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Enhancement of the impacts 2050 model to enable a whole system sustainability assessment of rideshare

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ABSTRACT

Emerging concepts, such as Mobility as a Service (MaaS), could evolve to provide sustainable mobility, especially in densely populated urban areas. However, recent studies highlight the challenge of evaluating how the complex interactions of user demographics, mode choice, vehicle automation, governance, and efficiency will impact the sustainability of future mobility. Given this challenge, this research identifies a whole system (STEEP - social, technical, economic, environmental, and political) framework as essential to assess the overall sustainability of emergent urban mobility systems such as rideshare. The need is a single tool that can rapidly explore the long-range sustainability impact of such alternative future mobility scenarios for a given city region. This paper documents enhancements made to Impacts 2050, a strategic-level model of urban mobility, to address this need, including updates to the statistical travel behavior model and the addition of rideshare including trip occupancy. Results obtained with the enhanced Impacts 2050 showed that, while rideshare use increased significantly for some scenarios, its overall mode share remained limited. In addition, though rideshare enabled users to shed car ownership, the overall percentage increase of "no car ownership" was low. An urban mobility sustainability scorecard based on STEEP and generated by output from the enhanced Impacts 2050 is presented.

1. Introduction

1.1. Context and motivation

Emerging concepts, such as Mobility as a Service (MaaS), rideshare, and vehicle automation, are being advanced as approaches to improve the sustainability of mobility, especially in densely populated urban areas. MaaS can be defined as the integration of various transport modes into a single service, accessible on demand, via a seamless digital planning and payment application. The transport modes considered for MaaS range from traditional options such as transit to newer choices, such as rideshare, to projected modes, such as automated taxis (Ho et al., 2020; Jang et al., 2021; Roukouni and Correia, 2020; Snelder et al., 2019). Recent studies have

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shown the potential for a reduction in the size of automobile fleets, with corresponding predicted improvements in congestion and environmental impact, that might be realized by the advent of automated vehicles as part of future mobility systems (Becker et al., 2020; Berge, 2019; Boesch et al., 2016; Burns et al., 2012; Crist and Martinez, 2018; Friedrich et al., 2018; Furtado, 2017; Luis and Petrik, 2017; Martínez, 2015; Petrik and Martinez, 2018).

However, these mobility studies indicate that no single analysis approach can address the complex interactions of user demographics, mode choice, vehicle automation, governance, and efficiency, or their impact on long-term sustainable mobility for an urban region. For example, there are emerging indications that current shared vehicles and rides, via ride-hailing services, are impeding transportation in some major urban areas of operation (Balding et al., 2019; Brown, 2020; Erhardt et al., 2019; Schaller, 2018). These include a declining number of trips on mass transit, more single-passenger trips in ride-hailing cars, and empty miles while awaiting or responding to passenger requests. In addition, research indicates private car owners may be reluctant to adopt MaaS, which could restrict its positive effects on sustainable mobility (van't Veer et al., 2023). These trends can increase road congestion, thereby decreasing travel speeds. Such unintended consequences could undermine the positive sustainability benefits that emerging mobility concepts, such as MaaS, rideshare, and vehicle automation, could provide.

The research hypothesis put forward in this paper is that a whole system, STEEP (social, technical, economic, environmental, and political) framework (Schmidt et al., 2015; Szigeti et al., 2011) is needed to explore emergent mobility concepts such as rideshare. Such a framework will enable a city to evaluate adoption strategies for these emerging mobility concepts. These evaluations can support decision-making relative to the overall sustainability impacts, both positive and negative, of changes to a mobility system across all stakeholder dimensions (STEEP).

The requirements of this STEEP approach include the ability to evaluate adoption scenarios for emerging mobility concepts and to provide a metrics scorecard for comparative assessment of sustainable mobility. For the approach to be effective, the framework must address the requirements defined above: user demographics, mode choice (including emergent modes), vehicle automation, governance, and efficiency. In addition, the ability to assess the impact of these parameters on sustainability is needed. Note that vehicle electrification is not a focus of this study but its adoption is assumed to grow and benefit sustainable mobility, especially as renewable electricity generation increases. Based on a review of models that would address these requirements and support assessment of future mobility concepts at a city level, Impacts 2050 was chosen as the model that best supported the goals of establishing this framework (Muller et al., 2021). This model and its suitability for this research are detailed in the next section.

1.2. Overview of Impacts 2050

Impacts 2050 was developed through research sponsored by the American Association of State Highway and Transportation Officials (AASHTO) and the Federal Highway Administration (FHWA) to examine how long-term socio-demographic changes will affect travel demand in a city region and the resulting types of transportation modes and infrastructure required (Zmud et al., 2014). It is used by U.S. transportation agencies in long-term planning (Fusco, 2016; Fusco and Davis, 2020). It models urban mobility at an aggregated level and addresses travel behavior informed by demographics, land use, and employment. The model structure is shown in Fig. 1, which depicts the main modules and the key variables for each. This type of model supports strategic planning to prepare for potential changes in future transport demand and supply.

Impacts 2050 models the urban mobility system for a city region, with a model timescale of 50 years. It uses a time-marching system dynamics approach, with stocks and flows modeling the complex interactions of the mobility system as they unfold over time. City-specific inputs define the initial conditions for the various stocks in the model (e.g. initial population for each age group) and the rates of change for the flows between the stocks (e.g. births, migration, deaths). The model then progresses through time, with the various stocks being updated at each time step per the feedback loops and rates of change specified for each stock. For example, increases to household income over time in the socio-demographic module may increase car ownership in the transport behavior module, which may in turn increase the number of trips taken and miles traveled. This increased level of travel may then cause the need for road capacity to increase, while decreasing travel speed, per the transport supply sector module. In this way, feedback loops in Impacts 2050 allow for the different city-level factors that impact transportation modeling to interact over a strategic-level period of five decades. Detailed flow diagrams of the Impacts 2050 model are provided in the model documentation (Zmud et al., 2014).

Travel behavior in Impacts 2050 is represented by statistical modeling of National Highway Transportation System (NHTS) travel behavior data (U.S. Department of Transportation, Federal Highway Administration, 2009). This statistical modeling is used to represent the elements of travel behavior shown in Fig. 1. The explanatory variables for the travel behavior models, mainly demographic in nature, are listed in Appendix A. Greater detail on this statistical modeling, and how it was enhanced for this research, will be described in the "Methodology" section of this paper.

In addition to statistical models, Impacts 2050 allows users to input their own values for time-varying exogenous factors to explore the impact of "what-if" trends. These factors modify the results of the statistical models to determine the effect on the overall system. This capability is particularly helpful in modeling long-term, 50-year periods. By applying user-tailorable factors, one can rapidly explore the potential effect of emergent trends such as increases in gasoline prices. These explorations of a wide range of potential outcomes support preparation for the future and should not be viewed as prediction of the future. Different combinations of these exogenous factors can be used to define a scenario for analysis. Listings of these exogenous factors are shown in Appendix B through Appendix E.

For governance, Impact 2050 provides inputs that serve as policy levers to promote shared rides and more sustainable transport modes (transit, walk/bike). These specific exogenous input factors (road capacity addition, rail capacity addition, gasoline price, land

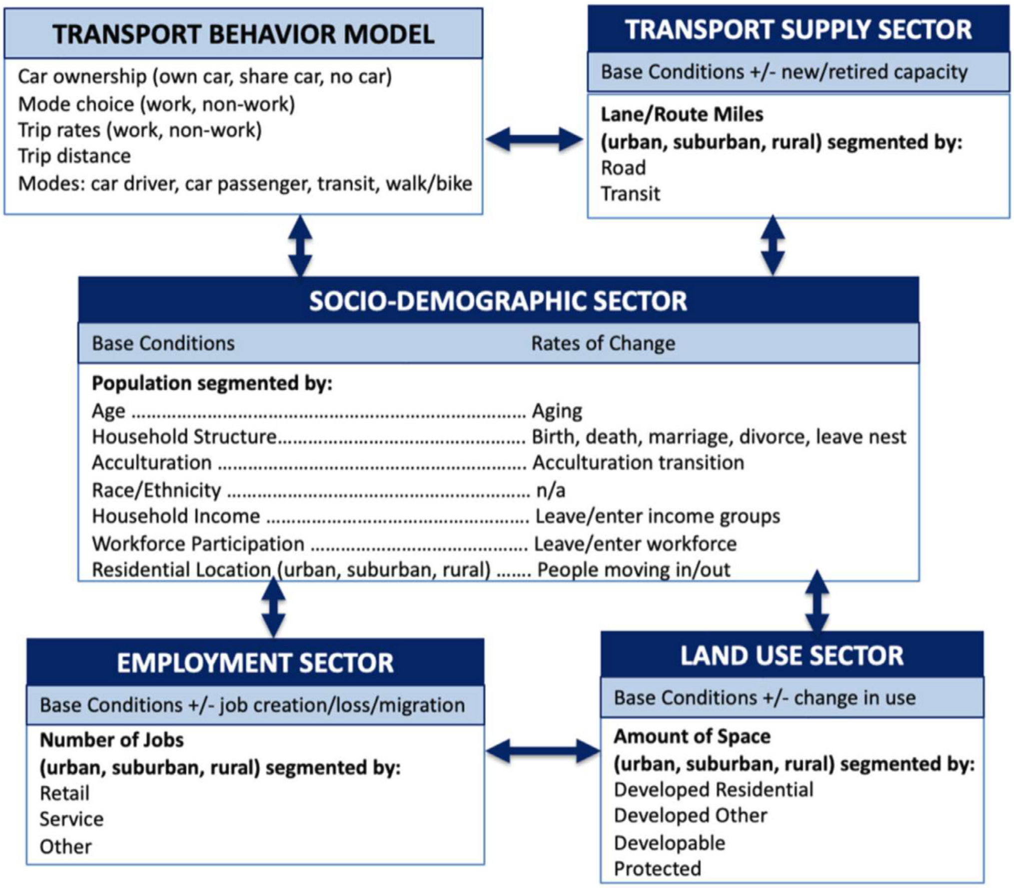

Fig. 1. Impacts 2050 model structure (Bradley et al., 2014).

protection) provide ways to represent the impact of governance policy on travel behavior. For example, one can discourage private car use through input of higher gasoline price/tax, delayed new road capacity, or restricted land development.

