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Autonomous electric vehicles can reduce carbon emissions and air pollution in cities

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ABSTRACT

Heavy dependence on personal vehicle usage made the transportation sector a major contributor to global climate change and air pollution in cities. In this study, we analyzed autonomous electric vehicles and compared their potential environmental impacts with public transportation options, carpooling, walking, cycling, and various transportation policy applications such as limiting lane-mile increases, and carbon tax. Fractional split multinomial logit and system dynamics modeling approaches are integrated to create a novel hybrid simulation model to process data from 929 metro/micropolitan areas in the U.S. for transportation mode choice behavior. The results show that the adoption of autonomous electric vehicles can reduce greenhouse gas emissions by up to 34% of the total emissions from transportation by 2050. This study has revealed that transportation-related impacts can only be reduced with a paradigm shift in the current practices of today's transportation industry, with disruptive reforms of automation, electrification, and shared transport.

1. Introduction

The transportation industry is heavily dependent on private vehicles in the U.S. compared to other developed countries such as those in the European Union. For instance, the number of persons per privately owned vehicle is approximately-two in France and the United Kingdom, whereas the corresponding ratio is 1.3 in the United States (US DOT, 2016). The National Household Travel Survey (NHTS) likewise highlights this large degree of private vehicle ownership in its 1990, 1995, 2001, and 2009 reports; in 2009, for instance, 23 % of the surveyed U.S. households owned 3 or more vehicles (Santos et al., 2011). As a result of the heavy dependence on private vehicles the U.S. transportation sector accounts for 29 % of the total annual greenhouse gas (GHG) emissions, making it the greatest contributor to overall GHG emissions in the U.S. (EPA, 2019). In addition, U.S. road transportation is the largest contributor to the number of premature deaths due to air emissions with 58,000 premature deaths caused every year (Caiazzo et al., 2013). Furthermore, although road transportation is not the largest contributor to the total air pollutant emission rate, it is the single greatest

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contributor to the number of mortalities in the U.S. due to emissions in highly populated urban areas, and unlike those of most rural-based energy generation plants, these emissions affect human health directly. In addition to these emission-related impacts, the significant energy consumption levels of today's relatively inefficient transportation modes are another crucial concern in terms of energy insecurity and its related socioeconomic problems (dependence on foreign oil, limited resources, availability of fossil fuels, etc.).

Considering the environmental and socioeconomic concerns, the use of alternative fuels in the transportation sector has been widely studied in literature to analyze more low-carbon fuels (Ercan et al., 2017, 2016a; Ercan and Tatari, 2015; Sen et al., 2020; Zhao et al., 2016). These studies have indicated a definite potential for significant reductions in transportation-related emissions and energy consumption by shifting from fossil fuels to alternative fuels, but efforts to decrease current trends in vehicle miles traveled (VMT) and in transportation-related air pollutant emissions are still incomplete (Ercan et al., 2017, 2016b).

The number of vehicles on today's roads continues to increase as the population increases, meaning that today's society and infrastructure cannot supply the demands of the transportation sector indefinitely. Therefore, it is highly recommended for alternative fuel deployments be merged with alternative transportation mode adoption efforts to improve the efficiency of the road transportation industry.

1.1. DecimalComplex,1.1.,DecimalComplex, literature Review: What are the barriers to achieving sustainable transportation in the US?

The heavy dependence on privately-owned vehicles in today's society has become a particularly important topic to federal and local government agencies, scholars, and research institutes over the last few decades (Curtis and Headicar, 1997; McIntosh et al., 2014; Newman and Kenworthy, 2015; Oakil et al., 2014; Wickham and Lohan, 1999). Real-world examples of alternative transportation mode incentives, congestion pricing policies, and other policy initiatives have demonstrated considerable decreases in private vehicle mode trends in many different parts of the world (Kim et al., 2013; Poudenx, 2008; Sabounchi et al., 2014). Although efforts to definitively shift transportation mode choice trends in the U.S. using these policies have proven to be more difficult than expected, privately owned vehicle use has been increasing constantly (Santos et al., 2011; US DOT, 2016). In the literature, most of the studies and policy analyses indicate the same challenge to decreasing personal vehicle use as the lack of "sustainable urban development" (Ewing and Cervero, 2001; Poudenx, 2008; Saunders et al., 2008), meaning that urban sustainability is the only possible marginal solution for reducing the environmental impacts of U.S. transportation sector (Banister, 2008; Ercan et al., 2017). Some studies clearly showed that public transportation doesn't increase to the desired levels despite extensive government support for infrastructure investment and reductions in roadway network investments, thus a paradigm shift in urban development is necessary for reducing the environmental impacts of transportation (Ercan et al., 2017, 2016b). On the other hand, neither achieving sustainable urban development nor creating a paradigm shift for urban development (changing the way we have been doing it) are easy goals to accomplish because it may take decades to reform the predominant "American" lifestyle in any given period. In this regard, autonomous vehicles, shared transportation, and electrification of transportation are disruptive technologies that might change how transportation modes will be in near future (Potoglou et al., 2020; Zhang et al., 2020). While environmental impact reduction potential of these revolutionary technologies may not be fully utilized due to the potential increase in travel demand with the introduction of autonomous vehicles' rebound effects (Le Hong and Zimmerman, 2021) and depending on the source of electricity generation (Onat et al., 2015a), their potential to reduce environmental impacts are still significant (Jones and Leibowicz, 2019; Patella et al., 2019).

1.2. Literature review: What are the trends and the knowledge gaps?

The U.S. transportation sector is experiencing a revolution thanks to the combined advances in three transportation-related innovations in this generation: electric mobility, autonomous vehicles (AV), and ride-sharing options. The literature investigated these new technologies and initiatives in an isolated way, particularly concerning their related effects on transportation-related environmental (i.e. air pollution emissions), economic, and social impacts. For instance, AV taxis have a great deal of potential to dramatically reduce the amount of overall light-duty vehicle (LDV) emissions in the U.S. (Greenblatt and Saxena, 2015). However, as Fulton et al.'s (2017) report suggests, these three options should also be analyzed together to gather their potential impacts. According to our literature search in the Scopus database (Accessed on Feb 17th, 2022) using the following keywords query "TITLE-ABS-KEY ("autonomous vehicles" AND "shared mobility" OR "shared transportation" OR "ride-share" AND "electric vehicles" OR "electric mobility" OR "electrification" AND "carbon footprint" OR "carbon emissions") AND (LIMIT-TO (SRCTYPE, "j"))", there is no study found which analyzed all these aspects together. One of the main novelties of this study is that we provided an integrated assessment approach rather than analyzing the abovementioned aspects in an isolated way. This allows us to see the relative performance of a wide range of transportation policies as well as disruptive reforms of autonomous vehicles, electrification and shared mobility options in terms of their potential to reduce environmental impacts.

The growing problems of increasing emissions, energy consumption, and land use in the U.S. transportation sector have been studied using various simulation methods (including discrete event simulation (DES), system dynamics (SD), and agent-based modeling) to project future trends and test the short-term and long-term effects of different policy solutions (Cheng et al., 2015; Ding et al., 2017; Innocenti et al., 2013; Liu et al., 2015; Rees et al., 2017; Reis, 2014; Shafiei et al., 2013). All these simulation methods have their shortcomings and limitations related to how they each simulate the actual structure and/or behavior. The DES method, for instance, is a broad approach consisting of various methods used to study different behaviors with different types of discrete data sets. It has been the most widely used method for studying transportation mode choice problems (Eluru et al., 2010; Sarwar et al., 2018; Sener et al., 2009). However, the DES method is limited to the given discrete data to estimate mode choice behavior. On the other hand, the system dynamics (SD) method can model the system being studied in a macro-scale environment where endogenous (dynamic) and exogenous (deterministic) parameters work together to send and receive feedback among all relevant parts of the system. However, the SD method is limited to the use of macro-level data sets and may fail to capture case-by-case variations in certain parameters due to human-based behavioral changes (discrete), which are easy to model in DES. Therefore, a combination of the DES and SD methods as part of a hybrid simulation method would be ideal for simulating problems such as those associated with transportation mode choice, which consists of both individual human behaviors and macro-level system dynamics. The literature studied for this research includes studies on such hybrid modeling approaches, including applications in health care, operational research, and construction management problems (Alvanchi et al., 2011; Brailsford et al., 2010; Helal et al., 2007; Morecroft and Robinson, 2005; Peña-Mora et al., 2008). However, to the author's knowledge, few literature studies thus far have applied any such hybrid simulation methodology to transportation problems (Mueller and Sgouris, 2011; Struben and Sterman, 2008). Oak Ridge National Laboratory (ORNL) published a publicly available tool named MA^3T and MA^3T-MobilityChoice that utilize hybrid modeling methods for advanced transportation mode choice (Lin et al., 2018). Thus, the main methodological and application-based contributions of this study can be summarized as follows:

- The proposed integrated dynamic model provides a comprehensive assessment of the environmental impacts of autonomous vehicle adoption, electrification of transportation, and shared mobility (ride sharing).
- The impacts of autonomous vehicles are tested with and without the implementation of prevailing transportation policies, to investigate corresponding trends in transportation externalities and mode choice.
- The DES and SD methods are integrated for transportation mode choice application for the first time and the methodological weaknesses of each are minimized with this integration.
- A set of transportation policies are investigated concerning different city sizes in the U.S. in terms of their population, and both bottom-up and top-down approaches are combined to investigate the potential impacts of national-level policymaking.
- The use of system dynamics modeling provides a systematic way to evaluate the feedback and internal/external mechanisms that can affect the mode choice patterns and overall long-term effectiveness of transportation policies.

2. Materials and methods

The method of this research combines two widely utilized simulation and forecasting tools for transportation system problems. The use of the DES method allows the researchers to present "sample paths" of the desired discrete behavioral data for its behavior (Fishman, 2013); Brailsford and Hilton (2001) describes the DES method as a stochastic approach that allocates distinct entities, scheduled activities, queues, and decision rules within a relatively narrow context. On the other hand, the SD method can cover a broader context and allocate external "outside world" interactions with the system being analyzed over longer periods (Brailsford and Hilton, 2001). Consequently, Brailsford et al. (2010) have referred to the combined use of these two powerful methods as part of a hybrid modeling approach as a "holy grail" of simulation modeling. Fig. 1 illustrates the general concept of the hybrid modeling approach to be used in this study.

