth, and transportation network changes, trips from TNC vehicles are estimated to cause 51% of the increase in vehicle hours of delay, 47% of the increase in VMT, and 55% of the decline in speeds between 2010 and 2016. Claims that TNCs increase congestion and VMT similar to those of SFTCA have also been reported in other major US cities (Washington Post, 2018).

With the above discussion, it is reasonable to expect that the impacts of ridesharing services on mode choices and regional VMT can vary based on the local context, the characteristics of the users, the land use features and the transportation alternatives that are available. In cities like San Francisco or New York where parking is a major issue, ridesharing provides mobility and convenience that few other modes can match. Thus, vehicles from TNCs can significantly increase VMT and cause congestion in these major cities.

2.2.5.3 Automated and Connected Vehicles

Automated Vehicles (AVs) and Connected Vehicles are two different technologies. AVs are vehicles that can operate without a human driver. CVs require driver operation but can automatically communicate with other vehicles for safety and operational purposes (Zmud et al., 2015). To date, it is still unclear when fully automated vehicles will become commercially available, and how quickly they will be adopted by consumers. However, several potential effects of AVs on passenger travel behavior have been discussed:

- AVs will likely lower the value of travel time for the users and increase use of the vehicles for a larger number of trips (Malokin et al., 2015).
- AVs will likely result in higher per-capita VMT due to latent demand and increased utility of using the vehicles (Fagnant and Kockelman, 2015).
- The overall effects of AVs and CVs on passenger travel will depend on the policies and regulations such as restrictions in some portions of the road network and regulations for specific categories of users (e.g. elderly, disabled or unaccompanied minors).

On June 13, 2019, the Governor of Florida signed a new law (effective July 1, 2019) that allows automated vehicles without humans to drive on all roads in Florida as long as the vehicles meet insurance and safety requirements outlined in the new legislation (Tampa Bay Times, 2019). This new law applies to Automation Levels 4 (High Automation) and 5 (Full Automation) vehicles (US DOT, 2018). With this new law, research in the context of Florida applications is urgently needed in order to better understand the impacts of AVs and CVs on travel demand and how various policies will affect mode choice involving AVs as the technologies are deployed.

2.2.5.4 Alternative Fuel and Electric Vehicles

Alternative fuels such as natural gas, biofuels, and hydrogen have the potential to replace petroleum as the mainstream fuel source of the future. Using these alternative fuels offers the benefits in reduced Green House Gas emissions and reduced energy costs (Sorensen, 2014). An obstacle for these vehicles to penetrate the market relates to the higher costs of these vehicles compared to conventional vehicles. Limited refuel locations also hinder wide application of these vehicles (Williams et al, 2018).

Plug-in Electric Vehicles (EV) have seen continuously increased sales since 2013. Shaheen et al. (2018) postulated that 80 percent of shared AVs could be electric by 2040. As market penetration of EVs gradually increases, an important issue nevertheless arises: fuel tax revenue diminishes with increased EVs on the roads. The same issue also applies to alternative fuel vehicles and, to a lesser extent, fuel-efficient vehicles. With the aforementioned new law that welcome AVs to the State, Florida needs to identify more reliable and equitable funding mechanisms to support its transportation systems (Williams et al., 2018).

Table 2-7 presents a summary of technology trends, potential indicators and expected impacts.

Table 2-7 Summary of Emerging Trends

Trends	Indicators	Impacts
Information Communication Technologies	Percent of people who work at home, e-commerce retail sales, Internet usage data	ICTs may reduce vehicle trips of various purposes, but no clear evidence exists.
Shared mobility	Car-sharing: usage data from the service providers Ridesharing: TNC licensed vehicles and monthly ridership by year	The impacts on VMT can vary based on the local context, the characteristics of the users, the land use features and the transportation alternatives that are available
Automated and Connected Vehicles	N/A	AVs can enhance mobility for people unable to operate a vehicle. AVs will likely result in higher per-capita VMT.
Alternative fuel and electric vehicles	Market shares of alternative fuel and electric vehicles	These vehicles can reduce GHG emissions. Fuel tax revenue will diminish with increased number of these vehicles.

2.3 Summary

We have reviewed up-to-date literature on the external factors and emerging trends of both passenger travel demand and freight transportation. Factors and trends general to the US and specific to the State of Florida are both discussed. Built upon these findings, 18 trends were identified and summarized that cover current and emerging trends in economic, demographic and technologic aspects. These trends were presented along with background information in the panel survey for evaluation of their potential impacts. The next section describes the survey effort.

3 METHODOLOGY

While we may have relatively long-standing understanding of the impacts of economic conditions and demographics on transportation demand, emerging trends intend to capture behavioral shifts and technology advancements that by definition are just arriving and probably still evolving. Therefore, traditional statistical correlation analysis may not be suitable for our study.

Given the above consideration, a qualitative assessment approach is proposed to evaluate the potential impacts of the emerging trends on the magnitude and direction of transportation demand. A panel survey targeting thought leaders from DOTs, planning organizations and other agencies will be conducted. Participants will be asked to provide their evaluation on the impacts of a list of identified emerging trends based on the literature review conducted in the previous task. The results of the survey will be analyzed to provide a qualitative assessment of the emerging trends.

Another approach proposed for this study explores data mining and extraction methods that can be used to collect information through social media and help monitor emerging trends in behavioral shift, policy implementation and technology advancement. Smartphone technologies and online social networks provide a unique communication means to share information in real-time to a broader audience. Social media platforms facilitate fast, easy, and rapid communication and information dissemination. Social media such as Twitter can be used as key source of information to undertake a comparative exercise of monitoring changes of user perception on emerging trends and their significance on travel demand (Power et al. 2014; Vieweg et al. 2010).

The results of qualitative assessment and data mining analysis will be presented in a focus group meeting. The focus group may be comprised of decision makers and planners from agencies, academia in the field of demand forecasting and thought leaders from industries. Facilitated discussions will be conducted to solicit inputs and evaluate findings from both analyses. The focus group will evaluate the findings and discuss methods and criteria to incorporate survey results to produce the final recommendation. The methods for trend monitoring as they relate to the feasibility and usefulness of tracking the identified trend indicators, will also be discussed.

The following sections describe the research plan for the survey and Tweet data analysis.

3.1 Impact Assessment Survey

Based on the external trends and factors identified in the first task, a web-based survey was developed to help assess the significance of each trend. This qualitative assessment approach is taken considering that while we may have relatively long-standing understanding of the impacts of the conventional economic conditions and demographics factors, these emerging trends are just arriving and probably still evolving.

Given the lack of observed historical data to support statistical analysis and data analytics, this panel survey will provide a qualitative assessment of the emerging trends. The following subsections describe the survey questionnaire design, implementation process, and findings from the pilot survey.

3.1.1 Survey Questionnaire Design

The survey focuses on two main aspects for each identified trend: how the factors and trends may affect transportation demand to what extent, and how these trends themselves may change over time. The survey looks at the impacts on passenger travel demand and freight demand separately, as the influential factors as well as the underlying mechanism are different for these two. The survey questionnaire contains four major sections:

- A brief description of the identified trends in economic, social and technological aspects.
- Impact assessment on passenger travel demand.
- Impact assessment on freight demand.
- Background information of the respondents.

Trend Description

This section provides the necessary background (with statistics obtained from reliable sources) for each trend to the respondents, so they may provide better assessment of the trends.

Impact Assessment on Passenger Travel Demand

This section contains two main questions. The respondents were first asked to rank how likely each trend may impact passenger travel demand in terms of vehicle miles traveled (VMT). A five-point Likert scale was used to capture the responses, with the options of "Decreases VMT Significantly", "Decreases VMT Moderately", "No Impact (Neutral)", "Increases VMT Moderately", and "Increases VMT Significantly". VMT was chosen as the measure to indicate potential impacts, as it reflects the total volume of passenger and freight activities, the spatial distribution of the movements which influences trip length and miles traveled, and the mode shift between transit and highway. Then the respondents were asked to indicate how they think each trend may progress in the next 10 to 20 years. A three-point Likert scale was used, with options of "Continue the Same Trend", "Level Off", and "Reversal of the Trend".

Impact Assessment on Freight Demand

Similarly, the respondents were asked to rank how likely each trend may impact freight transportation demand, and how they think each trend may progress in the next 10 to 20 years. This section shares some trends with the passenger assessment section, it also has some trends that unique to freight demand.

Background Information

This section collects some basic background information from the respondents, in terms of position type, location, education background, years of experience, etc. It helps us to gain some understanding on how the respondents' views might vary based on their background and experiences. The participants were also provided the opportunity to add or elaborate on any additional trends or factors that may affect future demand. In addition, at the end of the questionnaire, the participants were asked about their willingness to participate in a post survey interview. Appendix A presents the questionnaire designed for this study.

3.1.2 Pilot Study Findings

A pilot survey was conducted to validate the survey method and instrument between December 12, 2019 and January 11, 2020. The online link for the survey was distributed internally (within FIU and FDOT) and to a consultant where it was also distributed within the firm which resulted in a few responses and valuable feedback regarding the survey design.

We were particularly interested to obtain feedback on whether the trend description was necessary or helpful, the reasonableness and clarity of the wording of the questions and the choice options, and whether there are critical trends that were missed. We received several feedbacks internally and externally. Wording of the questionnaire was revised and finalized; sections were made clearer. Particularly, there were two comments on the interdependencies between the trends, and the baseline reference for VMT changes, which we were found were very critical. As a result, we added two notes for the impact assessment questions to add more clarity.

3.1.3 Survey Implementation

Once the survey questionnaire was finalized, recruitment took place via different channels, including individual email recruitment, in-person recruitment at the TRB annual meeting, and email-list distribution to the FHWA TMIP group, and various TRB committees. The survey was implemented online through FIU Qualtrics from January to March 2020. In total, 400 attempts were recorded, among which 152 complete responses were collected and used for this study.

3.2 Tweet Data Analysis

The rapid advancements of technologies, emerging mobility options, evolving traveler behavior, and preferences, as well as changing socio-economic and demographics of the society are changing the landscape of the transportation industry. Shared mobility services connected and automated vehicles (CAVs), along with information and communication technologies (ICTs) are expected to bring dramatic changes in how we define mobility (Malokin et al., 2015). These technologies and services not only enable higher levels of safety, comfort, and reliability but also offer individuals without car mobility that is otherwise unattainable. An in-depth understanding of these changing transportation and mobility trends are needed to better design the nation's transportation infrastructure to meet people's mobility needs over the next decades.

At the same time, socio-economic and demographic trends are also reshaping transportation priorities and needs. Several demographic trends that have impacts on passenger travel demand were discussed in the National Cooperative Highway Research Program (NCHRP) Report 750, including slow population growth, aging population, changes in population distribution by race/ethnicity, change in workforce composition, smaller household size and family structure(Zmud et al., 2014). Besides, the younger generations are expected to have different behavior and attitudes toward personal trip-making compared to the older generations (Circella et al., 2016) as each group possesses distinct lifestyle and household formation preferences that can determine how members of the group make travel decisions. It was observed that Millennials tended to own fewer cars, drive less, and use non-motorized modes more often, preferred living in urban spaces with more transportation options (Blumenberg et al., 2012; Kuhnimhof et al., 2013). These demographic trends may result in declining vehicle miles traveled and increased use of shared mobility and non-motorized modes. However, it is still not entirely clear how these demographic trends, behavior shifts, and technological advancements may work together and influence future demand. A few studies have explored emerging transportation trends through online and mail surveys (Circella et al., 2019), GPS data (Ge et al., 2017), and the National Household Travel Survey (NHTS) dataset (Harper et al., 2016). Other studies employed text mining techniques to identify trends through published transportation-related articles (Das et al., 2020; Sun & Yin, 2017), bibliometric, and patent analysis (Daim et al., 2006).

3.3 Motivation and Prior Work

Social Media Platforms (SMP) provides good opportunities to monitor and track emerging transportation trends. SMP generates spontaneous expressions of public opinion at large. Social signals, from messages posted on social networking sites, record users' daily activities and create large amounts of data that can be used for traffic and transportation analysis (He et al., 2015). SMPs provide a cost-effective and reliable means for information sharing and communication. More than 48 million active users on Twitter made it one of the most widely used SMPs in the USA ("Twitter by the Numbers: Stats, Demographics & Fun Facts," 2020). As such, SMPs holds the potential to provide large-scale data with detailed temporal and spatial information that could help transportation agencies to understand travelers' mobility patterns and travel behavior. Recent studies have explored the potential of using SMPs to retrieve useful data that could provide valuable insights in various areas, including travel demand forecasting (Golder & Macy, 2014; Tasse & Hong, 2014; Yin et al., 2015), mass mobility patterns (Cheng et al., 2011; Jurdak et al., 2015; Noulas et al., 2012), activity-pattern modeling (Chang & Sun, 2011; Hasan & Ukkusuri, 2014; Hasan et al., 2013; Lian & Xie, 2011), mass transit evaluation (Collins et al., 2013; Pender et al., 2014; Schweitzer, 2014), traffic incident management

(Ribeiro Jr et al., 2012; Steur, 2015; Wanichayapong et al., 2011), and disaster management (Lindsay, 2011; Pender et al., 2014; Wang & Taylor, 2014; Wang & Taylor, 2015) among others.

The novelty of this study is in the demonstration of the capability of large-scale social media data using natural language processing techniques to capture emerging transportation trends and mobility indicators, which is quite limited through survey-based and other conventional approaches. We explored emerging travel trends in North America using data obtained from Twitter for around 20 days from Dec. 16, 2019–Jan. 4, 2020. The main purpose of this study was to understand public opinion and identify emerging transportation trends based on social media interactions, with enriched space and time information. This study aimed to achieve the following objectives:

- Identify spatiotemporal characteristics of relevant social media interactions on shared mobility, vehicle technology, built environment, user fees, e-commerce, and telecommuting, which can give an understanding about the spatial and temporal distribution of the relevant tweets describing the emerging transportation trends;
- Measure public sentiments and perceptions on emerging transportation trends through natural language processing such as sentiment analysis, which can allow the classification of tweets based on sentiment scores (highly positive, positive, neutral negative, and highly negative);
- Explore spatiotemporal differences of user sentiments by classifying sentiment scores on transportation and mobility indicators which can make sense about the spatial and temporal distribution of tweets concerning their sentiment direction;
- Extract emerging transportation topics and user concerns from social media interactions through Latent Dirichlet Allocation (LDA), which is a machine learning approach to identify the patterns of the filtered relevant tweets to recognize the emerging transportation trends

3.3.1 One-Week Pilot Exploration

The research team created a Twitter developer account using Twitter Apps (apps.twitter.com/). In order to conduct a pilot and assess the credibility of the data to serve the needs of this project, the team retrieved one-week (Nov. 18, 2019–Nov. 25, 2019) worth of preliminary data using Twitter Streaming API (application programming interfaces). Python programming language was used to collect the data, and associated Python libraries were used.

The data collection was done in two different ways: (i) keyword-based and (ii) location-based. For location-based data collection, a bounded box was created to include the entire state of Florida and some parts of Georgia and Alabama (Figure 3-1). This was to ensure all the tweets in this dataset were geo-tagged. In this case, all tweets that occurred within this box during the one-week period were collected.

For keyword-based data collection, no geographical boundaries were set, but only relevant tweets were collected. Relevancy was established if the tweet contained at least one of the keywords identified for the purpose of this study. In total 210 keywords in six major categories were identified relevant to emerging trends. The six major categories include:

1. **Shared Mobility:** *shared, mobility, carpool, car, uber, lyft*
2. **Vehicle Technology:** *autonomous, automated, self-driving, connect, connected*
3. **Built Environment:** *walk, gym, cycle, activity, sidewalks, bypass, access, bus, station*
4. **User Fees:** *toll, express, lane, mileage, price, gas, gallon, fee, fare, tax, booth*
5. **Telecommuting:** *telecommute, job, flexible, hours, dollar, commute, telework, mobile, remote*
6. **Ecommerce:** *ecommerce, amazon, deliver, delivery, walmart, publix, ebay, fedex, ups*

The complete list of keywords is presented in Table 4-1. By nature, not all tweets collected in the keyword-based dataset have location information (i.e., geo-tagged).

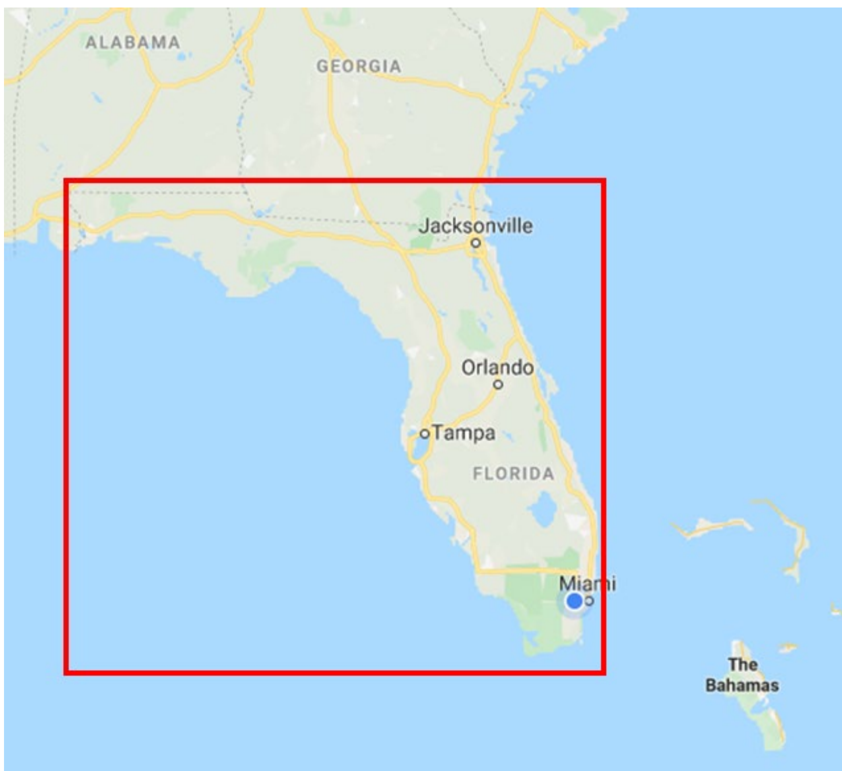


Figure 3-1 Bounded box used for the location-based data collection

3.3.2 Preliminary Data Processing and Analyses

For the pilot data, the raw data in .json format was first converted to .csv format which is a more usable format to generate data analytics. However, some of the texts in the raw data include non-English tweets and other irrelevant punctuations and symbols which need to be filtered out. To make sure each of the cleaned tweets be relevant to the objectives of this project, we apply relevance filtering by making sure that each tweet contains at least one of the keywords identified in the previous section.

Explorative data analysis was conducted to check for the credibility of the data. Differences between the location-based dataset and keyword-based dataset were also compared. Please note that the data from keyword-based data collection do not require relevance filtering since relevancy was ensured during the time of data collection.

Figure 3-2 shows the occurrence probability of the most frequent words (top 20) in decreasing order of their presence with respect to the clean and relevant number of total tweets. The highlighted words are the relevant keywords. There are 7 and 6 keywords at the top 20 wordlists for location-based dataset and keyword-based dataset, respectively. In both cases the most frequent words were also relevant keywords that we are interested in.

(a)

Word	Percent (%)
work	1.0239
job	1.0236
fl	0.6777
home	0.6062
stop	0.5785
school	0.4383
see	0.4368
go	0.4255
time	0.4164
video	0.367
great	0.3557
want	0.3505
link	0.3398
know	0.3302
people	0.3255
need	0.3228
wish	0.3213
via	0.3213
disney	0.3194
bio	0.3179

(b)

Word	Percent (%)
work	0.8151
job	0.7252
home	0.4654
time	0.4321
stop	0.417
see	0.4044
go	0.3618
people	0.3438
love	0.3273
great	0.3228
know	0.3158
want	0.3109
need	0.3107
school	0.3049
good	0.2876
new	0.2778
got	0.2716
back	0.2667
link	0.2666
via	0.2607

Figure 3-2 Word occurrence probability: (a) location-based data; (b) keyword-based data (20 most frequent words)

Figure 3-2 represents the word frequency heatmap for the top 50 words in decreasing order of frequency. Heatmaps for location based dataset and keyword based dataset are similar and in both heatmaps it can be seen that people were less active on twitter on Nov 22, 23 and 25. Figure 3-4 is a two-dimensional representation of tweeting activities based on tweet originating dates and the most frequent 50 locations for both keyword based and location based dataset.

In the heatmaps, places such as Los Angeles, Manhattan, Houston, Chicago, Florida were among the most tweet-active locations. People from these locations were likely to be more expressive of emerging mobility trends through social media interactions as evident from Twitter. In contrast, places such as New Delhi, London, New York generated low tweets per day on emerging trends.

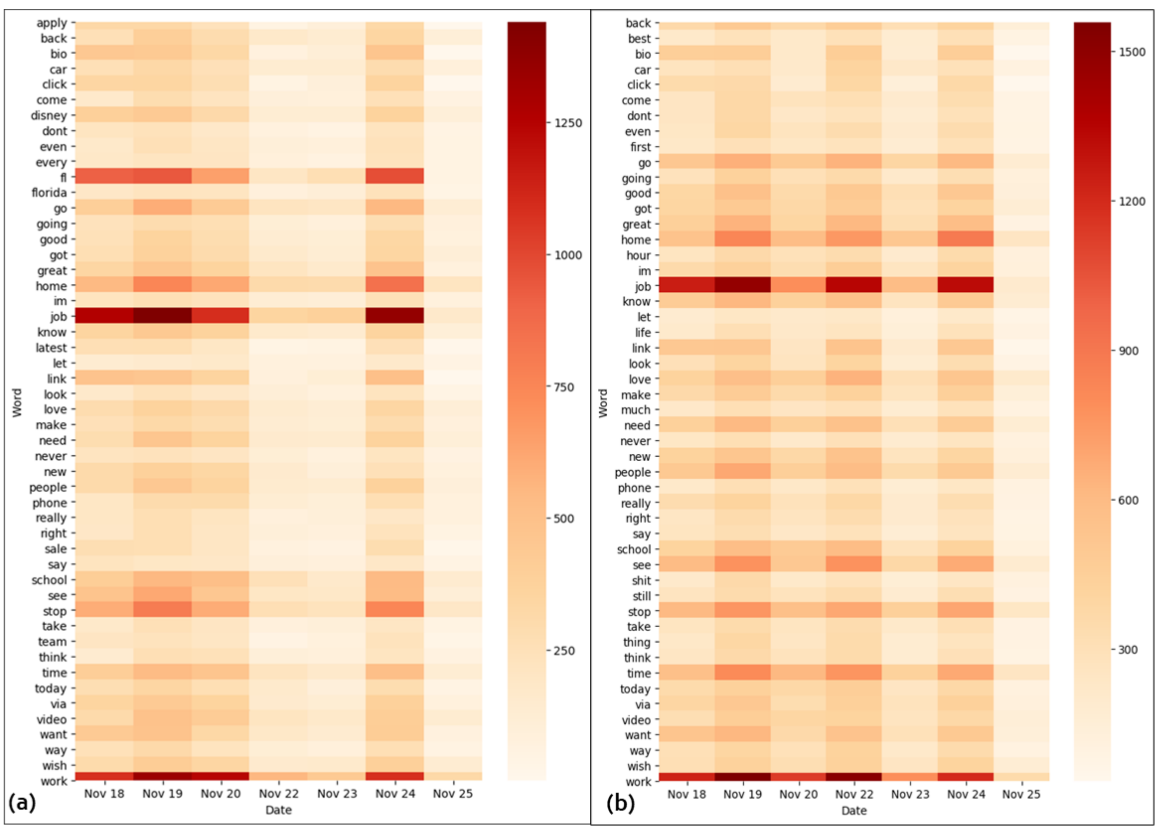


Figure 3-3 Heat map for word frequency over time: (a) location-based data; (b) keyword-based data (50 most frequent words in the relevant data)

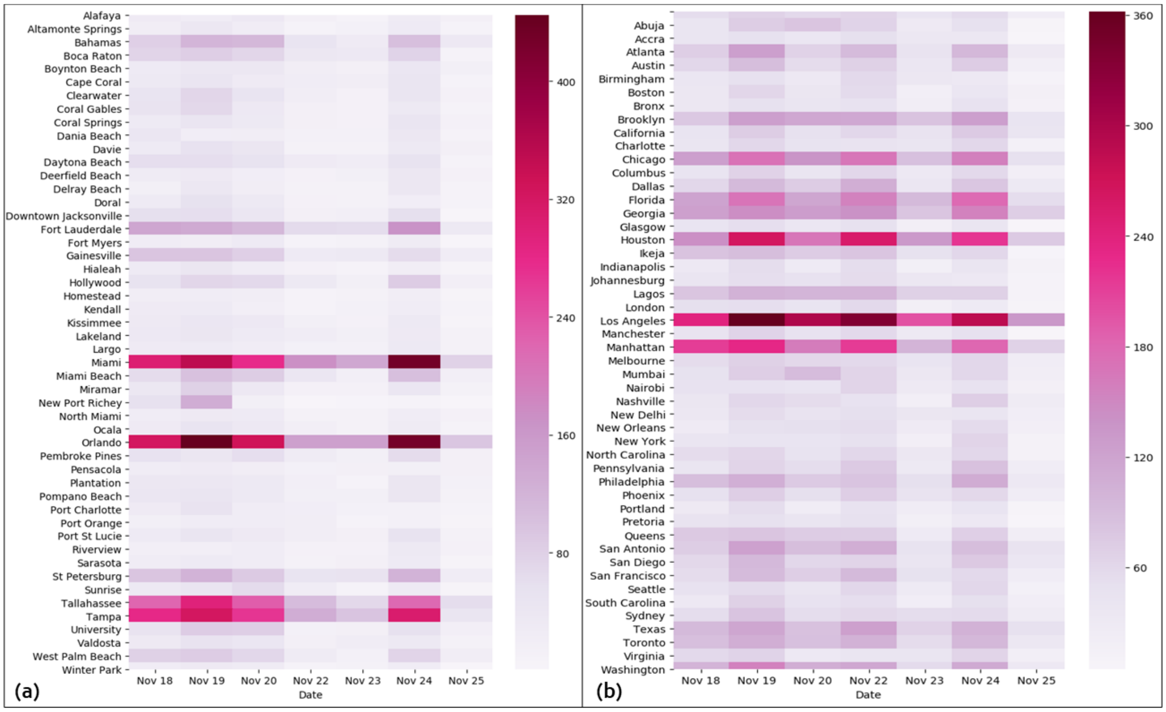


Figure 3-4 Spatiotemporal distribution of relevant tweet: (a) location-based data; (b) keyword-based data (Top 50 location)

Table 3-1 shows the comparative summary results for the two different datasets. Around just 0.4% of the keyword-based dataset was in English and geo-tagged, while the location-based dataset has around 80%.

Table 3-1 One-Week Pilot Dataset Description

	Keyword-based dataset	Location-based dataset
File size (.json)	190 GB	1.68 GB
Total tweet count	23.84 M	0.46 M
English tweet count	11.36 M (47.65%)	0.37 M (80.44%)
Geo-tagged tweet count	0.16 M (0.67%)	0.46 M (100%)
Geo-tagged English Tweet Count	0.0954 M (0.40 %)	0.37 M (80.44%)

Moreover, preprocessing and filtering of the keyword-based dataset was time-consuming (around twice the time spent for the location-based data) due to its huge volume but produced a very small portion of credible tweets that were suitable for further spatial and temporal analysis. On the other hand, the location-based dataset is very promising in fulfilling the research objective as most of the tweets are geo-tagged and it is less time-consuming to preprocess and filter. Based on the explorative analysis, we continued with the location-based data collection approach for the full analysis. Twitter data was collected for around 20 days covering all areas in North America.