1.3. Modeling gaps and research objective

As an aggregated city-level model, Impacts 2050 addresses the whole system approach defined for this research. Such an aggregated model combined with a scenario-based approach is supported by recent research (Bauranov, 2021; Muller et al., 2021). In addition, Impacts 2050 models additionally critical elements beyond travel behavior, including the interactions with demographics, land use, and employment over the space of decades during which emerging transportation concepts will appear. However, there are additional enhancements required to make it suitable for the goals of studying future mobility concepts. The model gaps to be addressed in this research are:

- Need for additional emergent mobility modes, such as rideshare
- Modeling travel behavior for the additional mobility modes by applying available data

The main objective of this study is therefore to develop a modeling approach for implementing these enhancements for Impacts 2050, to further its use for exploring long-term travel behavior, including emergent mobility concepts, and the resulting impact on sustainability. The result is what we call an “enhanced Impacts 2050 model” that supports transportation planners to evaluate emerging mobility concepts, such as rideshare and their potential impact on the overall sustainability of an urban mobility system in the United States. By using an aggregated modeling approach, this study supports the exploration of “what-if” scenarios, valuable when evaluating long-term developments with accompanying uncertainty.

This paper is organized as follows: first, the literature is reviewed to outline a method for enhancing Impacts 2050 to represent the emergent mobility concepts of rideshare impact on travel behavior. The methodology is shown and explained in detail. A set of scenarios used to exercise the model are described. Then, the results of the enhanced Impacts 2050 with these scenarios are presented using an urban mobility sustainability scorecard. The paper ends with the main conclusions drawn from this work and a description of potential future research.

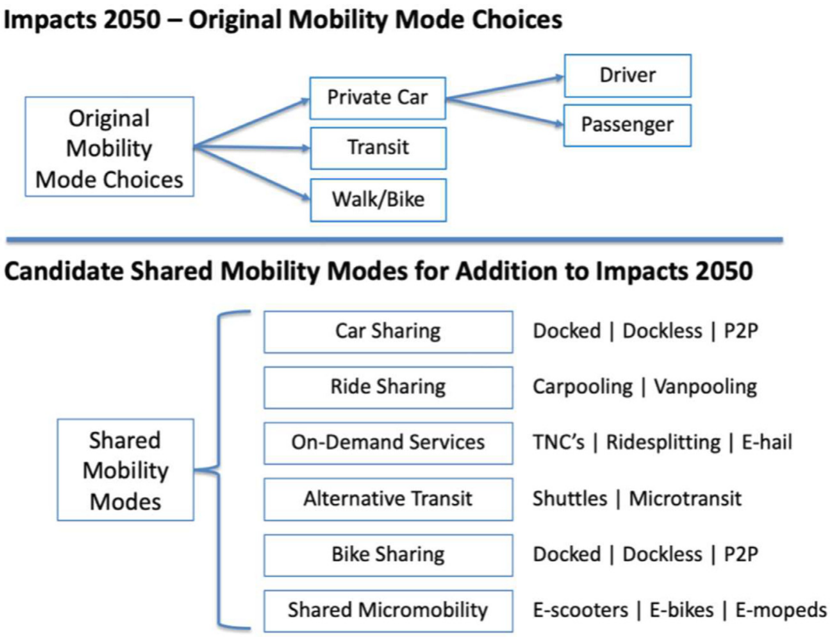

Fig. 2. Candidate shared mobility modes for addition to Impacts 2050.

2. Literature review

A literature review was conducted to guide the development of a methodology to enhance Impacts 2050, per the identified model gaps listed above. Models were sought that would be candidates for integration with Impacts 2050. This is an aggregated model based on system dynamics that is suitable for modeling systems with multiple competing inputs, feedback loops, and considerable uncertainty (Zmud et al., 2014).

2.1. Modeling additional mobility modes

To better represent emergent mobility concepts, especially the projected trend of people purchasing rides versus owning vehicles (e.g., rideshare), the mode choices in Impacts 2050 had to be expanded beyond the original options of car driver, car passenger, transit, and walk/bike. A range of candidate transportation modes are described in the literature (Ho et al., 2020; Jang et al., 2021; Snelder et al., 2019). Fig. 2, informed by these references, shows the large variety of shared mobility modes and services that could be part of future urban mobility implementations. These include, for example, taxi-like on-demand transportation network company (TNC) services. These modes were all candidates for addition to Impacts 2050, subject to the availability of suitable data for the aggregated modeling approach.

2.2. Modeling travel behavior for additional mobility modes

To incorporate additional travel modes within Impacts 2050, data was required to generate the input table of statistical coefficients needed by its travel behavior model. The data had to quantify traveler choice of newer transport modes shown above, such as on-demand rideshare/TNC services, relative to the other transport modes already represented in Impacts 2050. In highly relevant research, a study of NHTS travel survey data from 2001 to 2017 found a growing customer use of rideshare/TNC services over that period (Wu and MacKenzie, 2021a). The 2017 NHTS travel survey data (U.S. Department of Transportation. Federal Highway Administration, 2017), which is directly compatible with the Impacts 2050 travel behavior model, can be used to add rideshare/TNC as part of the modeling approach. It would enable the addition of a rideshare mode on the same mathematical basis as the existing modes of transport, in support of the research goals. This research uses 2017 NHTS rideshare survey data to augment the existing Impacts 2050 travel behavior model to represent rideshare.

Additional relevant rideshare research was identified. A travel survey of 11,902 individuals living in rideshare/TNC-served areas was conducted in the U.S. in 2017 (Bansal et al., 2020). The study provides user preference data for rideshare mode choice relative to demographic parameters of age, household size, income, area type, and car ownership. This was relevant to U.S. travel preferences, nationwide in scope, and addressed most of the explanatory variables required for the Impacts 2050 travel behavior model, per Appendix A. However, it did not link mode choice between rideshare/TNC and other traditional modes, so it could not support this research. A similar focus was provided by a travel survey of 878 individuals in thirteen North American metropolitan areas, also conducted in 2017 (Asgari et al., 2018). It provided insights into traveler preferences towards emerging mobility options such as ride-sourcing and AV technologies. Another study, (Middleton et al., 2021), explored factors that influence traveler decisions about driving or taking a shared ride, but not in comparison with traditional travel modes. Research was identified on rideshare preferences in California (Alemi et al., 2018), while another study (Clewlow and Mishra, 2017) characterized ride-hailing in seven major U.S. cities. Therefore, while travel preference research was found in these references for North American populations, it did not contain all explanatory variables needed for Impacts 2050.

Research for non-US populations was reviewed related to rideshare mode choice. In one study (Snelder et al., 2019), the challenge of representing travel behavior for emergent future transport modes where data does not exist was acknowledged as a challenge. Another study (Jang et al., 2021), explores the effect of different bundling and pricing schemes of MaaS offerings on improving sustainable transportation in the Netherlands context. Related research (Ho et al., 2020) explores how travel needs and socio-economic settings contribute to defining appealing mobility plans. In a doctoral thesis (Matyas, 2020), survey data are collected and analyzed for London and Manchester to understand individual preferences for MaaS plans. This non-US research provided context for the planned enhancements to Impacts 2050.

In addition, modeling approaches were sought with a specific focus on aggregated approaches to modeling rideshare. One study (Wei et al., 2020), makes use of an aggregated approach, but its goal is to account for day-to-day traffic dynamics while modeling a transport network that includes ridesharing services. In another study (Altshuler et al., 2019), a data set of over 14 million taxi trips in New York City provides a basis for statistical modeling of the dynamics of ride-sharing utilization over time. A review of detailed mathematical formulations relevant to hailing, standing, and dispatching of taxis was found (Salanova et al., 2014). However, these modeling approaches did not account for the long timeframes or key variables of interest for this current study, especially demographic effects.

2.3. Literature review summary

To support this study's objectives, the literature review focused on identifying models and data that could be integrated to enhance Impacts 2050 for use as a whole system sustainability assessment tool. Rather than modeling a specific emergent transportation mode and exploring its performance and sustainability impact, this study is taking an aggregated, strategic-level approach to support long-term decision-making for mobility systems.

The gap to be addressed in this paper is the representation of emergent mobility modes. Multiple candidate modes were identified; however, rideshare was selected for inclusion as a mode that is supported by a recognized data source from NHTS. The 2017 NHTS data utilized for this study was pre-pandemic. It is recognized that travel patterns were impacted by the pandemic and these changes are still being observed and analyzed. A 2023 study concluded that transit utilization is down 30 percent (Pendyala et al., 2023). In advance of estimating new model coefficients for Impacts 2050 using post-pandemic travel data, the projected travel behavior from this work can be modified using inputs to the model via exogenous variables to approximate the trends being observed and their impact on travel behavior projected by Impacts 2050. For this work, however, the data set met the objectives and scope.

The next section will describe the specific methodology developed by applying the results of the literature review.

3. Methodology

A methodology was developed, informed by the literature review, to enhance Impacts 2050 in a way that is compatible with its system dynamics approach and addresses the identified modeling gaps. This methodology, summarized in Fig. 3, will be described in the following sections.

3.1. Modeling additional mobility modes

While many candidate mode choices were identified (see Fig. 2), determining which would be added to Impacts 2050 was informed by the literature survey, the Impacts 2050 code structure, and the available travel behavior data. As discussed above, 2017 NHTS travel survey data was identified as the basis of travel behavior enhancements to Impacts 2050. The transport mode choices available in the 2017 NHTS data are shown in Table 1. The NHTS data set provides both unweighted and weighted trip count values. Table 1 contains the weighted totals. The main categories of transport represented in Impacts 2050 are shown in the left-most column, while the next column to the right shows the transport modes available in the 2017 data set. By grouping "walk/bike" together, this mode category represents healthy forms of transport.