For the DES analysis in this study, the demographic and commuter mode choice characteristics from the 2015 American Community Survey (ACS) for the surveyed U.S. metropolitan and micropolitan areas are gathered and converted into a proportional dataset. In addition, 929 cities within the selected geographic boundary are classified into 4 groups based on their respective population sizes; these groups include "very large" (population (P) $\geq$ 1 M), "large" (500 K $<$ P less than 1 M), "medium" (200 K $<$ P $\leq$ 500 K), and "small" cities (200 K $\leq$ P), as shown in Fig. S1 (which illustrates a more detailed map of the classified cities) in the Supplemental Information (SI) document. The processed data from the ACS is then modeled using a multinomial fractional split model for

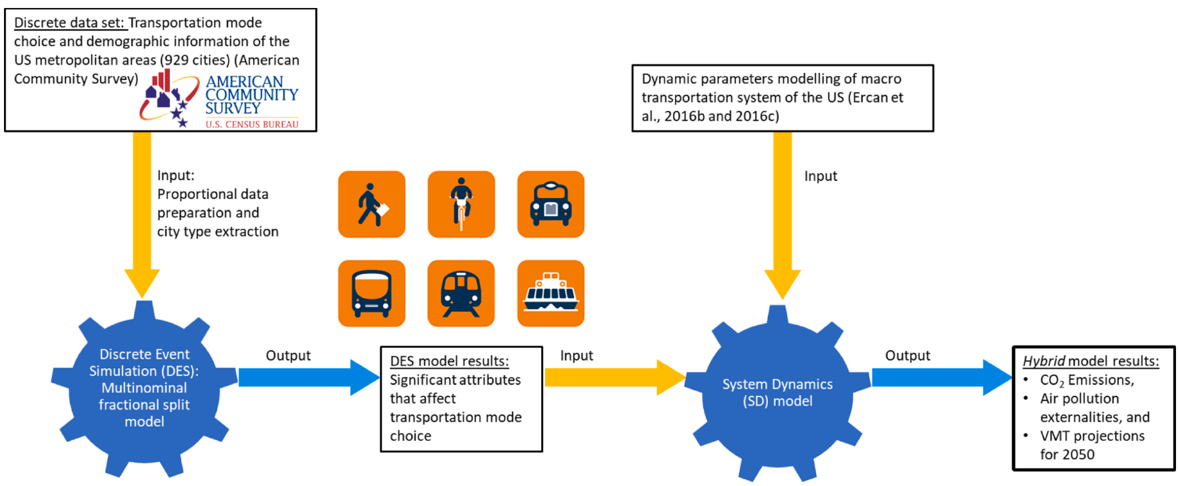

Fig. 1. Concept for hybrid modeling of simulation methods.

commuters' transportation mode choice trends in different city types, and the results of this discrete event model provide information about the most significant attributes that affect transportation mode choice, as well as the mathematical relationships (i.e. utility functions) associated with these attributes (please refer to SI Section S1.1 for DES method and formulation). Afterward, an SD model can be developed that includes the statistically significant attributes and other relevant parameters as applicable to the U.S. transportation system. The finalized hybrid model is developed using the VENSIM software, and can then be used to evaluate trends in transportation mode choices, vehicle miles traveled (VMT), CO_2 emissions, and the air pollution externalities of different city types and the nation as a whole, which can be projected as far ahead as the year 2050 (please refer to SI Section S1.2 for SD method).

By analyzing five available modes of transportation for commuters, the SD modeling approach allows us to identify relevant feedback mechanisms in the U.S. transportation sector as a whole and its related components. However, to start formulating and identifying the parameters of the dynamic model itself, the problem to be solved and the system to be modeled should first be explored on a conceptual basis. For this purpose, a causal-loop diagram (CLD) has been drawn in Fig. 2 to illustrate the interconnections and feedback loops within the modeled system. Real-world systems operate primarily based on feedback that decision-makers gather in the form of qualitative and/or quantitative data over time; regarding such feedback, Sterman (2000) has stated that "learning is a feedback process", and it can therefore be stated that all of the parameters within the modeled system are directly or indirectly connected via multiple simultaneous cause-and-effect relationships. As seen in Fig. 2 below, the parameters are linked with each other through multiple individual connections between variables and the resulting interconnected loops, and the influence transferred through each link is indicated using a polarity symbol (Sterman, 2000).

Fig. 2 provides broad guidance to visualize and formulate the impacts of the transportation sector on urban area commuters in the U.S., which also provide feedback to the system (e.g. climate change's drawback impact on life expectancy and the subsequent impacts on population and GDP). For this system, the CLD shows four feedback loops within the system, including three balancing loops ("B") in which an increase in any single factor causes a subsequent decrease, as well as one reinforcing loop ("R") in which an increase in any single causes a subsequent additional increase (Ercan et al., 2017; Sterman, 2000). Each feedback loop is presented in Fig. 2 with its respective rotations and labels. Due to the nature of the identified system, most loops share many parameters, which may make it difficult to locate some of the loops in the CLD, so all of the feedback loops in the CLD from Fig. 2 are summarized in SI Table S1.

2.1. Hybrid simulation model development

In light of the findings and methodologies available from the literature that are discussed in SI Section S1.3, the authors have chosen to use a combination of the DES and SD modeling approaches (Ercan et al., 2017, 2016b). Ercan et al. (2016c) conclude that sustainable mobility is extremely sensitive to trip generation parameters, which also explains why current policy efforts have so far been unsuccessful in reaching sustainable mobility goals. Ercan (2019) also showed the importance of the interconnectedness of transportation policy parameters, urban development structures, and the effect of emerging technologies on the sustainability impacts

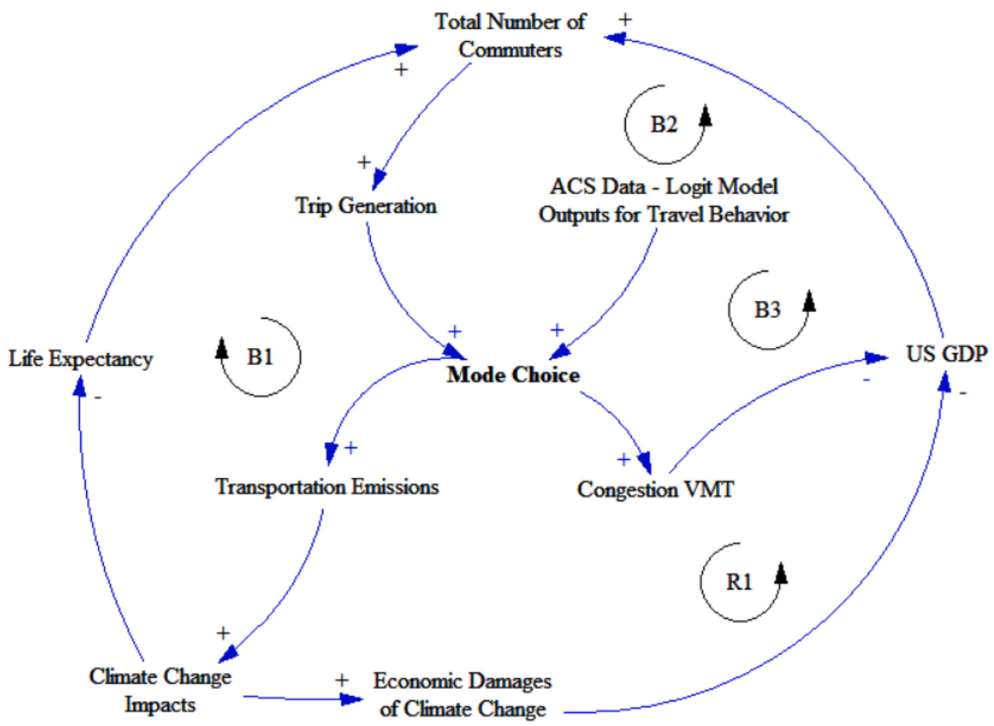

Fig. 2. Causal-loop diagram (CLD).

of transportation (Ercan, 2019). Therefore, it should be noted that transportation-related impacts cannot be addressed with only subsidized or myopic policies but should instead be addressed using policies that would actively involve all stakeholders in the transportation sectors. Similarly, Banister (2008) highlights the importance of stakeholder involvement at all possible levels to achieve the desired sustainability mobility goals. Banister's research is an important reference for this study since it reinforces the authors' point as to the necessity of SD modeling, which can integrate the impacts and feedback of these stakeholders and other possible contributors into a macro-level simulation of the transportation sector as it applies to this problem. Thus, the stakeholders can provide feedback to discrete events corresponding to mode choice behavior.

Although transportation system modeling requires an interconnected macro-level design, the key component of the modeled system for this study is travel mode choice, which is a personal behavior that can vary widely due to a variety of factors. A qualitative survey approach has provided valuable insight into commuters' driving/transit choices, which can be affected by the level of service, comfort, availability, and other related factors, but is still mainly a person's choice (Beirão and Sarsfield Cabral, 2007). This finding is also in agreement with Innocenti et al.'s (2013) study, which likewise found that mode choice is not always a rational behavior but can still be affected by psychological (mental) models that may cause heuristic and biased decisions. Therefore, it is also crucial to include discrete event modeling estimations in this study for mode choice behaviors. These modeling concepts have confirmed the need for a hybrid modeling approach.

The model development and formulation process are conceptually illustrated in Fig. 3. As CLD (Fig. 2) illustrates for the overview of interconnected sub-models, Fig. 3 provides more details of each sub-model and their input–output parameter relationships in greater detail. Each sub-model interconnection is explained in detail in SI Section S1.3. Some parts of the sub-models are adopted from the authors' previous modeling studies; these include the population, trip generation, public transportation mode choice impacts, air pollution externality calculation, total emission and externality, and climate change sub-models (Ercan et al., 2017, 2016b). The sub-model interconnection description in the SI is followed by model parameters (numerical value tables), each sub-model's stock-and-flow diagram along with formulation, and model validation in Sections S1.4, S1.5, and S2 respectively.