3.3.3 Data Cleaning and Pre-Processing

Tweets retrieved from the streaming API contains additional information such as user id, profile information, and creation time along with the tweet text. Only tweet texts are considered for analysis in this study. Given the inherent ambiguity of tweets (e.g., non-standard spelling, inconsistent punctuation and/or capitalization), the following preprocessing steps are performed to extract clean tweet text which is suitable for analysis.

- In the first step, a smaller .csv file was created by extracting necessary information for each tweet from the .json file such as time of the tweet, user id, user name, tweet id, tweet text, tweet language, and tweet location from 'created_at', 'user', 'id', 'text', 'lang', and 'place' fields respectively.
- In the second step, the .csv file size was reduced just removing all the non-English tweets by filtering with the tweet language information.
- In the third step, 'noise' from the text data was removed which are considered the following:
    1. Html tags and attributes (i.e., /<^>+>/).
    2. Html character codes (i.e., &...;).
    3. URLs, @-mentions with 'at_user' & Whitespaces.
    4. Numbers, stop-words (i.e., articles, prepositions)
    5. Duplicate or repeated text
- In the fourth step, emojis, and stop words are removed. Emojis and Exclamation marks, Question marks are those words within a sentence that offer negligible or no information for the text analysis. In this paper, a list including stop words and emojis are created with the lists available from multiple online resources.
- In the fifth step, the tweets are tokenized, which is the process of splitting a tweet text into a list of meaningful processing units, called tokens (e.g., phrases, syllables, or words). Each tweet text S is split into tokens, t, expressing each tokenized tweet S as:

$$t = \{t_1, t_2, t_3, \ldots, t_i, \ldots, t_N\} \tag{1}$$

where t_i is the i-th tokenized word for each tweet text S of length N.

- In the sixth and final step, the tokens of the tokenized tweet Lemmatized with Python nltk package which reduces the inflected words properly ensuring that the root word (lemma) belongs to the language in a canonical form, dictionary form, or citation form. For example, walks, walking, walk are all forms of the word walk, therefore run is the lemma of all these words.

3.3.4 Data Analysis Methodology

3.3.4.1 Spatial and Temporal Analysis

Twitter allows users to share their location from where the user posted the tweet, which is a confined area, generated automatically with the tweet if the location of the user's device remains enabled. Geolocational information and timestamp of tweets were extracted from the 'place' and 'created_at' fields, respectively. Temporal or time series analysis is one of the best techniques to understand the internal patterns (trends, temporal variation) within data over time. A heatmap was produced to represent the correlation between the most frequently used words in relevant tweets and the dates when they were tweeted. This illustrates the daily variation of popular words that have been tweeted, which provides insight into the temporal variation of the most popular and unpopular trends over time. Another heatmap, plotting the inter-relationship between the most frequently used word and tweet location, was also created. It is a very efficient way to understand the spatial variation of the popularity of transportation trends. For this reason, geotagged tweets were considered as a source to improve situational awareness and improve the understanding of real-world transportation trends.

3.3.4.2 Sentiment Ratings

Sentiment analysis or opinion mining is the computational study of opinions, sentiments, and emotions. It tries to infer people's sentiments based on their language expressions expressed in a text. It usually uses a sentiment lexicon to provide sentiment scores on the generated corpus (a textual body clustered by required class or cluster) (Indurkhya & Damerau, 2010). The analysis focuses on individual sentence targets to determine whether a sentence expresses an opinion or not (often called subjectivity classification) and, if so, whether the opinion is positive or negative (called sentence-level sentiment classification) (Indurkhya & Damerau, 2010). Assume an opinionated document or tweet w, which expresses an object or a group of objects. Generally, $w = (w_1, w_2, \ldots w_i, \ldots, w_n)$, where w_i is a sentence. An opinion passage on a feature f of an object o evaluated in w is a group of consecutive sentences in w that expresses a positive or negative opinion on f. Additionally, sentiments also contain subjectivity. A subjective sentence expresses some personal feelings or beliefs. Sentence-level sentiment classification involves two definite tasks with a single assumption (Indurkhya & Damerau, 2010). These are stated below:

- Task: Given a sentence s, two subtasks are performed:
  1. Subjectivity classification: Determine whether s is a subjective sentence or an objective sentence,
  2. Sentence-level sentiment classification: If s is subjective, determine whether it expresses a positive or negative opinion.
- Assumption: The sentence s expresses a single opinion from a single opinion holder

In this study, we used a Python package called VADER, or the Valence Aware Dictionary and sEntiment Reasoner (https://github.com/cjhutto/vaderSentiment) that detects the sentiment value of a short text, for analyzing the sentiments of relevant tweets about the emerging transportation trends. This is a lexicon-based method that makes use of a pre-defined list of words (VADER lexicon), where each word is associated with a specific sentiment.

VADER belongs to a type of sentiment analysis that is based on the lexicons of sentiment-related words. In this approach, each of the words in the lexicon is rated as to whether it is positive or negative, and in many cases, how positive or negative. VADER produces four sentiment metrics from these word ratings. The first three, positive, neutral, and negative, represent the proportion of the text that falls into those categories. The final metric, the compound score, is the sum of all the lexicon ratings which have been standardized to range between -1 and 1 (Gilbert and Hutto, 2014).

To decide on a range to categorize highly negative, negative, neutral, positive tweets, and highly positive, a heatmap of the sentiment scores was produced and used to gauge roughly where scores were landing -1 to -0.6 (highly negative), -0.6 to -0.2 (negative), -0.2 to 0.2 (neutral), 0.2 to 0.6 (positive), and 0.6 to 1.0 (highly positive) were ultimately set as the bounds for the three categories. VADER considers currently frequently used slang and informal writings - multiple punctuation marks, acronyms, and an emoticon to express how a person is feeling, which makes VADER great for social media text. Some real tweets were presented here as examples to demonstrate the categories:

(1) "*thank you for creating vision for sustainability and leading the way not only electric cars but also solar autonomous software energy storage among other accomplishments im looking forward seeing what you and your team create*"-Highly Positive (Score 0.7992);
(2) "*loves tesla though it's the worst drive during holiday who knew*"-Positive (Score 0.3182);
(3) "*bosch finally making lidar sensors for autonomous cars*" – Neutral (Score 0);
(4) "*They'd stop fighting long enough maybe we'd all have autonomous self-driving cars the road now*" – Negative (Score -0.296)*;*
(5) "*autonomous cars are highly susceptible risk being commandeered visual spoofing attacks*" – Highly Negative (Score -0.6461)

3.3.4.3 Topic Mining

To identify the patterns of the filtered tweets to recognize the emerging transportation trends, Latent Dirichlet Allocation (LDA) or topic modeling approach (Blei et al., 2003) was applied which is built on the classical probabilistic latent semantic analysis (pLSA) model (Hofmann, 1999). Being an unsupervised machine learning approach, LDA does not demand the prior annotation or labeling of the documents (tweets). Though the topic model has been widely used in machine learning, it has been recently used in transportation studies. For example, in travel behavior and activity research, LDA has been used to analyze the human location and activity data to discover structural daily routines (Farrahi & Gatica-Perez, 2011; Hasan & Ukkusuri, 2014; Huynh et al., 2008).

The probabilistic procedure for document (tweet) generating is adopted in LDA which starts with choosing a distribution ψ_k over words in the vocabulary for each topic k ($k \in$ *1, K*) (Steyvers & Griffiths, 2007). Here, ψ_k is picked from a Dirichlet distribution $Dirichlet_v(\beta)$. After that, another distribution θ_d over K topics is sampled from another Dirichlet distribution $Dirichlet_k(\alpha)$ to generate a document d (a collection of word w_d). Thus, a topic is assigned for each word in $\boldsymbol{w_d}$ and then choosing each word w_{di} based on θ_d . LDA first samples a particular topic z_{di} $\in$ *1, K* from multinomial distribution $Multinomial_k(\theta_d)$ in generating each word w_{di} . Finally the word w_{di} is selected from multinomial distribution $Multinomial_v(\psi_{z_{di}})$. Figure 3-5 shows the graphical representation of LDA where Sun and Yin (Sun & Yin, 2017) summarized the process into three steps.

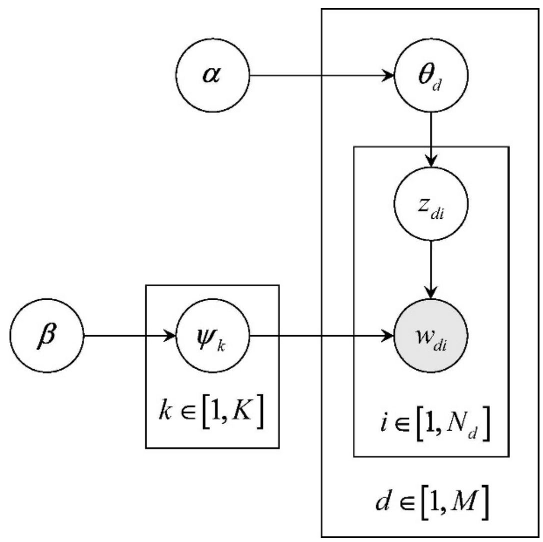


Figure 3-5 Graphical model representation of LDA (Sun & Yin, 2017)

1. Word distribution of each topic k is determined by $\psi_k \sim Dirichlet_v(\beta)$
2. Topic distribution for each document d is determined by $\theta_d \sim Dirichlet_k(\alpha)$
3. For each document d, for each word w_{di} in d,
   - Choose a topic $z_{di} \sim Multinomial_k(\theta_d)$
   - Choose a word $w_{di} \sim Multinomial_v(\psi_{z_{di}})$

The inference of LDA models can be done by applying the variational expectation-maximization (VEM) algorithm (Blei et al., 2003) or through Gibbs sampling (Griffiths & Steyvers, 2004). The posterior of document-topic distribution θ_d and topic-word distribution ψ can be efficiently inferred by both methods which allow us to discover the latent thematic structure from a large collection of documents(Sun & Yin, 2017).

The key steps involved in the data analysis for the Tweet data are summarized in Figure 3-6.

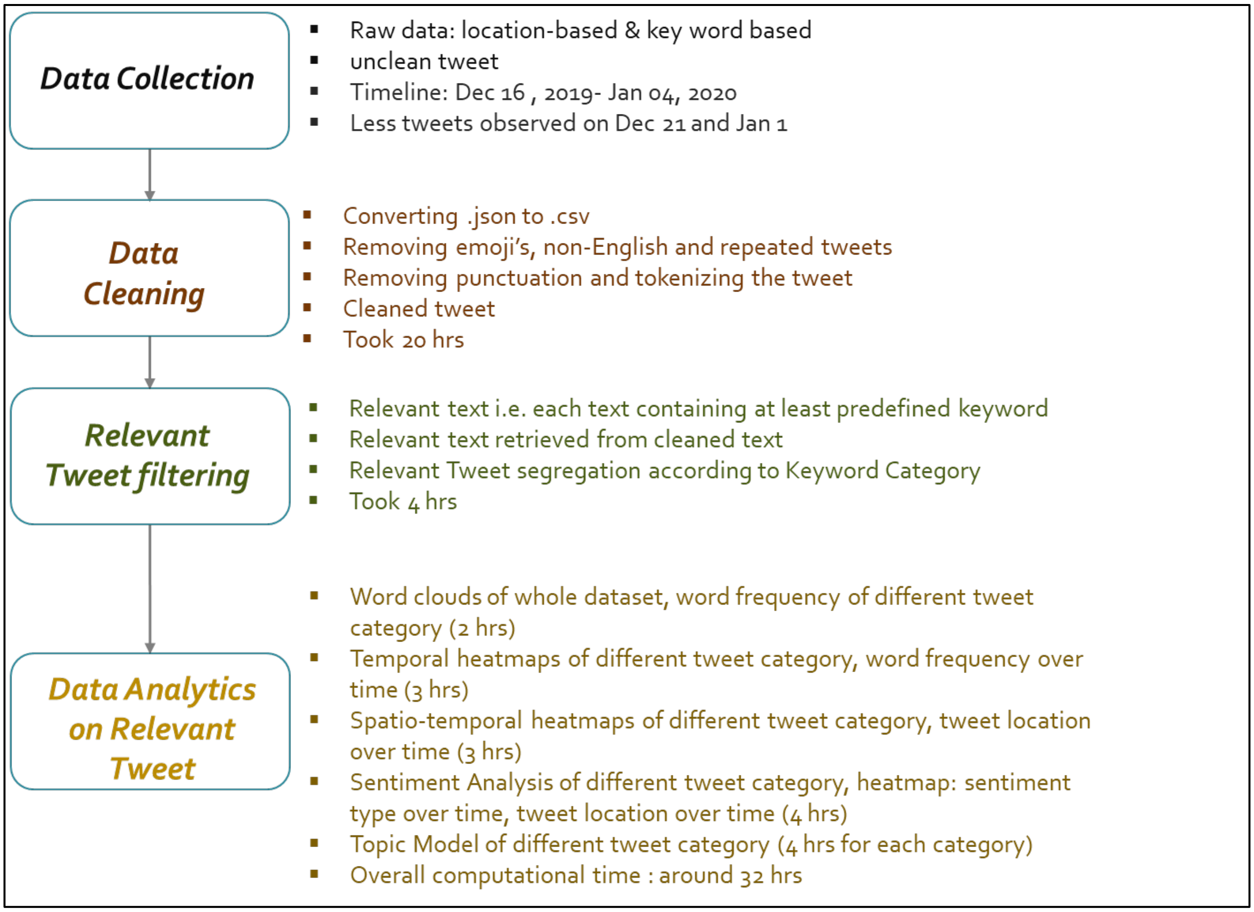


Figure 3-6 Key steps in producing data analytics

4 TWEET DATA ANALYSIS RESULTS

4.1 Final Data Description

The main focus of this study is English geo-tagged tweet as tweet geographic information is a potential parameter for spatio-temporal analysis, the location-based data collection method produced a more suitable and reliable dataset that serves the goal of the study. As a result, tweets from North America and its surrounding area (as most of the people in this region speak English), confined by approximately (14.4439373, -18.324324) and (71.218493, -169.3692058) coordinates, are collected using a location-bounding box for around 20 days (Dec 16th, 2019- Jan 4th, 2020) which covered USA, Canada, Mexico, Cuba, Puerto Rico, and part of Guatemala and Greenland (Figure 4-1).

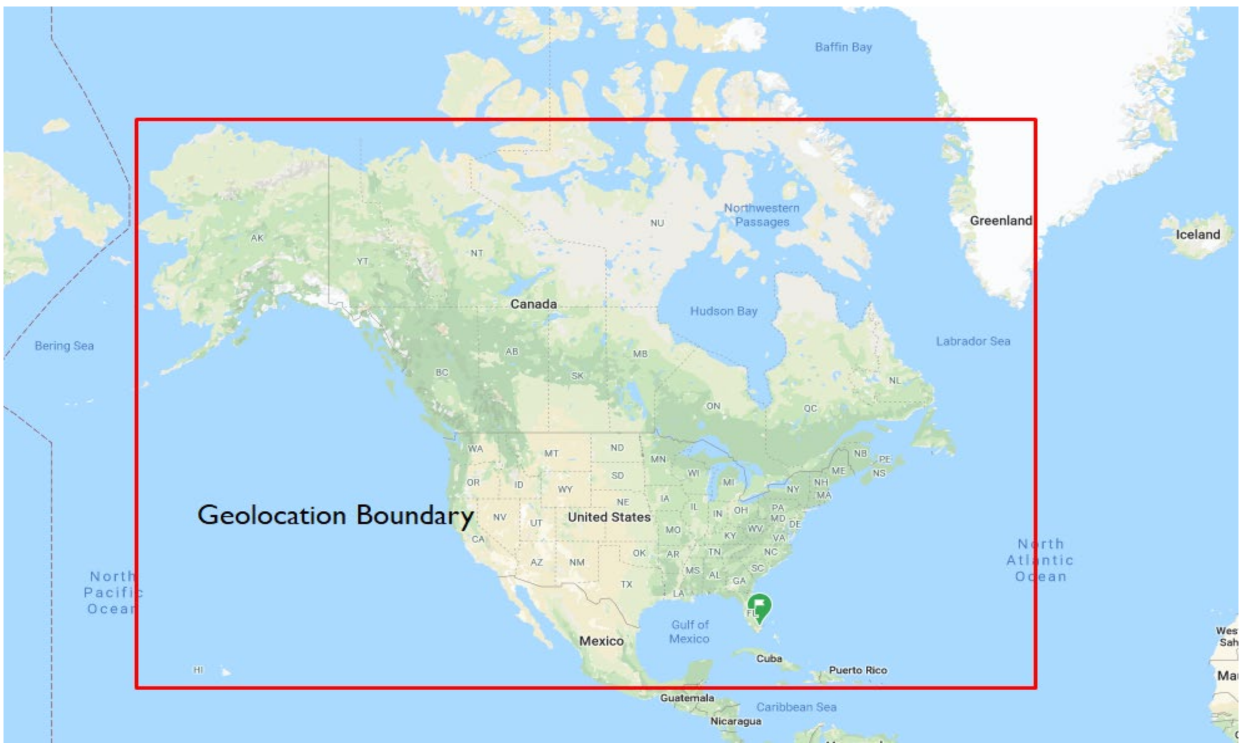


Figure 4-1 Bounded box used for the data collection for North America

No additional features or keywords were used to collect the tweets. The raw data was saved in a .json file (46.5 GB) containing approximately 12.9M tweets. Approximately 100% of tweets are geotagged and mostly in English (~ 77%) with around 0.97 M unique users. Python programming language was used to collect the data and associated Python libraries have been used.

Tweets retrieved from the streaming API contains additional information such as user id, profile information, and creation time along with the tweet text. Only tweet texts were considered for analysis in this study. To be consistent with the objectives of the study and to avoid "false positives" (messages with no relevance to Emerging trends), tweets were filtered with a wordlist of 205 words of six major categories (Table 4-1) to retrieve only the tweets that are relevant to emerging mobility trends after cleaning and preprocessing the data according to article 2.3. Although this list of keywords may filter out some related tweets, it ensures that all relevant tweets involving these keywords were included in the filtered dataset.

After filtering the dataset, a total number of 1.25 M (9.68% of the total tweets) relevant English tweets were obtained for this study. Table 4-1 presents the keywords used to filter relevant tweets by category. The percentage value represents the percentage of tweets that contained specific keywords concerning the whole dataset.

Table 4-1 Complete List of Keywords Used for Keyword-Based Data Collection

Category	Relevant keywords	Tweet Count
Shared Mobility (44 words)	shared, mobility, carpool, car, Uber, Lyft, tnc, share, zipcar, waze, juno, driver, passenger, ride, maas, e-hail, ehail, carclubs, bicycle, via, uberpool, hail, scooter, flexdrive, vehicle, zebra, flexwheels, e-scooter, escooter, lime, wheels, spin, bird, mobi, bike, evo, gogo, jax, rental, curb, wingz, birdj, traffic, fdot	170,289 (1.31%)
Vehicle Technology (26 words)	autonomous, automated, self-driving, connect, connected, v2v, v2i, v2x, tesla, electric, hybrid, google, drive, platoon, airbags, energy, phonefob, vpa, telematics, ai, b2v, eascy, automation, artificial, intelligence, map	74,144 (.60%)
Built Environment (49 words)	built environment, walk, gym, cycle, activity, sidewalks, bypass, access, bus, station, stop, transit, mile, metro, rail, mover, land, work, office, shop, school, bank, airport, flight, plane, restaurant, park, malls, theater, bar, pick-up, pickup, drop-off, dropoff, atm, fitbit, train, subway, universal, disney, hyperloop, everglades, tour, tourist, arrive, depart, destination, eta, home	631,697 (4.87%)
User Fees (20 words)	toll, express, lane, mileage, price, gas, gallon, fee, fare, tax, booth, market, charge, payment, tariff, dues, levy, duty, liter, litre	66,668 (.51%)
Telecommuting (32 words)	telecommute, job, flexible, hours, dollar, video-conference, videoconference, commute, telework, mobile, remote, workplace, technology, home-sourced, home sourced, e-work, ework, outwork, operation, mode, labor, regime, freelance, screen, voice, chat, video, phone, yammer, zoom, virtual, employee	344,868 (2.66%)
Ecommerce (34 words)	ecommerce, amazon, deliver, delivery, walmart, publix, ebay, fedex, ups, browse, purchase, e-business, ebusiness, online, trade, internet, sale, retail, transaction, paperless, macy's, macys, wish, lowe's, lowes, best buy, bestbuy, target, home depot, homedepot, etsy, rakuten, groupon, ebates	142,101 (1.10%)

Figure 4-2 shows the description of the dataset.

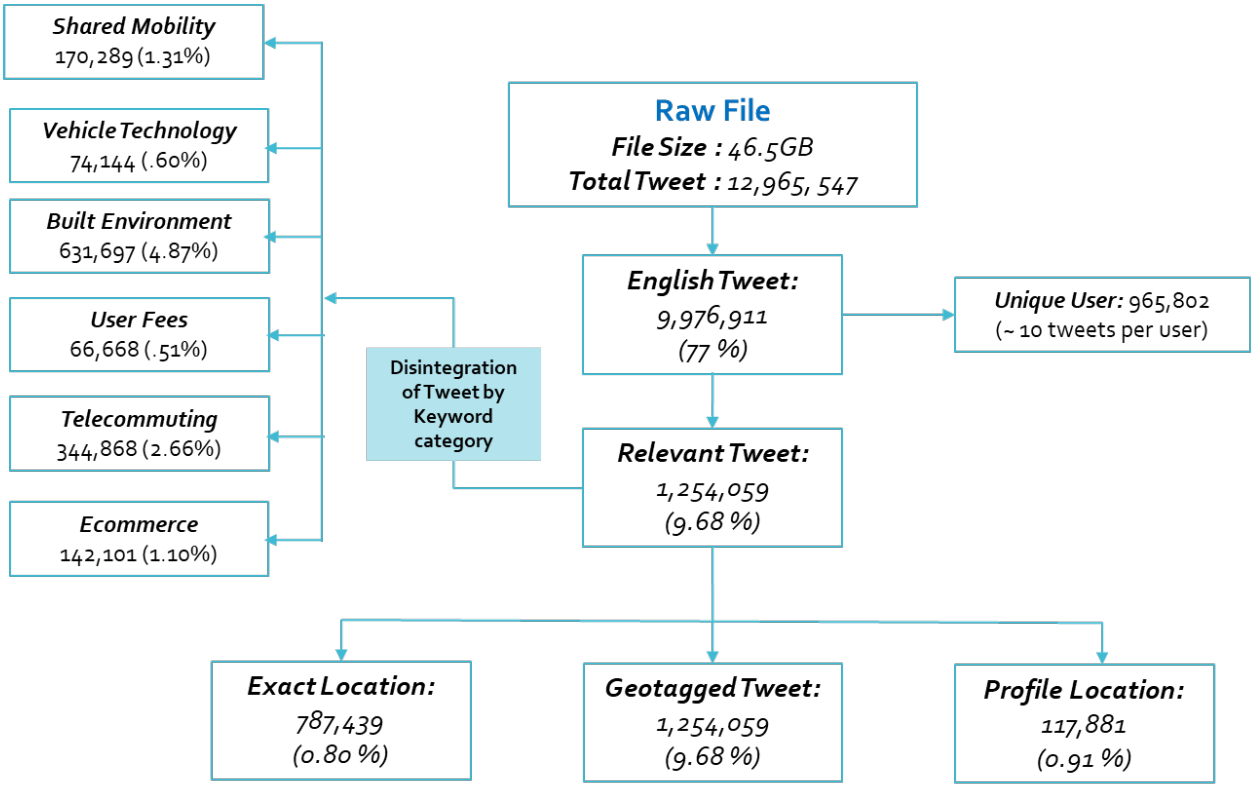


Figure 4-2 Description of dataset

4.2 Results and Discussions

4.2.1 Spatiotemporal Heatmaps of Tweets

Spatio-temporal distribution of tweeting activities can broaden the understanding of the credibility and representativeness of the datasets over space and time. Almost identical spatiotemporal distribution patterns were observed across all categories i.e. shared mobility, vehicle technology, built environment, user fees, telecommuting, and e-commerce. Figure 4-3 and 4-4 present the heatmaps of tweeting activities based on tweet originating dates for the top 50 locations, and top 100 locations, respectively.

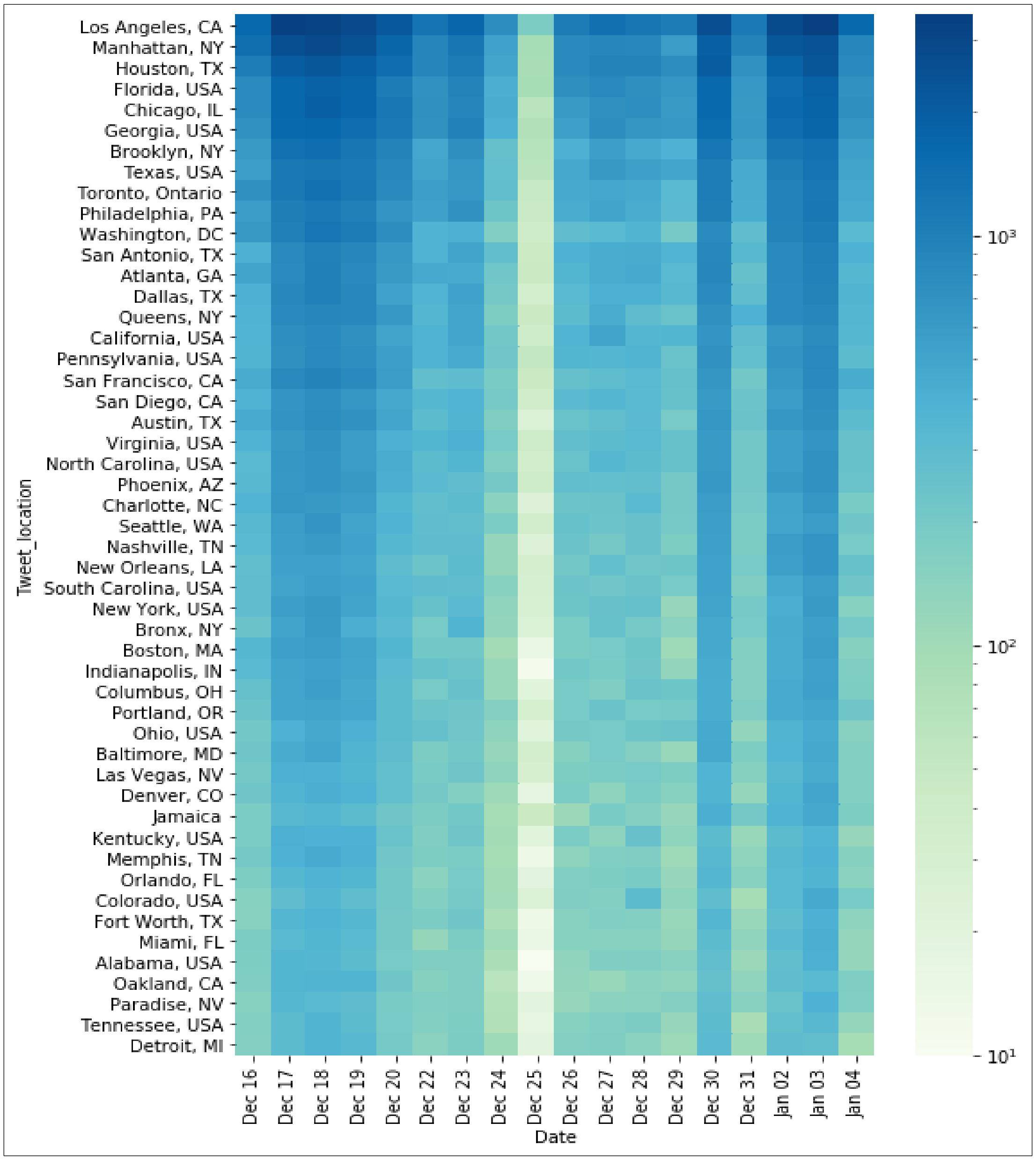


Figure 4-3 Spatiotemporal distribution of relevant tweet (Top 50 location)

Cities such as Los Angeles, Manhattan, Houston, Chicago, Brooklyn, Philadelphia, and states such as FL, GA, TX, and Washington D.C. were among the most frequent locations and generating more ~1K tweets daily on emerging transportation trends. People from these locations were likely to be more expressive of emerging mobility trends through social media interactions as evident from Twitter. In contrast, cities like Detroit (MI), Paradise (NV), Las Vegas (NV), Oakland (CA), Denver (CO), Memphis (TN) and states like AL, CO, KY, OH generated as low as only 100 tweets per day on emerging trends. Other locations that appear in Figure 4-3 represent moderate levels of concern among social media users (~100-1000 tweets on average). Between Dec 17th to Dec 19th and Dec

30th to Jan 3rd, most of the cities of the 2nd top 50 places produced more than 100 tweets daily on emerging transportation trends (Figure 4-4).