After considering the new candidate modes relative to the available data shown in Table 1, the selected approach was to add the rideshare mode to Impacts 2050, where "rideshare" is defined for this research as representing taxis and TNC providers. This approach is illustrated in Fig. 4, showing modes provided by Impacts 2050 in white and the rideshare mode to be added in red. When rideshare is included, the mode categories represented by Impacts 2050 account for 96.7% of trip records, as shown in Table 1. Adding rideshare allows Impacts 2050 to represent more of the main transport modes in use. As documented above in "Modeling Travel Behavior", 2017 NHTS travel survey data was identified for use in generating the needed statistical coefficients. The results of this statistical modeling are described later in the "Results" section.

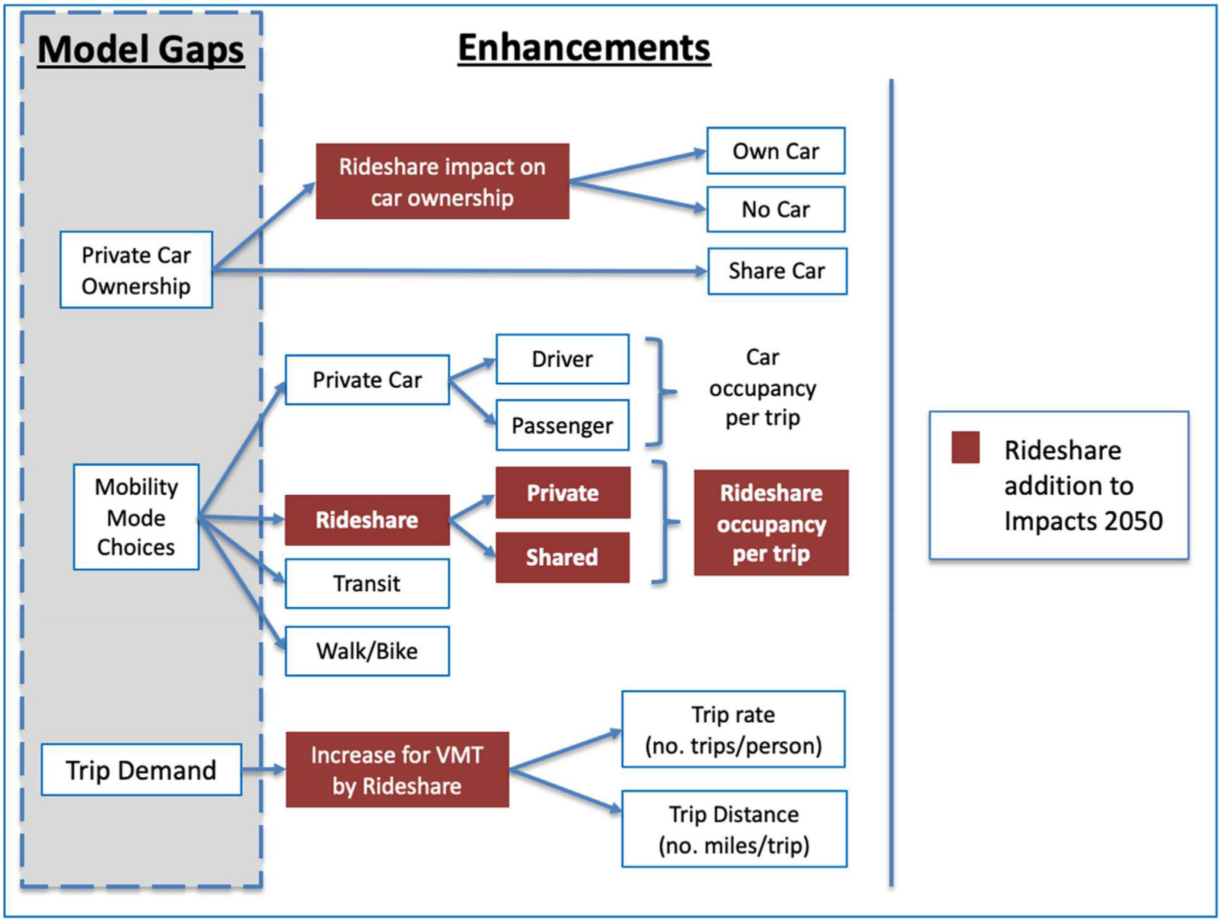

Fig. 3. Enhancement summary for Impacts 2050.

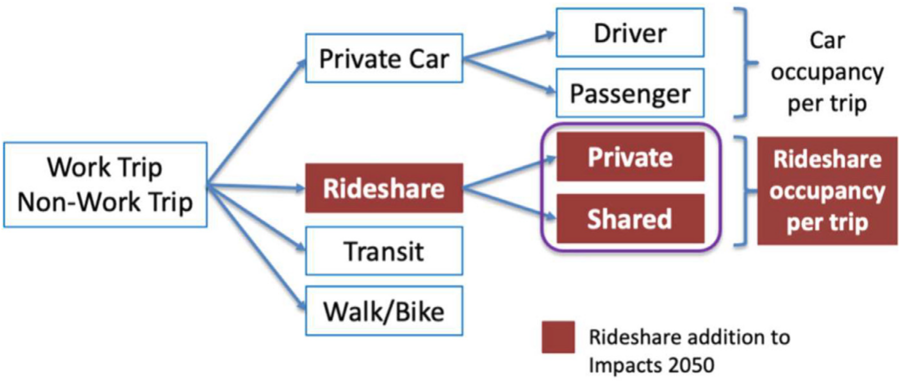

Fig. 4. Transport mode upgrade plan for Impacts 2050.

3.2. Modeling the addition of rideshare mode

To add rideshare to Impacts 2050, the approach was compatible with that used for the original modes (e.g., car driver, car passenger, transit, walk/bike). The approach required updated internal calculations and new statistical coefficient inputs. A summary of the methodology used in Impacts 2050 for modeling car ownership, mode choice, daily trip rate, and daily trip distance is presented next to provide context for the modeling enhancements.

Table 1
Summary of mode distribution for weighted 2017 NHTS data.

Impacts 2050 Mode Category	NHTS Mode of Transport (TRPTRANS)	Weighted NHTS Trip Count	Weighted NHTS Trips (%)	Weighted Trips by Impacts 2050 Mode Category (%)
Walk/Bike	01=Walk	38,947,037,420	10.5%	11.5%
	02=Bicycle	3,574,587,699	1.0%	
Car	03=Car	156,940,151,690	42.3%	82.1%
	04=SUV	84,658,857,084	22.8%	
	05=Van	27,857,323,984	7.5%	
	06=Pickup truck	35,114,968,859	9.5%	
Transit	11=Public or commuter bus	5,300,300,058	1.4%	2.7%
	12=Paratransit / Dial-a-ride	393,289,932	0.1%	
	15=Amtrak / Commuter rail	794,284,793	0.2%	
	16=Subway / elevated / light rail / street car	3,349,921,876	0.9%	
Rideshare	17=Taxi / limo (including Uber / Lyft)	1,849,203,080	0.5%	0.5%
Other	Other modes and undefined (-9,-8,-7,07-10, 13,14,18-20, 97)	12,372,045,049	3.3%	-
	GRAND TOTAL	**371,151,971,524**	**100.0%**	**96.7%**

3.2.1. Impacts 2050 travel behavior modeling

Impacts 2050 uses a set of statistical coefficients based on models of the NHTS data to model car ownership, mode choice, daily trip rate, and daily trip distance. The same overall expression is used to model each of these four aspects of travel behavior for each time step. For car ownership and mode choice, the expression represents a multinomial logistic regression model for utility. For trip rate and trip distance, the expression represents a log-linear regression model. For this expression, only the coefficients are presented since they are always multiplied by a binary variable for each characteristic of the population. For example, for car ownership, Age_j^e is the coefficient associated with people in age group j sharing a household, for travel model e defined below, holding all the other characteristics fixed. The general form of this expression is:

$$U_{jklmnocp}^{e} = \Big(C^e + Age_j^e + HouseholdType_k^e + Ethnicity_l^e + Worker_m^e + Income_n^e + AreaType_o^e + City_c^e + CarOwnership_p^e + GasPrice^e\Big) \tag{1}$$

The terms in this equation are statistical coefficients representing the model demographic variables and the additional explanatory variables of city location and gasoline price. This expression is evaluated for all combinations of these variables, per the indices $jklmnocp$ defined below. The coefficient values and indices represented in Eq. 1 are:

$U_{jklmnocp}^{e}$	for car ownership (index e = "own") and mode choice (index e = "mode"), this expression represents the utility for each population group per the demographic variables and their indexed range of values; for trip rate (index e = "rate") and trip distance (index e = "distance"), this expression represents the linear component of a log-linear regression model for each population group per the demographic variables and their indexed range of values
E	user-input exogenous, time-varying factors that modify the model-provided values of $U_{jklmnocp}^{e}$, applied as follows: for car ownership utility and mode utility: $E*U_{jklmnocp}^{e}$ for trip rate and trip distance: $E*(e^{U_{jklmnocp}^{e}}-1)$
C^e	a statistical constant for each $U_{jklmnocp}^{e}$
Age_j^e	age group coefficient with the index j varying by group as follows: 0-15, 16-29, 30-44, 45-59, 60-74, 75+ years
$HouseholdType_k^e$	household type coefficient with the index k varying by type as follows: (single without child, single with child, couple without child, couple with child)
$Ethnicity_l^e$	ethnicity coefficient with the index l varying by the following categories: (white, non-white, foreign-born, US <20 yrs; foreign-born, US >20 yrs)
$Worker_m^e$	work status coefficient with the index m varying by the following categories: (yes, no)
$Income_n^e$	household income coefficient with the index n varying in the following categories: (low, medium, high)
$AreaType_o^e$	area type coeffcient with the index o varying in the following categories: (urban, suburban, rural)
$City_c^e$	city coefficient with the index c varying for the following cities: (Atlanta, Boston, Detroit, Houston, Seattle)
$CarOwnership_p^e$	household car ownership coefficient with index p varying for the following categories: (own car, share car, no car) – Not used when computing utility of car ownership
$GasPrice^e$	coefficient for the effect of gasoline price ($/gallon) on transportation behavior

See Appendix A for additional information on the explanatory variables for the Impacts 2050 travel behavior model.