2.2. Policy scenarios

One of the greatest advantages of utilizing an SD modeling approach is its ability to test various policy scenarios and predict their long-term effectiveness (Alirezaei et al., 2017; Onat et al., 2017, 2014). This study aims to test four such policy scenarios as applicable to the U.S. urban transportation system for future reference concerning transportation modes, emissions, and social impacts. These four policy scenarios are as follows:

- The Business-As-Usual Scenario (BAU), in which only alternative fuel adoption rates and fuel economy values increase, but no other policies are applied as default.
- The Lane-Mile Scenario (LM), simulates a decrease in the usual lane-mile decrease.

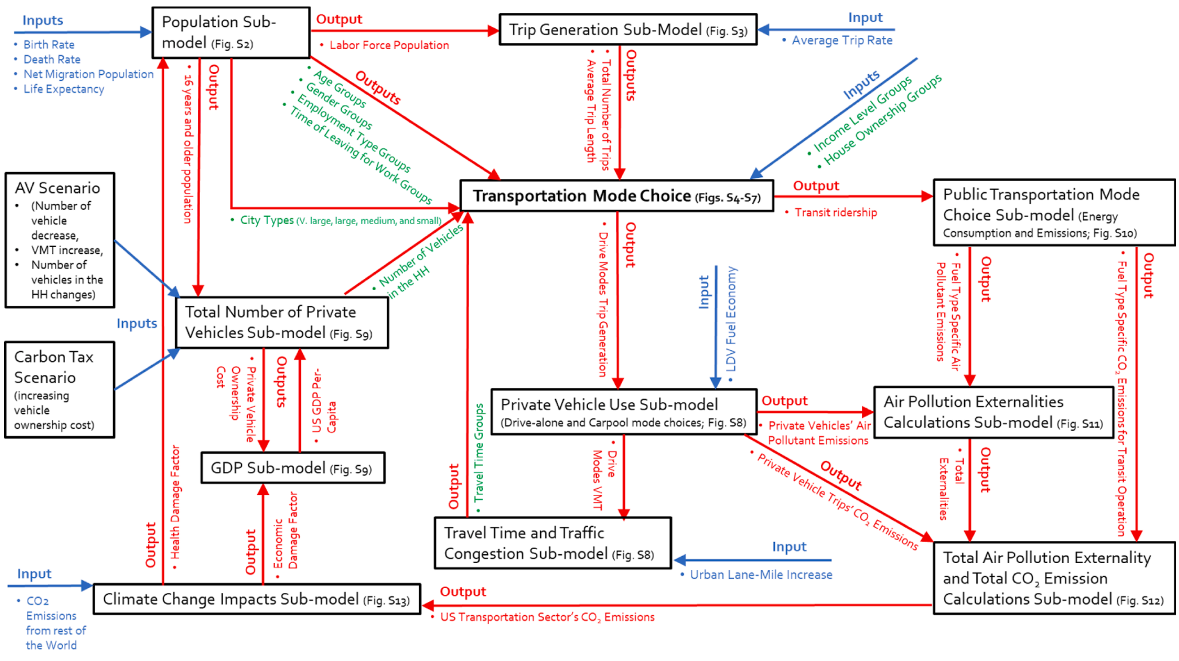

Fig. 3. Conceptual interconnections of sub-models and scenarios (Legend: Red arrows indicate outputs of the sub-model that input for associated sub-model, Blue arrows indicate exogenous inputs to the sub-models, and Green arrows indicate output parameters as well as significant parameters from the discrete model). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

- The Carbon Tax Scenario (CT), simulates a federal policy to collect tax revenue from vehicle owners based on their annual emission estimates.
- The Autonomous Vehicle Scenario (AV), simulates the potential for AV market penetration and analyzes its associated impacts on the U.S. transportation sector (VMT from AV deployment, number of vehicles, and overall fuel economy change).

This model takes into account the expected improvements in vehicle efficiency in the US with greater alternative fuel deployment and the aid of federal policies and incentives (Noori et al., 2016; Noori and Tatari, 2016; Onat et al., 2016b, 2016a, 2015b). Therefore, projections from the U.S. Department of Energy (US DOE) regarding the average fuel economy of passenger vehicle fleets are used in this study as the default (BAU) scenario (Argonne National Laboratory, 2014). In addition, based on current trends, the percentage shares for fuel/energy sources of transit vehicles are projected to shift more toward alternative fuels (Ercan and Tatari, 2015; Neff and Dickens, 2015).

The number of lane miles (roadway expansion projects) increases to supply the demand of an increasing number of vehicles and VMT so that the level of service can be maintained at a reasonable level and traffic congestion problems can be reduced. However, alternative transportation modes cannot realistically compete with the convenience of driving (especially driving alone) unless there is a significant increase in average travel time, and the number of lane miles cannot increase indefinitely due to land use limitations. Therefore, the historical rate of increase in lane miles is assumed to decrease by approximately 50 % after the year 2020 (U.S. Bureau of Transportation Statistics, 2015).

Metcalf (2009) reviews the potentials and criticisms of carbon tax policies in the U.S., which would apply a mandatory tax to vehicle/fleet owners based on estimates of their annual carbon emissions. Such carbon taxes are said to be a necessary step toward reducing emissions while also supporting the U.S. economy, which is currently going through various challenges due to climate change impacts (Stern, 2007). However, as Metcalf (2009) also indicates, a carbon tax of \$15/tonne of CO_2 can only increase the price of gasoline by 13 cents per gallon, or less than a 7 % increase relative to the original price. Therefore, this slight price increase is not expected to significantly change any pre-existing trends in drive mode or travel demand behaviors. For purposes of this study, a policy scenario (CT) is applied that adopts a constant carbon tax of \$13/tonne of CO_2 emissions from 2025 until 2050 (WorldBank, 2014).

Finally, AV market penetration scenarios (AV) are tested to account for current technological developments in the transportation sector and analyze the possible future of the transportation industry. The available literature on AVs and AV-related policies is still in its developing stages, especially since fully AVs are still not yet available in today's market but are currently still being tested, meaning that current research efforts must rely entirely on estimation data. Fagnant and Kockelman (2015) estimate remarkable projections regarding AV penetration levels and their associated behavioral changes, including increases in VMT, decreases in the total number of vehicles, and fuel savings for the overall U.S. vehicle fleet. Wadud et al. (2016) provide crucial insights into AV impacts on environmental emissions and energy consumption trends. Similar to other AV literature, Wadud et al. (2016) also highlight the projected negative impacts of AV on travel demands. Litman (2017) expands AV literature even further by estimating the benchmark years for AV market penetration levels and projects that AV market penetration levels will reach up to 50 % in 2045, but also notes that further development is still uncertain, as such development can increase exponentially at certain market levels. An extensive literature review on the potential effects of AV summarizes the benefits and impacts of different scenarios (Milakis et al., 2017). More recent studies presented the definitions and potential of shared autonomous driving and mobility-on-demand concepts for the future of the transportation industry (Shaheen et al., 2020; Shaheen and Cohen, 2018). This research is limited to the potential of privately-owned autonomous vehicles for metropolitan households, by simply assuming these vehicles will be used as a shared ride within the household and reduce the number of vehicle ownership (Fagnant and Kockelman, 2015).

Table 1 summarizes the changes in key parameters for the AV scenario as observed in both literature studies. Therefore, all parameters are interpolated from the results of both of these literature studies to complete the estimations for this study's target year of 2050 (Fagnant and Kockelman, 2015; Litman, 2017). This study also applies lane-mile and carbon tax policy scenarios to analyze their overall impacts compared to only the introduction of AVs in the AV scenario and tests combinations of all three scenarios as well.

2.3. Data preparation

The U.S. Census Bureau publishes data from the American Community Survey (ACS), and this data is also available through the American Fact Finder website, which allows users to modify and create custom datasets (US Census Bureau, 2016). Based on many available geographic boundary selections, this study uses metropolitan and micropolitan statistical areas to only consider urban U.S. areas. Regarding urban areas, the US Census Bureau defines micropolitan statistical areas as having populations ranging from 20,000

Table 1
AV Scenario Addition Parameters.

	Estimated Year for Market Penetration				Reference
	2020	2030	2045	2050	(Litman, 2017)
Market Penetration	1 % – 2 %	10 %	50 %	60 %	(Fagnant and Kockelman, 2015)
VMT Increase	1 %	2 %	8 %	8 %	
Total number of vehicles	−1%	−5%	−24 %	−28 %	
Fuel Savings	11 %	13 %	18 %	20 %	
Fuel Savings in overall fleet	0.17 %	1.30 %	9.00 %	11.85 %	

to 50,000 and defines metropolitan statistical areas as having populations of 50,000 or more. This geographic boundary consists of 929 urban areas in the U.S. (including Puerto Rico), and the data for the population of each urban area includes data on the following attributes:

- Transportation mode choices* (Drive alone, carpool, public transportation, walk, and other),
- Age groups* (16 to 24, 25 to 44, 45 to 54, 55 to 64, and 65 + years),
- Gender groups*,
- Native and foreign-born population percentages,
- Employment type* (government, private sector, self-employed),
- Income levels* ($1 to $24,999, $25,000 to $34,999, $35,000 to $49,999, and $50,000 +),
- Employment industry (ACMT, sales, finance, education, and other),
- Occupation type (management, service, sales, natural),
- House ownership (owner or rent),
- Poverty level (100-, 100 to 149, and 150 +),
- Time of leaving home to go to work* (12:00 am to 6:59 am, 7 am to 7:59 am, 8 am to 8:59 am, and 9 am to 11:59 pm),
- Travel time* (less than 10 min, 10 to 14 min, 15 to 19 min, 20 to 24 min, and 25 min or more), and
- The number of vehicles available per household* (no vehicle availability, 1 vehicle, 2 vehicles, and 3 or more vehicles).

As mentioned before, the data classification for metropolitan areas consists of significant variations in population; for example, the upper limit for the population reaches almost 10 million for the greater New York area alone. City size will have an impact on transportation mode choice, so the data is disaggregated into four major city size groups as described below (Table S4 of the SI document provides descriptive analysis results for each city size group):

Table 2
Fractional split multinomial model results.