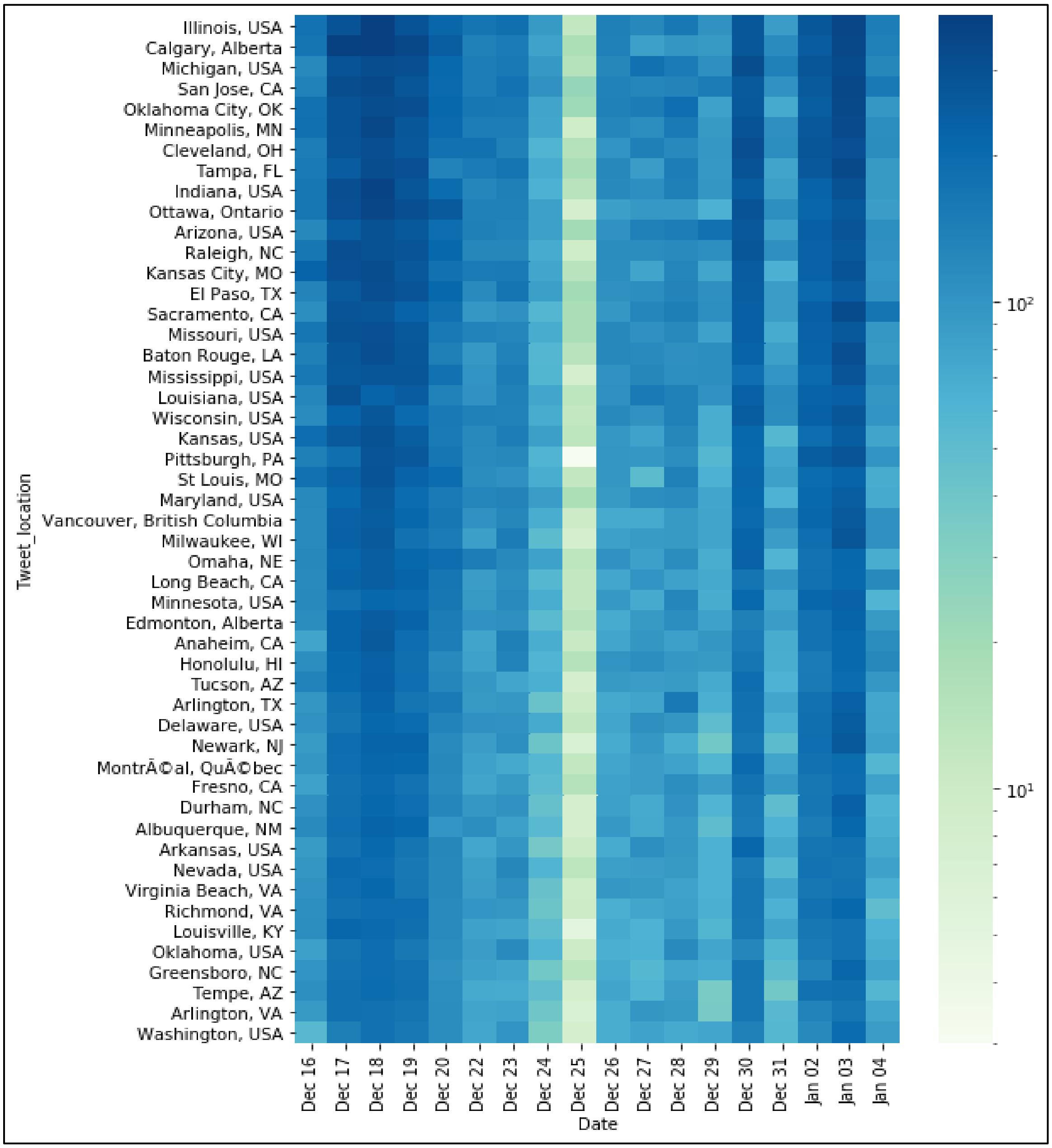


Figure 4-4 Spatiotemporal distribution of relevant tweet (51st to 100th location)

Locations that did not appear in Figure 4-3 and 4-4 were inactive with less than ten tweets a day. These findings indicate the spatial diversity of the transportation-related needs and concerns people express through social media channels and the need to utilize such information to develop new policies meeting the diverse needs people may have in different locations. Moreover, the temporal patterns for almost all locations indicate people were less expressive of such concerns during and immediately before/after a government holiday such as Christmas and New Year.

4.2.2 Temporal Heatmaps of Tweet Keywords

To delve deeper into the understanding of social media interactions on different categories i.e. shared mobility, vehicle technology, built environment, user fees, telecommuting, and e-commerce, temporal heatmaps of tweet keywords were generated (Figure 4-5).

The word frequencies in the heatmaps indicate that people tweeted more about user fees and e-commerce, followed by vehicle technology, telecommuting, built environment, and shared mobility. This indicates the potential to utilize such information to rank people's social media interactions and leverage social sharing platforms to promote user interests on emerging trends based on similar word clustering. A closer look at the word heatmaps by categories shows the following findings:

Shared Mobility

- 'via' is highly prominent. It is a commonly used word, also an emerging ridesharing platform
- 'car', 'share', 'ride', 'driver' also showed strong presence, followed by 'traffic', 'uber', 'vehicle', 'bird', 'shared', and 'bike'
- 'Uber' was more popular than 'Lyft'
- Emerging platforms such as 'Waze', 'Zipcar', 'escooter', 'uberpool' were found less frequent on Twitter
- 'bike' and 'bicycle' showed less prominence compared to 'car'. This is indicative of the need to leverage social media for bike-sharing

Vehicle Technology

- 'energy' was highly prominent. This is a commonly used word, also a fuel-efficient transportation platform
- 'drive', 'google', 'intelligence', 'connect' also showed strong presence, followed by 'tesla', 'electric', 'map', 'connected', and 'hybrid'
- 'electric' was more popular than 'hybrid'
- emerging platforms such as 'automation', 'artificial', 'automated', 'autonomous' were found less frequent on Twitter
- 'hybrid' and 'autonomous' showed less prominence relative to 'energy'. This is indicative of the need to leverage social media for hybrid and autonomous transport

Built Environment

- 'work' was highly prominent.
- 'home', 'stop', 'school', 'office' also showed strong presence, followed by park', 'walk', 'bar', 'gym', 'station', and 'shop'
- 'park' was more popular than 'gym'

- emerging platforms such as ‘subway’, ‘transit’, ‘bus’, ‘sidewalks’ were found less frequent on Twitter
- ‘pickup’ and ‘dropoff’ showed less prominence. This is indicative of the need to leverage social media for online shopping

User Fees

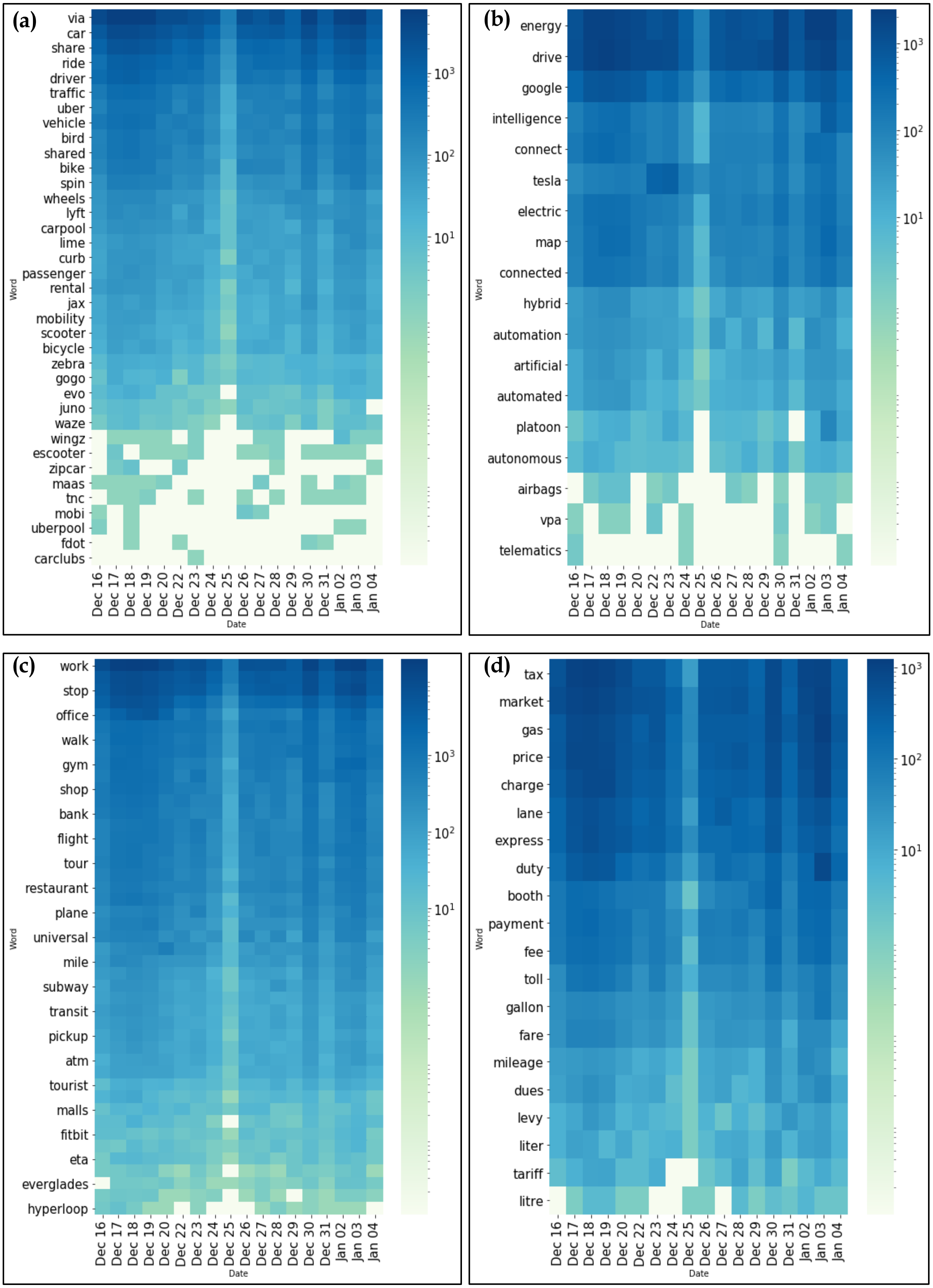
- ‘tax’ was highly prominent.
- ‘market’, ‘gas’, ‘price’, ‘charge’ also showed strong presence, followed by ‘lane’, ‘express’, ‘duty’, and ‘booth’
- Financial activities such as ‘dues’, ‘levy’, ‘liter’, ‘tariff’ were found less frequent on Twitter
- ‘toll’ and ‘tariff’ showed less prominence relative to ‘tax’. This is indicative of the need to leverage social media for the charge on using bridge or road and the duty on imports and exports

Telecommuting

- ‘job’ is highly prominent. This is also an important telecommuting platform
- ‘video’, ‘hours’, ‘phone’, ‘voice’ also showed strong presence, followed by ‘dollar’, ‘mobile’, ‘screen’, and ‘technology’
- emerging platforms such as ‘freelance’, ‘outwork’, ‘telework’, ‘yammer’ was found less frequent on Twitter
- ‘zoom’ showed less prominence relative to ‘phone’. This is indicative of the need to leverage social media for zoom meeting

Ecommerce

- ‘wish’ was highly prominent. This is a popular e-commerce platform
- ‘retail’, ‘online’, ‘trade’, ‘internet’ also showed strong presence, followed by ‘sale’, ‘amazon’, ‘delivery’, ‘target’, ‘shared’, and ‘bike’
- ‘Walmart’ was more popular than ‘Publix’
- platforms such as ‘Macy's’, ‘home depot’, ‘BestBuy’, ‘paperless’ were found less frequent on Twitter
- ‘Walmart’ and ‘target’ were less frequent relative to ‘amazon’. This is indicative of the popularity of ‘amazon’ over ‘Walmart’ and ‘target’ as an e-commerce platform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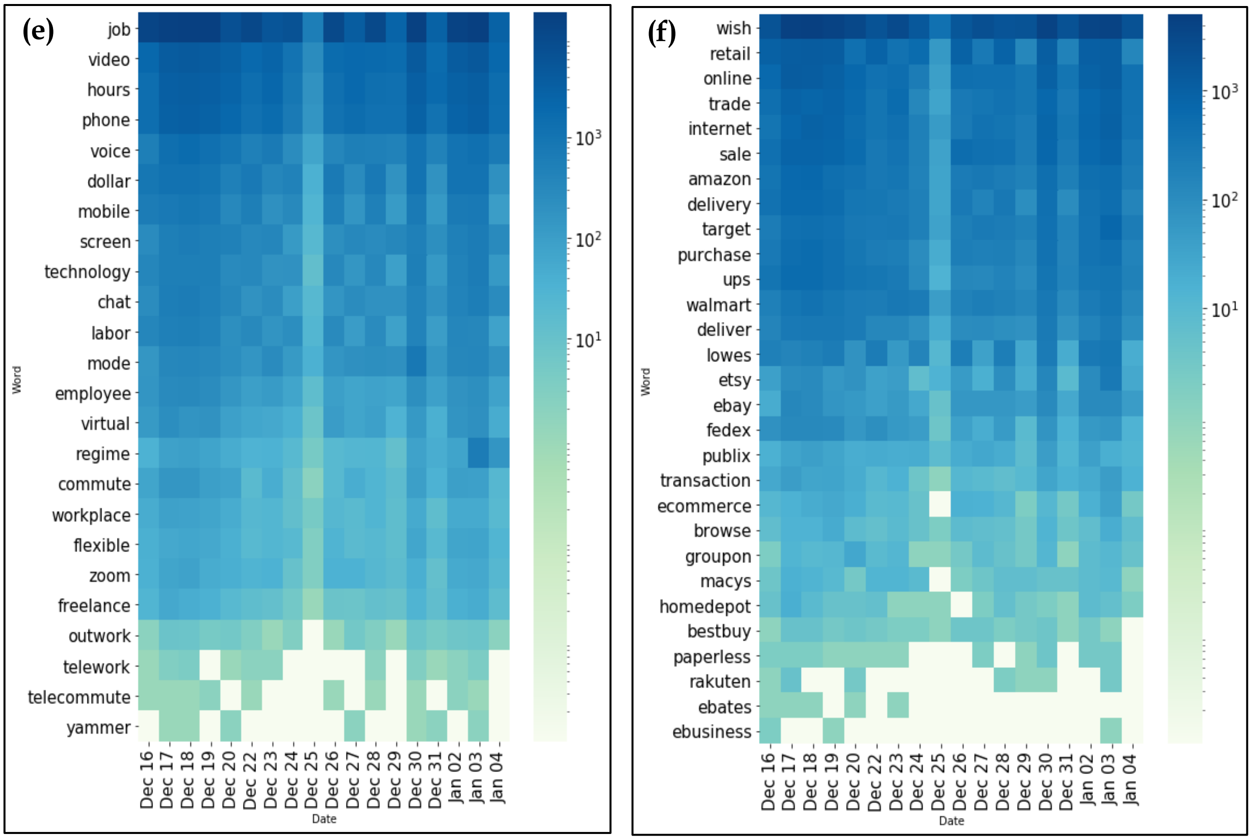

Figure 4-5 Word frequency over time for six categories: (a) shared mobility; (b)vehicle technology; (c) built environment; (d) user fees; (e) telecommuting; (f) ecommerce

4.2.3 Sentiment Analysis

While the heatmaps of tweeting keywords provided the significance of individual keywords representing social media user concerns on transportation and mobility trends, the combined effects of multiple words in each tweet were analyzed to quantify user emotion or sentiments based on such interactions. Sentiment analyses of tweets were performed by the VADER python package and corresponding user sentiments were reported as highly negative, negative, neutral, positive, and highly positive. Figure 4-6 shows the temporal distribution of relative sentiments i.e. percentage distribution (relative to the total number of relevant tweets) of five different sentiment types on a day for each category. Sentiment variations based on tweeting location i.e. sentiments over space are presented in Figure 4-7 to Figure 4-12 for each category i.e. shared mobility, vehicle technology, built environment, user fees, telecommuting, and e-commerce.

Major findings on sentiment over time include:

- Shared Mobility: a majority of the tweets on shared mobility were positive, with relatively uniform distributions over time

- Vehicle Technology: a majority (about half of the tweet) held positive views, about one-fifth expressed negative views, with relatively uniform distributions over time
- Built Environment: The tweets were relatively less positive compared to shared mobility and vehicle technology
- User Fees: A similar pattern with the built environment
- Telecommuting: Like vehicle technology, around half of the tweets expressed a positive view on telecommuting, about one-tenth expressed negative views
- Ecommerce: in general, more positive compared to other categories
- Generally, no clear distinctions across the days; Friday seemed to exhibit more negative tweets on user fees.

Figure 4-6 Sentiment analysis over time for six categories: (a) shared mobility; (b)vehicle technology; (c) built environment; (d) user fees; (e) telecommuting; (f) ecommerce

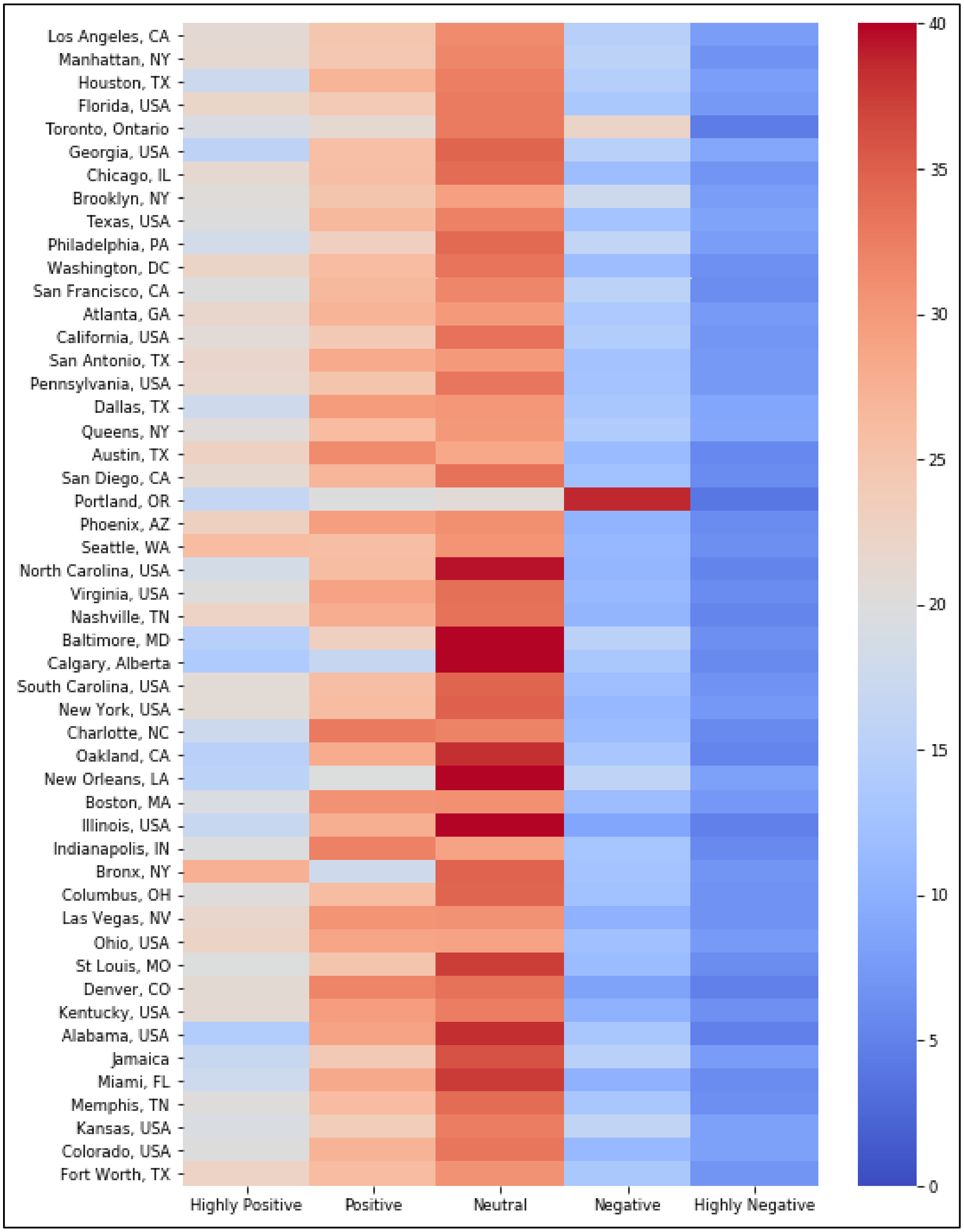

Figure 4-7 Sentiment analysis over space for categories: Shared Mobility

- Portland, OR showed a considerably higher share of negative tweets on shared mobility
- Toronto also showed higher share of negative tweets compared to other locations
- Tweets originated from Bronx, Seattle and Fort Worth seemed to be more likely to be highly positive, and Charlotte, Indianapolis, Denver, Boston, and Austin showed higher shares of positive tweets.

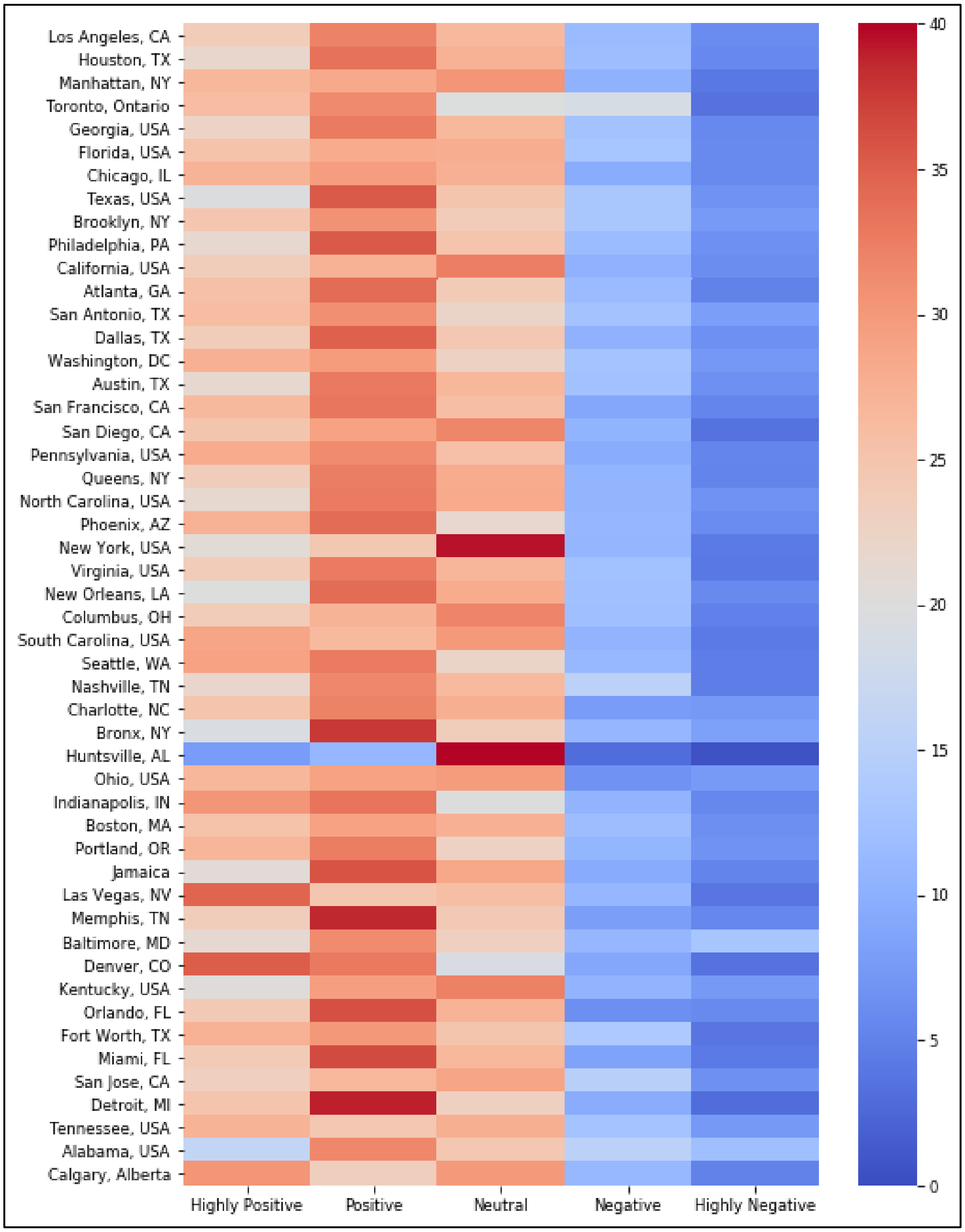

Figure 4-8 Sentiment analysis over space for categories: Vehicle Technology

- Most locations exhibited positive tweets
- Except for Huntsville, AL which remained mostly neutral, and New York
- Alabama also stands out as being less likely to be highly positive and more likely to be negative or highly negative
- Denver and Las Vegas showed considerably higher shares of highly positive tweets related to vehicle technology
- Other places that were more likely to be positive include Detroit, Memphis, Bronx, Miami, Orlando, Jamaica, and to a lesser degree Dallas, Philadelphia, and Texas