3.2.2. Impacts 2050 modeling of car ownership

To model car ownership, Impacts 2050 uses a multinomial logistic regression model per Eq. 1, without the $CarOwnership_p$ term, to determine the utility of each category of car ownership. The ownership categories are "own car" (the reference value), "share car", and "no car". An exogenous variable E can be used to modify the utility over time for each car ownership option. The relative probability of each of the three categories of car ownership is then computed using the multinomial logit model as referred:

$$P^{own_i} = \frac{E * e^{U^{own_i}}}{\sum_{s \in S} E * e^{U^{own_s}}} \tag{2}$$

where P^{own_i} is the probability of car ownership category i, U^{own_i} is the utility of car ownership category i, and S is the number of categories of car ownership.

3.2.3. Impacts 2050 modeling of mode choice

To model mode choice, Impacts 2050 uses a multinomial logistic regression model, per Eq. 1, to determine the utility of each transport mode choice option. The mode choice options are car driver (the reference value), car passenger, transit, walk/bike, and rideshare (added for this research). An exogenous variable E can be used to modify the utility over time for each mode choice option. A multinomial logit model is then used to determine the relative probability for each mode choice for the trip purpose categories of work and non-work. The multinomial logit model for mode choice is:

$$P^{mode_d} = \frac{E * e^{U^{mode_d}}}{\sum_{r \in R} E * e^{U^{mode_r}}} \tag{3}$$

where P^{mode_d} is the probability of transport mode choice d, U^{mode_d} is the utility of transport mode d, and R is the number of transport modes. Note that the original Impacts 2050 used a multinomial logistic regression approach to model mode choice. It assumed the Independence of Irrelevant Alternatives (IIA), that the mode choice options are not correlated with each other. This study also uses that assumption, namely that rideshare is different enough from the other modes represented in Impacts 2050. That said, the possibility that there may be a correlation between modes cannot be ruled out.

3.2.4. Impacts 2050 modeling of daily trip rate

The daily trip rate, which is the daily number of trips per person per day, is modeled by Impacts 2050 for the trip purpose categories of work trips and non-work trips. The model coefficients are estimated using a log-linear regression model to predict the number of trips for each trip purpose category, using the form of Eq. 1. An exogenous variable E can be used to modify the daily trip rate over time for each trip purpose category. The resulting model values for trip rate can then be used to determine the total number of daily trips as a function of population size ($Population$) for each combination of demographic variables, per the indices $jklmnocp$ defined above for Eq. 1. The equations for total number of daily work trips Tw and non-work trips Tnw, based on the daily trip rate and the parameters defined above are:

$$Tw_{jklmnocp} = Population_{jklmnocp} * \left(e^{U^{rate,\ work}_{jklmnocp}} - 1 \right) * E \tag{4a}$$

$$Tnw_{jklmnocp} = Population_{jklmnocp} * \left(e^{U^{rate,\ non-work}_{jklmnocp}} - 1 \right) * E \tag{4b}$$

3.2.5. Impacts 2050 modeling of daily trip distances

The daily trip distances are modeled in Impacts 2050 for each transport mode choice option and each trip purpose category using a log-linear regression model, per the form of Eq. 1. The mode choice options are car driver (the reference value), car passenger, transit, and rideshare (added for this research). The daily trip distances for walk/bike are not computed. The trip purpose categories are work and non-work trips. An exogenous variable E can be used via user inputs to modify the daily car trip distances over time. The resulting model values for trip distance by mode and trip purpose can then be used to determine the total trip distances traveled by multiplying these values by the daily trip rate, per Eq. 4a and 4b.

A challenge of the Impacts 2050 approach to modeling travel behavior is the projection of current trends over 50 years into the future. A key assumption for this study is that there is some stability in the supply of the main travel modes (car driver, car passenger, transit, walk/bike, rideshare) and that they are all available through the period being modeled.

3.2.6. Modeling the impact of rideshare on car ownership

As part of incorporating the rideshare travel mode to Impacts 2050, its effect on car ownership was added. Research has projected that rideshare could decrease the car-owning population as some percentage of rideshare users stop owning a private car (Nieuwenhuijsen et al., 2018). Impacts 2050 computes car ownership based on 2017 NHTS data, per the multinomial logit model in Eq. 2. To model the impact of rideshare on car ownership over time, Eqs. 5-7 show how A_{WC} affects the car-owning population:

$$Own^1_{jklmnoc} = Population_{jklmnoc} * \left(P^{own_1} - P^{own_1} * A_{WC} \right) \tag{5}$$

$$Own^2_{jklmnoc} = Population_{jklmnoc} * P^{own_2} \tag{6}$$

$$Own^3_{jklmnoc} = Population_{jklmnoc} * \left(P^{own_3} + P^{own_1} * A_{WC} \right) \tag{7}$$

where $Own^{p}_{jklmnoc}$ is the number of people in each category of car ownership, the superscript $p = 1$ to 3 indicate the category of car ownership (“own car”, “share car”, and “no car), the subscripts $jklmnoc$ represent the various combinations of demographic variables as defined for Eq. 1, and A_{WC} is the percentage of the rideshare user population that sheds car ownership. As rideshare use grows, A_{WC} decreases the baseline probability of P^{own_1}. For no-car individuals, A_{WC} increases P^{own_3} by the car owners that give up ownership, $Population_{jklmnoc} * P^{own_1} * A_{WC}$.

3.2.7. Modeling the impact of rideshare on VMT per passenger trip

Transportation by rideshare can cause additional vehicle miles traveled (VMT) in comparison with personal use of automobiles, referred to as “deadheading” (Henao and Marshall, 2019). As noted by one study, (Balding et al., 2019), the VMT incurred while transporting the passenger can be increased by rideshare drivers moving while waiting for a passenger assignment and by moving to pick-up a passenger once assigned. This extra VMT is not captured in the travel behavior modeling based on the 2017 NHTS data; however, accounting for it enables improved characterization of the impact of rideshare. The magnitude of this added VMT varied in the literature that was reviewed. In one study, (Schaller, 2021), the increase ranged from 97% to 157%. In other studies, (Henao and Marshall, 2019; Wu and MacKenzie, 2021b), the VMT increase ranged from 40.8% to 83.5%, while a value of 60% was also found (Wu and MacKenzie, 2021b). After considering the literature review, a multiplication factor $Rvmt$ was defined based on the distribution of VMT miles among three rideshare phases with the rideshare-added VMT factors per (Balding et al., 2019) as follows:

$$Rvmt = P1 + P2 + P3 \tag{8}$$

where:

P1= Percent of trip VMT while driver waiting for passenger = 0.64

P2 = Percent of trip VMT while driver picking up passenger = 0.18

P3 = Percent of trip VMT while driver transporting passenger = 1, the base condition

$Rvmt$= P1 + P2 + P3 = 1.82

This factor $Rvmt$ is then applied to modify the daily miles traveled for rideshare generated by the enhanced Impacts 2050. Note that this factor, approximately 80%, was representative of the range of values found in the literature review and is based on a study using Uber and Lyft data from six major U.S. cities (Balding et al., 2019). The P1 and P2 values shown above are the observed percentage shares normalized by the reference value of P3, with values per (Balding et al., 2019).

3.2.8. Modeling the occupancy (number of passengers) on rideshare trips

Vehicle occupancy is a metric highly relevant to the sustainability of emergent mobility concepts, such as rideshare. Higher vehicle occupancy levels indicate more efficient use of vehicles. The original Impacts 2050 computes vehicle occupancy for personally owned cars as an average for each time step because it models travel behavior in an aggregated manner and does not track individual trips. In Impacts 2050, the average occupancy for cars is computed for work and non-work trips as shown here:

$$Co_t = \frac{Nd_t + Np_t}{Nd_t} \tag{9}$$

where Co_t is the average number of occupants per car for a given time step t, Nd_t is the total number of car driver trips (work and non-work) for a given time step t, and Np_t is the total number of car passenger trips (work and non-work) for a given time step t. Since each car driver trip equates to a vehicle, this equation divides the total number of car occupants by the total number of vehicle trips to yield average car occupancy.

For this study, the ability to calculate vehicle occupancy for rideshare had to be added to Impacts 2050. To use an approach compatible to that used by Impacts 2050 for car occupancy, a method of determining the number of rideshare driver trips/vehicle trips was needed (i.e. the denominator of Eq. 9). A linear regression model was developed for the number of people on a rideshare trip, which was available in the 2017 NHTS data. This model estimates the number of rideshare occupants sharing a vehicle trip, Nt , for a given time step as a function of the demographic variables used in Eq. 1, but without the $GasPrice$ coefficient, as follows:

$$Nt_{jklmnocp} = C^{Nt} + Age^{Nt}_{j} + HouseholdType^{Nt}_{k} + Ethnicity^{Nt}_{l} + Worker^{Nt}_{m} + Income^{Nt}_{n} + AreaType^{Nt}_{o} + City^{Nt}_{c} + CarOwnership^{Nt}_{p} \tag{10}$$

where the values for $jklmnocp$ are as defined for Eq. 1. Note that Eq. 10 is evaluated for rideshare only. The values predicted for Nt are used to compute the number of rideshare vehicle trips $Rt_{jklmnocp}$ for each combination of demographic variables per $jklmnocp$ at each time step t as follows:

$$Rt_{jklmnocpt} = \frac{Tw_{jklmnocpt} + Tnw_{jklmnocpt}}{Nt_{jklmnocpt}} \tag{11}$$

where for rideshare mode, $jklmnocp$ are as defined for Eq. 1, Tw are the number of work trips per Eq. 4a, and Tnw is the number of non-work trips per Eq. 4b. The number of rideshare vehicle trips is obtained by dividing the total number of rideshare occupants for work trips Tw and non-work trips Tnw by the number of occupants per rideshare vehicle trip, Nt. Using $Rt_{djklmnocpt}$ the average rideshare vehicle occupancy Ro_t is computed for each time step t, similar to the method used for personally owned cars, as follows:

$$Ro_t = \frac{\sum_{jklmnocp} Tw_t + \sum_{jklmnocp} Tnw_t}{\sum_{jklmnocp} Rt_t} \tag{12}$$

where for rideshare mode, the values for $jklmnocp$ are as defined for Eq. 1. Using this approach, the method used in Eq. 9 to compute car occupancy is adapted to compute rideshare occupancy per Eq. 12. The rideshare occupancy metric then incorporates the relative weighting contribution of different population sizes for each demographic combination. This aggregated method for computing rideshare occupancy is compatible with the overall Impacts 2050 modeling approach.