Variable	Drive Alone		Car Pool		Public Transit		Walking		Other Mode	
	Parameter	*t*-value	Parameter	*t*-value	Parameter	*t*-value	Parameter	*t*-value	Parameter	*t*-value
Constant	0	–	−3.88	−19.36	3.4	0.82	10.18	5.4	−3.21	−4.35
City Size (Base: Small City)										
Medium city	–	–	–	–	0.62	4.8	–	–	–	–
Large City	–	–	−0.07	−2.36	0.95	7.28	–	–	–	–
Very Large City	–	–	–	–	1.81	7.31	–	–	–	–
Proportion of Gender (Base: Proportion of Female)										
Proportion of Male	–	–	2.37	8.28	5.53	2.61	–	–	2.63	3.86
Proportion of No. of Vehicle in Household (Base: Proportion of 0 vehicle)										
Proportion of 1 vehicle	–	–	–	–	−13.61	−2.74	−4.9	−2.29	–	–
Proportion of 2 or 3 vehicles	–	–			−12.88	−3.1	−6.79	−3.67	−2.5	−3.72
Proportion of Age Group (Base: Proportion of 16 to 24 years old)										
Proportion of 25 to 44 years	–	–	–	–	–	–	−8.32	−9.78	−2.45	−3.87
Proportion of 45 to 54 years	–	–	–	–	–	–	−4.56	−3.8	−3.77	−3.06
Proportion of 55 years and over	–	–	1.21	4.3	–	–	−6.09	−7.02	–	–
Proportion of Income (Base: Proportion < $25 K)										
Proportion > $25 K	–	–	–	–	–	–	–	–	0.78	2.5
Proportion of Travel Time (Base: proportion of commuters with travel time less than 10 min)										
Proportion of 10 to 14 min	–	–	–	–	–	–	−3.45	−3.41	–	–
Proportion of 15 to 19 min	–	–	–	–	–	–	−1.71	−2.49	–	–
Proportion of 20 min and more	–	–	−0.28	−3.71	−1.22	−2.4	−2.14	−4.91	–	–
Proportion of Employment Type (Base: Proportion of Private Sector)										
Proportion of Government	–	–	–	–	–	–	1.29	4.68	–	–
Proportion of Self Employed	–	–	–	–	–	–	4.5	5.82	4.64	6.51
Proportion of Time of Leaving for Work (Base: Proportion of 12.00 am to 6.59 am)										
Proportion of 7.00 am to 7.59 am	–	–	–	–	–	–	−2.67	−5.73	–	–
Proportion of 8.00 am to 8.59 am	–	–	–	–	5.97	3.56	2.21	3.81	–	–
Proportion of House Occupied (Base: Proportion of Owner)										
Proportion of Rented	–	–	1.48	11.43	3.99	4.34	–	–	2.73	6.03
Number of cities	929									
Log Likelihood of constant only Model	−677.02									
Log Likelihood at Convergence	−538.36									

*All the coefficients are statistically significant at a 95% confidence level.

- Very Large City (Population is greater than 1 million)
- Large City (Population ranges from 500,000 to 1 million)
- Medium City (Population ranges from 200,000 to 500,000)
- Small City (Population is less than 200,000)

The ACS dataset used in this study for metropolitan/micropolitan areas of the U.S. only includes the labor force population and the commuter population, which reduces the percent representation of the total population to 45 % of the total population, as noted in Table S4 of the SI document; this gap is mainly due to rural area populations and elderly and younger population groups that are not included in the considered data for this study. Although this population representation percentage indicates that less than half of the total population is represented, this portion can be the most frequent and most routine contributor to transportation activities.

Several transformations of the variables were undertaken to test different specifications in the fractional split model. For instance, the number of male populations in the urban regions is transformed to compute the proportion of the male population. In addition, some attributes consist of several parameters that can be grouped, including income level (which is divided into "less than $25,000" and "$25,000 or more"), time of leaving home for work, travel time, and the number of vehicles per household (Table 2). The DES model is designed after preparing the necessary data needed, but it was observed that some attributes ("native or foreign-born information", "employment industry", "occupation type", and "poverty level") have no statistically significant relationship with transportation mode choice; the statistically significant attributes are marked with asterisks (*) in the list of parameters above.

3. Results

3.1. How do demographic parameters affect mode choice behavior?

Based on the parameters from the ACS data, the fractional split multinomial logit model is simulated and indicates significant influence from the demographic attributes of different cities on the transportation mode choice trends in each city cluster. Table 2 summarizes all the significant ACS data attributes, which are also used as a guide to model the parameter connections in the SD model. Before proceeding with the dynamic modeling of the U.S. urban areas, this table should be investigated more closely to understand the interconnections among all the attributes.

Commuters in medium, large, and very large cities are more likely than small-city commuters to choose public transit, and transit ridership is positively correlated with population and city size, which is not surprising since larger metropolitan areas in the U.S. tend to have higher transit ridership ratios than smaller cities. The only other mode choice impact connected to city size is a negative correlation to carpooling by large-city commuters, meaning that commuters from large cities are slightly less likely to carpool.

Carpooling trends are also positively correlated with the male population. For instance, commuters who are 55 years old or older and commuters who rent their places of residence are not likely to own a private vehicle. This could mean that males are more likely to carpool relative to females due to potential differences in the importance of safety in their choice (Amaba and Dalgetty, 2014). There is also a correlation between the percentage of commuters who live in rental properties and the percentage of commuters who choose to carpool. This can be connected to economic reasons since carpooling is known to be able to save money while property owners generally may have higher household incomes. Finally, commuters who travel for longer than 20 min per trip are less likely to carpool, as an increase in travel time may lead to difficulties in finding other commuters who are traveling to the same area.

Public transportation ridership has significant positive connections with the attributes of "city size", "the male percentage of the population", and "the time when commuters would leave home for work (especially for commuters who leave home for work between 8 am – 8:59 am)", and "the percentage of people who live in rental properties". As with carpooling, females are less likely than males to use transit mode compared to the male population, which is an arguable result compared to the findings of Portoghese et al., (2011). Moreover, compared to earlier time groups (12:00 am − 6:59 am and 7:00 am − 7:59 am) for leaving to work, commuters in the 8:00 am – 8:59 am group may find it more convenient to ride transit modes, which can explain the positive correlation between public transit mode choice and the time when one leaves for work. Lastly, rental property occupants tend to use more public transportation than homeowners, this could be again associated with economic reasons or the greater availability of rental properties in residential communities, as well as the relatively easier access to transit systems from rental properties (i.e., high-rise apartment communities). On the other hand, any increase in the number of vehicles per household will decrease commuters' willingness to use public transportation due to the increased availability of privately owned vehicles (while commuters who do not own any vehicles at all are more likely to depend on public transportation), while travel times of 20 min or more will tend to discourage public transportation ridership.

Walking, as an alternative and more active transportation mode choice is faced with negative impacts from many attributes, whereas only employment type and late-morning commuting hours (the 8 am − 8:59 am group) tend to increase the walking mode choice proportion. Conversely, personal vehicle availability in a household reduces the likelihood of walking as a mode choice, which confirms the transit mode choice results as previously discussed. Regarding commuter age, the youngest commuter age group (16 to 24 years old) is more likely than any other age group considered in this analysis (25 to 44, 45 to 54, and 55 or older) to choose to walk as a mode choice. There is no statistical evidence to connect this impact to vehicle availability, but it must be noted that the youngest population group are less likely to have their cars or other personal vehicle and/or may choose to walk for personal and/or health reasons. However, commute times of more than 10 min tend to discourage commuters from walking, which is understandable given year-round weather impacts (heat, cold, rain, snow, etc.). The two "time of leaving home to go to work" attribute groups have an adverse but controversial impact on walking as a mode choice. While the early commute hours from 7:00 am to 7:59 am are less likely to walk, the commuters in the next group (8:00 am to 8:59 am) are more likely than the base group of commuters (12:00 am to 6:59

am) to choose to walk, as commuting too early in the morning is more likely to cause discomfort due to traveling in the dark (especially in times of the year with fewer daylight hours in certain regions) while also raising additional safety concerns for commuters. Lastly, government-employed, and self-employed commuters tend to choose to walk more often than commuters employed in the private sector.

Other possible modes of transportation (taxicabs, motorcycles, bicycles, and others) have been aggregated into one mode choice in the available dataset, making it more difficult to interpret the results of the “Other” mode choice, which consists of many different transportation modes that can each have their unique interactions with different influencing factors and may each respond to various degrees to the same influence. As previously noted for carpooling and public transit, male commuters tend to use other modes of transportation (cycling, taxicab, etc.) more often than female commuters do, as are commuters with income levels of $25,000 or more, self-employed commuters (as opposed to government-employed and private-sector commuters), and rental property occupants (as opposed to homeowners). On the other hand, the use of other modes of transportation is more likely to decrease for a household owning 2 vehicles or more. Lastly, the results of this study identify-two commuter age groups (25 to 44, and 45 to 54) that are less likely than younger commuters (16 to 24) to use other transportation modes.

3.2. Policy implementations for different city sizes

The outcomes of the DES model generate utility functions for each mode choice, which are then used as a guide for hybrid (SD)