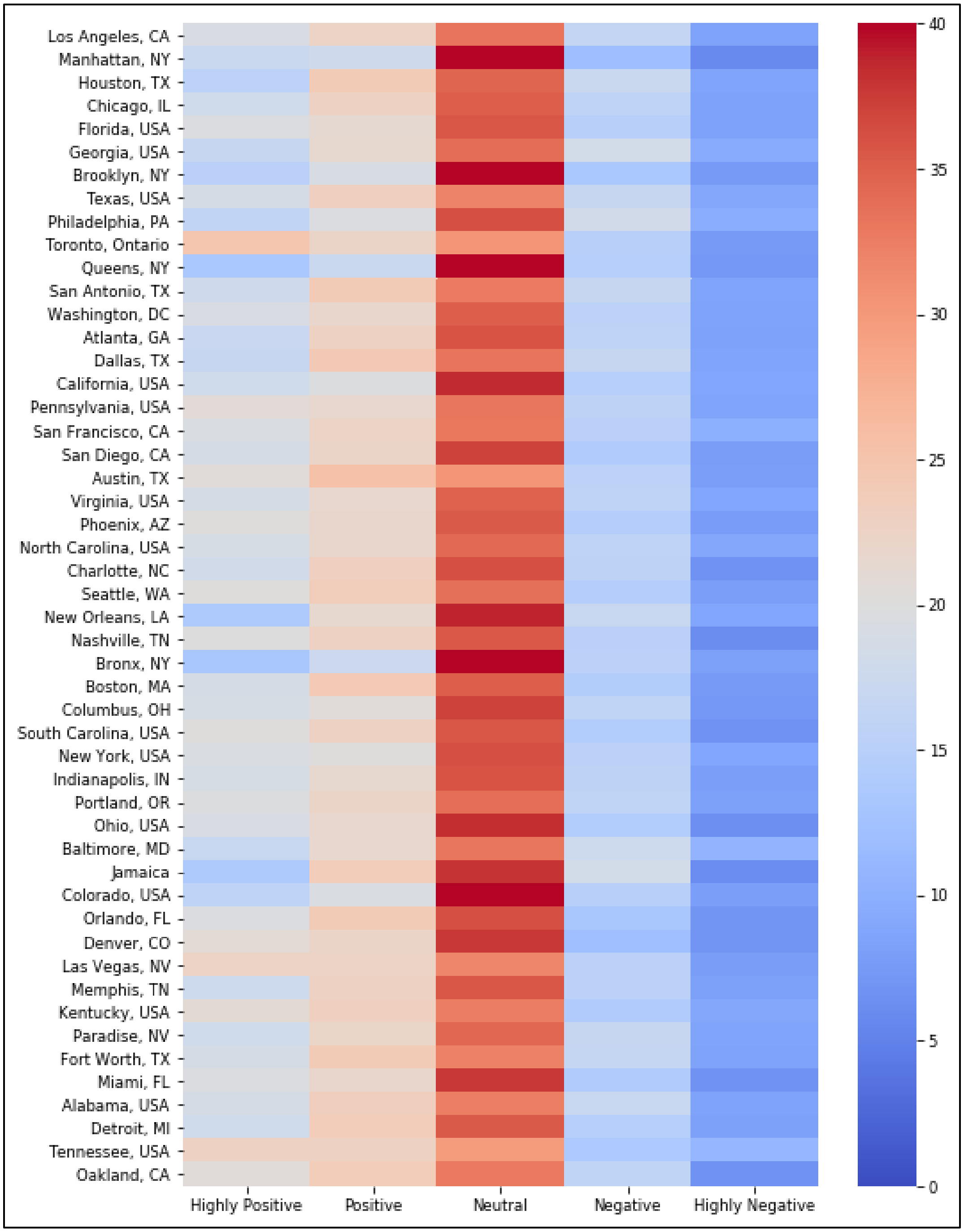

Figure 4-9 Sentiment analysis over space for categories: Built Environment

- Relatively uniform patterns across the locations
- Toronto exhibited higher share of highly positive tweets
- Texas (Houston, Texas, Dallas, Austin, Fort Worth) seemed to more positive than other locations
- Oakland, Manhattan, Jamaica, Ohio, Miami, Nashville, Charlotte were less likely to be highly negative

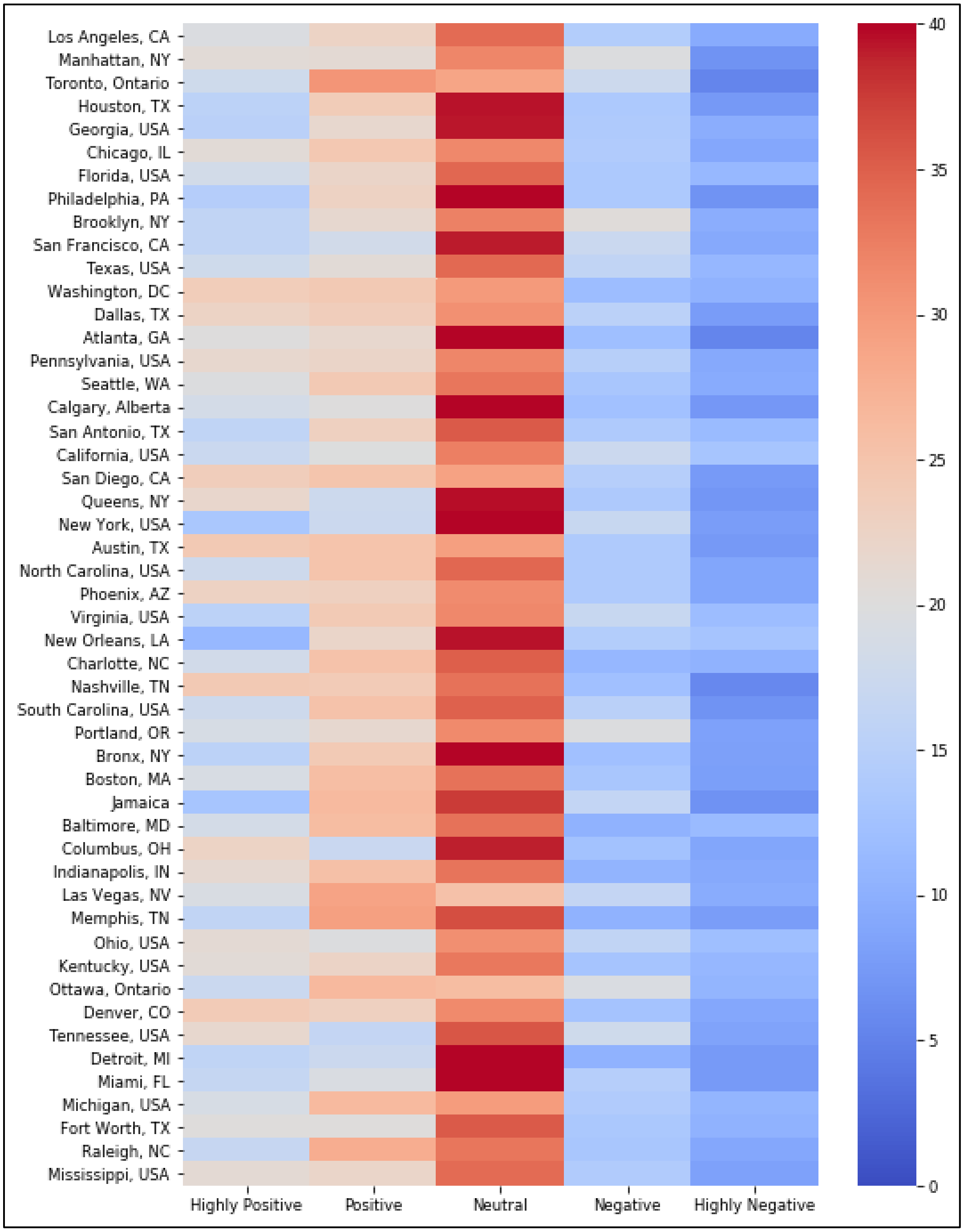

Figure 4-10 Sentiment analysis over space for categories: User Fees

- San Diego, Austin, Nashville, Denver, DC, Phoenix showed higher shares of highly positive tweets
- Toronto also stands out as less likely to be highly negative and more likely to be positive
- Atlanta and Philadelphia were also less likely to be highly negative and more likely to be neutral on user fees

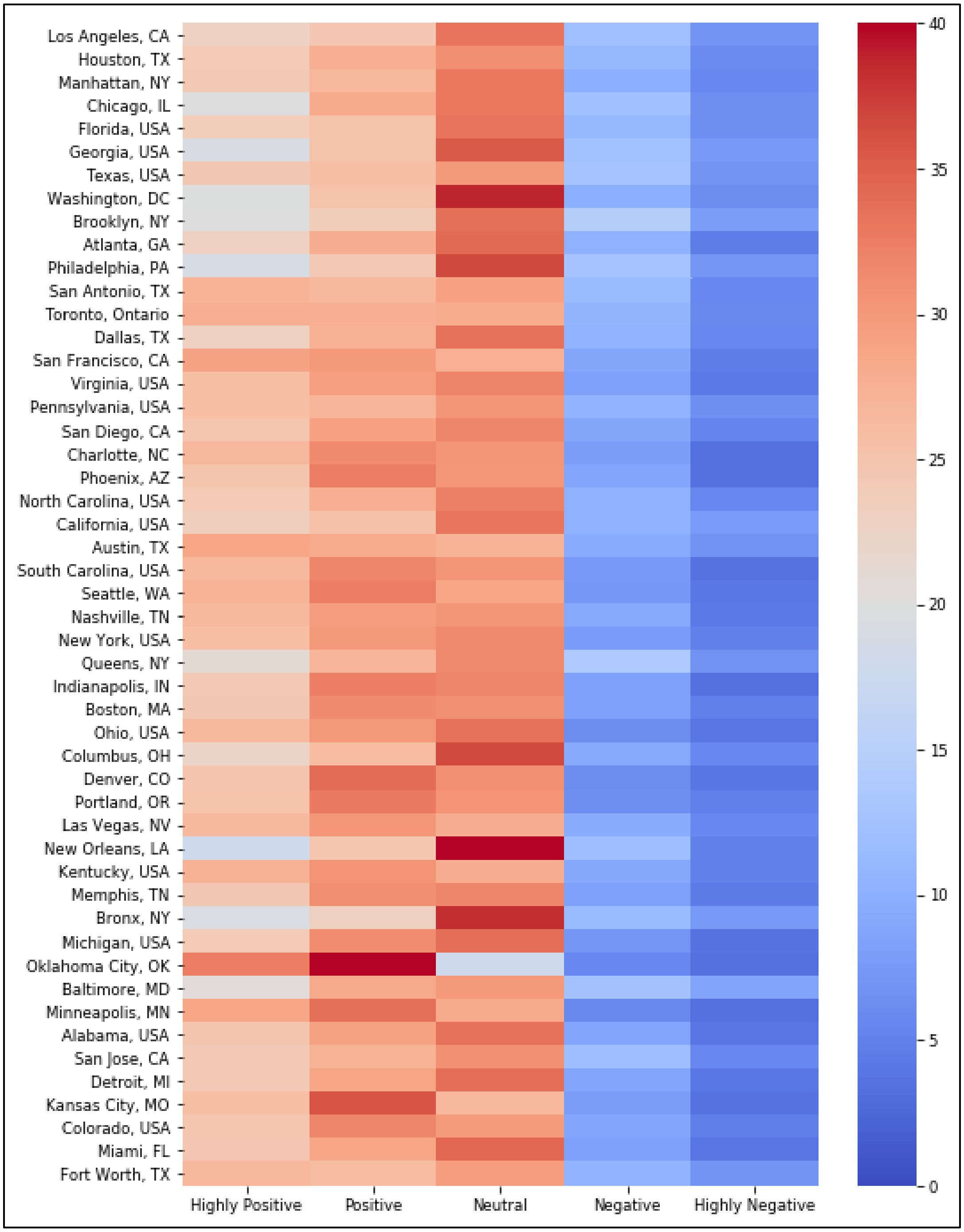

Figure 4-11 Sentiment analysis over space for categories: Telecommuting

- Oklahoma and Minneapolis showed considerably higher shares of positive tweets than other locations
- Interestingly, Georgia, New Orleans, Chicago, DC, Brooklyn, Bronx, Philadelphia, and Baltimore were less likely to be highly positive, and more likely to be negative

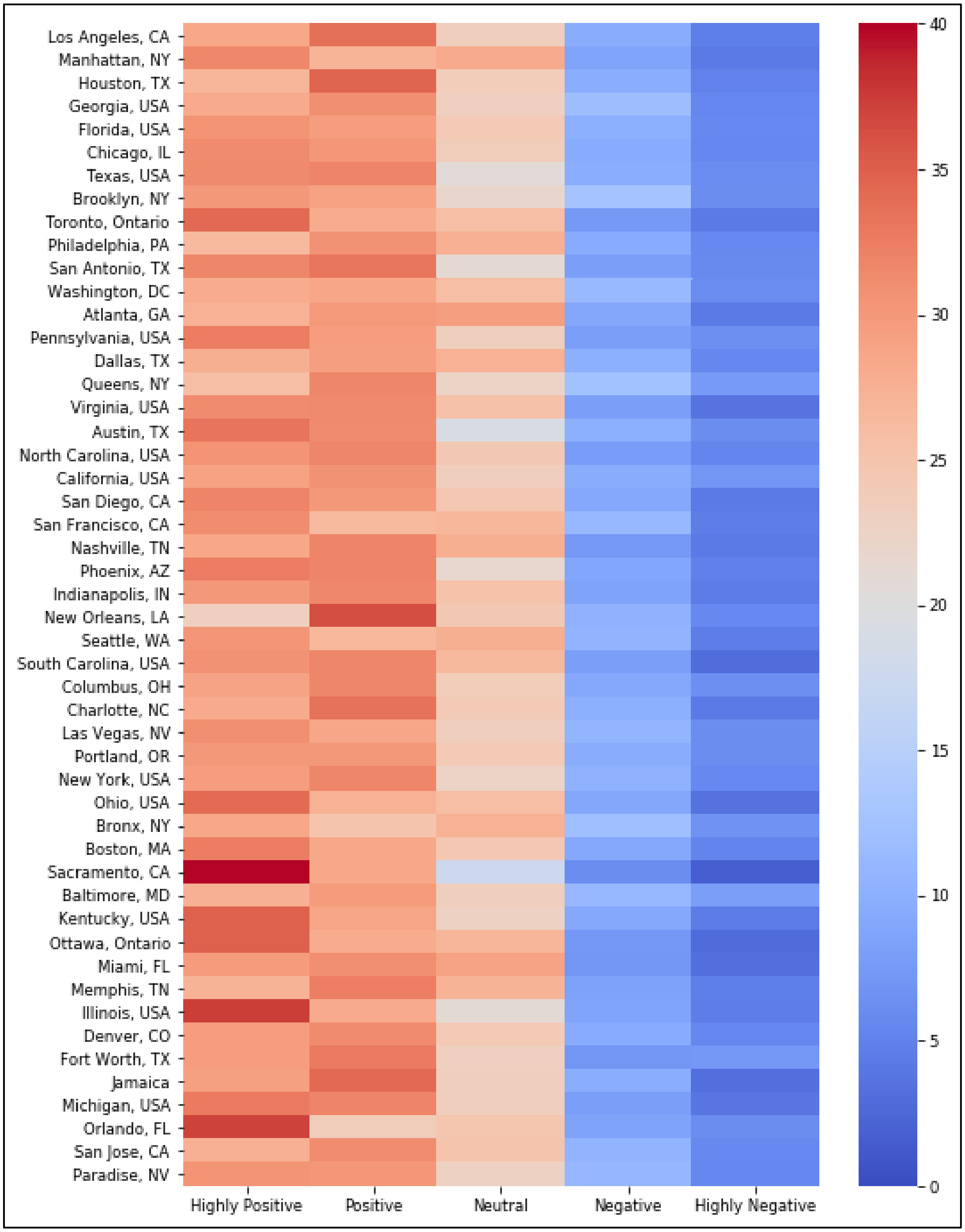

Figure 4-12 Sentiment analysis over space for categories: Ecommerce

- Sacramento, Illinois, and Orlando stand out with highly positive views on e-commerce, followed by Kentucky, Ottawa, Michigan, Boston, Ohio, Toronto, Austin, Phoenix, among others.
- Baltimore, Bronx, Queens, Brooklyn were associated with higher shares of negative tweets.

A few key observations from sentiment analysis are summarized here:

- About one-third conversations, overall, were neutral in all categories.
- More importantly, comparisons across different categories indicated that tweets carried more positive views on vehicle technology, telecommuting, and e-commerce, whereas more negative views on shared mobility, user fees, and built environment.
- Uniform daily distributions of different sentiments types were also observed among different trend categories.
- Tweets in different locations predominantly carried neutral views for all different categories. However, on shared mobility, Portland (or) and Toronto were found more negative.
- Overall, most locations showed a more positive attitude towards shared mobility, vehicle technology, telecommuting, and e-commerce, whereas relatively more negative on the built environment and user fees.

4.2.4 Topic Modeling

Finally, the study adopted a topic modeling approach (discussed in section 3.3.4.3) to investigate how different combinations of words in the data may constitute social interaction topics of transportation trends. While sentiment analyses helped to quantify positive, neutral, or negative attitudes of social media users, topic models typically provide more insights into the actual topics that exist in text data. Topic coherence is the average or median of the pairwise word-similarity scores of the words in the topic, and it has been used to specify the number of unique topics (Ahmed et al. 2020). Good topic modeling depends on higher coherence which depends on two predefined parameters: (a) number of topics and (b) number of iterations. The optimal number of topics and iterations were estimated after several trials. The LDA program in Python provides two variables, alpha and beta, which help to fine-tune the optimal number of topics and iterations as well as a good coherence value. Here, alpha represents document-topic density. With a higher alpha, documents are made up of more topics, and with lower alpha, documents contain fewer topics. Beta represents topic-word density. With a higher beta, topics are made up of more words in the corpus, and with a lower beta, they consist of fewer words.

A good topic model output should contain a minimum amount of overlap of words among the topics. So, the optimum number of topics is an important parameter in topic modeling for a good result. Based on the topic coherence value for the different models having a different number of topics, the optimum number of topics was determined for shared mobility, vehicle technology, built environment, user fees, telecommuting, and e-commerce, which was later used in the topic modeling function as a parameter.

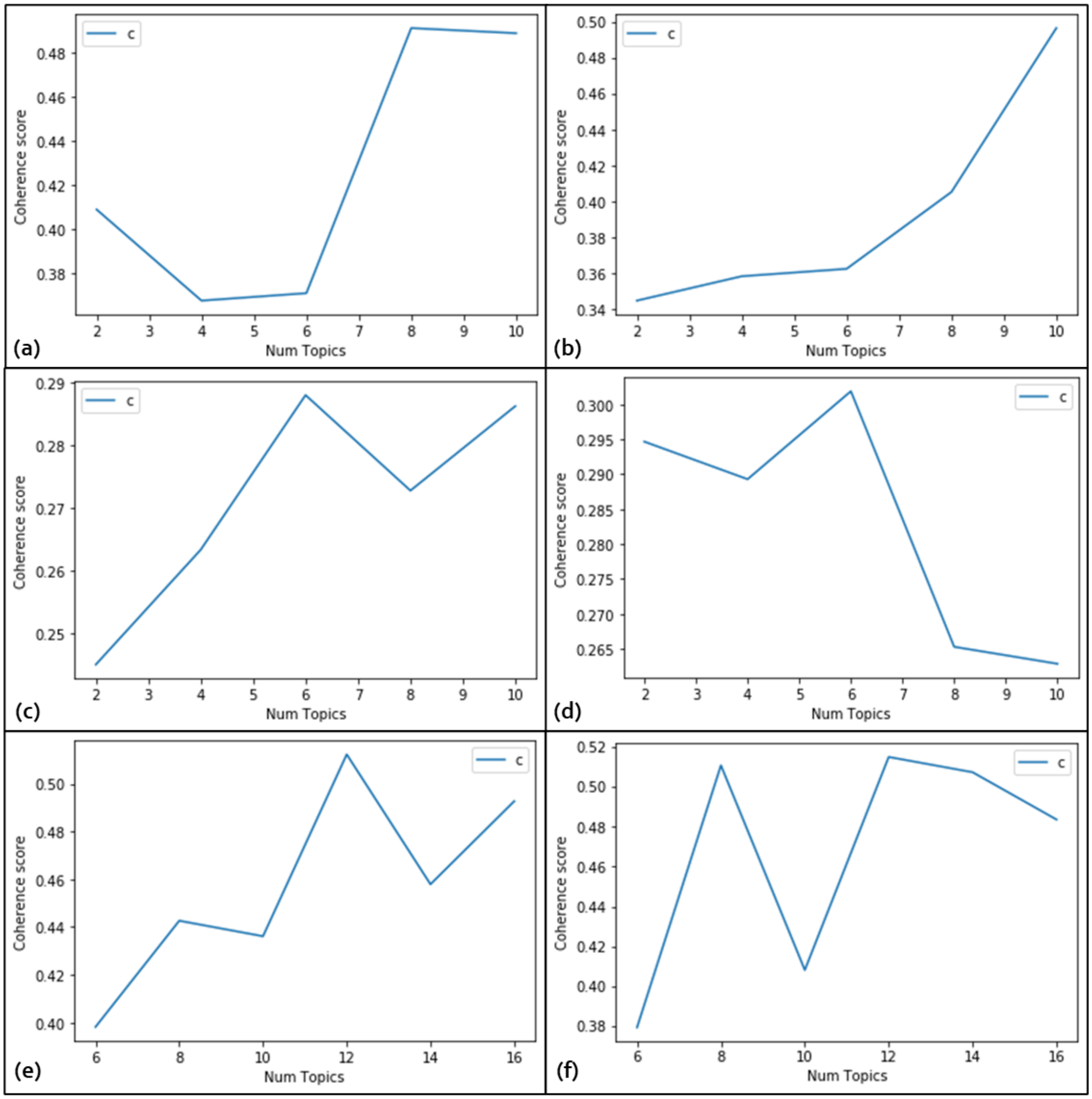

Figure 4-13 Coherence score for the different number of topics: (a) shared mobility; (b) vehicle technology; (c) built environment; (d) user fees; (e) telecommuting; (f) ecommerce

Figure 4-13 shows the changes in coherence, concerning a different number of topics. Normally at an optimal number of topics, the coherence score suddenly drops after having peak value (User fees, Telecommuting). If no sudden drop of coherence after having peak was experienced or model outputs had no distinct topics with a minimum level of overlap of words, the model was run at a different number of topics until getting results having distinct topics with a minimum level of overlap of words (Shared Mobility, Vehicle Technology, Built Environment, Ecommerce). For example, the shared mobility category is described here. After running the model for a different number of topics in the case of a shared mobility category, it was found that at topic number 4 the model gave distinct topics with a minimum level of overlap of words among 4 topics (Figure 4-14 and 4-15). The visualization for the remaining 5 categories is presented in Appendix A and B.

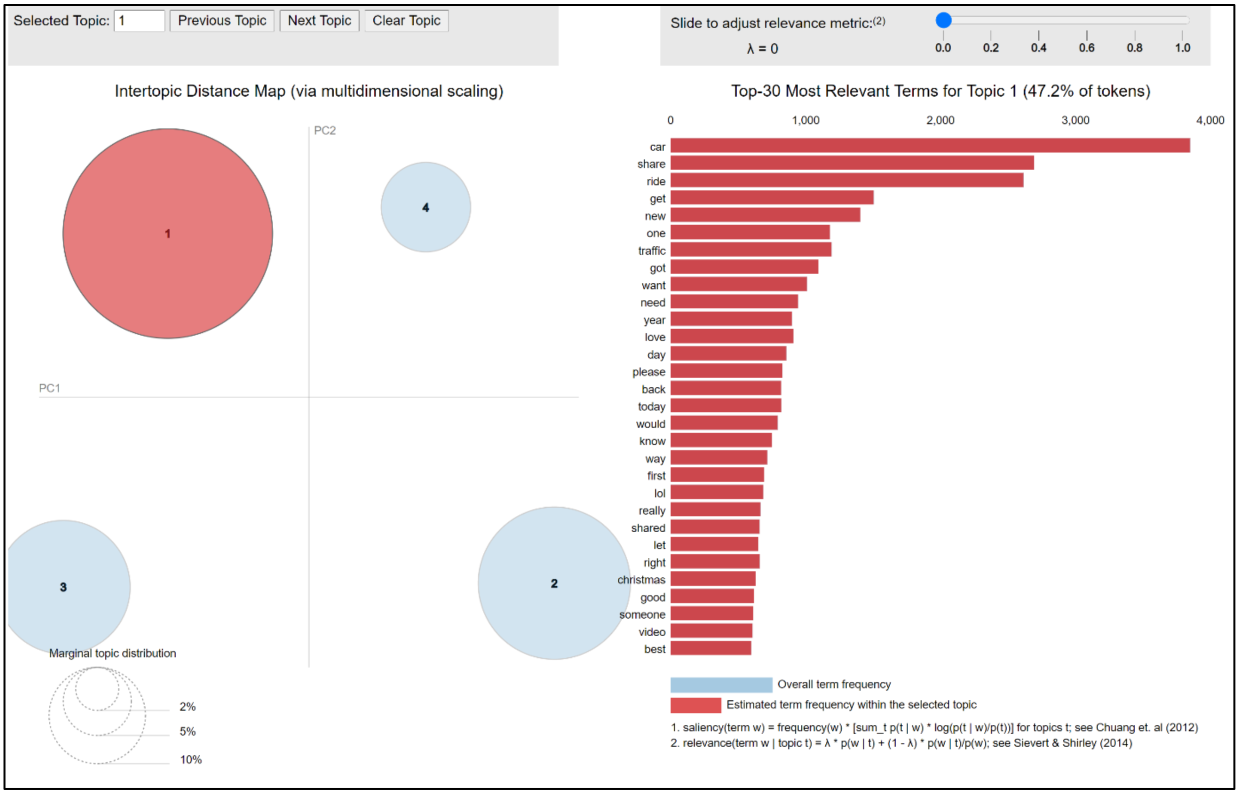

Figure 4-14 LDAvis intertopic distance map for shared mobility

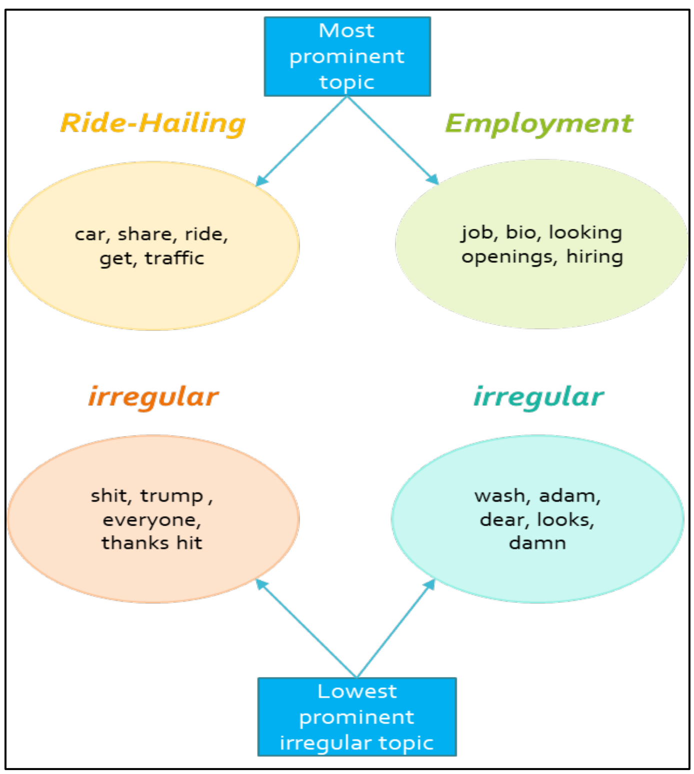

Figure 4-15 Visualization of topics generated for shared mobility

A total of 17 topics related to emerging transportation tends to have been reported (Table 4-2). Table 4-2 reports the topic modeling coherence score for each category as well as the probable interaction topics with their probability in that category and the five most frequent associated words contributing to the formation of a topic with their probability at that topic (in brackets). Only the top 5 words were reported here for illustration purpose.