4. Results

This section presents key results obtained with the enhanced Impacts 2050 through implementation of the methodology documented above. These results were selected to focus on the evaluation of the enhancements relative to the rideshare mobility being modeled. In addition, an urban mobility sustainability scorecard is defined to assist this evaluation. It is comprised of output metrics from the enhanced Impacts 2050 that were selected to represent the five STEEP categories.

4.1. Application of enhanced Impacts 2050 to mobility scenarios

The enhancements to Impacts 2050 were exercised using a set of four planning scenarios. These were used in the original development and publishing of Impacts 2050, per (Zmud et al., 2014), and are defined in Table 2. Exogenous inputs are defined for each of these scenarios to impose different trends per the scenario definitions. The exogenous inputs that were used are shown in Appendix B, Appendix C, Appendix D, and Appendix E.

These four scenarios were exercised for a set of five urban regions from the United States. These urban regions, selected from the five major census regions, are shown in Fig. 5.

These regions were used in the initial development of Impacts 2050 tool, provide a basis for comparison to published results, and reflect differences in:

Table 2
Original planning scenarios for Impacts 2050 model.

Scenario name	Scenario description
Momentum (M): Extreme Gradualism	Momentum can be considered a baseline scenario for comparing outcomes with the other three scenarios. All model trends are constant from initial time step onward: • Socio-Demographic – no rate change • Travel Behavior – no rate change • Employment – no rate change • Land use – no rate change • Transport Supply– no rate change
Tech Triumphs (TT): Tech Nirvana	Technology Triumphs, notably with socio-demographic benefits, decreased trip rates, and higher capacity growth for road and transit. Some trends are: • Socio-Demographic – death rates decline, people work longer, growth in number of high income households, slight decrease in foreign immigration • Travel Behavior – reduction in gasoline price, reduction in sharing car/no car • Employment – job creation and job movement increase • Land use – residential space per household increases • Transport Supply – road vehicle capacity/lane and transit capacity/route increase
Gentle Footprint (GF): Clean and Green	Gentle Footprint represents a future state with positive environmental impact, especially mobility. Some trends are: • Socio-Demographic – birth rates decline, people live/work longer, growth in number of low income households, decline in growth of high income households, slight increase in foreign immigration • Travel Behavior – gasoline price triples, decrease in car ownership, increased use of shared mobility (passenger, transit, walk/bike), trip rates decrease • Employment – no rate change • Land use – residential space/household and non-residential space/job decreases, land protection increases • Transport Supply – addition to road capacity decreases; transit capacity increases
Global Chaos (GC): Neo-Isolationism	Global Chaos represents a largely negative future state with increasing gasoline prices motivating increases in shared mobility. Some trends are: • Socio-Demographic – birth and death rates decline, growth in number of low income households, decline in growth of high income households, slight decrease in foreign immigration • Travel Behavior – gasoline price doubles, increase in sharing car/no car, trip rates decrease, increase in car passenger and walk/bike modes • Employment – job loss rate increases • Land use – land protection decreases • Transport Supply – addition to road and transit capacities decrease (Zmud et al., 2014)

Fig. 5. Urban regions modeled with enhanced Impacts 2050.

Table 3
NHTS Summary statistics for travel behavior for 2009 vs 2017.

Parameter	NHTS Data Set		Difference (%)
	2009	2017	
No. of persons	308,901	264,234	-14%
No. of households	140,000	129,696	-7%
No. of work trips	244,000	104,295	-57%
No. of non-work trips	750,000	686,692	-8%
No. of child trips	135,000	67,548	-50%
Total Trips	**1,129,000**	**858,535**	**-24%**

- Population distribution: age, household type, education, wealth, and housing.
- Spatial distribution: land area and population density.
- Economic base: socioeconomic status, income disparity, unemployment rate.
- Diversity: household structures, age, and racial/ethnic composition.
- Transportation system: highway versus transit supply, congestion levels, mode share.

Guided by these considerations, the cities selected for each region represent a range of mobility systems. Boston and Seattle had more public transit supply than the other city regions, while Atlanta and Houston had more road capacity.

4.2. New data set 2017 NHTS

To accomplish the addition of rideshare as a new transportation mode in Impacts 2050, new statistical model coefficients were estimated based on the most recent travel survey data that included rideshare (U.S. Department of Transportation. Federal Highway Administration, 2017). Summary statistics comparing the 2009 NHTS travel survey data set, used in the original Impacts 2050, and the 2017 NHTS data sets are shown in Table 3. The 2017 data set was overall smaller than the 2009 data set, especially in the number of work and child trips. A smaller data set can affect the estimation of the statistical model coefficients used by Impacts 2050 to represent travel behavior, especially for work trips. Statistical measures of fit (McFadden pseudo R^2, Deviance Chi^2, and t-statistic) were used to assess the statistical models. Also, some combining of explanatory variables was required to address initial coefficient estimates with less than desired statistical certainty of difference.

4.3. Modeling the addition of rideshare mode

The statistical coefficients estimated for the 2017 NHTS data provide Impacts 2050 with the necessary inputs for its travel behavior model, including the new rideshare mode. Table 4 provides a summary of the models used for each travel behavior component whose coefficients were estimated using the SPSS software. Table 4 also summarizes the measures of fit that were obtained for each set of coefficients. The t-statistic and McFadden pseudo R-square values for the coefficients computed for the 2017 NHTS data were comparable to those for the 2009 coefficients published with Impacts 2050 (Bradley et al., 2014), indicating a comparable goodness of fit for the coefficients. The deviance statistics for the linear and log-linear regression models suggest there is no apparent reason to doubt the adequacy of the model fit.

Table 4
Statistical models for Impacts 2050 travel behavior input coefficients.

Travel Behavior Model		Statistical Model Type	Measure of Fit		
			McFadden pseudo-R^2	Deviance Chi^2	t-statistic > 1.9
Car ownership		multinomial logistic regression	0.162		see Table 5
Mode Choice: non-work trips		multinomial logistic regression	0.146		see Table 5
Mode Choice: work trips		multinomial logistic regression	0.225		see Table 5
Trip Rate (no. trips/person/day)	non-work trips	log-linear regression	-	0.21	see Table 6
	work trips	log-linear regression	-	0.07	see Table 6
Trip Distance (no. miles/trip)	car driver	log-linear regression	-	0.82	see Table 6
	car passenger	log-linear regression	-	0.84	see Table 6
	transit	log-linear regression	-	0.60	see Table 6
	rideshare	log-linear regression	-	0.47	see Table 6
Number of People per Rideshare Trip (NUMONTRP) – passengers for work and non-work trips		linear regression	-	1.69	see Table 7

Table 5
Model Coefficients for car ownership and mode choice for 2017 NHTS data.

	Car Ownership		Mode Choice: Non-work Trips				Mode Choice: Work Trips			
Dependent variable	0 < Cars < Adults	0 Cars	Car pass.	Transit	Walk/ bike	Ride-share	Car pass.	Transit	Walk/ bike	Ride-share
Independent variable	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Constant	-1.247	-2.947	-2.256	-4.528	-2.039	-5.954	-3.657	-2.613	-2.468	-1.484
Age 00-15	-0.695	-0.807	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Age 16-29	0.441	-0.125	0.707	0.517	0.353	0.535	0.614	0.074	0.258	0.673
Age 45-59	0.078	-0.149	-0.139	-0.222	-0.281	-0.710	-0.053	-0.454	-0.364	0.595
Age 60-74	-0.152	-0.594	-0.155	-0.517	-0.517	-0.865	-0.122	-0.165	-0.100	-1.122
Age 75-up	0.201	-0.530	0.179	-0.965	-0.738	-1.400	0.081	-0.548	-0.981	-0.727
couple	0.000	0.000	1.062	-0.203	-0.129	-0.118	0.399	-0.581	-0.777	-2.106
Children in household	0.319	-0.927	0.820	-0.800	-0.565	-0.937	0.338	-0.848	-1.025	-2.464
Single with children	-1.211	-0.622	0.397	-0.443	-0.414	-0.840	0.383	-0.154	-0.575	-1.672
Ethnic (non-white)	0.381	0.843	0.077	0.257	-0.365	-0.366	0.006	0.299	-0.373	-0.861
Born outside US	0.467	0.532	0.047	0.229	-0.254	-0.530	0.178	0.497	-0.316	-2.104
In US under 20yrs	1.241	1.178	-0.038	0.297	-0.064	-0.124	0.051	0.402	-0.316	0.500
Worker	-0.623	-1.008	-0.762	-0.476	-0.519	-0.001	0.000	0.000	0.000	0.000
Low income	0.883	2.228	0.006	0.021	-0.082	-0.409	0.304	-0.043	-0.079	-0.479
High income	-0.539	-0.400	0.064	0.424	0.287	0.631	0.067	0.606	0.620	0.469
Urban	0.760	1.654	-0.039	1.450	0.982	1.295	0.138	2.220	1.424	1.713
Rural	-0.383	-0.520	0.140	-1.156	-0.274	-0.601	0.154	-1.493	-0.367	-1.157
Atlanta	-0.037	-0.288	-0.100	0.323	0.007	0.638	0.083	0.225	-0.019	0.540
Boston	0.422	0.859	0.100	0.816	0.607	-0.332	0.038	0.791	0.722	0.803
Detroit	-0.156	-0.244	-0.015	-0.657	-0.208	-0.286	-0.571	-1.047	-0.434	-21.117
Houston	-0.014	-0.425	0.014	-0.380	-0.333	-0.455	0.021	-0.702	-0.826	-0.745
Seattle	-0.001	-0.140	-0.037	0.583	0.048	-0.283	-1.137	0.333	0.255	-0.226
No car ownership	N/A	N/A	3.273	5.764	4.413	5.201	4.042	6.005	5.144	5.119
Shared car ownership	N/A	N/A	0.607	1.688	0.798	0.724	1.623	1.995	1.429	1.613
Gas Price	N/A	N/A	0.064	0.098	0.195	0.362	-0.066	-0.664	-0.025	-1.173
Note: red text indicates that t-statistic is less than 1.9, needed for 95% certainty of statistical difference										