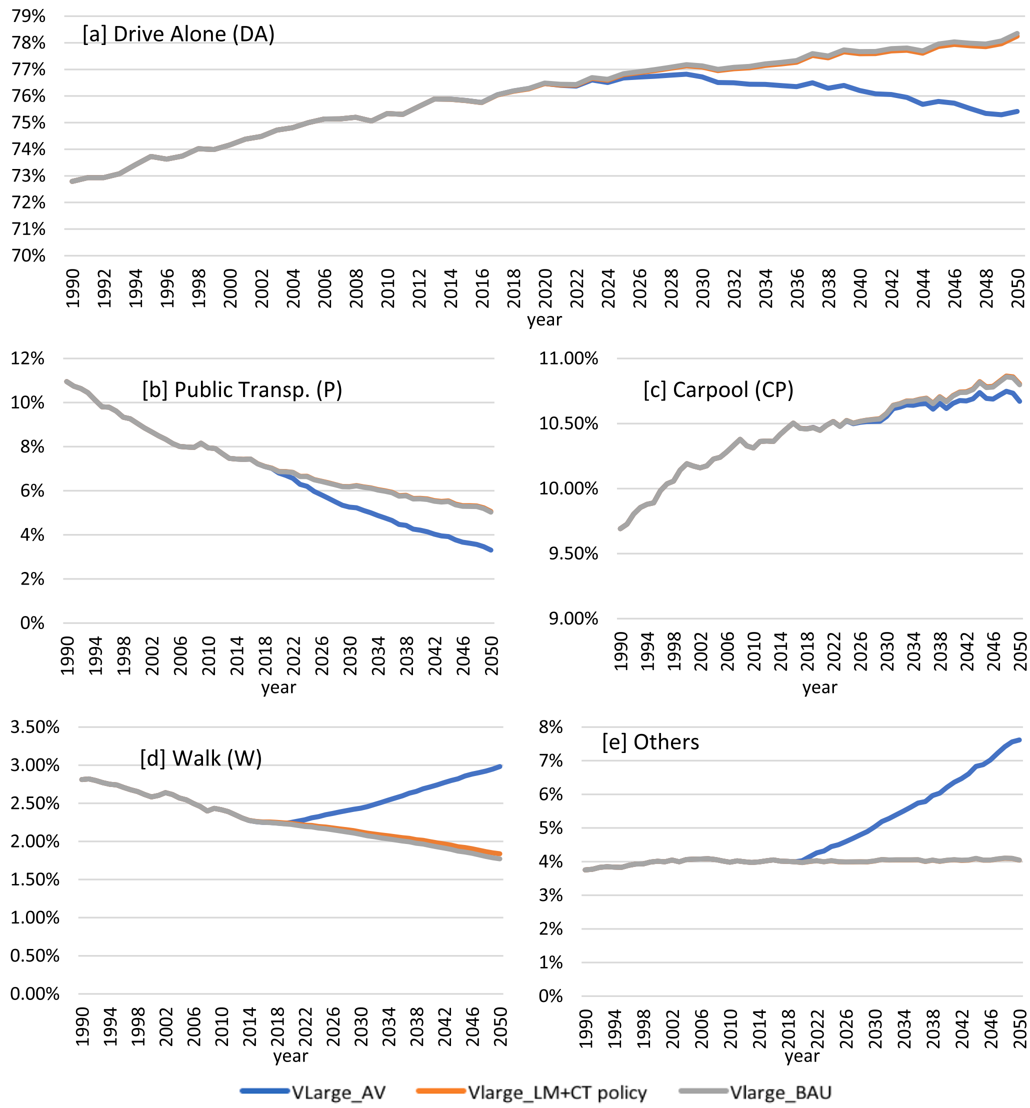

Fig. 4. Transportation mode choice of **Very Large** cities: [a] Drive Alone (DA) mode choice; [b] Public Transportation (P) mode choice; [c] Carpool (CP) mode choice; [d] Walk (W) mode choice; [e] Other mode choice.

modeling parameter selection. Finally, the SD model is run for the overall urban transportation system in the U.S., thereby revealing mode choice and impacts results for different city sizes with various policy scenarios. The combination of four different city size groups with five different mode choices is used to generate many crucial result graphs for various impacts. However, the manuscript is limited to showing only some of these results, specifically those involving changes in mode choice and overall transportation system impacts (CO_2 emissions, air pollution externalities, marginal CO_2 emission changes) for each city size classification, as discussed in the following sections. Additional result graphs are provided in the Supporting Information (SI) document, including results for the total number of personal vehicles (Fig. S15), the number of available vehicles per household (Fig. S16 through S18), drive mode VMTs (Fig. S19), and total annual CO_2 emissions (Figure S20) of each city group under different policy scenarios.

3.2.1. Very large city

Very large cities are expected to have lower proportions of commuters driving alone while also having greater public transportation ridership levels, compared to average trends in U.S. urban area transportation (US Census Bureau, 2016). As expected, Fig. 4a and 4b show a similar behavioral pattern for very large cities, with the drive-alone (DA) mode choice ranging from 73 % to 78 % while public transportation (P) ridership ranges from 5 % to 11 %. As seen in the graph, the results for the BAU, Lane Mile (LM), and Carbon Tax (CT) policy scenarios are all quite similar, but the LM + CT scenario results in a decrease in DA mode choice by 0.1 % by the year 2050. This slight impact of the LM + CT policy scenario is also observed on all other transportation modes and does not result in any behavioral changes. However, the AV scenario demonstrates interesting trends, especially in that it shifts the behavior of the DA, P,

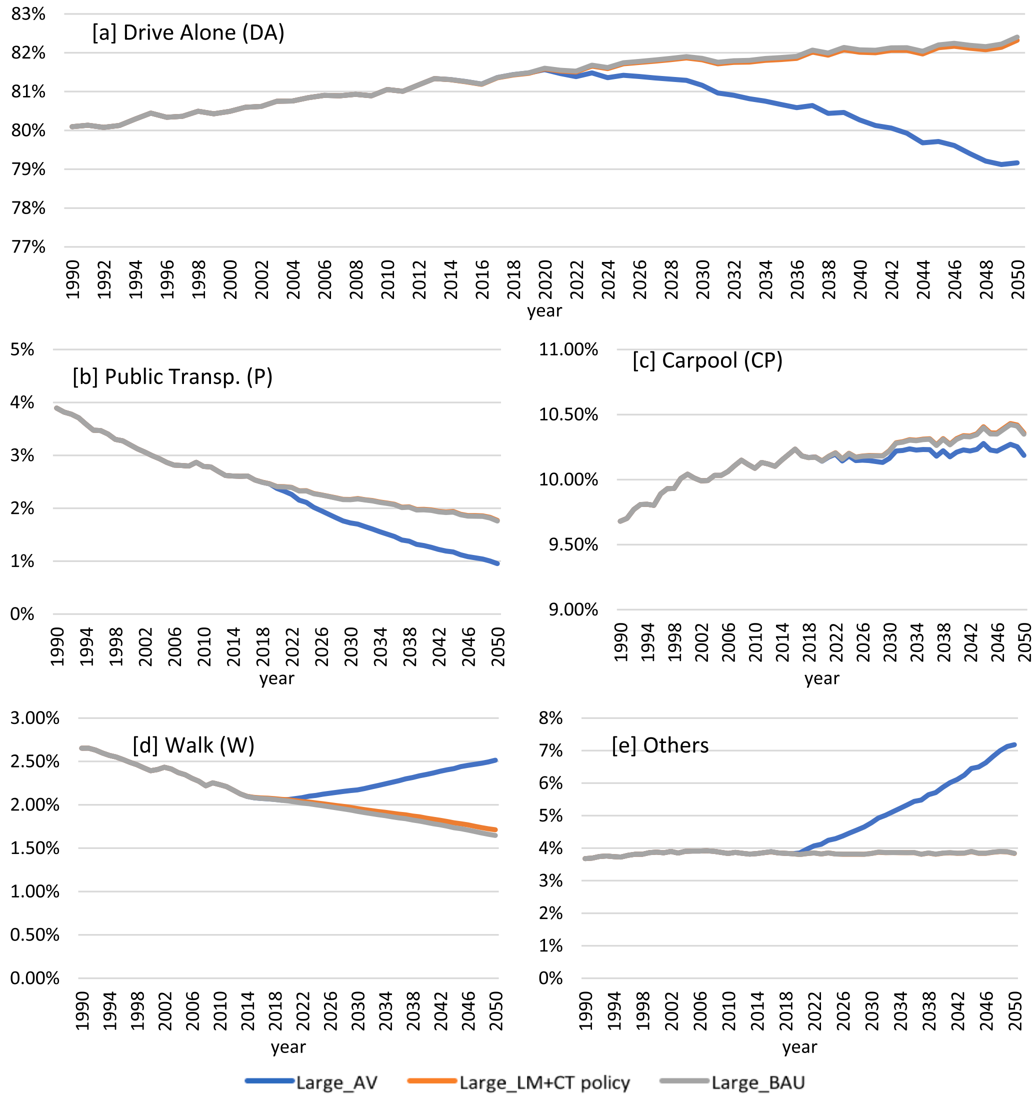

Fig. 5. Transportation mode choice of **Large** cities: [a] Drive Alone (DA) mode choice; [b] Public Transportation (P) mode choice; [c] Carpool (CP) mode choice; [d] Walk (W) mode choice; [e] Other mode choice.

walk (W), and "Other" mode choices.

Unlike the LM + CT scenario, the AV scenario decreases the DA mode by almost 3 % by the year 2050. Although 27 very large cities have been considered in this study, these cities collectively represent a significant portion of the commuter population (21 % of the total population as shown in Table S4 of the SI document), and this annual rate change can provide tremendous energy consumption savings and emission reductions from personal vehicle usage. The only mode choice not significantly affected under the AV scenario is the CP mode choice, which can be explained due to the statistical relationship previously indicated in Section 4.1., which shows that only four attributes (gender, the oldest age group, longer commute times, and rental property occupancy) have any significant effect on the CP mode choice. Thus, the AV scenario does not directly affect any of these four attributes, limiting the resulting decrease to only 0.13 % in 2050 compared to the BAU scenario.

Public transportation mode already has a decreasing trend for very large cities under the BAU scenario, and this decrease is typically associated with increasing personal vehicle ownership shares and travel times. Under the AV scenario, however, this decreasing trend becomes even stronger, reaching as low as 3.5 % in the year 2050. The AV penetration scenario indicates that it will become more likely for households to own at least one vehicle, and this attribute becomes the dominant effect on the system, resulting in a decrease under the AV scenario. It can then be projected that VMT will increase under the AV scenario, while transit ridership decreases as commuters become more likely to choose to drive alone or use other modes of transportation.