Table 4-2 Emerging Transportation Trends Related Most Coherent Topics

Trend Category *(Coherence score)*	**Interaction Topics**	**Topic Probability**	**Most probable words incoherent topic**
Shared Mobility ***(0.363)***	Ride-Hailing	0.472	Car (0.016), share (0.011), ride(0.011), get(0.006), traffic (0.005)
	Employment Opportunity	0.192	Job(0.027), bio(0.026), looking(0.017), openings (0.017), hiring(0.12)
Vehicle Technology ***(0.321)***	Fuel Efficiency	0.561	Energy(0.026), drive(0.016), tesla(0.008), map(.005), electric(.005)
	Trip Navigation	0.168	Google(0.039), discover(0.03), big(0.022), map(.009), coming(0.008)
Built Environment ***(0.325)***	Daily Activities	0.569	home(0.012), Work(0.011), job(0.023), stop(0.007), school(0.007)
	Shopping	0.152	Bus (0.017), car(0.016), times(0.007), cycle(0.007), shop (0.005)
	Recreation	0.063	Park(0.023), station (0.023), incident (0.01), school (0.007), college (0.007)
User Fees ***(0.338)***	Gas Price	0.582	Price(0.01), market(0.01), gas(0.01), charge(0.007), duty(0.005)
	Tax and Expressway	0.064	dollars(0.023), tax(0.019), trip(0.009), express(0.006), booth(0.006)
	Lane Blockage	0.065	lane(0.018), blocked(0.013), FedEx(0.013), avenue(0.012), drive(0.012)
Telecommuting ***(0.353)***	Holiday	0.5	call(0.032), Christmas(0.026), amazing(0.023), business(0.022), tonight(0.021)
	Healthcare	0.303	Healthcare(0.06), nurse(0.01), specialist(0.044), care(0.045), video (0.022)
	Supply Chain Management	0.055	manager(0.036), operations (0.021), retail(0.036), mobile(0.026), supply chain(0.023)
	Customer Services (Recommendations)	0.077	anyone(0.137), recommend(0.134), customer service(0.048), labor(0.043)
	Sales (Hiring)	0.266	Great(0.06), fit(0.042), sales(0.041), hiring(0.040), opening(0.033)
Ecommerce ***(0.390)***	Sales (Online)	0.523	Wish(0.023), summer(0.01), kid(0.01), online(0.006), sale(0.006)
	Customer Services (Item Delivery)	0.192	customer service(0.025), item(0.01), hiring (.078), team(0.05)

People primarily discussed ride-hailing and employment opportunities as part of shared mobility. On vehicle technology, interactions mainly included topics on fuel efficiency and trip navigations. Regular activities on a day-to-day basis are among the built environment topics in addition to shopping and recreational activities. Under the user fees category, people were more concerned about gas price, tax, and expressways along with their probable frustration towards lane blocks while driving. On telecommuting, people talked more about the holiday season and healthcare activities, customer services related to item delivery was among the predominant topics on e-commerce. Such topics and associated words provide better insights on how to identify and connect to social media users based on their topics of interest and the use of specific keywords that can maximize influence.

4.3 Limitations

This study results showed that there seem to be significant potentials for using social media data to develop models for the identification of emerging transportation indicator and long-term planning purposes. However, special caution is required to the biases associated with social media data, which is reducing, as social media users are growing to make the sample a close representation of the population. The acquisition cost of obtaining the data for prediction of future travel trends through surveys or from various other sources is significantly large. Twitter is a very cheap way to a reliable source of data that encompasses information revealed by users in realistic situations, especially if the data comes with text content, then such data is free from sampling, surveying, or laboratory biases. The results of the Spatio-temporal distribution of relevant tweets and their sentiments are valuable information for transport planning, management, and operation purposes concerning future transportation trends.

Twitter data cannot cover all discussion topics or sentiment of people which is a limitation of the study as everyone does not use twitter or every user does not tweet about the specific topic. Another limitation is that Twitter data was not able to collect all the tweets during that period as the streaming API used for collecting tweets. Because that specific API does not allow collecting all data. To make this type of online social media research more authentic and comprehensive, a different type of paid twitter API (Power track, Enterprise) and other social media platforms (Facebook, LinkedIn, etc.) can also be used for future research which will collect most of the tweets. Moreover, further research like, the topical analysis, the sentiment analysis, and the frequency analysis on the twitter dataset are encouraged to perform separately to explore Emerging transportation trends to have a broad overview.

4.4 Summary of Tweet Analysis

Transportation researchers, in recent times, used SMPs extensively for problems related to travel demand forecasting, activity pattern modeling, transit service assessment, traffic incident, and disaster management among others. Yet, there is still much more to explore how such information can contribute to understanding public perception and attitude towards emerging transportation trends and mobility indicators. As such, the goal of this study is to mine and analyze large-scale public interactions from SPMs enriched with time and location information and develop comparative infographics of emerging transportation trends and mobility indicators using natural language processing and data-driven techniques.

About 13M tweets for about 20 days (Dec 16th, 2019- Jan 4th, 2020) were collected using Twitter API. Tweets closely aligned with emerging transportation and mobility trends such as shared mobility, vehicle technology, built environment, user fees, telecommuting, and e-commerce were identified. Data analytics captured Spatio-temporal differences in social media user interactions and concerns about such trends as well as topics of discussions formed through such interactions. Key observations include:

- Los Angeles, Manhattan, Houston, and Chicago are among the highly visible cities discussing such trends. Likewise, states such as FL, GA, TX, and Washington D.C showed prevalence.
- In contrast, cities like Detroit (MI), Paradise (NV), Las Vegas (NV), Oakland (CA), Denver (CO), Memphis (TN), and states like AL, CO, KY, OH were found to interact less on transportation trends.
- Being neutral overall, people carried more positive views on vehicle technology, telecommuting, and e-commerce, while being more negative on shared mobility, user fees, and the built environment.
- Uniform daily distributions of different sentiments types were also observed among different trend categories.
- People primarily discussed ride-hailing and employment opportunities as part of shared mobility. On vehicle technology, interactions mainly included topics on fuel efficiency and trip navigations.
- Regular activities on a day-to-day basis are among the built environment topics in addition to shopping and recreational activities.
- Under the user fees category, people were more concerned about gas price, tax, and expressways along with their probable frustration towards lane blocks while driving.
- For telecommuting and e-commerce, major conversations include online sales, healthcare-related activities, customer services on item delivery.

The social media data-driven framework presented in this study would allow real-time monitoring of transportation trends by agencies, researchers, and professionals. Potential applications of the work may include: (i) identify spatial diversity of public mobility needs and concerns through social media channels; (ii) develop new policies that would satisfy the diverse needs at different locations; (iii) leverage SMPs to promote user interests on emerging trends based on similar word clustering; (iv) design and implement more efficient strategies to improve and influence public interest and satisfaction. While data biases may exist in such an approach, large-scale observations would help to predict patterns with heightened statistical power.

5 IMPACT ASSESSMENT SURVEY

A web-based survey was developed to help assess the significance of 18 identified trends. This qualitative assessment approach is taken considering that while we may have a relatively long-standing understanding of the impacts of the conventional economic conditions and demographics factors, these emerging trends are just arriving and probably still evolving. Given the lack of observed historical data to support statistical analysis and data analytics, this panel survey will provide a qualitative assessment of the emerging trends. The following subsections describe the identified trends, survey implementation process, data analysis, results, and summary conclusion from the survey.

5.1 Identified Trends

This section provides the necessary background (with statistics obtained from reliable sources) for each trend to the respondents, thus allowing the respondents to provide a more reliable assessment of the impact of the trends. A list of the identified trends along with the brief descriptions was presented to the respondents for passenger travel demand (Table 5-1). Similarly, Table 5-2 represents the identified trends along with the brief descriptions that were presented to the respondents for freight transportation demand.

Table 5-1 Identified Trends for Passenger Travel Demand

ECONOMIC TRENDS	
Income inequality	Income inequality (average income difference between higher and lower population quantiles) in the US is currently at its highest level since the Census Bureau began tracking five decades ago (Source: US Census Bureau).
GDP shift from manufacturing to service	The manufacturing industry's percent share of GDP has continuously fallen since 1980 while that of the service industry continued to rise (Source: US Bureau of Economic Analysis).
Increasing E-commerce sales	E-commerce retail sales in the US have increased annually since 2000, maintaining an average of 15% increase annually from 2010 to 2018 (Source: US Census Bureau).
DEMOGRAPHIC TRENDS	
Slow population growth	US national population grew by just 0.6% between July 1, 2017, and July 1, 2018, which is at its slowest pace since 1937 (Source: US Census Bureau).
Aging population	The number of people 65 years and older in the US is expected to exceed those under the age of 18 by 2035 (Source: US Census Bureau).
Increasing race/ethnicity mix	Distribution of race in the US population is more diverse in the younger (<40) population groups than the older (≥40) groups (Source: US Census Bureau).
Smaller household size	The average US household size has declined steadily from 3.33 in 1950 to 2.63 in 2018 (Source: US Census Bureau).
Delay in retiring	More people continue working beyond the age of 65, resulting in higher shares of labor forces above age 55 (Source: US Census Bureau).

Table 5-1, continued.

DEMOGRAPHIC TRENDS	
Delay in marriage and childbearing	There has been a small but significant increase in the number of childless women in their early 30s over the past decade (Source: US Census Bureau).
Urban population growth	The US urban population increased by 12.1 percent from 2000 to 2010, outpacing the nation's overall growth rate of 9.7 percent for the same period (Source: US Census Bureau).
Increasing awareness of environmental issues	In the past decade, more and more people became aware that we need to sustainably manage our planet's resources and ecosystems (Source: Huffington Post).
TECHNOLOGICAL TRENDS	
Availability of communication technologies	Increasing internet and cellular connectivity to work, school, shopping, and social opportunities without physical travel.
Shared mobility	Transportation services and resources that are shared among users on an as-needed basis include carsharing (e.g. Zipcar), bike-sharing, and ridesharing (e.g., Uber and Lyft).
Autonomous and connected vehicles	Self-driving cars and cars that can communicate with other vehicles or entities.
Alternative fuel and electric vehicles	Vehicles that use alternative fuels, such as biodiesel, electricity, and natural gas help to reduce carbon emissions and increase energy security.
Micro mobility	Use of bicycles, scooters, or any other non-motorized means for short-distance trips or connection to transit trips.
Automation in jobs	Increasing Artificial Intelligence and automation can result in a reduction in touch labor, turning what once took multiple technicians into work that one person can do in a matter of hours.
Increasing international trade volume	Total combined import and export goods value grew with an annual growth rate of about 3.5% from 2010 (3.19 trillion USD) to 2018 (4.2 trillion USD) (Source: US Census Bureau).

Table 5-2 Identified Trends for Freight Transportation Demand

ECONOMIC TRENDS	
GDP shift from manufacturing to service	The manufacturing industry's percent share of GDP has continuously fallen since 1980 while that of the service industry continued to rise (Source: US Bureau of Economic Analysis).
Increasing E-commerce sales	E-commerce retail sales in the US have increased annually since 2000, maintaining an average of 15% of increase annually from 2010 to 2018 (Source: US Census Bureau).
TECHNOLOGICAL TRENDS	
Automated freight vehicles	Self-driving freight truck that can communicate with other vehicles or entities.
Alternative fuel freight vehicles	Freight vehicles that use alternative fuels, such as biodiesel, electricity, and natural gas help to reduce carbon emissions and increase energy security.
Increasing international trade volume	Total combined import and export goods value grew with an annual growth rate of about 3.5% from 2010 (3.19 trillion USD) to 2018 (4.2 trillion USD) (Source: US Census Bureau).

5.2 Sample Description

Figure 5-1 shows the basic sample composition by employment type, position at work, work experience, and education levels. It shows that the sample is well distributed among different types of employment (government agencies, private firms, academia, and non-profit agencies), and various work positions (management, project manager, professional, etc.). Most of the respondents (118) have a master's degree or higher, which reflects the knowledge and experiences of the group. Although about one-third of the respondents indicated less than 5 years of experience, a follow-up investigation with the respondents indicated that this only reflects the experience at their current position, rather than the overall professional experience they have had including previous positions.

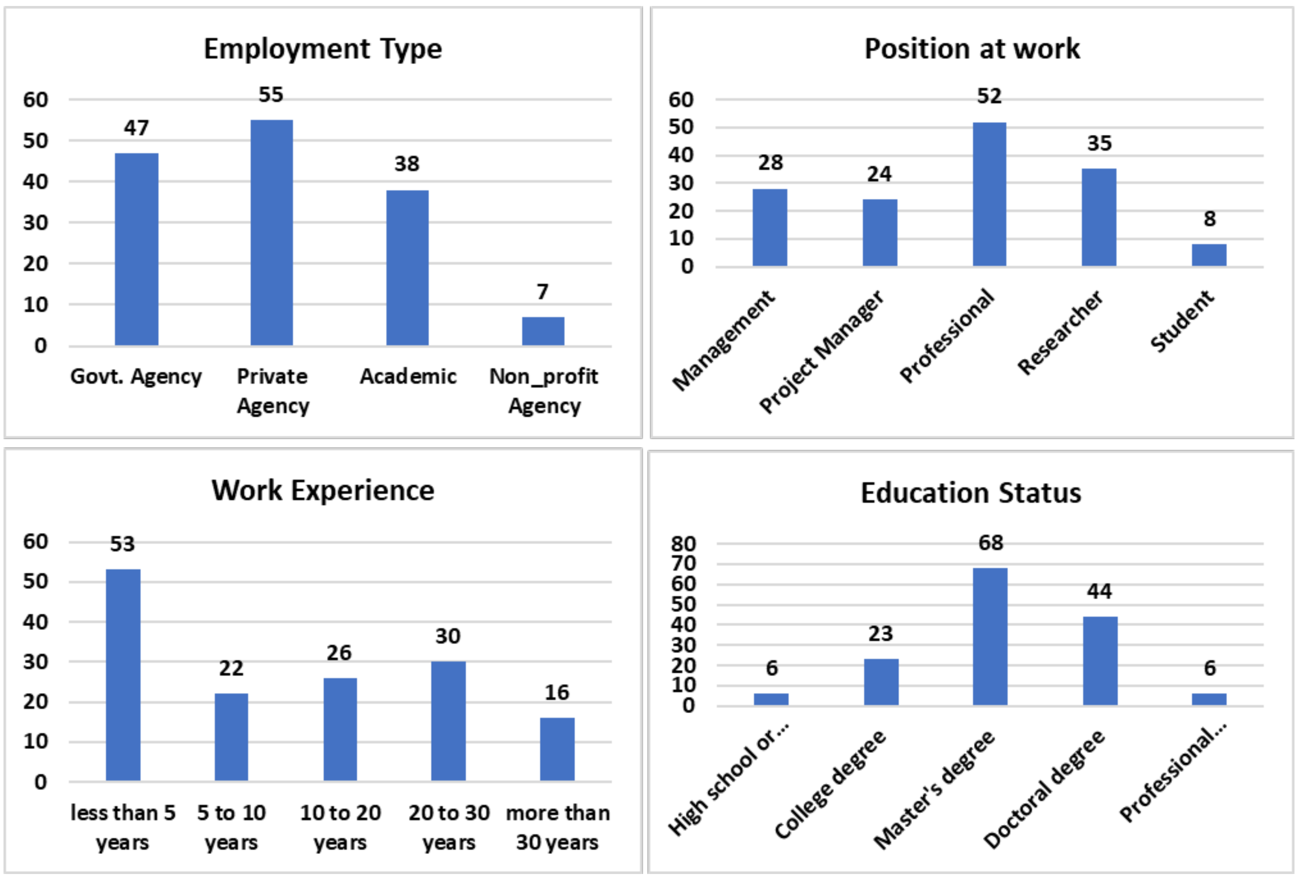

Figure 5-1 Sample composition by work and education attributes

5.3 Survey Data Analysis Methodology

The analysis of the survey results aimed at addressing the following research questions:

- Based on all the responses, what are the most likely impact of each trend on travel demand?
- How would the respondents' assessment of the impacts of the trends differ by segment, including employment type, position, years of experience, and education level?
- Based on all the responses, how likely would each trend progress in the next 10-20 years?
- How would the respondents' view on the trends' progress differ by segment, including employment type, position, years of experience, and education level?

To address the research questions, three statistical analysis methods were used, including mean indexing, Kruskal-Wallis H test, and Mann-Whitney U Test.

Mean indexing is commonly used in exploratory and descriptive data analysis (Malokin et al., 2015). In this study, it is used as the basis to offer the rankings of the trends. For Q1 above, values of "**-2**" through "**2**" were used to weight the responses from *Decreases VMT Significantly* to *Increases VMT Significantly.* Weighted average scores were calculated for each trend. A negative score means that overall, the trend was considered to have a negative impact on VMT, while a positive score indicates an impact of increasing VMT. Similarly, for Q2, values of "**1**", "**0**" and "**-1**" were assigned to responses of Continue *the Same Trend*, *Level Off*, and *Reversal of the Trend*. Then weighted average scores were calculated for each trend to indicate how likely each trend may progress in the next 10-20 years.

Kruskal-Wallis H test is a non-parametric test that is used for comparing the differences between three or more independent sets of data ("Laerd Statistics. (2020). "The ultimate IBM SPSS guides." ", Jul 24, 2020). In this study, it is used to assess whether each of the trends was rated differently across different groups of respondents based on their employment type, position, experience, and education levels, respectively. The results were interpreted based on the p-values. A significant difference exists across the groups if the p-value is less than 0.1. When significant differences were identified for certain trends, post-hoc pairwise comparison tests (Mann-Whitney U Test) were then conducted to identify which two sets of data have differences. The Statistical Package for Social Sciences (SPSS) was used to conduct these statistical analyses.

5.4 Survey Results

5.4.1 Impacts on Passenger Demand

Figure 5-2 presents the summary of responses in assessing the likely impacts of the 17 identified trends on passenger travel demand in terms of VMT. As it shows, aging population and urban population growth were the top two trends that may significantly decrease VMT, followed by increasing e-commerce sales, availability of communication technologies, and automation in jobs. Other influential factors that may decrease VMT include slow population growth, micro-mobility, and increasing awareness of environmental issues. On the other hand, based on all the responses, connected and automated vehicles (CAVs) and increasing e-commerce were considered as the top two trends that may increase VMT significantly. Delay in retiring was the top trend that would increase VMT moderately. Other influential trends that may increase VMT include smaller household size, GDP shift to service. Overall, increasing race/ethnicity mix, alternative fuel, and electric vehicles were considered by most respondents to have less impact (neutral) on passenger VMT, followed by income inequality and delay in marriage and childbearing.

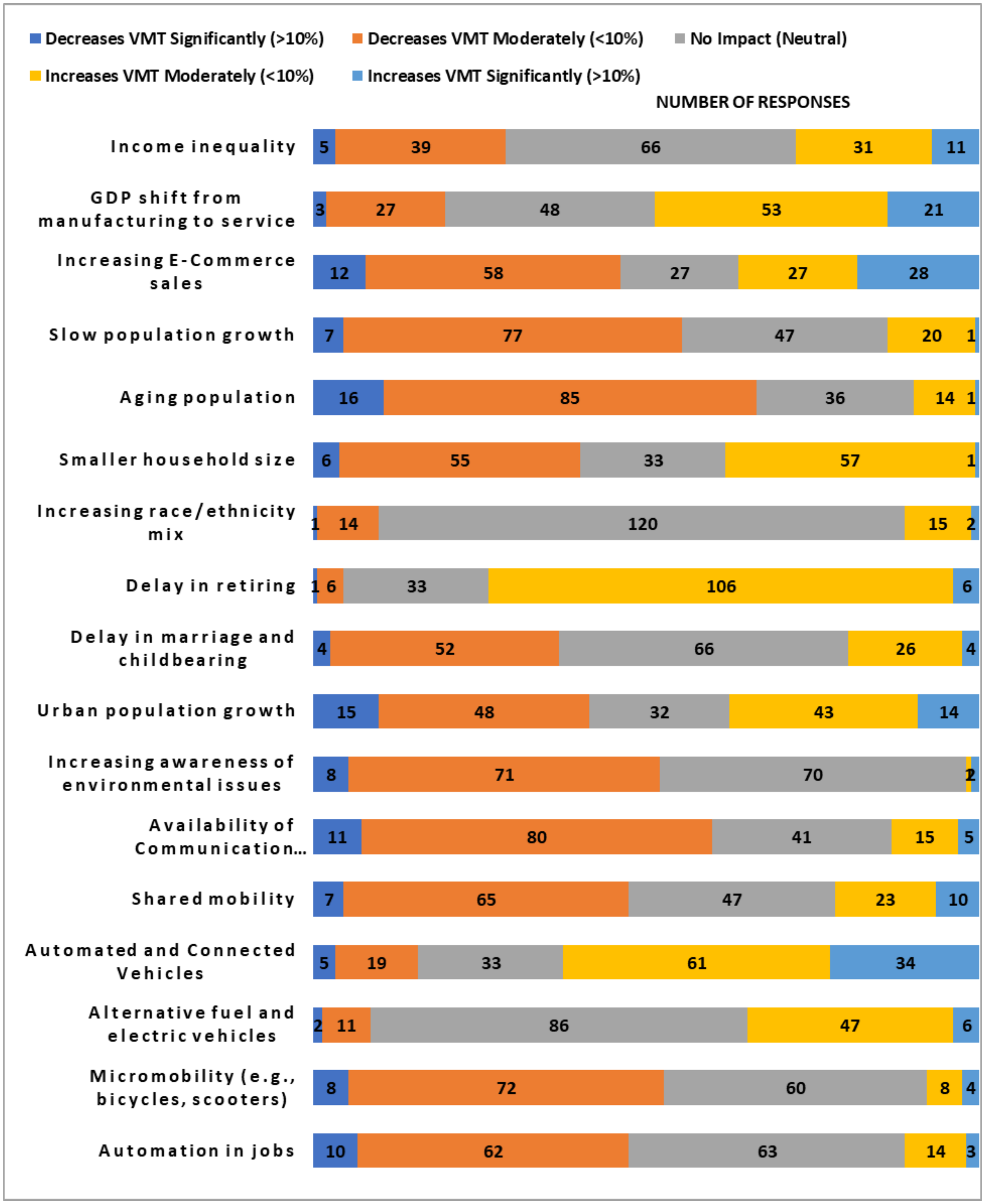

Figure 5-2 Likely impacts of each trend on passenger travel demand in terms of VMT

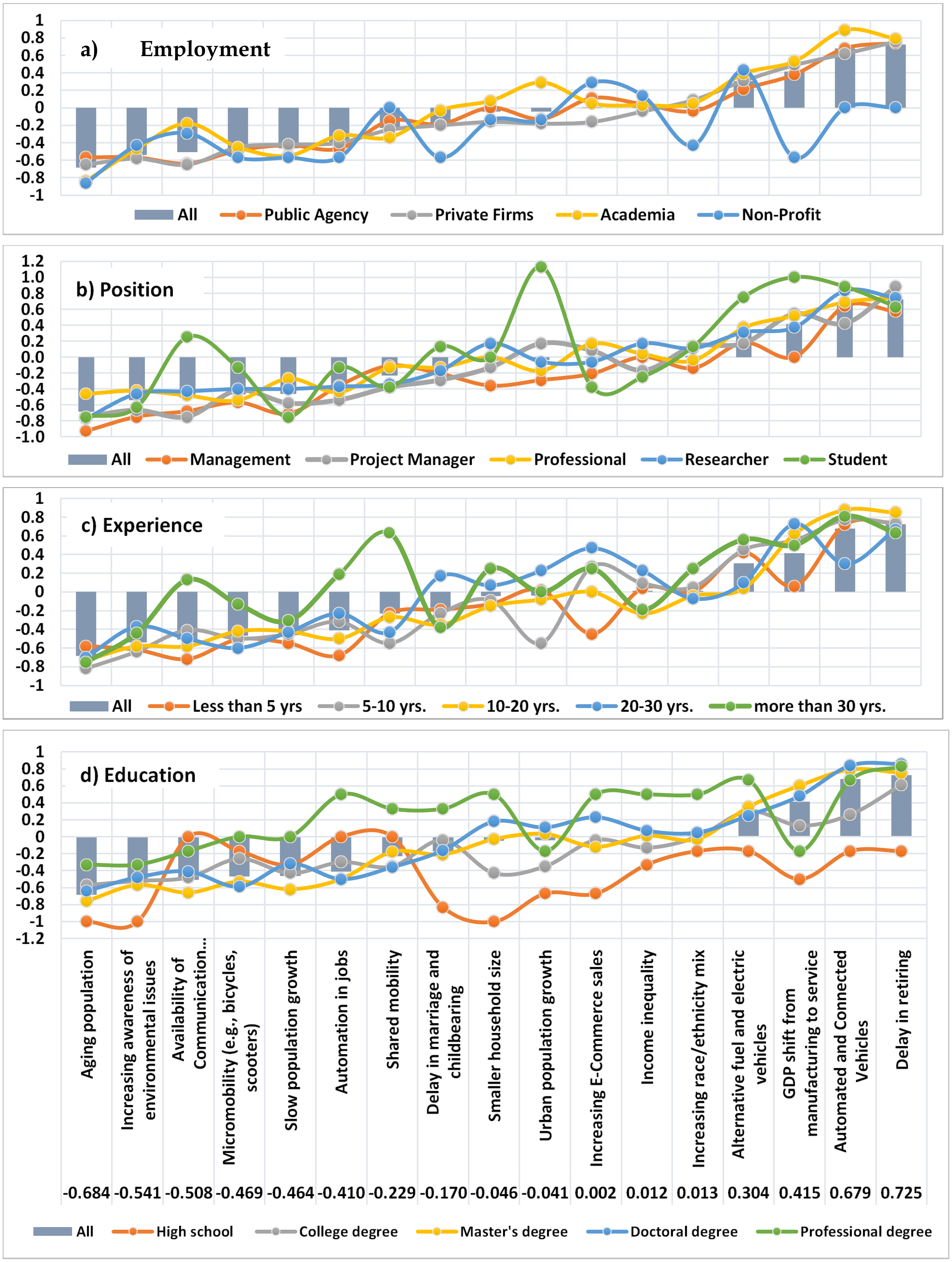

Figure 5-3 Average impacts of each trend by segment

Figure 5-3 presents the weighted average scores (vertical axis) of each trend for all respondents as shown in the grey columns, also by different segmentation groups as shown in the curved lines. There are four charts in Figure 5-3, representing the weighted means of each trend by employment type, position, experience, and education, respectively. All four charts share the same horizontal axis, which reflects the ranking from the smallest value (the highest negative impact on VMT) to the highest value (the highest positive impact on VMT) from left to right.

Looking at the overall results by all respondents, the aging population, increasing awareness of environmental issues, availability of ICTs, micromobility, slow population growth, and automation in jobs had the highest impacts on decreasing passenger VMT. This was generally consistent among respondents across different segments, except that academic respondents gave a significantly lower rating to ICTs in terms of their impacts on decreasing VMT, most likely due to the studies on induced demand due to ICT. This may indicate that the concept of induced demand has yet to be made aware or convincing to those outside of academia.

On the other hand, the respondents collectively believed that delay in retiring, CAVs, alternative and electric vehicles, and GDP shift to service had the highest impacts of increasing VMT, although there were some discrepancies among the segments, which will be investigated in detail in the next subsection.