4.3.1. Estimating 2017 NHTS travel behavior coefficients and adding rideshare

The model coefficients that were estimated from the 2017 NHTS data for car ownership, mode choice, trip rate, and trip distance are shown in Table 5. For each category of explanatory variables, one variable is not shown because it is the reference value for that category: “Age 30-44” for age group, “single without child” for household type, “white” for acculturation/ethnicity, “not in workforce” for workforce status, “medium” for household income, “suburban” for area type, and “own car” for car ownership. Because of challenges experienced in estimating coefficients with the desired level of statistical significance, the Impacts 2050 explanatory variable categories for “acculturation group” and “race/ethnicity” were combined into “acculturation/ethnicity” for this study.

Table 6
Model coefficients for trip rates and trip distances for 2017 NHTS data.

	Trip Rates		Trip Distances			
Model	Non-work trips	Work trips	Car driver trip distance	Car passenger trip distance	Transit trip distance	Rideshare trip distance
Dependent variable	LN(Trips+1)	LN(Trips+1)	LN(Dist.+1)	LN(Dist.+1)	LN(Dist.+1)	LN(Dist.+1)
Independent variable	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Constant	1.635	0.875	1.603	1.628	1.632	1.568
Age 00-15	-0.212	0.000	-0.046	-0.200	-0.341	-0.261
Age 16-29	-0.105	-0.032	0.042	0.019	-0.090	-0.033
Age 45-59	-0.008	0.002	-0.012	0.053	0.024	-0.038
Age 60-74	0.024	0.015	-0.095	0.008	0.049	0.029
Age 75-up	-0.027	-0.046	-0.176	0.017	-0.271	0.227
couple	-0.081	-0.037	0.104	0.025	0.178	0.045
Children in household	-0.052	-0.051	0.043	0.050	0.234	0.229
Single with children	0.020	-0.048	-0.028	-0.038	0.207	0.436
Ethnic (non-white)	-0.027	-0.018	0.042	0.003	0.130	0.046
Born outside US	-0.087	-0.040	0.114	0.151	0.142	0.213
In US under 20yrs	-0.078	-0.035	0.089	0.012	0.093	0.228
Worker	-0.201	0.000	0.357	0.163	0.178	-0.074
Low income	-0.013	-0.027	-0.133	-0.104	-0.156	-0.168
High income	0.031	0.007	0.052	0.024	0.174	0.214
Urban	0.012	0.006	-0.041	-0.040	-0.154	-0.307
Rural	-0.022	0.003	0.190	-0.040	-0.154	-0.307
Atlanta	0.003	-0.019	0.141	0.074	0.288	0.196
Boston	0.041	0.019	-0.046	-0.034	-0.299	-0.053
Detroit	-0.011	-0.055	0.162	0.005	-0.133	-1.051
Houston	-0.028	-0.014	0.134	0.143	0.217	0.228
Seattle	-0.041	0.011	-0.006	0.124	0.075	-0.332
No car ownership	-0.096	-0.013	-0.251	-0.182	-0.462	-0.260
Shared car ownership	-0.012	-0.012	-0.074	-0.131	-0.400	-0.188
Gas Price	N/A	N/A	0.017	0.050	0.230	0.078
Note: red text indicates that t-statistic is less than 1.9, needed for 95% certainty of statistical difference						

For car ownership, as shown in Table 5, owning a car was the reference condition equal to 1 and coefficients are not presented. Some of the largest coefficients were for household income, time living in the U.S., and residence area type, indicating these have a significant influence on car ownership. For example, households with low income were more likely to share a household car or to not own a car. In comparison to these influential coefficients, the impact of city on car ownership was relatively small, except for Boston. For Boston, the input data indicated that much more transit is available than for the other cities, contributing to the greater prevalence of households either sharing or not owning cars.

For adult non-work and work trips, the new rideshare coefficients in Table 5 showed positive influence on mode choice with younger age groups (16-29 years), urban area types, and no car ownership. For adult non-work trips, travelers aged 15 years and younger were not included. Some of the largest coefficients were for car ownership, age group 16-29 years, household structure, and household car ownership, indicating these have significant influence on mode choice for non-work trips. The traveler's status as part of the workforce also showed an influence on non-work mode choice. Note that the price of gasoline coefficients for walk/bike and rideshare are the largest among the non-work trip modes, and the gasoline price coefficients are larger than for the 2009 NHTS data (Bradley et al., 2014).

For adult work trips, travelers aged 15 years and younger were not included. Because these coefficients were for work trips, the values for the coefficient "worker" were not computed. The age group of 16-29 and household car ownership seem to be the largest and therefore most significant coefficients influencing mode choice for work trips. A difference with the 2009 Impacts 2050 coefficients (Bradley et al., 2014) is the greater significance of the price of gasoline in 2017, especially for the rideshare mode, which has the largest gasoline price coefficient for all the 2017 modes.

For trip rate, the number of trips per day per person, trip purpose was divided into work and non-work categories. The results of the 2017 coefficient estimates for trip rate are shown in Table 6. The age category of 15 years and below was disregarded for work trips, and gasoline price was disregarded as an explanatory variable for work and non-work trips, as it was in the baseline Impacts 2050. Apart from the constants, the largest values for each set of coefficients were people in the workforce (e.g. "worker"), indicating its significance for the number of trips taken. This is similar to what was found for the 2009 coefficients (Bradley et al., 2014).

For daily trip distance, the model coefficients, estimated for all the transport modes except walk/bike, are shown in Table 6. The model used by Impacts 2050 for daily trip distance is a log-linear regression with the dependent variable equal to the log of the distance of each trip + 1 in miles. To avoid the impact of outliers, trip distances of greater than 100 miles were excluded. The trip

Table 7
Model coefficients for number of people per rideshare trip.

Model	Work & Non-Work Trips
Dependent variable	Rideshare Occupancy
Independent variable	Coef.
Constant	2.275
Age 00-15	1.019
Age 16-29	0.359
Age 45-59	-0.232
Age 60-74	-0.210
Age 75-up	-0.096
couple	0.066
Children in household	0.315
Single with children	-0.662
Ethnic (non-white)	-0.067
Born outside US	0.183
In US under 20yrs	-0.322
Worker	-0.351
Low income	0.347
High income	0.187
Urban	0.014
Rural	0.677
Atlanta	N/A
Boston	N/A
Detroit	N/A
Houston	N/A
Seattle	N/A
No car ownership	-0.539
Shared car ownership	-0.691
Gas Price	N/A
Note: red text indicates that t-statistic is less than 1.9	

distance coefficient with the largest value was that for work trip, which seems to be the most significant contributor to trip distance. This is especially true for mode choice of car driver.

4.3.2. Modeling occupancy (number of passengers) on rideshare trips

A linear regression model was developed using 2017 NHTS data for the number of occupants per rideshare trip. The coefficients for this model of rideshare trip occupancy are shown in Table 7. This set of coefficients was selected for use after evaluating the goodness of fit for several options, including a separate model for work and non-work trips. Note that city location and gasoline price were not included to improve overall goodness of fit. As before, the t-statistic was used to assess the variables' statistical significance. While some coefficients had a t-statistic lower than 1.9 (i.e., age 75 and up, ethnic group) the overall goodness of fit was comparable to the other model coefficients presented above. The coefficients for travelers aged 29 and under show a positive influence on rideshare trip occupancy, while travelers aged 45 and above show a negative influence. The coefficients for household income indicate that households with low income might have higher rideshare trip occupancy than households with high income. Shared and no car ownership also have a relatively large negative impact on the number of occupants per rideshare trip.

4.3.3. Impacts 2050 outputs with 2017 travel behavior model and rideshare mode

To exercise the updated 2017 travel behavior model, the original four scenarios published with Impacts 2050 as summarized in Table 2 were run with the enhanced Impacts 2050. The model was run for the 50-year period from 2010 to 2060. The results are shown for the five cities and four scenarios of interest. Scenario differences in results are driven by the exogenous variables (see Appendix B through Appendix E). In addition, each city has its own unique characteristics, such as demographic profile and associated travel behavior coefficients, mix of area type (urban, suburban, rural), and road capacity versus public transit capacity, which can impact the results. Note that these results were generated assuming a base gasoline price of $3 per gallon (Valev, 2023) and a car service life of 10 years (Nieuwenhuijsen et al., 2018).

In Table 8, the predicted mode share values are shown for the year 2060, including rideshare. In this table, the distribution of car, transit/walk/bike, and the newly added rideshare is shown as a percentage of total daily trips.

Results show the dominance of the car and the relatively small percentage of total trips taken via rideshare. The percentage of rideshare trips ranges from 0.4% to 2.3% of total daily trips taken in 2060, the end of the simulated period. When compared to

Table 8
Mode share distribution including rideshare for 2060.

Metrics	Atlanta				Boston				Detroit				Houston				Seattle			
	M	TT	GF	GC	M	TT	GF	GC	M	TT	GF	GC	M	TT	GF	GC	M	TT	GF	GC
Car mode share (%)	85.6	85.9	75.2	80.5	76.5	77.1	62.6	68.1	85.3	86.2	75.0	79.9	86.0	86.7	78.8	83.0	83.9	84.2	72.9	77.8
Transit/Walk/Bike mode share (%)	13.4	12.9	22.5	18.6	22.9	22.0	36.6	31.5	14.3	13.4	23.7	14.3	13.6	12.8	20.3	16.6	15.6	15.2	26.1	21.8
Rideshare mode share (%)	1.0	1.2	2.3	0.9	0.6	0.9	0.8	0.4	0.5	0.4	1.3	0.5	0.4	0.5	0.9	0.3	0.5	0.6	1.0	0.4
TOTAL (%)	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Table 9
Urban mobility sustainability scorecard with rideshare for 2010-2060.

Metrics	Atlanta				Boston				Detroit				Houston				Seattle			
	M	TT	GF	GC	M	TT	GF	GC	M	TT	GF	GC	M	TT	GF	GC	M	TT	GF	GC
SOCIAL																				
No car ownership (% change)	3	6	2	2	0	0	4	11	2	4	2	4	-1	3	-1	1	-1	1	-1	1
Rideshare mode share (% change)	38	69	217	28	11	67	62	-28	35	32	295	52	39	73	219	25	23	59	169	8
TECHNOLOGICAL																				
Peak traffic speed (actual/posted) (% change)	-27	-20	-5	-23	-34	-15	0	-16	-58	-30	-4	-47	-45	-26	-12	-33	-20	-6	0	-9
SAE Level 5 Automation (% change in total fleet fraction)	86	86	85	85	85	85	84	84	86	86	85	85	86	86	86	86	83	83	83	83
ENVIRONMENTAL																				
Cars per capita (% change)	-3	0	-6	-11	-3	1	-8	-15	-2	0	-6	-11	-3	0	-7	-12	-2	1	-6	-11
Transit/Walk/Bike mode share (% change)	27	22	115	77	16	11	85	60	19	11	98	63	28	20	91	56	20	17	101	68
Auto VMT/capita per day (% change)	-17	-5	-62	-54	-21	-8	-66	-60	-12	1	-59	-50	-8	6	-56	-48	-19	-8	-63	-54
ECONOMIC																				
Transit/Walk/Bike mode share for Lower Income (% change)	8	2	78	49	-4	-8	43	25	-7	-13	52	29	9	2	56	30	0	-3	62	38
Ratio of trips per capita (upper/lower income) (% change)	4	3	4	6	5	4	5	7	5	5	5	8	2	2	2	4	5	4	5	8
POLITICAL																				
Ratio Developed Land per Capita (% change)	-11	20	-29	12	-9	21	-27	14	-7	24	-26	16	-8	24	-25	17	-10	20	-29	13
Road density-total lane miles/total surface area (% change)	-7	-7	-8	-7	-8	-9	-9	-9	-7	-7	-8	-7	-7	-7	-8	-7	-8	-9	-9	-8

the 2017 NHTS data shown in Table 1, where rideshare is 0.5% of the trip records, these results predicted for 2060 show limited growth. Another observation is the influence of scenario inputs on results. For example, the “Gentle Footprint” (GF) scenario, the most supportive of sustainable transportation outcomes, generally has the lowest mode share for car and the largest mode share for rideshare.

More comprehensive results are shown in Table 9 using a set of sustainable mobility metrics selected for this research as an urban mobility sustainability scoreboard. The metrics are grouped into the STEEP categories of social, technological, environmental, economic, and political to demonstrate the whole system sustainability approach. In this table, the results shown are the percentage change over the simulated 2010 to 2060 time period.

Across the four scenarios, the metric “No car ownership” showed similar, slight increases of about 3% for Atlanta, Boston, and Detroit, while Houston and Seattle had nearly no change. For “Rideshare mode share”, there was an increase of 8-295% in rideshare usage across all cities and scenarios, except for an outlier decrease in Boston for the “Global Chaos” scenario. For this outlier, note that in Table 5 the Boston-specific coefficients for transit/walk/bike mode choice are much larger than those for the other cities, and the coefficient for non-work trips for rideshare is negative. Together, these coefficients explain the outlier result for rideshare in Boston. These results reflect the modeling of city-unique travel behaviors, such as the greater availability and appeal of transit/walk/bike in a city like Boston experiencing conditions like the “Global Chaos” scenario, Detroit had the largest increases, while Boston and Seattle had the smallest. However, though the rate of change was high in some cases, note the overall rideshare mode share as shown in Table 8.

In the scenario where “rideshare mode share” increased most, “Gentle Footprint”, there is a corresponding decrease in “Cars per capita”. The “Cars per capita” decreased for all cities across most scenarios, and the changes (-5 to -6%) were comparable across all cities. The reason for similar decreases in “Cars per capita” in “Gentle Footprint” and “Global Chaos”, two very different scenarios, can be seen in their exogenous inputs (see Appendix D and Appendix E). The inputs that drive gasoline price, shared-car and no-car ownership, and non-car driver mode share are comparable for both scenarios.

Sustainable trends are also observed in increases for “Transit/Walk/Bike mode share” for both “Gentle Footprint” and “Global Chaos”. In “Gentle Footprint”, a push for sustainability includes higher gasoline taxes, more compact development, and transit investment; whereas, “Global Chaos” results from severe climate change that makes everything more expensive. This stimulates more walking and biking, as driving becomes less affordable.

In Table 9 the ratio of actual to posted speeds declined from 0-58% over the time period modeled. These values correspond to a traffic volume to capacity ratio of approximately 1.0 to 1.3 per the MTC approach (Singh and Dowling, 1999). As a basis of comparison, a published set of traffic congestion data was identified from the U.S. Bureau of Transportation Statistics (BTS) (“Table 1-71: Annual Roadway Congestion Index,” 2013). This data set contains Roadway Congestion Index (RCI) data for 1982 to 2011 for 101 cities in the United States including those cities modeled for this research. The RCI is a measure of vehicle travel density on major roadways for an urban area (Hanks, Jr and Lomax, 1992). The RCI is the ratio of actual daily vehicle miles traveled (DVMT) per lane mile divided by DVMT found to correspond to congested conditions. RCI values exceeding 1.0 indicate increasingly undesirable congestion and slower speeds on freeways and principal roadways during the peak period. RCI values in the BTS data set ranged from 1.02 to 1.15 for the five cities in 2011, with changes in RCI of 14-30% over the 1982-2011 time period. This BTS data provides a point of comparison for the MTC-based congestion metrics added for this research.

For “SAE Level 5 Automation (% change in total fleet fraction)” the percentage increased 84-86% across all cities and scenarios. These outcomes are comparable because the main parameters that drive AV development and adoption, such as research and development funding per (Nieuwenhuijsen et al., 2018) were kept fixed for this set of results. Overall “Auto VMT/capita per day (% change)” decreased for all scenarios, which corresponds with the decrease in car mode share shown in Table 8.

The metrics categorized as economic address aspects of transportation equity. For the metric, “Transit/Walk/Bike mode share for lower income”, values increased 24-34% for all scenarios in Atlanta and Houston, while decreasing slightly in the “Momentum” and “Tech Triumphs” scenarios in Boston, Detroit, and Seattle. The metric “Ratio of trips per capita (upper/lower income)” showed changes that ranged from 4-8% across the cities evaluated. The pattern was comparable across scenarios, indicating a very slight increase in upper class trips per capita. This ratio is intended to determine the relative utilization of the transportation system as a function of household income.

Finally, for the metrics categorized as political, the metric “Ratio Developed Land per Capita” had changes that ranged from -29% to 24%, with decreases for the “Momentum” and “Gentle Footprint” scenarios and increases for “Tech Triumphs” and “Global Chaos” scenarios, reflecting the influence of the scenario definitions on this metric. As for “Road density”, the values ranged from -7% to -9% across the cities and scenarios that were evaluated, with relatively little difference across city and scenario.

5. Conclusions and future work

5.1. Conclusions

The results demonstrate an enhanced Impacts 2050 model that represents the rideshare mode and generates metrics for a sustainable urban mobility scorecard. Together, these results address the model gaps that were identified for an enhanced model that can support whole system sustainability assessments. This model can be used to assess a set of transport mode choices that include emergent concepts, such as rideshare. Through definition of a STEEP metrics scorecard, the enhanced Impacts 2050 can be used to evaluate the overall high-level sustainability impact of emergent mobility concepts, such as rideshare on an urban transportation system.

The addition of rideshare to Impacts 2050 influenced related metrics, such as cars per capita and car ownership. Rideshare mode share was shown to increase significantly on a percentage basis in some city-scenario combinations over the 50 year period modeled, especially for the scenario with the most environmentally favorable conditions. However, the overall resulting mode share remained limited, ranging from 0.3% to 2.3%. In addition, though a model enhancement enabled rideshare users to shed car ownership, the percentage increase in “no car ownership” was not found to be very significant. The basis of the travel behavior model in 2017 NHTS data, actual travel behavior reported for that period, retained a strong influence on modeling future mode choice.

Changes in output metrics were shown to be highly sensitive to the scenario definitions and the associated exogenous inputs that drive model behavior. For example, for the “Gentle Footprint” scenario, the most environmentally optimistic scenario, the exogenous factor “Transit/Walk/Bike Mode Share” ranges from 1 to 1.5 over the 50-year period that was modeled (see Appendix D). This is in comparison to the “Momentum” scenario where there are no changes over time from current trends, i.e. all factors remain 1. These differences are reflected in observed differences when comparing mode share results (see Table 8).

5.2. Future work

Recommendations for future work include further enhancement of the model's travel behavior coefficients when the next set of NHTS data is published, with special focus on any changes in rideshare travel behavior. Such an update might enable addition of further emerging modes (e-bikes, scooters, other types of rideables) per Fig. 2. Note that the Impacts 2050 travel behavior model is based on travel behavior at a given point in time (e.g. 2017 NHTS data) which is then extended into the future. Exogenous variable inputs are provided to enable exploration of the potential impact of behavior changes over time. Future work could examine adding modeled effects of generational change on travel behavior (e.g., mode choice) to Impacts 2050 using published research that quantifies the behavior changes being explored.

A challenge of modeling rideshare in Impacts 2050 was the fact that rideshare is an emergent and relatively rare travel mode compared to the other modes (e.g. car, transit). In updating the travel behavior model for Impacts 2050 with 2017 NHTS data, challenges were experienced in estimating the coefficients of the required multinomial logistic regression models while still including all the desired explanatory variables and the new rideshare mode. In future work on modeling emergent travel modes, where the number of occurrences may be even less than rideshare (e.g. e-bikes), different modeling approaches could be explored such as using Firth's Penalized likelihood method. This method provides a way to deal with rare events or separation within large data sets and is included in commercial software packages. It applies a penalty term to the standard function used for generation of parameter estimates and standard errors in a logistic regression model. A benefit is that it resolves the issue of overly large coefficients, but it may underestimate the likelihood of occurrence of rare events. This method could be a useful approach; for example, if future updates of the NHTS data set become available with additional emergent but low occurrence modes of transport.

The parameters used to model the effect of rideshare effects on increased VMT (i.e., the percent of trips where the driver is waiting for a passenger, picking up a passenger, or transporting a passenger) could be made variable to account for differences in scenario, population density, or other conditions of interest. The model for rideshare vehicle occupancy could be extended to explore population density effects.

Additional future work could include a sensitivity study to further explore the behavior of the model enhancements for rideshare and further include AV adoption, especially regarding the impact of the age and income demographic on car ownership (including AVs; i.e., buying cars vs. buying rides). To support this future work, new scenarios could be developed and exercised with the methodology, with a more specific focus on exploring alternative rideshare adoption scenarios, and the potential impacts of AV development and deployment. The future mobility adoption scenarios found in the literature review for this research were more narrowly defined than the four scenarios that were published with Impacts 2050, which were focused on four contrasting future states that could impact overall mobility, especially with respect to climate change and overall technology enhancements.

In contrast, alternative future mobility (e.g. rideshare, MaaS) adoption scenarios that were identified in the literature review focused more narrowly on the effects of income levels, population density, and public vs private business models. Such scenario-based research would offer further opportunity to enhance Impacts 2050. Income and population density are addressed in the enhanced Impacts 2050 travel behavior model and the four scenarios published with the model. Household income is one of the explanatory variables in the travel behavior model. Population density is addressed via residential location type (urban, suburban, rural), an explanatory variable in the travel behavior model, and through model inputs for the number of people living in each residential location type for a specific city. Future analysis with Impacts 2050 scenarios focused on income or population density would isolate their specific effects on travel behavior. However, exploring public vs. private business models with the enhanced Impacts 2050 would require additional future work in modeling competing MaaS providers. This would require additional enhancements to Impacts 2050, including: developing a model of traveler decision-making relevant to selecting among multiple mobility MaaS providers, adding variables to track the resultant distribution of trips between different MaaS providers over time, and outputting the results for analysis, including metrics showing potential to increase VMT caused by competing MaaS vehicle fleets.

To further enhance Impacts 2050 as a sustainable mobility model, potential additional areas of future work include addressing the following: the impact of political scenarios on the mobility system, the impact of competing rideshare companies, modeling the transition for gasoline to electric propulsion (including charging infrastructure), the effect of adding bike lanes, adding transport modes, modeling trips that involve multiple modes of transport, modeling curb congestion, and further examination of the effect of demographics on travel behavior. The main scope of this research was to add an emergent transportation mode, rideshare, to Impacts 2050, with the approach informed by the existing model structure. Addressing these further enhancements within the structure of Impacts 2050 would require additional data and modeling effort that were beyond the research scope.

Potential approaches for some of these additional enhancements can be outlined here. Political scenarios could be implemented by defining different sets of exogenous inputs for Impacts 2050 (for example: road capacity addition, rail capacity addition, gasoline price, and land protection, to represent contrasting policy implementations). Approaches for modeling competing rideshare companies are discussed later in this section. Vehicle electrification was not the focus of this research, and the Impacts 2050 travel behavior model assumes gasoline as the energy source with dollars per gallon being an explanatory variable from the NHTS 2009/2017 databases. However, future work could account for travel behavior changing in response to car fleet electrification over time. Vehicle electrification could be modeled similarly to the AV model that was integrated in this current research. Specifically, a model could be developed and integrated into Impacts 2050 that accounts for the adoption of electric vehicles over time, computing the changing relative mix of the car fleet (gasoline vs electric). With this addition, the travel behavior model would need to be adapted to respond to the costs of both gasoline and electricity as car energy sources. Adding a transportation capacity for bike lanes could be considered, like the method used by Impacts 2050 to model road and rail capacity. Additionally, new models would be required to account for additional transport modes or trips that involve multiple modes of transport, including the ability to output multi-mode trip metrics.

The focus of this research was on sustainable mobility for people, and concern for how the addition of rideshare and AV technology might adversely affect urban congestion. However, it should be noted that curb management for rideshare and AVs, as well as e-commerce and last-mile freight delivery, are also contributors to congestion and could be considered in future work. While Impacts 2050 does model road and rail capacity, it does not currently model curb capacity. Such capacity modeling would need to be added to support the modeling of curb congestion and output of relevant congestion metrics.

While this research focused on modeling travel behavior for urban, suburban, and rural areas within MPO regions, future work could focus more specifically on rural areas. The provision of satisfactory mobility delivered on-demand in less densely populated areas would be a key issue to explore, especially how population density impacts per trip ridership, waiting times, and non-revenue VMT enroute to a rural passenger pick-up. The expected scarcity of travel behavior data to support modeling of emergent mobility modes (e.g., rideshare) in rural areas would be a key challenge. An approach could be considered like that proposed above for modeling emergent travel modes.

The Impacts 2050 model provides exogenous input factors to enforce desired time-varying behavior in the model and represent expected future trends (e.g., a future scenario). The four scenarios selected for presentation in this paper were those originally published with Impacts 2050. They are used here to provide a basis of comparison with that work. These scenarios have many exogenous parameters changed simultaneously to define a given scenario, which can obscure the attribution of a specific cause and effect. When used to support a specific decision-making issue, changing fewer parameters at a time across scenarios would be done to ease the interpretation of the results. For example, if the focus was the effects of extended working-from-home on travel behavior, one would set all exogenous variables to 1 (i.e. the "Momentum" scenario) and vary only "Work Trip Rate". The resultant effects of decreases in work trips could then be observed on metrics such as VMT and congestion.

This research focused on rideshare as part of a whole system assessment of a city's sustainable mobility; however, there is a need to measure the adoption of MaaS. Research on MaaS adoption (Shaheen et al., 2016) highlights the challenge of defining and tracking metrics for shared, multi-mode mobility needed by transportation planners and policy makers. Car ownership rates may be one candidate indicator. Future work could focus on development of MaaS adoption metrics as part of the overall whole system approach. This current research added the rideshare mode to enhance Impacts 2050; however, additional model enhancements would be required to better represent the multi-modal nature of the MaaS concept (e.g., modeling trips that involved multiple modes of transport, and the resultant adoption metrics).

Developed as a decision support tool, Impacts 2050 can aid transportation planners and stakeholders in examining a broad set of alternative future scenarios. Once the necessary input data has been prepared, the model's runtime allows rapid exploration of potential outcomes. By enabling users to define different future scenarios via the exogenous input parameters, and by providing a scorecard and framework to apply stakeholder weightings, urban agencies can apply the enhanced Impacts 2050 model to explore the relative impact of parameters that might affect a sustainable mobility outcome. For example, planning agencies examining urban sprawl could use the exogenous variable "Car Trip Distance" set above values of 1 to model the greater travel distances brought about by further outward spread of urban regions. These examples highlight the potential application of this whole systems approach towards seeking sustainable mobility outcomes.

Finally, investigating the impact of stakeholder weightings on the STEEP metrics scorecard developed for this research would provide additional insight relative to its use for transportation planning.

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Data availability

Not applicable.

Supplementary materials

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Appendix A. Explanatory Variables for Travel Behavior in Impacts 2050 Model

Explanatory Variable	Variable Definition	Travel Behavior Models (based on NHTS data)			
		Car ownership	Trip rate (no. trips/person)	Mode Choice (work, non-work, child)	Trip Distance (no. miles/trip)
Age Cohort	0-15 16-29 30-44 45-59 60-74 75+	X	X	X	X
Household Structure	Single without Child Single with Child Couple without Child Couple with Child	X	X	X	X
Acculturation Group	Foreign born, In US <20 years Foreign born, in US >20 years US born	X	X	X	X
Race/ethnicity	White, other Asian Black Hispanic	X	X	X	X
Workforce Status	In workforce Not in workforce	X	X	X	
Trip Purpose	Work Non-work		X	X	
Trip Mode Choice				X	X
Household Income	Low - $0-$34,999 Medium - $35,000-$99,999 High - $100,000+	X	X	X	X
Residence Area Type	Urban Suburban Rural	X	X	X	X
Household Car Ownership	**"Own car":** number of cars is equal to (or greater than) the number of driving age adults, each person can drive their "own" vehicle. **"Share car":** household has one or more cars, but fewer cars than the number of driving age adults, at least two adults may need to share a vehicle. **"No car":** household with zero vehicles.		X	X	X
Gasoline Price	$/gallon			X	X

per (Bradley et al., 2014)
Note: X indicates explanatory variable contributes to one of the travel behavior models

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