Under the BAU and LM + CT scenarios, the Walk (W) mode demonstrates a decreasing trend while the 'Others' modes continue to show a relatively steady trend throughout the entire study period. However, AV market penetration implies surprising impacts on these

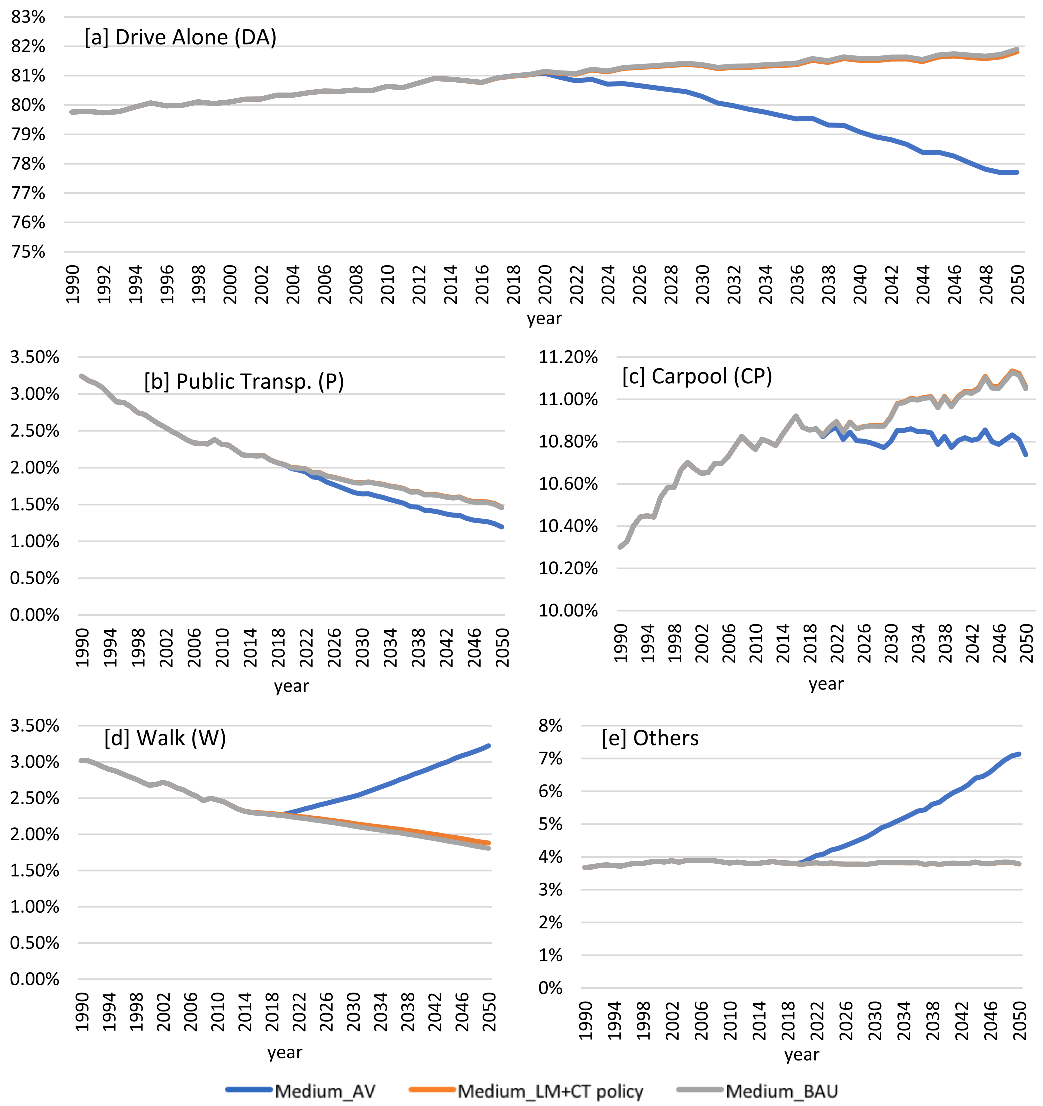

Fig. 6. Transportation mode choice of **Medium** cities: [a] Drive Alone (DA) mode choice; [b] Public Transportation (P) mode choice; [c] Carpool (CP) mode choice; [d] Walk (W) mode choice; [e] Other mode choice.

same transportation modes, changing their behavior and increasing the proportions of both mode choices. The proportion of commuter households that own two or more vehicles has a dominant impact on the Walk mode choice, and a dramatic decrease in this attribute as AV market penetration increases caused an increase in the proportion allocated to the Walk mode choice. It should be noted that this increase indicates a behavioral change in Fig. 4d, but the final difference in the year 2050 is only 1.2 % compared to the BAU scenario results. It is more difficult to interpret the results for other mode choices ("Other"), which consist of the aggregated results associated with several different modes (cycling, taxi, etc.), each of which has its unique dynamics. Similar to the W mode choice, a dramatic change in the number of vehicles has a dominant impact on the "Others" mode choice, while the impacts of the remaining significant attributes all neutralize each other. Subsequently, as households begin tending to own fewer vehicles, commuters begin to switch to alternative modes of transportation.

3.2.1.1. Large city. The large cities in this study consist of 24 metropolitan areas in the U.S. that altogether represent 6 % of the total population. As opposed to very large cities, large cities already have DA mode choice proportions of more than 80 %, and this rate tends to increase linearly in future years. The LM + CT policy scenario manages to slightly decrease this trend by 0.08 % in the year 2050, but the AV scenario changes this trend much more drastically with a 3.25 % decrease in DA ridership by 2050, as shown in Fig. 5a. Since

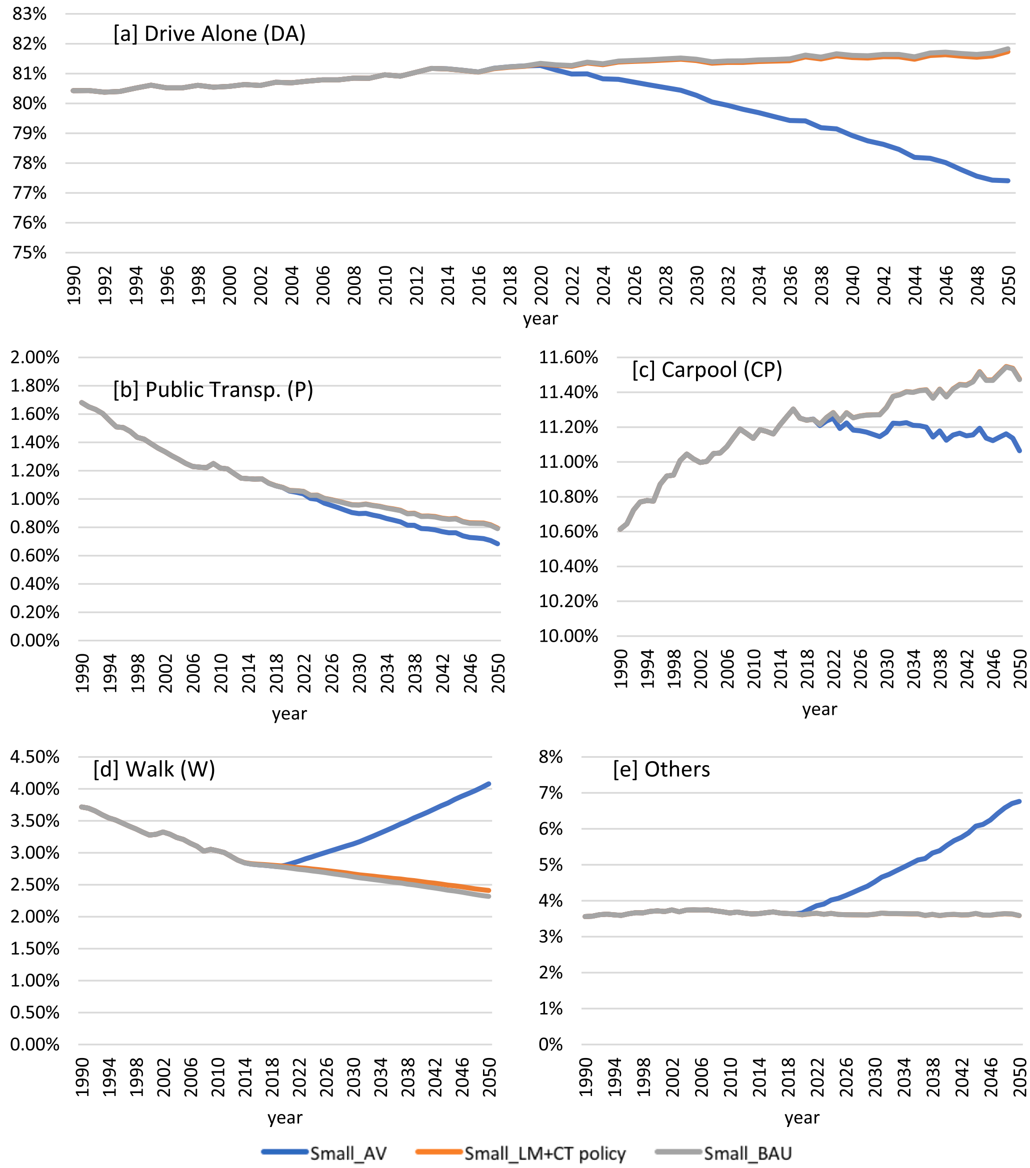

Fig. 7. Transportation mode choice of **Small** cities: [a] Drive Alone (DA) mode choice; [b] Public Transportation (P) mode choice; [c] Carpool (CP) mode choice; [d] Walk (W) mode choice; [e] Other mode choice.

the DA mode choice is the base mode choice for the DES model, all the most significant attributes in the model have an impact on DA mode choice estimates throughout the study period. In addition, the feedback relations simulated in the SD model demonstrate how the DA mode choice is subject to the simultaneous influences of all model parameters. However, the resulting drastic change in the number of vehicles per household may be especially responsible for the dramatic decrease in DA ridership as AV penetration increases, as it was previously noted that the LM + CT policy scenario did not yield any significant changes despite its increases in travel times and vehicle ownership costs. As another drive mode, the CP mode choice slightly increases its share in future years under the BAU scenario, while the AV scenario demonstrates a decrease in CP as shown in Fig. 5c. However, this change in CP is limited to only 0.16 % in 2050 between the BAU and AV scenarios. Moreover, the overall change in CP from 1990 to 2050 is only 0.67 %.

Transit ridership for large cities is already less than half of the shares for the P mode choice in very large cities and is expected to decrease throughout the study period as shown in Fig. 5b. AV penetration impacts cause a steeper decrease in the P mode choice share, but this impact is no less than 1 %, as the impact on the P mode choice is limited due to its small scale. The W and other mode choice shares increase under the AV scenario, but only the change in the other mode share can be considered significant with a 3.3 % difference in 2050 between the BAU and AV scenarios, as opposed to a corresponding change of 0.8 % for the W mode choice.

3.2.1.2. Medium city. The medium cities in this study consist of 63 metropolitan areas in the U.S. that altogether represent 6 % of the total population. Medium and large cities demonstrate similar mode choice results in terms of scale and representation area; for instance, the DA mode choice shares for both city types have a range of approximately 80 % to 82 % under the BAU scenario, and a similar scale can be observed in the remaining mode choice graphs in Fig. 6a through 6e. However, the decrease in DA ridership under the AV scenario is more significant for medium cities at 4.2 % in 2050 compared to the BAU scenario. Likewise, the influence of the AV scenario on the W mode choice is around 1.5 % and is as much as 3.35 % for the Other mode choice.