Shared mobility and delay in marriage and childbearing were considered to have moderate effects on decreasing VMT. Smaller household size, urban population growth, increasing e-commerce sales, income inequality, and increasing race and ethnicity mix were considered to have minor impacts on passenger VMT.

Interestingly, all the economic trends (GDP shifts, income inequality, and increasing e-commerce sales) were on the positive side, increasing VMT either significantly or slightly, while most of the demographic trends were on the negative side, decreasing VMT, except for the delay in retiring, which showed the highest positive impacts on VMT. The technology-related trends showed mixed impacts, some highly discouraged VMT (such as ICT, micromobility and automation), while others were considered to have high impacts on increasing VMT (such as CAVs and alternative fuel and electric vehicles, both related to vehicle technologies).

As explained in the previous section, the Kruskal-Wallis H test and Mann-Whitney U test were conducted to identify whether there are significantly different opinions on the impacts of the trends among the groups. Table 5-3 presents the weighted means by the group for each trend. Grey cells highlight the groups that showed statistically significant differences between the groups, and bolded cells indicate the specific group(s) that significantly differed from the other groups (that are highlighted in grey cells).

It seems that position at work showed the least variation, meaning the respondents' views on the impacts of the trends were generally consistent and not likely to differ by their positions at work. The only trend that showed significant variation was urban population growth, where students gave it a much higher rating in terms of the positive impacts on VMT increase.

Because of employment type, as indicated earlier, respondents in academia were more likely to give less rating to the availability of ICTs on decreasing VMT, probably because of their higher awareness or belief in the induced demand that could potentially result from ICTs. Non-profit agency respondents seemed to underestimate the impacts of a few trends on increasing VMT and demonstrated opposite signs on the impacts of increasing race/ethnicity mix and GDP shift to service, compared to the other groups. They also did not think the delay in retiring would increase VMT.

Looking at years of experience, most of the differences lie in technology-related trends. For example, those with more than 30 years of experience thought ICTs, automation in jobs, and shared mobility would have positive impacts on VMT increase, which was the opposite of the other groups. This might indicate their views of the induced demand or shifted travel-activity patterns that could potentially result from ICT, job automation, and shared mobility. On the other hand, those with 10-30 years of experience gave a significantly lower rating to alternative fuel and electric vehicles in terms of their impacts on increasing VMT. Those with less than 5 years of experience did not think GDP shift to service and e-commerce would be as influential on VMT as the rest of the respondents indicated.

People with different education levels also showed different views on several trends. Automation in jobs was considered as having a positive impact on VMT for those with professional degrees (JD or MD, etc.). CAVs were less likely to increase VMT because of those with college degrees or less, they were also more likely to consider smaller household sizes with a negative impact on VMT. Those with high school degrees considered GDP shift to service and delay in retiring with a negative impact on VMT.

While this analysis provides an understanding of how people view the impacts of the trends and how their views may differ, there is not enough information to relay the underlying reasons or the factors that influenced their choices. During the survey, we asked whether the respondents were interested to know the results of the study and whether they can be contacted for further study. 62 respondents left their email addresses and indicated that we can contact them for further information to improve the study. The next step of this study is to reach out to those respondents and form a focus group session or multiple sessions if necessary, to discuss our findings and look into what considerations went into their selections and what factors might have contributed to the differences in their views.

Table 5-3 Weighted Means for Trend Impact by Respondent Attribute

Avg. Score	Trend	Public agency	Private firms	Academia	Non-Profit	Manage-ment	Project manager	Professional	Researcher	Student	Less than 5 years	5-10 years	10-20 years	20-30 years	more than 30 years	High school	College degree	Master's degree	Doctoral degree	Professional degree
-0.684	Aging population	-0.57	-0.65	-0.84	-0.86	-0.93	-0.75	-0.46	-0.77	-0.75	-0.58	-0.82	-0.73	-0.70	-0.75	-1.00	-0.57	-0.76	-0.64	-0.33
-0.541	Increasing awareness of environmental issues	-0.57	-0.58	-0.47	-0.43	-0.75	-0.67	-0.42	-0.46	-0.63	-0.62	-0.64	-0.58	-0.37	-0.44	-1.00	-0.52	-0.57	-0.48	-0.33
-0.508	Availability of Communication Technologies	-0.64	-0.65	**-0.18**	-0.29	-0.68	-0.75	-0.48	-0.43	0.25	-0.72	-0.41	-0.58	-0.50	**0.13**	0.00	-0.48	-0.66	-0.41	-0.17
-0.469	Micromobility (e.g., bicycles, scooters)	-0.49	-0.45	-0.45	-0.57	-0.57	-0.42	-0.54	-0.40	-0.13	-0.51	-0.50	-0.42	-0.60	-0.13	-0.17	-0.26	-0.53	-0.59	0.00
-0.464	Slow population growth	-0.43	-0.42	-0.55	-0.57	-0.71	-0.58	-0.27	-0.40	-0.75	-0.55	-0.45	-0.42	-0.43	-0.31	-0.33	-0.43	-0.62	-0.32	0.00
-0.410	Automation in jobs	-0.47	-0.40	-0.32	-0.57	-0.36	-0.54	-0.44	-0.37	-0.13	**-0.68**	-0.32	-0.50	-0.23	**0.19**	0.00	-0.30	-0.50	-0.50	**0.50**
-0.229	Shared mobility	-0.15	-0.25	-0.34	0.00	-0.11	-0.38	-0.13	-0.34	-0.38	-0.23	-0.55	-0.27	-0.43	**0.63**	0.00	-0.35	-0.18	-0.36	0.33
-0.170	Delay in marriage and childbearing	-0.19	-0.20	-0.03	-0.57	-0.21	-0.29	-0.13	-0.17	0.13	-0.19	-0.23	-0.35	0.17	-0.38	-0.83	-0.04	-0.21	-0.16	0.33
-0.046	Smaller household size	0.00	-0.16	0.08	-0.14	-0.36	-0.13	0.00	0.17	0.00	-0.13	-0.09	-0.15	0.07	0.25	**-1.00**	**-0.43**	-0.03	0.18	0.50
-0.041	Urban population growth	-0.13	-0.18	0.29	-0.14	-0.29	0.17	-0.17	-0.06	**1.13**	0.02	-0.55	-0.08	0.23	0.00	-0.67	-0.35	0.03	0.11	-0.17
0.002	Increasing E-Commerce sales	0.11	-0.16	0.05	0.29	-0.21	0.08	0.17	-0.06	-0.38	**-0.45**	0.27	0.00	0.47	0.25	-0.67	-0.04	-0.12	0.23	0.50
0.012	Income inequality	0.04	-0.04	0.03	0.14	0.00	-0.17	0.04	0.17	-0.25	0.04	0.09	-0.23	0.23	-0.19	-0.33	-0.13	0.01	0.07	0.50
0.013	Increasing race/ethnicity mix	-0.04	0.09	0.05	**-0.43**	-0.14	0.13	-0.04	0.11	0.13	0.00	0.05	-0.04	-0.07	0.25	-0.17	0.00	-0.03	0.05	0.50
0.304	Alternative fuel and electric vehicles	0.21	0.31	0.39	0.43	0.18	0.17	0.37	0.31	0.75	0.42	0.45	**0.04**	**0.10**	0.56	-0.17	0.30	0.35	0.25	0.67
0.415	GDP shift from manufacturing to service	0.38	0.49	0.53	**-0.57**	0.00	0.54	0.52	0.37	1.00	**0.06**	0.55	0.62	0.73	0.50	**-0.50**	0.13	0.60	0.48	-0.17
0.679	Automated and Connected Vehicles	0.68	0.62	0.89	0.00	0.64	0.42	0.69	0.83	0.88	0.72	0.77	0.88	0.30	0.81	**-0.17**	**0.26**	0.79	0.84	0.67
0.725	Delay in retiring	0.74	0.76	0.79	**0.00**	0.57	0.88	0.75	0.74	0.63	0.74	0.73	0.85	0.67	0.63	**-0.17**	0.61	0.75	0.86	0.83

Note: grey cells highlight statistical differences among the groups; bold cells indicate the group(s) that statistically differed from the other groups.
trends in pink cells are economic-related, in blue cells are demographic-related, in green cells are technology-related.

5.4.2 Trend Progression

Figure 5-4 presents the responses for each trend in three options, continue the trend, level off (no change, maintain an existing level or gap), or reversal of the trend (e.g. from increasing sales or service adoption to decreasing sales or adoption, or from slow population growth to increasing population growth, etc.). As it shows, most respondents selected continue the trend for all 17 trends. Aging population, slow population growth, delay in retiring showed a relatively higher percentage of respondents that indicated a potential reversal of the trends.

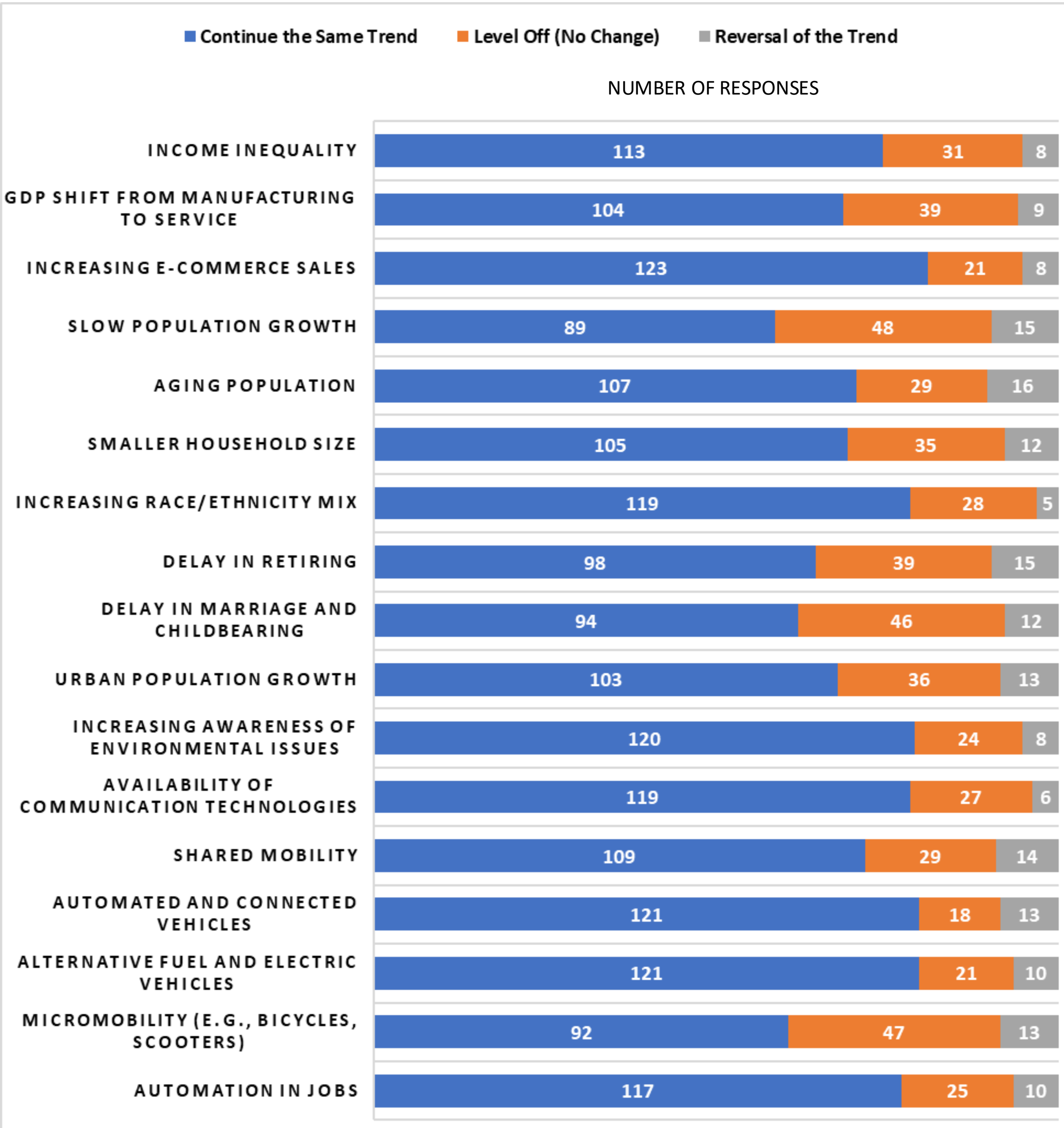

Figure 5-4 Likely progression of each trend in the next 10–20 years

Figure 5-5 presents the analysis results based on weighted means of all respondents and each respondent group based on their attributes. From left to right, the horizontal axis represents the highest value (the most likely to continue the current trend) to the smallest value (the least likely to continue the current trend). Overall, the patterns were generally consistent across the different groups, except for education levels, which showed larger differences among respondents with different educational attainment.

Looking at the overall results by all respondents, the top trends (within the top quartile based on the average scores) that were most likely to continue the same trend include increasing e-commerce sales, increasing race/ethnicity mix, availability of ICTs, increasing awareness of environmental issues, and CAVs. Trends in the bottom quartile include slow population growth, Micro mobility, delay in marriage and childbearing, and delay in retiring. It sounds reasonable as these demographic trends can only progress to a certain degree, and Micro mobility may be appealing to a certain market (e.g., short trips in high-density areas). In general, economic and technology trends were more likely to continue the same trend as they were still relatively new.

Similarly, Table 5-4 presents the weighted means by the group for each trend in terms of their likely progression in the next 10-20 years. Based on Kruskal-Wallis H tests and Mann-Whitney U tests, grey cells highlight the groups that showed statistically significant values across the groups. As it shows, most of the ratings were similar across the groups, but larger discrepancies were observed when the respondents were segmented by education levels. It seems that those with high school degrees were more likely to give significantly lower values (which means less likely to continue the same trend) to various economic, technology, and demographic trends compared to the rest of the groups, while those with Master’s degrees were more likely to give higher values indicating a continuing trend.

Looking at the other segments, it seems that respondents from non-profit organizations generally showed lower values on increasing environmental awareness and alternative fuel and electric vehicles, while researchers showed lower values on smaller household size and delay in marriage and childbearing, indicating that they believe these trends were less likely to present long-term forces. Those with more than 30 years of experience were less likely to see ICT as a long-term trend, while those with less than 5 years of experience showed higher values for the delay in marriage and childbearing. This might be related to the respondents’ age, where older professionals were less likely to highlight the roles of ICTs (as shown in Table 2-7) and younger people were more likely to agree with the new lifestyle, such as delay in marriage and childbearing, therefore saw it with longer-term impact.

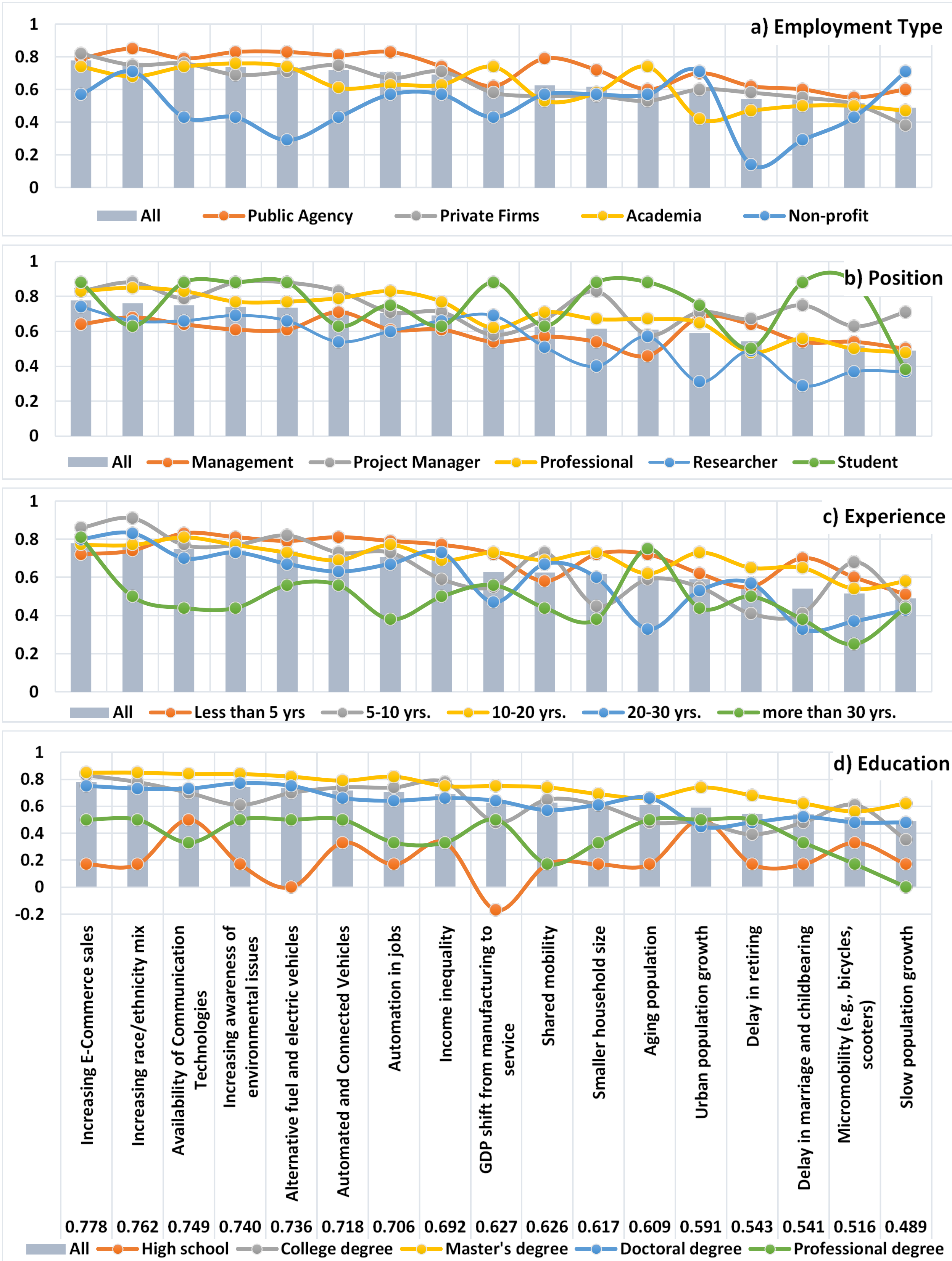

Figure 5-5 Average impacts of each trend by segment

Table 5-4 Weighted Means for Trend Progression by Respondent Attribute

Avg. Score	Trend	Public Agency	Private Firms	Academia	Non-Profit	Management	Project Manager	Professional	Researcher	Student	Less than 5 years	5-10 years	10-20 years	20-30 years	more than 30 years	High school	College degree	Master's degree	Doctoral degree	Professional degree
0.778	Increasing E-Commerce sales	0.79	0.82	0.74	0.57	0.64	0.83	0.83	0.74	0.88	0.72	0.86	0.77	0.80	0.81	**0.17**	0.83	0.85	0.75	0.50
0.762	Increasing race/ethnicity mix	0.85	0.75	0.68	0.71	0.68	0.88	0.85	0.66	0.63	0.74	0.91	0.77	0.83	0.50	**0.17**	0.78	0.85	0.73	0.50
0.749	Availability of Communication Technologies	0.79	0.76	0.74	0.43	0.64	0.79	0.83	0.66	0.88	0.83	0.77	0.81	0.70	**0.44**	0.50	0.70	**0.84**	0.73	0.33
0.740	Increasing awareness of environmental issues	0.83	0.69	0.76	**0.43**	0.61	0.88	0.77	0.69	0.88	0.81	0.77	0.77	0.73	0.44	**0.17**	0.61	**0.84**	0.77	0.50
0.736	Alternative fuel and electric vehicles	0.83	0.71	0.74	**0.29**	0.61	0.88	0.77	0.66	0.88	0.79	0.82	0.73	0.67	0.56	**0.00**	0.70	0.82	0.75	0.50
0.718	Automated and Connected Vehicles	0.81	0.75	0.61	0.43	0.71	0.83	0.79	0.54	0.63	0.81	0.73	0.69	0.63	0.56	**0.33**	0.74	0.79	0.66	0.50
0.706	Automation in jobs	0.83	0.67	0.63	0.57	0.61	0.71	0.83	0.60	0.75	0.79	0.73	0.77	0.67	0.38	**0.17**	0.74	**0.82**	0.64	0.33
0.692	Income inequality	0.74	0.71	0.63	0.57	0.61	0.71	0.77	0.66	0.63	0.77	0.59	0.69	0.73	0.50	0.33	0.78	0.75	0.66	0.33
0.627	GDP shift from manufacturing to service	0.62	0.58	0.74	0.43	0.54	0.58	0.62	0.69	0.88	0.72	0.55	0.73	0.47	0.56	**-0.17**	0.48	0.75	0.64	0.50
0.626	Shared mobility	0.79	0.56	0.53	0.57	0.57	0.67	0.71	0.51	0.63	0.58	0.73	0.69	0.67	0.44	0.17	0.65	**0.74**	0.57	0.17
0.617	Smaller household size	0.72	0.56	0.58	0.57	0.54	0.83	0.67	**0.40**	0.88	0.72	0.45	0.73	0.60	0.38	0.17	0.61	0.69	0.61	0.33
0.609	Aging population	0.60	0.53	0.74	0.57	0.46	0.58	0.67	0.57	0.88	0.72	0.59	0.62	0.33	0.75	0.17	0.48	0.66	0.66	0.50
0.591	Urban population growth	0.70	0.60	0.42	0.71	0.68	0.71	0.65	0.31	0.75	0.62	0.55	0.73	0.53	0.44	0.50	0.48	0.74	0.45	0.50
0.543	Delay in retiring	0.62	0.58	0.47	0.14	0.64	0.67	0.48	0.49	0.50	0.55	0.41	0.65	0.57	0.50	0.17	0.39	0.68	0.48	0.50
0.541	Delay in marriage and childbearing	0.60	0.55	0.50	0.29	0.54	0.75	0.56	**0.29**	0.88	**0.70**	0.41	0.65	0.33	0.38	0.17	0.48	0.62	0.52	0.33
0.516	Micromobility (e.g., bicycles, scooters)	0.55	0.51	0.50	0.43	0.54	0.63	0.50	0.37	0.88	0.60	0.68	0.54	0.37	0.25	0.33	0.61	0.56	0.48	0.17
0.489	Slow population growth	0.60	0.38	0.47	0.71	0.50	0.71	0.48	0.37	0.38	0.51	0.45	0.58	0.43	0.44	0.17	0.35	0.62	0.48	0.00

Note: grey cells highlight statistical differences among the groups; bold cells indicate the group(s) that statistically differed from the other groups.
trends in pink cells are economic-related, in blue cells are demographic-related, in green cells are technology-related.

5.4.3 Integrated Analysis of Trend Impact on Passenger Demand and Progression

Considering both the impacts of the trends as well as their potential duration, Figure 5-6 presents the combined results. The horizontal axis indicates the likely impact on passenger VMT, while the vertical axis shows the likelihood of continuing the trend in the next 10-20 years (the closer the value to 1, the more likely that the trend will persist) according to the survey responses. Each bubble represents one trend, and the size of the bubble indicates the magnitude of its impact on VMT. As can be seen, the closer the trends to the middle of the horizontal axis the smaller the impacts on VMT, and the higher the trends in the vertical direction the longer the impacts may sustain.

The figure shows that most technological trends were highly influential and very likely to have long-term impacts (those on the upper right and left corners). They presented mixed impacts in terms of effects on passenger VMT; the availability of ICTs and automation in jobs would likely to decrease VMT, while alternative fuel and electric vehicles, and CAVs were likely to lead to more passenger travel.

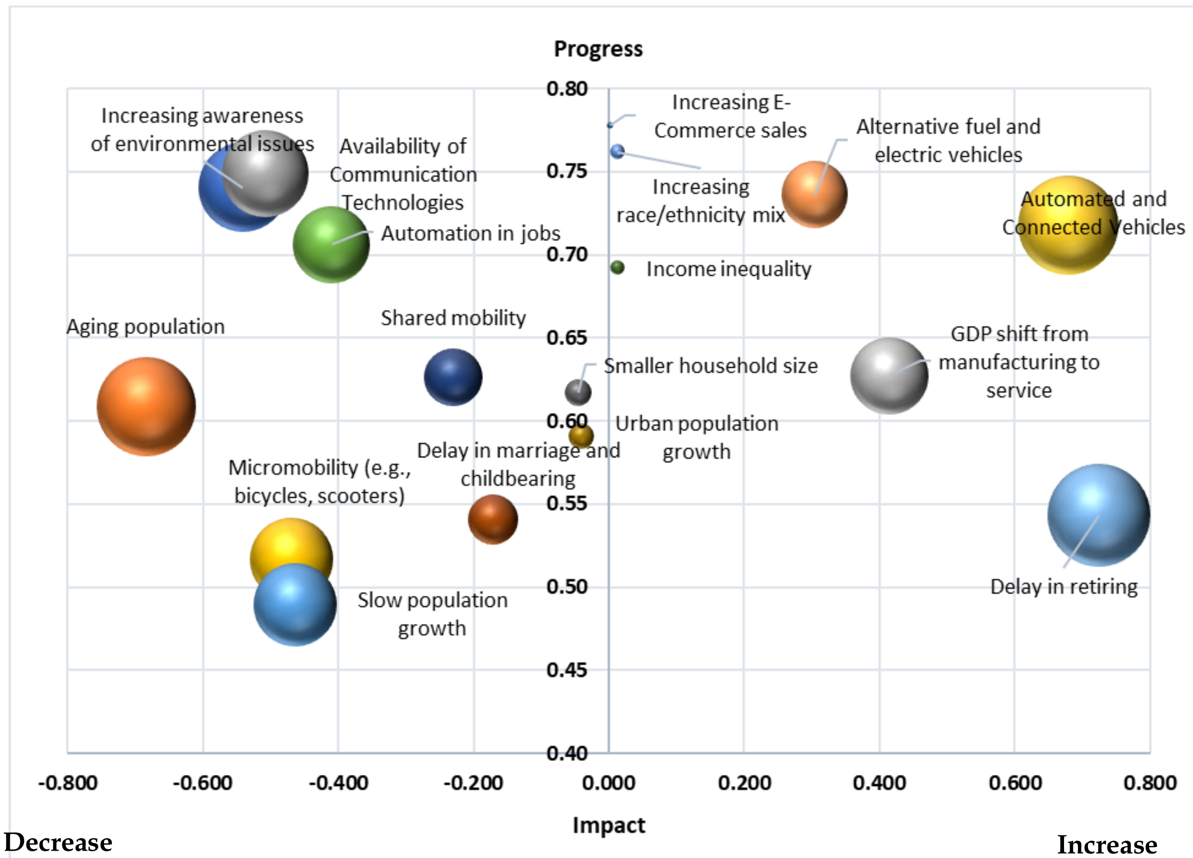

Figure 5-6 Survey results for trend impact versus duration of the trend

The demographic trends were mostly located in the lower-left corner, showing decreasing effects on VMT, partially reflecting the lifestyles and preferences of the younger generation, and partially reflecting the current demographic structure of the population (e.g., aging population). There is one exception, delay in retiring was considered to have the largest impact on increasing VMT, although the trend itself may not last very long. Another exception is increasing awareness of environmental issues, which was very influential in decreasing VMT and very likely to continue in the next 10-20 years. This indicates promising changes in attitudes and travel behavior to favor more sustainable transportation options and reduce environmental impacts.

The only economic trend that showed an influential impact on VMT is GDP shift from manufacturing to service, which was likely to lead to more passenger travel. Surprisingly, e-commerce was not considered to have a significant impact on passenger demand. This is probably indicative of the uncertain effects of online shopping on trip reduction. The literature has identified both substitution and supplementary effects of online shopping on instore shopping (Wilson et al., 2015). This may indicate a potential area for further research. Income inequality was also not considered an influential trend in terms of travel demand.

5.4.4 Impacts on Freight Transportation Demand

Figure 5-7 presents the summary of responses in assessing the likely impacts of the 5 identified trends on freight travel demand in terms of VMT. As it shows, GDP shift from manufacturing to service and increasing e-commerce sales were the top two trends that may significantly decrease VMT, followed by automated freight vehicles, increasing international trade volumes, and alternative fuel freight vehicles. On the other hand, based on all the responses, increasing e-commerce, and increasing international trade volumes were considered as the top two trends that may increase VMT significantly. Interestingly these were the top two trends that would increase VMT moderately by reverse order concerning increase VMT significantly. Overall, alternative fuel freight vehicles, automated freight vehicles were considered by most respondents to have less impact (neutral) on passenger VMT, followed by GDP shift from manufacturing to service.

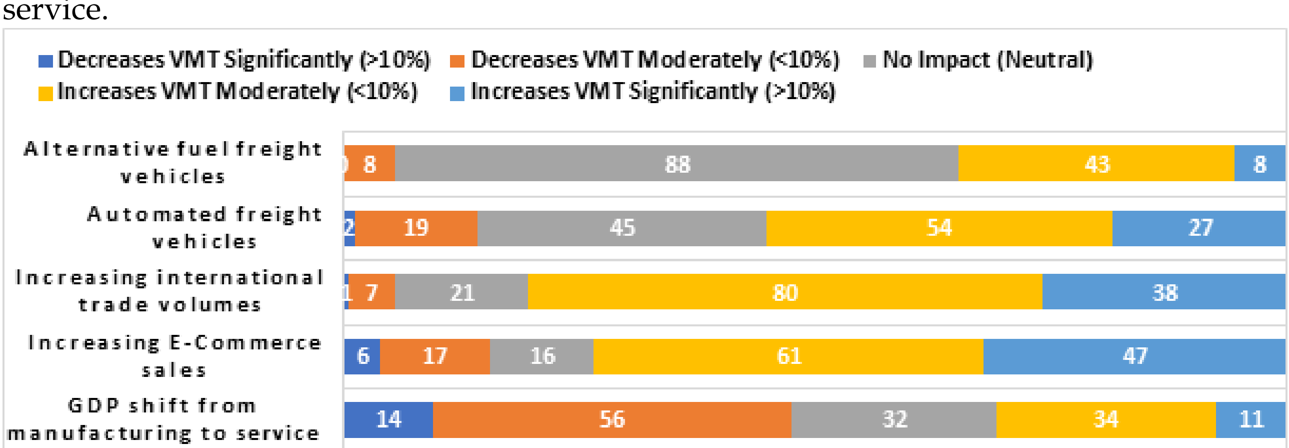

Figure 5-7 Likely impacts of each trend on freight travel demand in terms of VMT

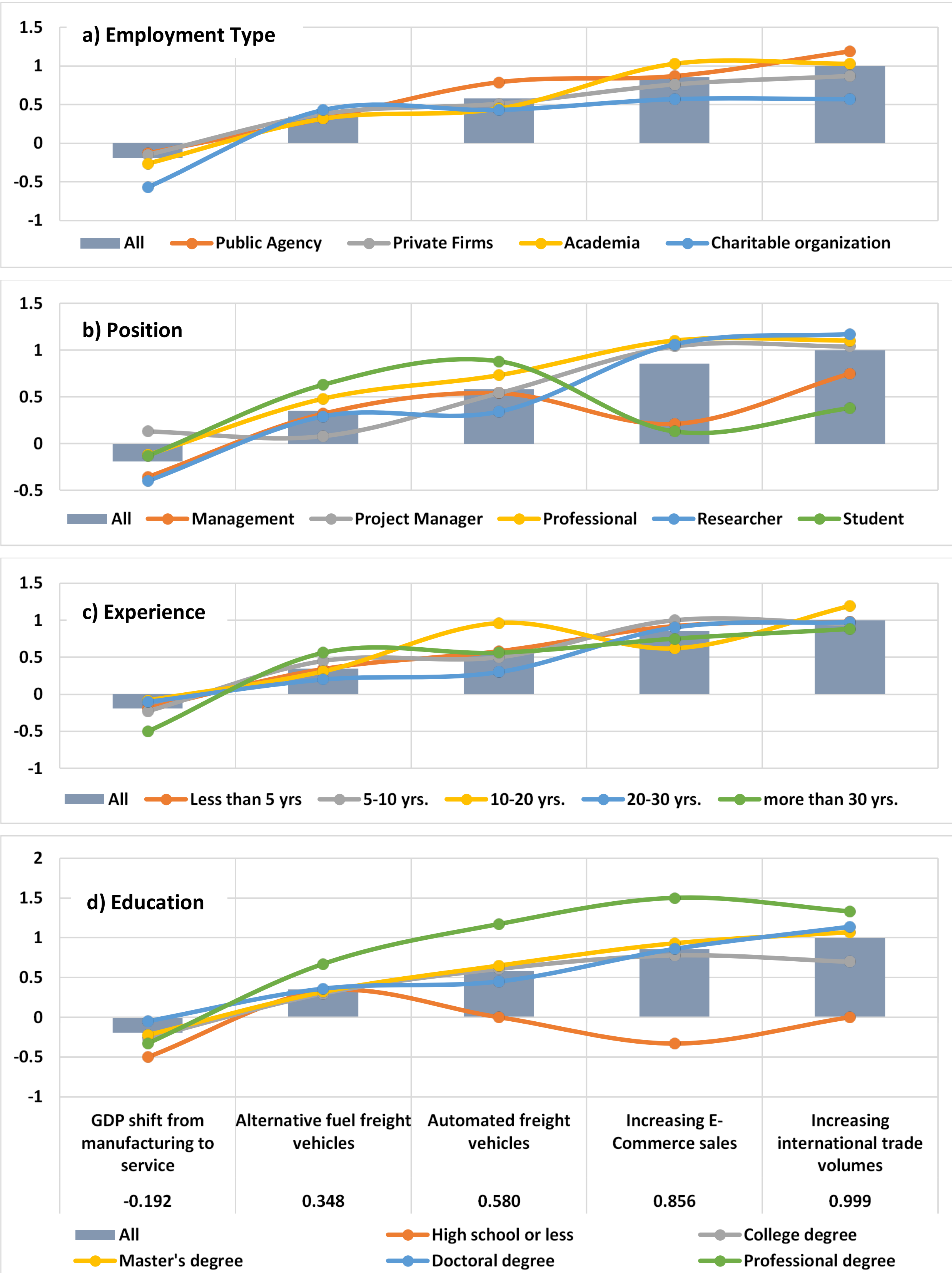

Figure 5-8 Average impacts of each trend by segment

Figure 5-8 presents the weighted average scores (vertical axis) of each trend for all respondents as shown in the grey columns, also by different segmentation groups as shown in the curved lines. There are four charts in Figure 5-8, representing the weighted means of each trend by employment type, position, experience, and education, respectively. All four charts share the same horizontal axis, which reflects the ranking from the smallest value (the highest negative impact on VMT) to the highest value (the highest positive impact on VMT) from left to right.

Looking at the overall results by all respondents, GDP shift from manufacturing to service had the highest impacts on decreasing freight VMT. And this was generally consistent among respondents across different segments. On the other hand, the respondents collectively believed that increasing e-commerce and increasing international trade volumes had the highest impacts of increasing VMT, although there were some discrepancies among the segments. Alternative fuel freight vehicles, automated freight vehicles were considered to have moderate effects on increasing VMT.

As explained in the previous section, the Kruskal-Wallis H test and Mann-Whitney U tests were conducted to identify whether there are significant different opinions on the impacts of the trends among the groups. Table 5-5 presents the weighted means by the group for each trend. Grey cells highlight the groups that showed statistically significant values between the groups, and bolded cells indicate the specific group(s) that significantly differed from the other groups (that are highlighted in grey cells).

It seems that employment type and work experience showed no variation, meaning the respondent's views on the impacts of the trends were generally consistent and not likely to differ by their occupational variation or difference in work experience.

In terms of position at work, project managers considered alternative fuel vehicles to be less influential in increasing VMT compared to the rest of the respondents. Students and those at management positions were less likely to consider e-commerce with significant impacts in increasing freight VMT. Respondents with high school degrees or less also showed significantly different views than other groups on the potential impacts of increasing e-commerce and increasing international trade sales. In both cases, they tended to underestimate their impacts in increasing freight VMT compared to other respondents.

Table 5-5 Weighted Means for Trend Impact by Respondent Attribute

Avg. Score	Trend	Public Agency	Private Firms	Academia	Non-Profit	Manage-ment	Project Manager	Professional	Researcher	Student	Less than 5 yrs	5-10 yrs.	10-20 yrs.	20-30 yrs.	more than 30 yrs.	High school	College degree	Master's degree	Doctoral degree	Professional degree
-0.192	GDP shift from manufacturing to service	-0.13	-0.15	-0.26	-0.57	-0.36	0.13	-0.12	-0.40	-0.13	-0.19	-0.23	-0.08	-0.10	-0.50	-0.50	-0.26	-0.22	-0.05	-0.33
0.348	Alternative fuel freight vehicles	0.32	0.38	0.32	0.43	0.32	**0.08**	0.48	0.29	0.63	0.34	0.45	0.31	0.20	0.56	0.33	0.30	0.32	0.36	0.67
0.580	Automated freight vehicles	0.79	0.51	0.45	0.43	0.54	0.54	0.73	0.34	0.88	0.58	0.50	0.96	0.30	0.56	0.00	0.61	0.65	0.45	1.17
0.856	Increasing E-Commerce sales	0.87	0.76	1.03	0.57	**0.21**	1.04	1.10	1.06	**0.13**	0.92	1.00	0.62	0.90	0.75	**-0.33**	0.78	0.93	0.86	1.50
0.999	Increasing international trade volumes	1.19	0.87	1.03	0.57	0.75	1.04	1.10	1.17	0.38	0.98	0.95	1.19	0.97	0.88	**0.00**	0.70	1.07	1.14	1.33

Note: grey cells highlight statistical differences among the groups; bold cells indicate the group(s) that statistically differed from the other groups.
trends in pink cells are economic-related and in green cells are technology-related.

Table 5-6 Weighted Means for Trend Progression by Respondent Attribute

Avg. Score	Trend	Public Agency	Private Firms	Academia	Non-Profit	Manage-ment	Project Manager	Professional	Researcher	Student	Less than 5 yrs	5-10 yrs.	10-20 yrs.	20-30 yrs.	more than 30 yrs.	High school	College degree	Master's degree	Doctoral degree	Professional degree
0.502	Increasing international trade volumes	0.57	0.53	0.47	0.00	0.50	0.63	0.52	0.40	0.50	0.47	0.59	0.54	0.57	0.31	0.33	0.39	0.57	0.48	0.50
0.627	GDP shift from manufacturing to service	0.62	0.58	0.74	0.43	0.54	0.58	0.62	0.69	0.88	0.72	0.55	0.73	0.47	0.56	**-0.17**	0.48	0.75	0.64	0.50
0.747	Alternative fuel freight vehicles	0.79	0.76	0.76	**0.29**	0.61	0.79	0.83	0.74	0.63	0.75	0.82	0.81	0.70	0.63	**0.00**	0.65	**0.82**	0.84	0.33
0.778	Increasing E-Commerce sales	0.79	0.82	0.74	0.57	0.64	0.83	0.83	0.74	0.88	0.72	0.86	0.77	0.80	0.81	**0.17**	0.83	0.85	0.75	0.50
0.795	Automated freight vehicles	0.89	0.82	0.71	**0.43**	0.75	0.92	0.85	0.69	0.75	0.81	0.82	0.81	0.8	0.69	**0.17**	0.78	0.85	0.84	0.5

Note: grey cells highlight statistical differences among the groups; bold cells indicate the group(s) that statistically differed from the other groups.
trends in pink cells are economic-related, in green cells are technology-related.

5.4.5 Freight Trend Progression

This section focuses on Q4 that aims to analyze how the identified trend might progress in the next 10-20 years. Figure 5-9 shows that most respondents selected continue the trend for all three trends. International trade volumes showed a relatively higher percentage of respondents that indicated a potential reversal of the trends.

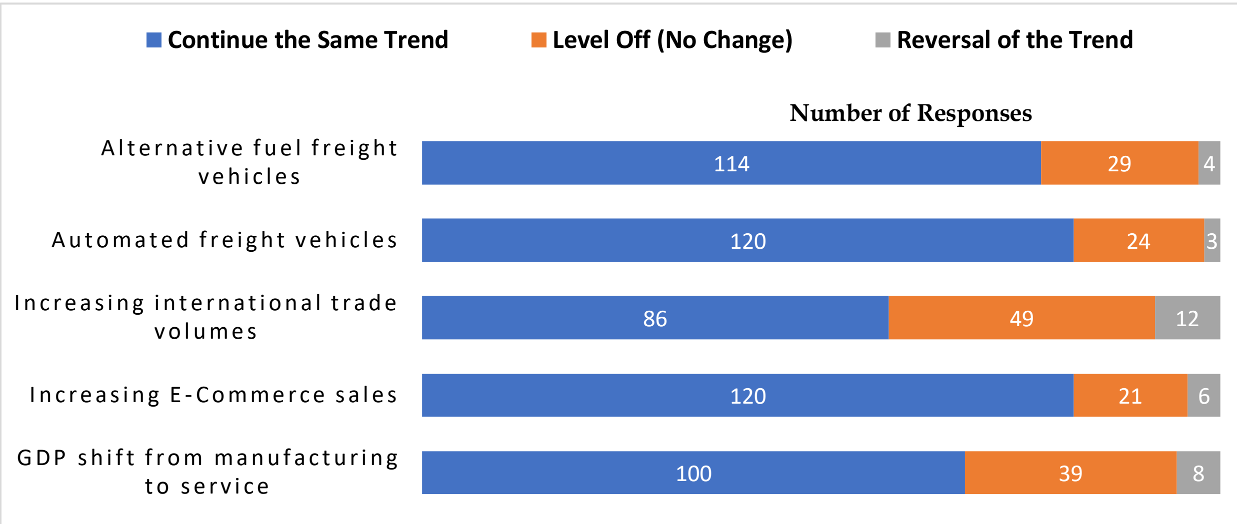

Figure 5-9 Likely progression of each trend in the next 10–20 years

Similarly, Table 5-6 presents the weighted means by the group for each trend in terms of their likely progression in the next 10-20 years. Looking at the overall results by all respondents, all trends were likely to continue, where automated freight vehicles are the top trend that most likely to continue, while and increasing international trade was the least likely to persist.

Based on Kruskal-Wallis H tests and Mann-Whitney U tests, grey cells highlight the groups that showed statistically significant values across the groups. As it shows, the views were consistent by work position and work experience. Some discrepancies were observed for freight vehicle technology trends by employment type and education level. Specifically, respondents from non-profit organizations or those with less education level (high school or less) were less likely to consider alternative fuel and automated freight vehicles to be long-lasting trends in the next couple of decades. Those with high school degrees or less were also less likely to view GDP shifts to service and increasing e-commerce sales to continue with the same direction of the trends.

5.4.6 Integrated Analysis of Trend Impact on Freight Demand and Progression

Similarly, Figure 5-10 presents the combined results of the impacts of the trends on freight demand and the progression of the trends themselves. As it shows, both technological trends were highly likely to have long-term impacts. They both presented moderate impacts on freight VMT compared to other trends, automated freight vehicles showed slightly higher impacts. Among the economic trends, GDP shift from manufacturing to service showed minor impacts on decreasing freight VMT, which was likely to continue for some of time. Surprisingly, though e-commerce showed mixed impact on passenger demand, it was considered highly influential in increasing freight VMT with long-term effect. This is probably indicative of the increasing effects of online shopping on freight VMT. This may indicate a potential area for further research. Increasing international trade volumes had the highest influence on freight VMT increase but likely for a shorter term compared to other trends.

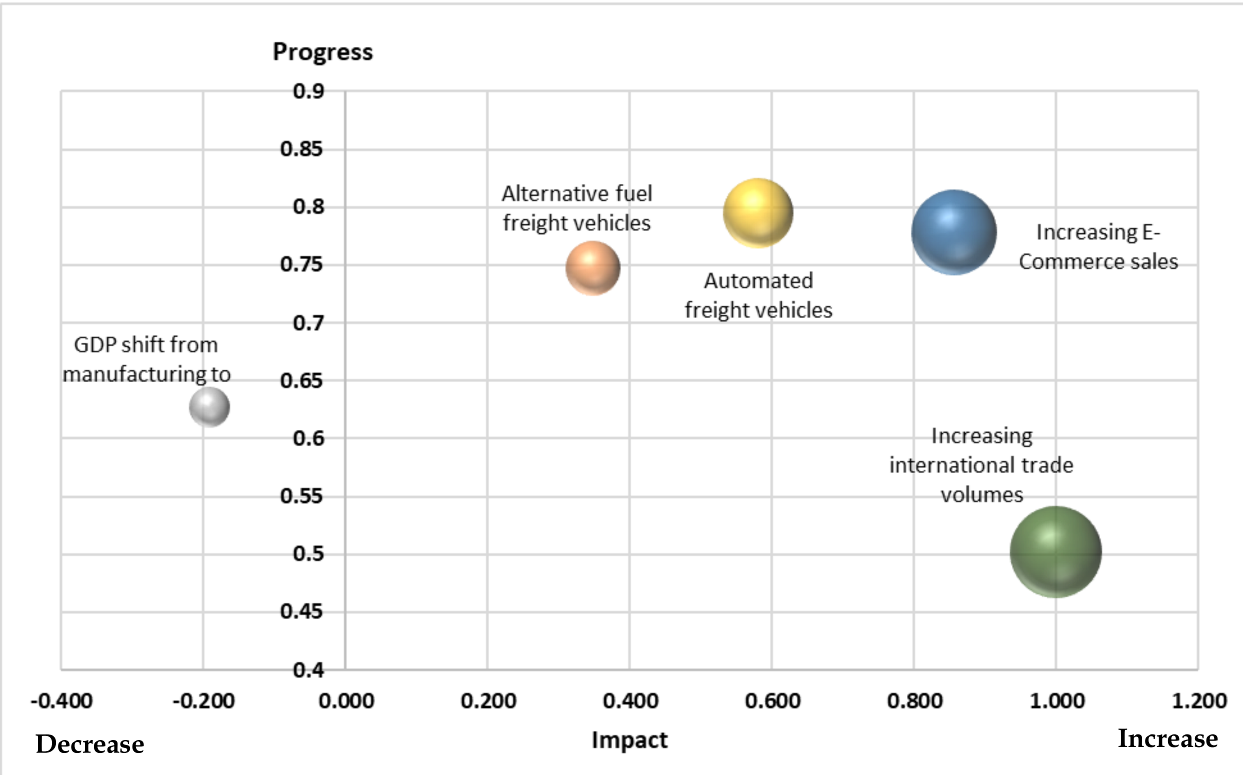

Figure 5-10 Survey results for trend impact versus duration of the trend

5.5 Summary of Impact Assessment Survey

This study explores the potential impacts of various existing and emerging trends. A national expert survey was conducted to solicit responses from transportation professionals with different backgrounds, including public agencies, private firms, and academia. Respondents rated the likely impact of each trend on passenger VMT, as well as to assess the likely progression of the trend within the next 10-20 years. The results indicate interesting findings. Particularly, most of the technology-related trends were considered highly influential, and since they were mostly emerging trends, their impacts were likely to persist for a long term, except for Micro mobility and shared mobility which was not as influential or as persistent probably due to the constraints of Micro mobility (i.e. mostly focusing on short trips or first mile/last mile connections) or attitudinal barriers toward shared services. Many of the demographic trends showed influential impacts on VMT decrease, although these trends may be diminishing as some of the existing demographic dynamics transition to the next phase. It is worth noting that increasing awareness of environmental issues was considered as both highly influential and highly likely to continue in the next 10-20 years, which may indicate a more sustainable future in terms of mobility.

On the freight side, increasing e-commerce sales was highly influential in terms of both its impacts on VMT increase and the long-lasting effects. Increasing international trade volumes was also considered highly likely to lead to increasing VMT but with relatively shorter timeframe. Technologies related to freight vehicles were likely to lead to increases in freight VMT and highly likely to continue in the next couple decades.

Segmentation analysis indicates that non-profit agencies, those with more than 30 years of experience, or those with low education levels exhibited different views compared to their counterparts. A follow-up survey will be conducted to gather additional information to investigate the underlying factors that contributed to their responses and the differences in their views. This additional information will help us develop a deeper understanding and potentially better estimate of the likely impacts of the trends.

This study puts an effort to evaluate the potential influence and relative importance of various trends that might impact transportation demand in the next decades. A better understanding of these trends would allow planners and decision-makers to incorporate these factors into the planning process and facilitate better investment and policy decisions. The findings of this study may also help improve the demand forecasting efforts and lead to better practices anticipating shifts in demand and transportation needs.

6 CONCLUSIONS

In the aims to inform the planning process and provide broader insights into the changing nature of transportation demand, this study puts an effort in advancing our understanding of the impacts of external trends on transportation demand. A nationwide survey was conducted to solicit opinions from transportation professionals to evaluate the potential influence and relative importance of various existing and emerging trends on transportation demand. In addition, geo-tagged Tweets were collected to extract public sentiments and topics related to those trends through text mining and infographics techniques.

The survey results indicate that most of the technology-related trends were considered highly influential and highly likely to persist for the long term, since they were mostly emerging trends. Many of the demographic trends showed influential impacts on VMT decrease, although these trends may be diminishing as some of the existing demographic dynamics transition to the next phase. It is worth noting that increasing awareness of environmental issues were considered as both highly influential and highly likely to continue in the next 10-20 years, which may indicate a more sustainable future in terms of mobility.

Tweets closely aligned with emerging transportation and mobility trends (such as shared mobility, vehicle technology, built environment, user fees, telecommuting and e-commerce) were identified. Los Angeles, Manhattan, Houston and Chicago were among the highly visible cities discussing such trends. Being neutral overall, people carried more positive views on vehicle technology, telecommuting and e-commerce, while being more negative on shared mobility, user fees and built environment. Ride hailing, fuel efficiency, trip navigation, daily as well as shopping and recreational activities, gas price, tax, product delivery were among the emergent topics.

Transportation planning agencies are charged with making transportation investments that often have long lasting effects to the traveling public and the society as a whole. A better understanding of these trends would allow planners and decision-makers to better account for these factors in the planning process and facilitate better investment and policy decisions. The social media data-driven framework would allow real time monitoring of transportation trends by agencies, researchers, and professionals. The findings of this study may also help improve the demand forecasting efforts, provide better understanding of future uncertainty, and lead to better practices in tracking external factors and trends to anticipate shifts in demand and transportation needs.

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8 APPENDICES

8.1 Appendix A: Trend Survey Questionnaire

Impacts of Emerging Trends on Transportation Demand Survey

Hello,

In order to develop strategies for effective planning and management of its transportation systems, the Florida Department of Transportation is looking to identify factors and trends that could potentially shape future transportation demand. This effort will help decision makers at the state and local levels make informed decisions in response to the rapid pace of change, which is often driven by even faster growing technologies.

The survey itself looks at economic, social and technological trends, identified from a comprehensive review of literature and the latest public data. These trends are explained in the next page for your reference. Please kindly provide us your thoughts as to how strongly and for how long these trends can impact future travel demand in the United States. Your response will help us develop a set of potential future scenarios and response strategies.

This survey should not take you more than 10 minutes to complete and it is completely anonymous. All collected information is completely confidential, and no individual respondents will be personally identified. This survey is, of course, totally voluntary. If you would like to obtain results of our survey, you may leave your email address at the end for us to send you the results.

Thank you in advance for your participation. You can go to this site:
https://fiu.qualtrics.com/jfe/form/SV_3En14xwaDzmRNZP or scan the QR code below.

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TREND DESCRIPTION

ECONOMIC TRENDS

1. **Income inequality** –Income inequality (average income difference between higher and lower population quantiles) in the US is currently at its highest level since the Census Bureau began tracking five decades ago (Source: US Census Bureau).
2. **GDP shift from manufacturing to service** – the manufacturing industry's percent share of GDP has continuously fallen since 1980 while that of the service industry continued to rise (Source: US Bureau of Economic Analysis).
3. **Increasing E-commerce sales** – E-commerce retail sales in the US have increased annually since 2000, maintaining an average of 15% of increase annually from 2010 to 2018 (Source: US Census Bureau).

DEMOGRAPHIC TRENDS

1. **Slow population growth** – US national population grew by just 0.6% between July 1, 2017 and July 1, 2018, which is at its slowest pace since 1937 (Source: US Census Bureau).
2. **Aging population** – the number of people 65 years and older in the US is expected to exceed those under the age of 18 by 2035 (Source: US Census Bureau).
3. **Increasing race/ethnicity mix** – distribution of race in US population is more diverse in the younger (<40) population groups than the older (≥40) groups (Source: US Census Bureau).
4. **Smaller household size** – the average US household size has declined steadily from 3.33 in 1950 to 2.63 in 2018 (Source: US Census Bureau).
5. **Delay in retiring** – more people continue working beyond age of 65, resulting in higher shares of labor forces above age 55 (Source: US Census Bureau).
6. **Delay in marriage and childbearing** – there has been a small but significant increase in the number of childless women in their early 30s over the past decade (Source: US Census Bureau).
7. **Urban population growth** – the US urban population increased by 12.1 percent from 2000 to 2010, outpacing the nation's overall growth rate of 9.7 percent for the same period (Source: US Census Bureau).
8. **Increasing awareness of environmental issues** – in the past decade, more and more people became aware that we need to sustainably manage our planet's resources and ecosystems (Source: Huffington Post).

TECHNOLOGICAL TRENDS

1. **Availability of communication technologies** – increasing internet and cellular connectivity to work, school, shopping, and social opportunities without physical travel.
2. **Shared mobility** – transportation services and resources that are shared among users on as-needed basis, includes carsharing (e.g. Zipcar), bikesharing, and ridesharing (e.g., Uber and Lyft).
3. **Autonomous and connected vehicles** – self-driving cars and cars that can communicate with other vehicles or entities.
4. **Alternative fuel and electric vehicles** – vehicles that use alternative fuels, such as biodiesel, electricity, and natural gas help to reduce carbon emissions and increase energy security.
5. **Micromobility** – use of bicycles, scooters, or any other non-motorized means for short distance trips or for connection to transit trips.
6. **Automation in jobs** – increasing Artificial Intelligence and automation can result in reduction in touch labor, turning what once took multiple technicians into work that one person can do in a matter of hours.
7. **Increasing international trade volume** - Total combined import and export goods value grew with an annual growth rate of about 3.5% from 2010 (3.19 trillion USD) to 2018 (4.2 trillion USD) (Source: US Census Bureau).

SECTION 1. IMPACT ASSESSMENT ON PASSENGER TRAVEL DEMAND

For each of the following trends, please indicate how likely they could IMPACT passenger travel demand in terms of Vehicle Miles Traveled (VMT).

Notes: 1. please evaluate the impact of each trend independent of other trends.
2. please evaluate the impact of in addition to base VMT growth (due to population growth) in the future.