3.2.1.3. Small city. Finally, the small cities in this study consist of 815 metropolitan and micropolitan areas in the U.S. which represent 11 % of the total population. Although the majority of the urban areas being considered are small cities, the population total for these small cities does not exceed the total population of very large cities. The LM + CT and AV policy scenarios both decrease DA mode choice projections compared to those of the BAU scenario, but the impacts of the LM + CT scenario are limited to a decrease of approximately 0.1 %, as opposed to a 4.4 % decrease under the AV scenario. The DA mode choice achieves its largest percent shares compared to those of other city groups, but these DA shares do not differ significantly from the DA ranges of large or medium cities.

In Fig. 7b, the P mode choice has its lowest percent shares in small cities compared to the corresponding shares for other city groups, due to the relative lack of effective or usable transit systems in some of the urban areas in the dataset. Moreover, the existence of public transit systems for small cities is questionable, since public transit ridership only ranges from 0.8 % to 1.6 % throughout the study period. The DES results also support these findings since small cities have the strongest negative correlation with P mode choice shares, while the AV scenario further reduces the already-decreasing P mode shares by 0.1 % in the year 2050 compared to the BAU scenario, making the policy impacts on this mode choice too insignificant to draw any meaningful conclusions.

The CP mode choice behaves the same way in small cities as in other city types, with a range of less than 1 %. The LM + CT policy scenario has a noticeable impact on the W mode (Fig. 7d) with a 0.09 % increase in 2050 compared to the BAU scenario, but this increase is still negligible compared to the corresponding 1.76 % increase under the AV scenario compared to the BAU scenario. Small cities also demonstrate a significant increase in “Other” mode choice shares under the AV scenario with an increase of up to 6.8 % in the year 2050.

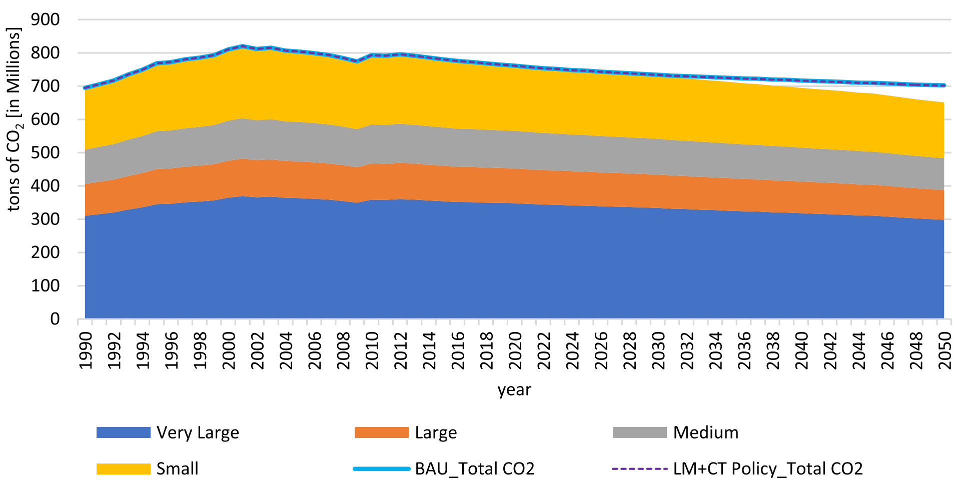

Fig. 8. Total annual CO_2 emissions from urban passenger transportation in the U.S. under the AV adoption scenario: Cumulative emissions of city sizes, Business as Usual (BAU) scenario, and Lane mile + Carbon Tax (LM + CT) Policy Scenario.

3.3. Overall transportation system impacts

As a result of the mode choice trends for urban area commuters, the two drive modes (DA and CP) and the public transportation (P) mode all contribute to the overall environmental impacts of the U.S. transportation system as previously described in Section 2.1. It should be noted here that other mode choices ("Other") include taxi cabs and motorcycles, both of which also have air pollution impacts, but these impacts are beyond the scope of this study. Recalling the policy scenarios previously described in Section 2.2, four policy scenarios (BAU, LM, LM + CT, and AV) are tested from 2017 to 2050. As indicated in previous mode choice estimates for different cities, the LM and CT scenarios are simulated together rather than separately due to their limited influence on their policy results compared to the results under the BAU scenario. The detailed results of the AV scenario for emissions and externalities are presented in the following figures for each city group.

Fig. 8 presents a cumulative graph of the total transportation-related annual CO_2 emissions under the AV scenario for all four of the city groups considered in this study. The total annual CO_2 emissions under the BAU and LM + CT scenarios are shown as a single line that indicates the total emission rate from all city groups. These CO_2 emissions are already experiencing a decreasing trend due to fuel economy improvements and alternative fuel adoption, which has already been included in the BAU scenario. The LM + CT scenario follows the same path in the graph as the BAU scenario, but only yields 0.64 million tons of annual CO_2 emission reductions by the year 2050. Conversely, the total CO_2 emissions under the AV scenario demonstrate a much greater reduction of up to 51.3 million tons (a 7 % decrease) between the BAU and AV scenarios by the year 2050. Although the emission reduction potential of the LM + CT scenario is not negligible despite being much smaller than that of the AV scenario, the CO_2 emission results clearly illustrate the potential of AV market penetration to reduce the number of vehicles on the roadway and improve energy efficiency despite its increases in the overall VMT of the U.S. transportation sector.

Fig. 9 illustrates the marginal differences for each city group for the AV and LM + CT scenarios separately, adding up each year's CO_2 emission differences compared to the results of the BAU scenario. Fig. 8 presents the annual CO_2 emission rates from commuter transportation activities; this time illustrating emission reductions and increases as a cumulative impact on the environment in addition to the emissions from the rest of the world. Therefore, illustrating the cumulative marginal differences in the LM + CT and AV scenarios relative to the BAU scenario for the duration of the study period can provide insightful information.

Hence, due to the increase in VMT and the slight benefits of the AV scenario in the initial years of AV market penetration, CO_2 emissions are increased, and this increase accumulates to almost 13.5 million tons of CO_2 for very large cities only. However, with the AV market penetration benefits previously observed, this behavior changes exponentially until the cumulative marginal difference for very large cities alone reaches up to almost 200 million tons of CO_2; the total summation of the corresponding marginal emission difference for all city groups under the AV scenario is 474 million tons of CO_2 by the year 2050, although it must be noted that this value is a net difference that accounts for the initial drawback impacts. On the other hand, the LM + CT scenario also yields crucial emission savings, but these savings cannot be seen in the graph due to their smaller scale; the total emissions from all city groups not shown in this regard for this scenario are limited to 13.7 million tons of CO_2.

All the hybrid-modeling results corresponding to the aforementioned insignificant impacts are shown in the remainder of this section for three possible policy scenarios. Fig. 10 presents these results in terms of the per-capita change in CO_2 emissions from 2017 to 2050 under all policy scenarios. As previously observed in Fig. 8, CO_2 emissions are already experiencing a decreasing trend, and this trend alone yields a 28 % emission reduction per capita under the BAU scenario. This emission reduction is not noticeably different from those of the LM or LM + CT policy scenarios, each of which only yields a change of 0.07 % compared to the BAU scenario. Conversely, the AV scenario yields a much more significant change of almost 34 % from 2017 to 2050, which amounts to a difference of

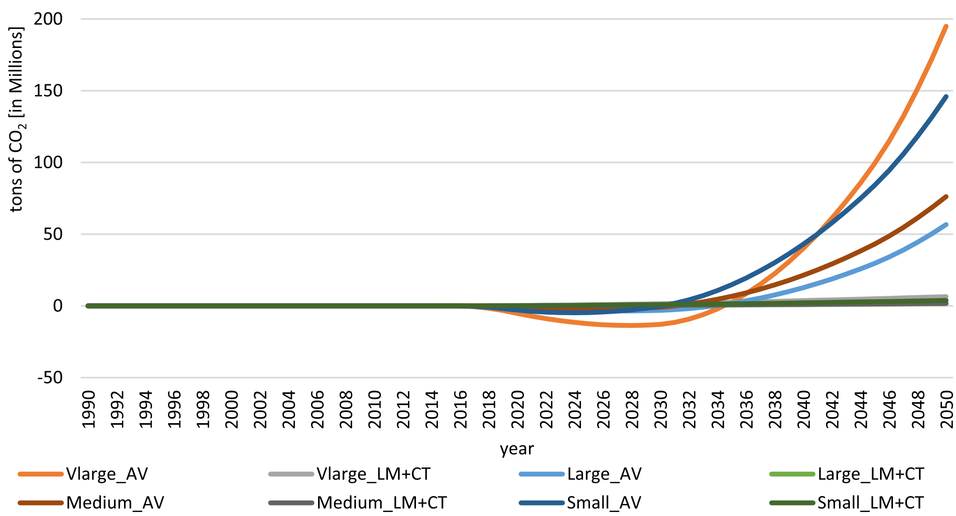

Fig. 9. Marginal cumulative differences (emission reduction potential) in CO_2 emissions compared to the BAU scenario for all city groups.

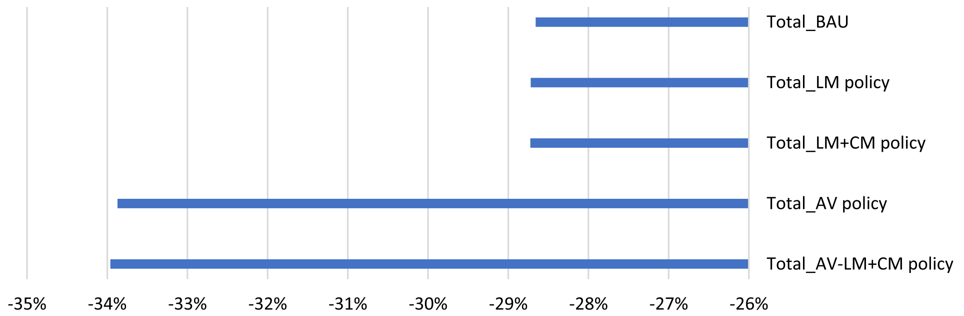

Fig. 10. Marginal per-capita CO_2 emission changes by all policy scenarios from 2017 and 2050.

5 % relative to the BAU scenario. The study also tested the impacts of all three scenarios combined to test the possibility of a greater collaborative impact from all policies operating simultaneously, but this combination (the AV + LM + CT scenario) does not demonstrate any noticeable difference from the results of the AV scenario.

The model also calculates the air pollutant emissions from personal vehicles (considered in this study to be light-duty vehicles) and transit vehicles in terms of CO, NO_X, SO_X, PM_{10}, $PM_{2.5}$, and VOC emissions in addition to CO_2 emissions. The marginal damages of these air pollutants (i.e., social cost or externalities) are converted into monetary values as explained in Section S1.4 and Table S3 of the SI document. These externalities are crucial for the sustainability assessment of urban transportation design since the ultimate goal of all of the accumulated literature and research in this regard is to improve air quality and (by extension) overall quality of life. Fig. 11 summarizes the results of the externality calculations under the AV scenario, which are shown as cumulative areas for each city group while the total BAU and LM + CT scenario results are shown as single lines. The improved energy efficiency projections under the BAU scenario already contribute to a relatively steady behavioral pattern in externality values, while the impacts of AV market penetration begin to show a visible influence in overall externality levels after the year 2040, although the AV scenario still shows an optimistic reduction trend in future years. Although the overall decrease under the AV scenario may seem limited, the difference between the externality results under the BAU and AV scenarios is approximately $1.5 billion in the year 2050. It should also be noted that this number only corresponds to a one-year difference, while the decreasing trend under the AV scenario predicts promising externality savings for future years at higher AV market penetration levels.

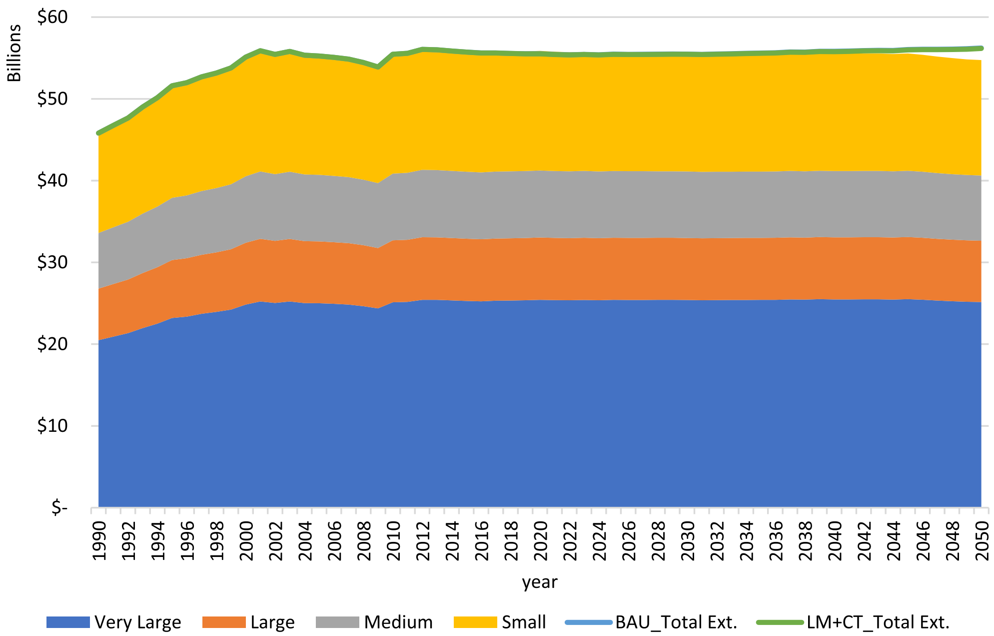

Fig. 11. Total annual air pollution externalities of urban passenger transportation in the U.S. under the AV adoption scenario: Cumulative emissions of all city sizes, Business as Usual (BAU) scenario, and Lane mile + Carbon Tax (LM + CT) Policy Scenario.

4. Conclusions

4.1. Discussions and limitations

In this study, we presented a more holistic perspective of urban commuter mode choice projections and potential environmental impacts of autonomous and other potential modes of transportation in terms of CO_2 emissions and air pollution externalities. This study distinguishes itself from previous transportation mode choice literature in several ways. A novel hybrid simulation modeling approach is developed to examine the U.S. transportation sector on a macro-level scale while also accounting for the micro-level discrete data on various urban areas. The conceptual connection of the transportation system with feedback loops as a whole and the statistical relationships among the analyzed discrete event data allowed us to test and forecast possible policy scenario impacts.

4.1.1. DES key findings

The DES modeling results indicated that city size only influences public transportation mode choice, whereas the number of vehicles owned per household was found to significantly impact almost all of the considered mode choices, which can provide a great deal of insight regarding the aforementioned vehicle dependency statistics in the U.S. As more vehicles are available per household, the more likely commuters are to become heavily dependent on drive modes, among other urban development impacts. Travel time is another key factor (particularly for the CP, P, and W modes), which overlays with current trends in U.S. transportation mode choice. These travel times are typically long due to low-density residential developments, disproportions between the residential and employment densities of a particular area, and increasing traffic congestion due to growing numbers of vehicles on roadways. The abovementioned factors all strengthen the already-predominant share of the DA mode choice and reinforce the urban development factors that worsen the current problems with today's transportation industry. These problems, therefore, cannot be properly addressed using only short-term policy resolutions, but will instead require a more long-term paradigm shift.

Other significant attributes in the DES model that cannot be realistically controlled or tested for policies included gender, age groups, employment, house occupancy (rental vS ownership), and the time when a commuter leaves home for work. Some might argue that the time when one leaves for work can be changed using workplace policies to encourage starting work at more optimal times of the day, and there are indeed some examples of such policies being implemented in several cities around the world. However, such policy applications aim mainly to reduce traffic congestion by distributing the peak-hour traffic load across a larger period. Such policy application impacts can still be tested, but this study has limited its scope by considering the time of leaving for work as an exogenous variable. The primary reason for this boundary limitation is that this model considers 929 urban areas nationwide whereas to model and test this policy would require very specific data from each urban area, thus requiring an overly extensive modeling process for only one attribute.

The hybrid model simulation was first used to illustrate the business-as-usual (BAU) results for transportation mode choice and emission impacts from 1990 to 2050. The BAU scenario itself showed interesting findings in terms of the mode choice behaviors of each city type, as the DA mode choice share increased while the P and W shares decreased, and the shares of the CP and Other modes remained almost steady throughout the study period. This behavior in the BAU scenario, which matched the current trends, was then subjected to a policy scenario analysis to identify the most efficient policies for decision-makers to resolve these issues. As previously explained, negligible effects of the LM + CT policy scenario indicated that traditional policy efforts that subsidize and/or punish different mode choices do not adequately support any meaningful long-term behavioral change. These policies are both considered "traditional" policies in this study because the transportation sector is currently undergoing a revolution by exponentially adopting electric vehicles, autonomous vehicles, and ride-share modes. Furthermore, past research efforts have already examined similar traditional policy scenarios but have all failed to produce any significant shift from drive modes to alternative transportation modes. Today's reformist era of transportation, in contrast, has the potential to radically change many of the factors and indicators related to transportation mode choice behaviors, including the built environment, vehicle ownership, air quality measures, and several other key factors.

4.1.2. SD key findings

To simulate an example of this technological revolution, AV market penetration was tested in this study as an external policy factor for its possible impacts on the transportation system. The results of the AV market penetration scenario in this regard indicate significant promise for considerable reductions in emissions and externalities, such as decreasing transportation-related CO_2 emissions up to 34 % and saving $1.5B of externality cost. The mode choice share indicates matching results with decreasing DA mode shares while also increasing the W and Other mode choice shares. However, AV market penetration also caused a rebound effect by increasing the VMT, most notably because a growing number of households own at least one vehicle, and society (especially vehicle owners) is expected to benefit from the relative convenience of AVs. This finding also aligns with a literature study that expects to add non-drivers, the elderly, and people with travel-restrictive medical conditions to the roadway commuter population in future roadway systems (Harper et al., 2016). This impact was observed in the model as a decrease in P mode choice shares with increasing AV market penetration. The AV scenario also resulted in an increase in mode choice shares for the W and Other modes by decreasing the number of households that has more than one vehicle available. It is therefore important to note that more active transportation modes (walking, cycling, etc.) are not only alternative transportation modes but also potentially crucial contributors to improvements in health and overall quality of life. Two well-cited articles highlight the critical impacts of mobility (or lack thereof) on human health due to increases in obesity, blood pressure, and other serious health problems, and both of these studies recommend improving the built environment by increasing the "walkability index" of U.S. neighborhoods to encourage more people to use active modes of transportation (Frank et al., 2006, 2004). The extent to which AV market penetration may or may not encourage commuters to use less active travel modes is still unclear in today's literature, but future research efforts can investigate the impacts of increased and more convenient mobility that may reduce harmful pollutants but may also decrease or increase activity levels.

Although AV market penetration can trigger a more dramatic decreasing trend in CO_2 emissions, its effectiveness is still limited in terms of reaching the desired deep carbon reduction goals, which Fulton et al.'s (2017) report has stated is possible with the full and combined adoption of the three aforementioned transportation reforms (EVs, AVs, and ride-sharing). This study and other recent literature studies have revealed that transportation-related impacts can only be changed with a paradigm shift in the current practices of today's transportation industry. Fortunately, this paradigm shift can become a reality soon with the introduction of the three aforementioned reforms, which will also bring about marginal improvements in the built environment and urban mobility.

4.2. Future work

In the future, the proposed SD model can benefit from specific attributes connected to the urban area that respond to and provide feedback from the use of policy scenarios to address the problems being analyzed. Such research data can be processed using geospatial analysis tools and included as SD model inputs; this may be possible in future research with the use of an Agent-Based Modeling (ABM) approach, which would be integrated with SD modeling. Lastly, the research in this study can also be extended in the future with a worldwide case study of successes and/or failures of transportation policies intended to encourage the use of alternative transportation mode choices and reduce the current dependence of the U.S. on conventional drive modes.

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Author contribution

The manuscript was written through contributions from all authors. All authors have approved the final version of the manuscript. Tolga Ercan, Nuri C. Onat, Nowreen Keya, Omer Tatari, Naveen Eluru, and Murat Kucukvar have all contributed equally to this study.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2022.103472.

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