	Decreases VMT			**No Impact**	**Increases VMT**		
Trends	**Significant (>10%)**	**Moderate (5-10%)**	**Minimal (<5%)**	**Neutral**	**Minimal (<5%)**	**Moderate (5-10%)**	**Significant (>10%)**
Income inequality							
GDP shift from manufacturing to service							
Increasing E-Commerce sales							
Slow population growth							
Aging population							
Smaller household size							
Increasing race/ethnicity mix							
Delay in retiring							
Delay in marriage and childbearing							
Urban population growth							
Increasing awareness of environmental issues							
Availability of communication technologies							
Shared mobility							
Automated and connected vehicles							
Alternative fuel and electric vehicles							
Micromobility (e.g., bicycles, scooters)							
Automation in jobs							

SECTION 2. TREND ANALYSIS

For the same list of trends, please indicate how you think they will PROGRESS within the next 10 to 20 years.

Trends	Continue the Same Trend	Level Off	Reversal of the Trend
Income inequality			
GDP shift from manufacturing to service			
Increasing E-Commerce sales			
Slow population growth			
Aging population			
Smaller household size			
Increasing race/ethnicity mix			
Delay in retiring			
Delay in marriage and childbearing			
Urban population growth			
Increasing awareness of environmental issues			
Availability of communication technologies			
Shared mobility			
Automated and connected vehicles			
Alternative fuel and electric vehicles			
Micromobility (e.g., bicycles, scooters)			
Automation in jobs			

SECTION 3 FREIGHT TRANSPORTATION DEMAND

a. Impact Assessment on Freight Transportation Demand

For each of the following trends, please indicate how likely they could IMPACT freight travel demand in terms of Vehicle Miles Traveled (VMT).

Notes: 1. please evaluate the impact of each trend independent of other trends.
2. please evaluate the impact of in addition to base VMT growth (due to population growth) in the future.

	Decreases freight VMT			No Impact	Increases freight VMT		
Trends	**Significant (>10%)**	**Moderate (5-10%)**	**Minimal (<5%)**	**Neutral**	**Minimal (<5%)**	**Moderate (5-10%)**	**Significant (>10%)**
GDP shift from manufacturing to service Industry							
Increasing E-Commerce sales							
Increasing international trade volumes							
Automated freight vehicles							
Alternative fuel freight vehicles							

b. Trend Analysis on Freight Transportation Demand

For the following trends, please indicate how you think they will PROGRESS within the next 10 to 20 years.

Trends	**Continue the Same Trend**	**Level Off**	**Reversal of the Trend**
Increasing international trade volumes			
Automated freight vehicles			
Alternative fuel freight vehicles			

SECTION 4. INTERVIEWEE INFORMATION

In order to understand the perspective of each respondent, we need to collect some basic information on your

company and industry. All of this information is completely confidential and cannot be used to identify an individual respondent.

Where are you employed?

PRIVATE-FOR-PROFIT company, business or individual, for wages, salary or commissions

NOT-FOR-PROFIT, tax-exempt, or charitable organization

Local GOVERNMENT employee (city, county, etc.)

State GOVERNMENT employee

Federal GOVERNMENT employee

SELF-EMPLOYED

UNIVERSITY

RESEARCH AGENCY

Other:

Which of the following best describes your position at work?

Management

Project Manager

Professional

Researcher

Student

Other:

How long have you been working in your current position?

less than 5 years

5 to 10 year

10 to 20 years

20 to 30 years

more than 30 years

What is the highest level of school you have completed or the highest degree you have received?

High school or less

College degree

Master's degree

Doctoral degree

Professional degree (JD, MD)

Other

In which state do you currently reside?

____

If you recognize any additional factors or trends that may affect future travel demand, please list the factors or trends and briefly explain how they may affect (e.g., increase or decrease) travel demand in terms of VMT.

____

If you would like to obtain results of our survey, please provide us with your email address below.

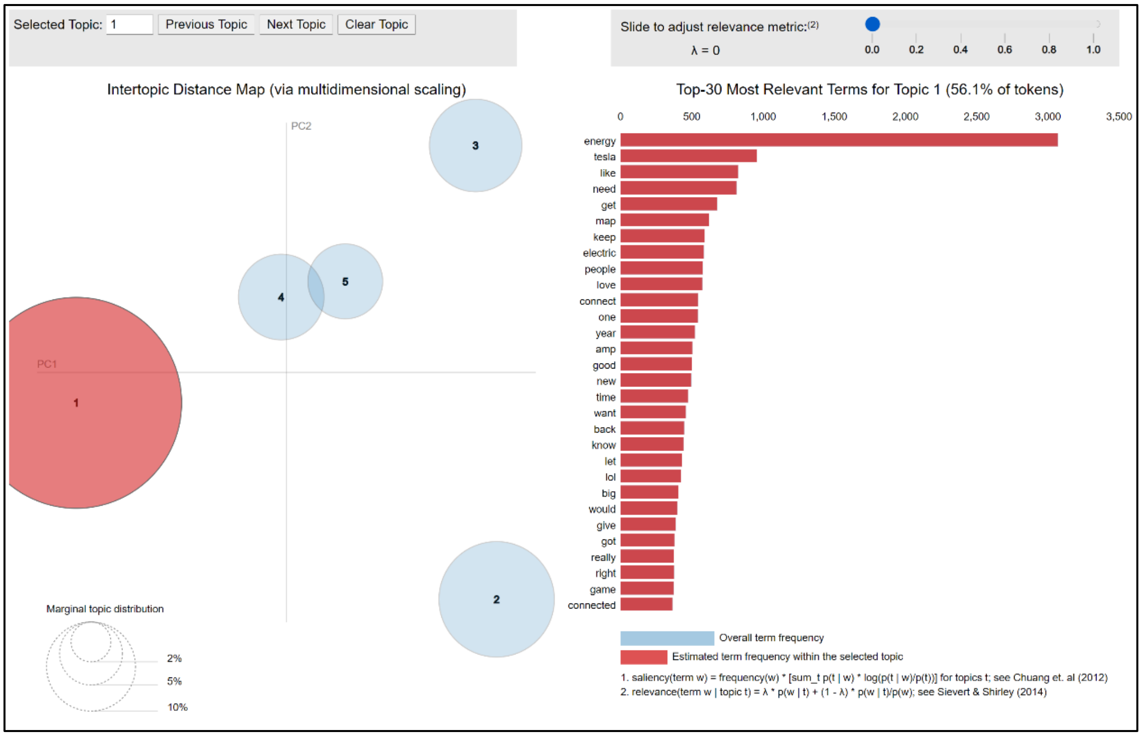
____

In the event that further information from you can help us improve our effort, may we contact you by email?

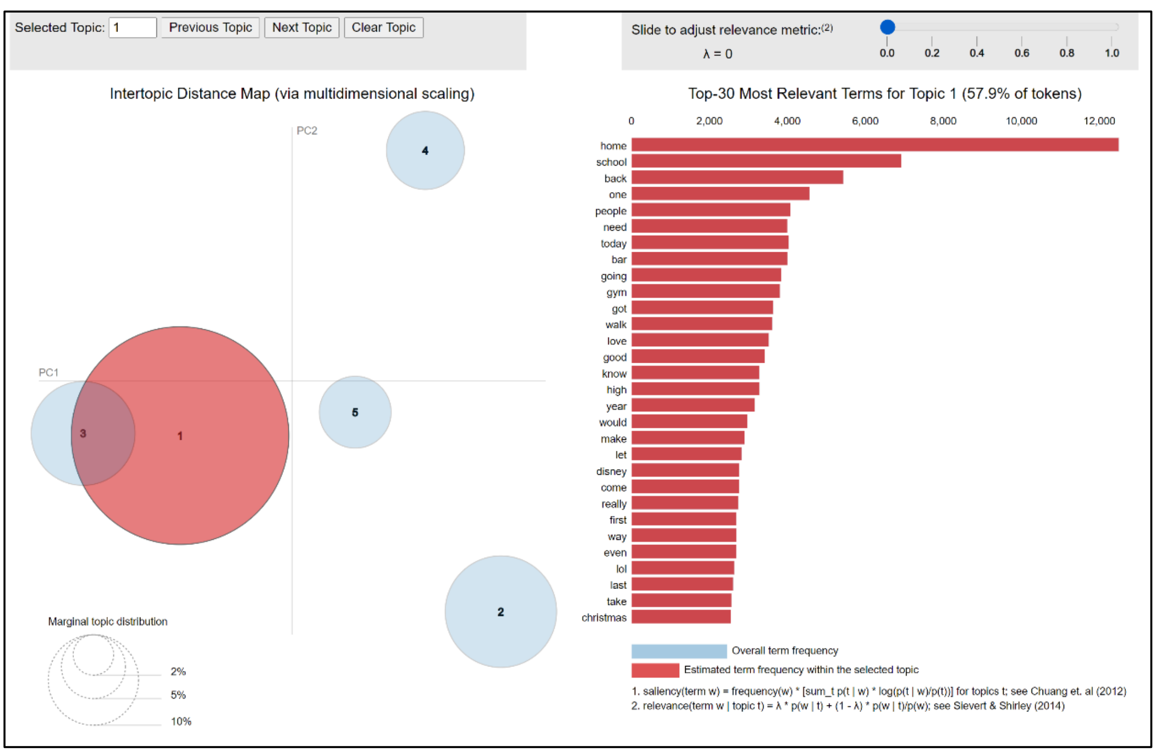
YES **NO**

8.2 Appendix B: LDAvis intertopical Distance Map

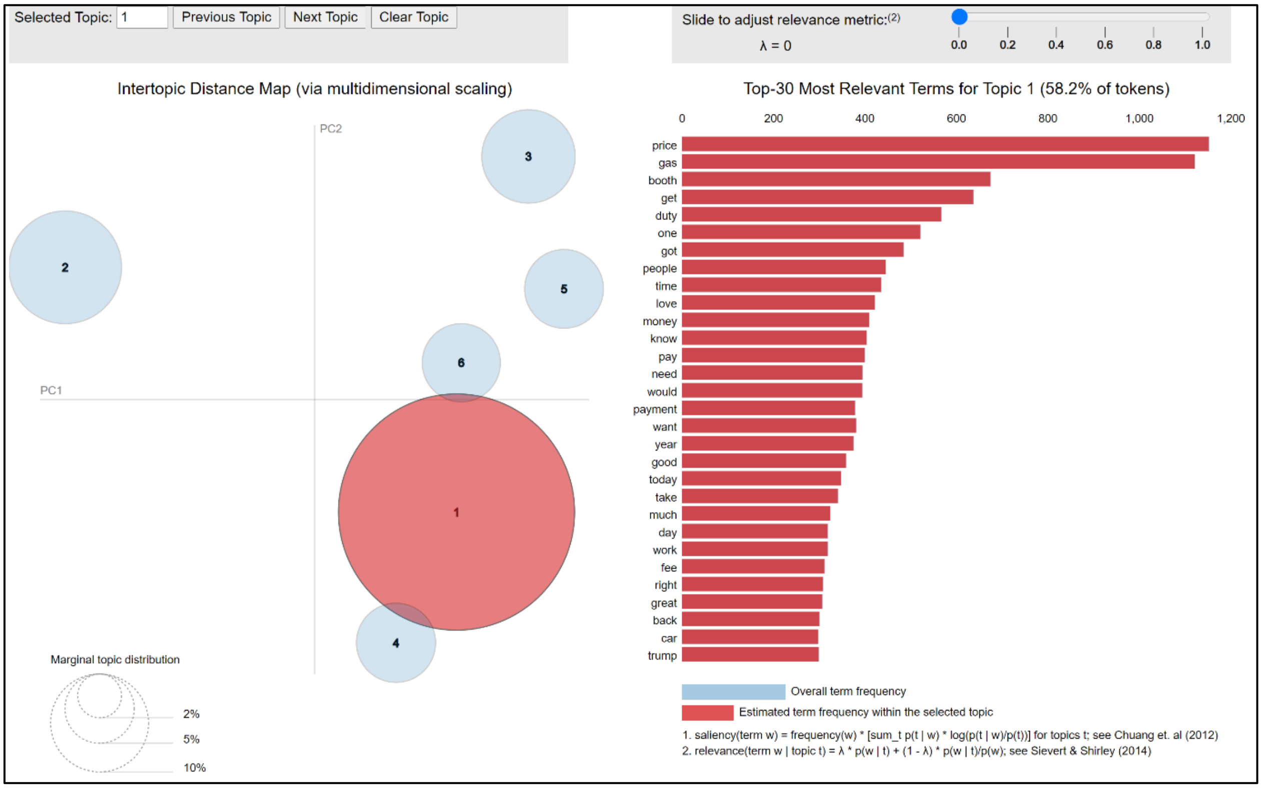
Vehicle Technology:



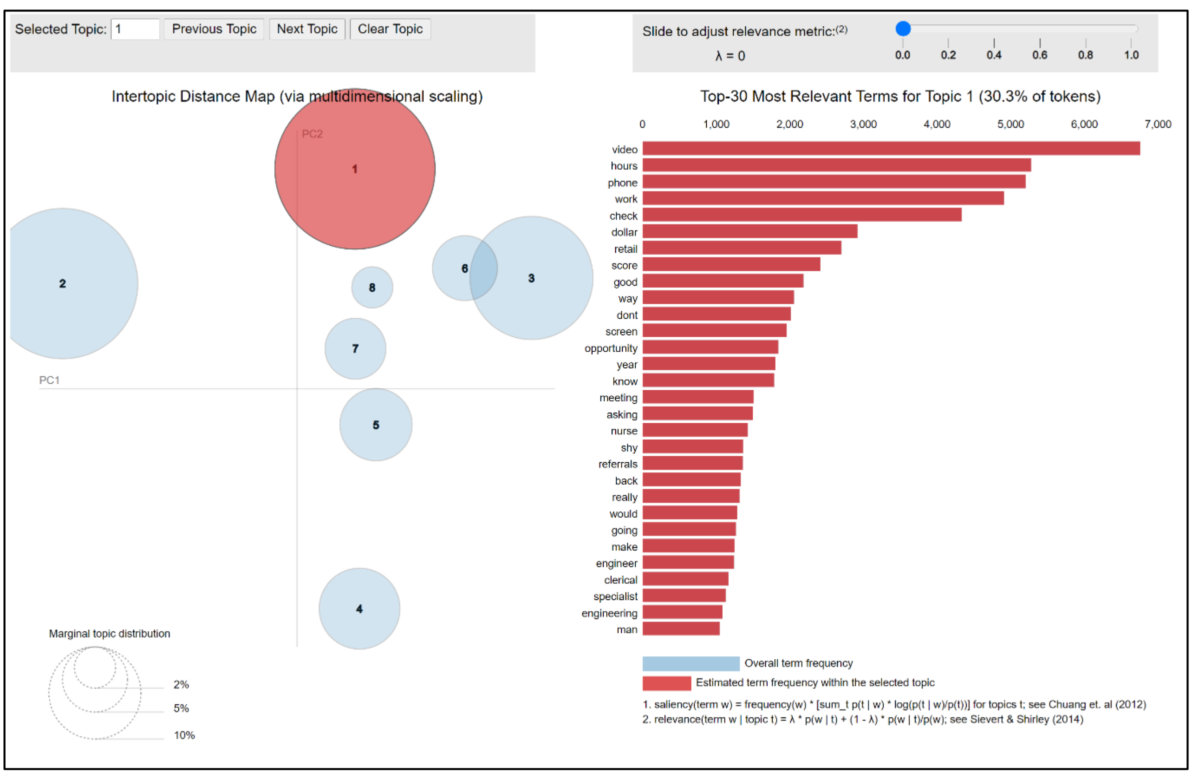
Built Environment:



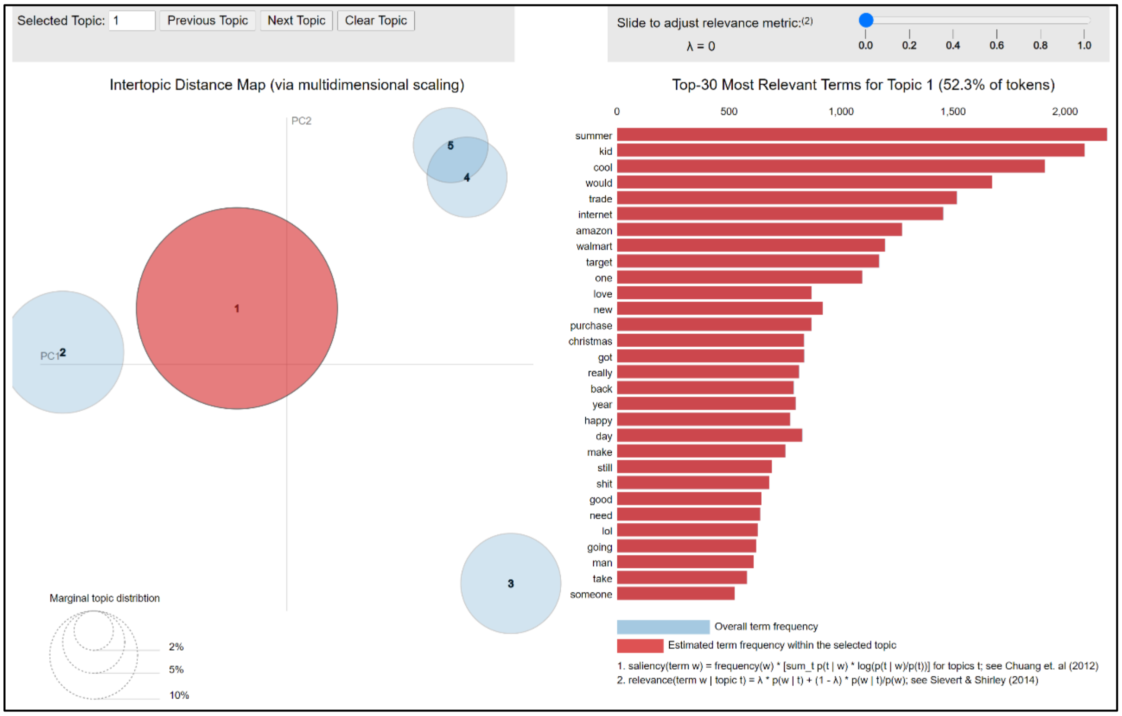
User Fees:



Telecommuting:

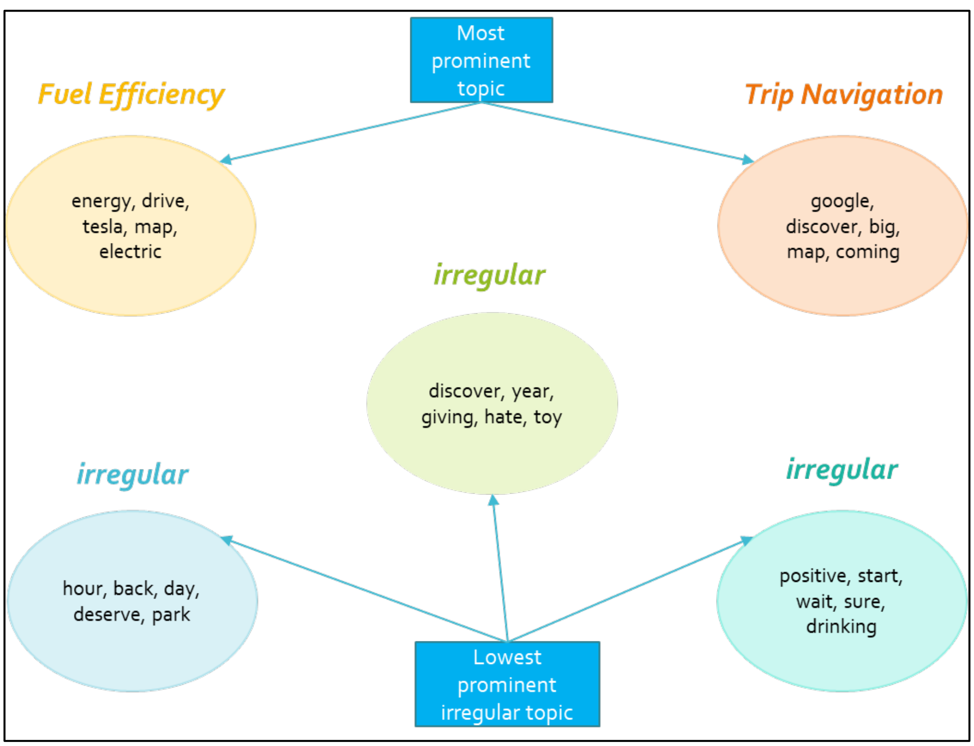


E-commerce:

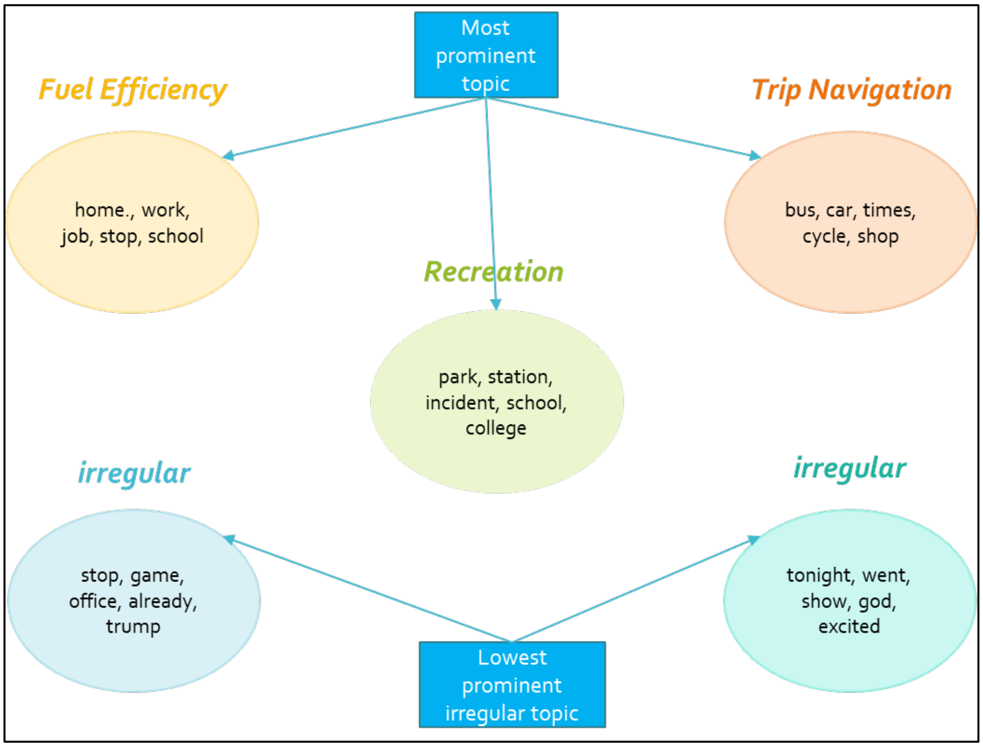


8.3 Appendix C: Topics Generated

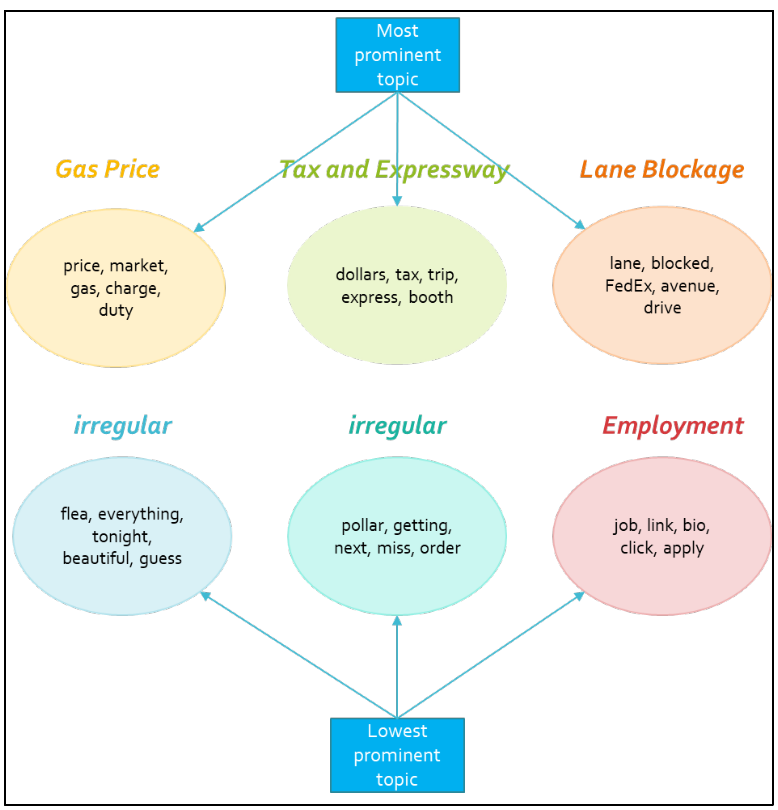
Vehicle Technology:



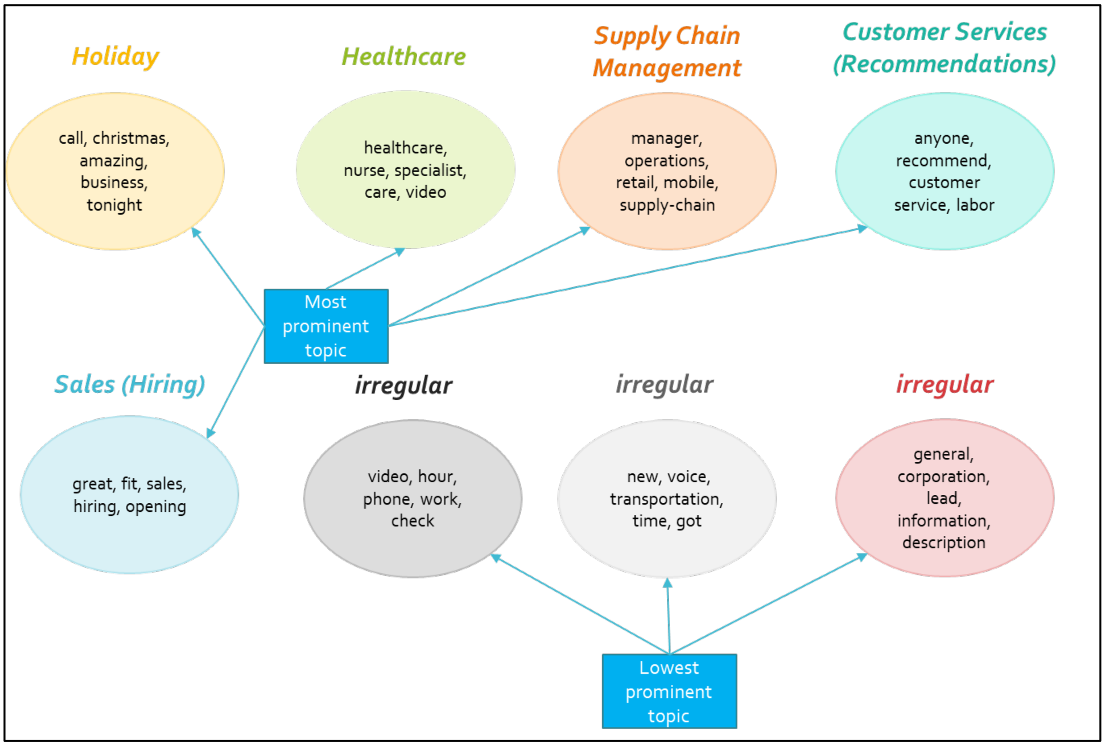
Built Environment:



User Fees:



Telecommuting:



Ecommerce: