U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

SMART Mobility

Mobility Decision Science Capstone Report

July 2020

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Foreword

The U.S. Department of Energy's Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium is a multiyear, multi-laboratory collaborative, managed by the Energy Efficient Mobility Systems Program of the Office of Energy Efficiency and Renewable Energy, Vehicle Technologies Office, dedicated to further understanding the energy implications and opportunities of advanced mobility technologies and services. The first three-year research phase of SMART Mobility occurred from 2017 through 2019, and included five research pillars: Connected and Automated Vehicles, Mobility Decision Science, Multi-Modal Freight, Urban Science, and Advanced Fueling Infrastructure. A sixth research thrust integrated aspects of all five pillars to develop a SMART Mobility Modeling Workflow to evaluate new transportation technologies and services at scale.

This report summarizes the work of the Mobility Decision Science Pillar. The Mobility Decision Science Pillar sought to fill gaps in existing knowledge about the human role in the mobility system including travel decision-making and technology adoption in the context of future mobility. The objective was to study how underlying preferences, needs, and contextual factors might constrain or hasten future transportation system scenarios. For information about the other Pillars and about the SMART Mobility Modeling Workflow, please refer to the relevant pillar's Capstone Report.

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List of Acronyms

ACC	Adaptive Cruise Control
ACS	American Community Survey
AFI	Advanced Fueling Infrastructure
API	Application Programming Interface
ATUS	American Time Use Survey
AV	Automated Vehicle
BART	Bay Area Rapid Transit
BEAM	Behavior, Energy, Autonomy, and Mobility
CAV	Connected and Automated Vehicle
CBD	Central Business District
CES	Consumer Economic Survey
CMAP	Chicago Metropolitan Agency for Planning
DOE	Department of Energy
EEMS	Energy Efficient Mobility Systems
EERE	Energy Efficiency and Renewable Energy Office
EPA	Environmental Protection Agency
EV	Electric Vehicle
Gen X	Generation X
GPS	Global Positioning System
JDEQSim	Java Deterministic Event-Driven Queue-Based Traffic Flow Micro-Simulation
MATSim	Multi-Agent Transportation Simulation
MDCEV	Multiple Discrete-Continuous Extreme Value
MDS	Mobility Decision Science
MMF	Multi-Modal Freight
MPG	Miles Per Gallon
NEP	New Ecological Paradigm

NHTS	National Household Travel Survey
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
SMART	Systems and Modeling for Accelerated Research in Transportation
SOV	Single Occupancy Vehicle
TAZ	Traffic Analysis Zone
TNC	Transportation Network Company
UA	Urban Areas
US	Urban Science
VHT	Vehicle Hours Traveled
VMT	Vehicle Miles Traveled
VOTT	Value of Travel Time

Executive Summary

Dramatic technological changes—from electrified and automated vehicles to communication technology that enables shared mobility, e-commerce, and telecommuting—are transforming the transportation system. Existing vehicle-level models can estimate the potential energy savings from specific vehicle technologies such as new powertrains in individual vehicles; however, assessing the system-wide impact of multiple simultaneous changes in vehicle technologies, and how people use them, produces large uncertainties. Previous studies have portrayed diverse visions of these future impacts. A better understanding of the contextual factors driving user preferences and their influence on the transportation system is critical for helping decision makers predict, prepare for, and shape system-level outcomes.

The U.S. Department of Energy's Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium is a multiyear, multi-laboratory collaborative dedicated to further understanding the energy implications and opportunities of advanced mobility technologies and services. The first three-year research initiative of SMART Mobility occurred from 2017 through 2019. Mobility Decision Science (MDS) is one pillar of the SMART Mobility Consortium. The MDS Pillar examines the underlying identity, preference, personality, lifecycle, geographical, and contextual factors that impact transportation behaviors. Of particular interest are factors that are, or could be, critical barriers to, or drivers of, adoption and use of emerging transportation technologies and services such as vehicle automation, vehicle electrification, ride-hailing, shared modes, and e-commerce. The MDS Pillar employed various methods and data sets. The WholeTraveler Transportation Behavior Study—which administered a survey in 2018 across a random sample of San Francisco Bay Area residents—provided the foundation for understanding the characteristics of likely adopters of transportation technologies and services and determining adopter use patterns and motivations across life stages. MDS methods also included the use of two agent-based models—POLARIS and Behavior, Energy, Autonomy, and Mobility (BEAM)—for simulating large-scale transportation systems. This Executive Summary includes key results from the MDS Pillar, which are detailed in the full report.

MDS research helped fill gaps in existing literature related to age with regard to both mode choice and technology adoption. In the WholeTraveler sample, younger generations drive both current adoption and interest in future adoption of ride-hailing. Most millennials are either interested in or already regularly use ride-hailing; they are 70% more likely to have adopted single-rider ride-hailing and almost 200% more likely to have adopted pooled ride-hailing, relative to Generation X (Gen X). In addition, millennials who have not yet done so are 50% more likely to express interest in adopting both of these ride-hailing service types compared to Gen X travelers who have not yet adopted. Overall, interest in and adoption of ride-hailing is higher for millennials compared to all previous generations.

To resolve ambiguous findings in the literature regarding the correlation between interest in automated vehicle (AV) technologies and age, MDS researchers found that both millennials and baby boomers are significantly more interested in AV technologies relative to Gen X. In the WholeTraveler sample, about half of millennials and baby boomers express interest in adopting partially automated vehicle technology, which is about 25% higher than for Gen X. Interest tends to be highest for the youngest and oldest respondents in the analyzed sample (those born in the 1990s and those born in the 1940s). This pattern holds for the case of interest in fully automated vehicles as well, with millennials (58%) and baby boomers (50%) both more likely to express interest in fully automated vehicles compared to Gen X (44%). In addition, with respect to electric vehicle (EV) technologies, WholeTraveler findings contrast with most previous findings, which indicated that EV ownership is driven by youth. In the WholeTraveler sample, current adoption of both plug-in electric vehicles (PEVs) and hybrid vehicles is driven by older generations. Although interest in owning a hybrid is significantly higher among the youngest millennials, interest in owning PEVs tends to be marginally highest among baby boomers. However, due to the WholeTraveler survey being conducted online, it may be the case that the older WholeTraveler respondents are more likely be open to new technologies relative to the broader population of the same age.

Such age-related findings are relevant to underlying patterns in mode use. For example, using data from the WholeTraveler Life History Calendar, MDS researchers demonstrated that vehicle dependence increases with age, stabilizing at around 70% regularly driving a private vehicle (more than twice per week) by about age 33 and persisting at that level thereafter. This increase comes largely at the expense of public transit, walking, and biking. However, if interest in adopting PEVs continues to follow the patterns observed and described above with regard to age, this could influence the energy implications of this underlying trend toward increased vehicle dependence with age.

MDS researchers also examined why people tend to make particular mode choices and how these dynamics might manifest in the context of emerging transportation options. This included using machine learning techniques to derive five cohorts defined by different archetypical life trajectory patterns. Analyses of these cohorts revealed that mode use is affected by the relative order of life events, and when certain key events occur earlier in life they are more strongly associated with changes in mode-use behavior compared with events occurring later. These timing and order effects can have lasting implications for mode use over entire life cycles. For example, the “Have-it-alls” cohort (almost 20% of the sample), finishes their education, starts working, partners up, and has children all in close proximity early in life, ramping up car use at each life transition after school. This results in the highest rate of car use occurring the earliest of all the cohorts (about 80% by age 30 as compared to about 70% by age 33 for the sample as a whole) (Figure ES-1). The WholeTraveler results show the extent to which, currently, this movement towards vehicle dependence is permanent. Having children concurrent with career formation is a major driver of earlier transition to vehicle dependence for people in the “Have-it-all” life trajectory. Having children tends to shift people who have not already transitioned to a more vehicle-dependent lifestyle towards regular personal vehicle use, and this shift tends to be permanent. This is especially true for women who simultaneously build their careers and have children early in life.

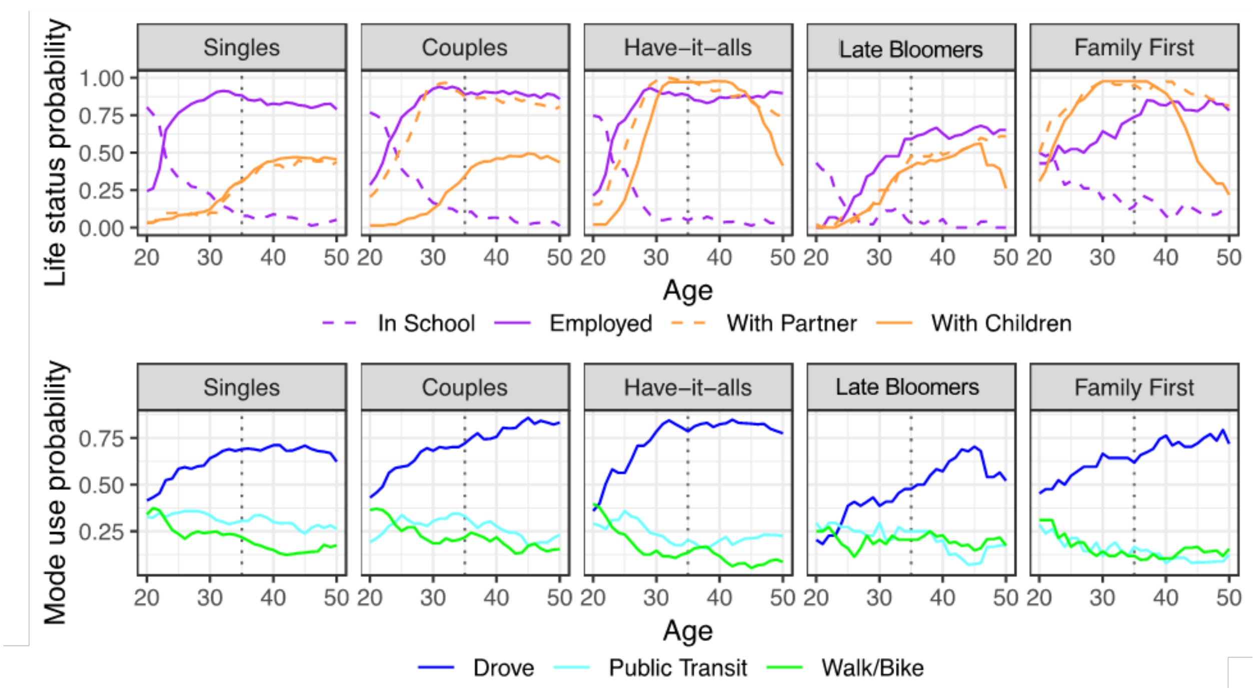

Figure ES-1. Life-course patterns in the family and career status of five life-course cohorts

Women in the WholeTraveler sample are significantly less likely to be interested in adopting PEVs and vehicles with high levels of automation compared to men. The gender gap in PEV adoption interest is found to be largely driven by a lower ability or willingness to pay by women as well as a misalignment between women’s vehicle needs and PEV characteristics, which tend not to have as much passenger or cargo capacity as conventional vehicle options, and are less likely to be preferred by women who place a high importance on the need to safely transport children or make multiple stops, such as would be needed to run household errands. The link between income, gender, and children also relates to the MDS finding that, when people have children relatively young (before age 26), they are less likely to drive regularly as a result, largely due to a lower probability that they work while having young children. Women in the WholeTraveler sample who had their children young had the highest probability of being in the lowest household income quartile and are the least likely to be in the highest income quartile relative to women who had their children later in life, or men overall.

These findings underscore the fact that people have needs and constraints when making transportation decisions. The tendency towards increased private vehicle dependence due to certain lifecycle factors suggests a need is being met by privately owned vehicles for much of the population. Those who have children in the WholeTraveler sample are less likely to live close to Bay Area Mass Transit (BART) stations compared to those without children, a finding consistent with a higher likelihood of moving to a more suburban environment when children are in the household. WholeTraveler results showed that owning more vehicles and moving to a new residential location when having children results in long-term impacts on mode use, because increased vehicle dependence tends to be permanent. In addition, other underlying characteristics of users can have implications for how much they are willing to rely on alternatives to private vehicles, such as shared modes like shared ride-hailing. For example, MDS researchers showed that introverts are less likely to currently use ride-hailing (either single-rider or pooled). This information can be used to assess the likelihood of significantly reduced private vehicle ownership and primary reliance on automated ride-hailing fleets, as suggested by some projections. The needs and preferences driving private vehicle dependence documented in MDS research (including personality characteristics, household management travel needs, and the presence of children) help to improve the understanding of how transportation decisions are made now and what may or may not change regarding these needs and preferences in the context of new mobility technologies and services in the future.

Factors limiting the use of public transit tend to be similar to factors limiting use of ride-hailing. Thus, if ride-hailing expands and becomes less expensive, it is likely to pull riders who otherwise do not have significant barriers to mass transit use (e.g., do not currently have children and also live close to mass transit stations) away from mass transit, as these modes currently tend to compete for a similar pool of riders. MDS research has shown that there is potential for ride-hailing to complement mass transit if priced low enough to enable increased mass transit access—but not so low as to make it more likely that people will take ride-hailing for their full commute instead of using it to access transit. Simulations by MDS researchers using POLARIS have demonstrated that ride-hailing can be a meaningful mechanism to increase transit ridership if rides to or from transit stops are provided at low cost to incentivize the complementary relationships, but general ride-hailing costs are not changed.

Simulation studies by MDS researchers using BEAM have shown that ride-hailing can induce increased mass transit use and decrease system-wide energy use. However, empirical studies analyzing the real-world impact of ride-hailing also conducted by MDS researchers portray a less optimistic story, in part due to the behavior of ride-hailing drivers. Specifically, based on an analysis relating when ride-hailing first entered different urban areas to characteristics of those urban areas across the United States, MDS researchers found that, especially in urban areas with lower per-capita vehicle ownership and high rates of economic growth, ride-hailing entering the market has increased the number of vehicle registrations by 0.7% on average, though with notable heterogeneity between urban areas. The reason for this effect is not fully identified in the research to date, but one hypothesis is that ride-hailing induces drivers of the service, who otherwise may not own a car, to acquire one in order to drive for the ride-hailing company. Additionally, in the case of RideAustin, a ride-hailing service that previously operated in Austin, Texas, drivers tend to commute relatively long distances (commute deadheading) and drive to reposition their vehicle between ride-hail trips (between-ride deadheading) enough to increase system-wide energy consumption by 41-90%, depending on assumptions about pooling and modal shift (Figure ES-2).

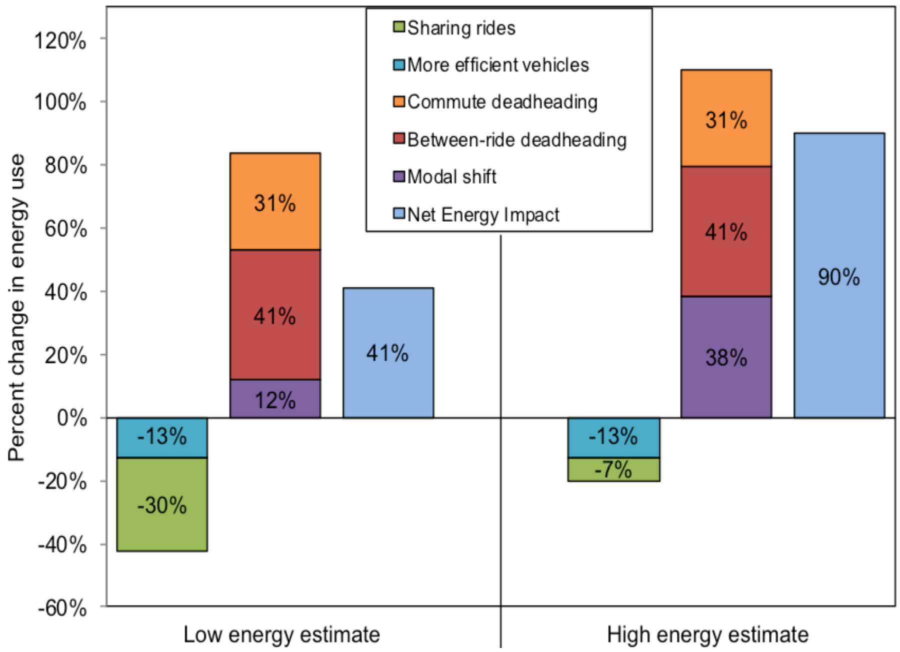

Figure ES-2. Low and high estimates of net energy impact of ride-hailing service in Austin

Increased e-commerce and delivery could also impact system wide energy use. A POLARIS simulation study of Chicago, using e-commerce engagement data from the WholeTraveler survey, showed that increasing per-capita weekly household deliveries from 0.5 to 1.4 results in a 33% decrease in transportation system-level energy consumption (Figure ES-3). This is consistent with WholeTraveler results that revealed, that in a typical week for survey respondents, a given delivery is about 1.7 times as likely to substitute for a shopping trip than not; of those that substitute, a given delivery is 300% more likely to substitute for a vehicle trip than a non-vehicle (walk, bike, public transit) trip. This overall pattern is relatively consistent in proportional terms across different product types studied (groceries; household items; clothing, shoes or accessories; and prepared meals), although the quantity of deliveries per household varies by product type.

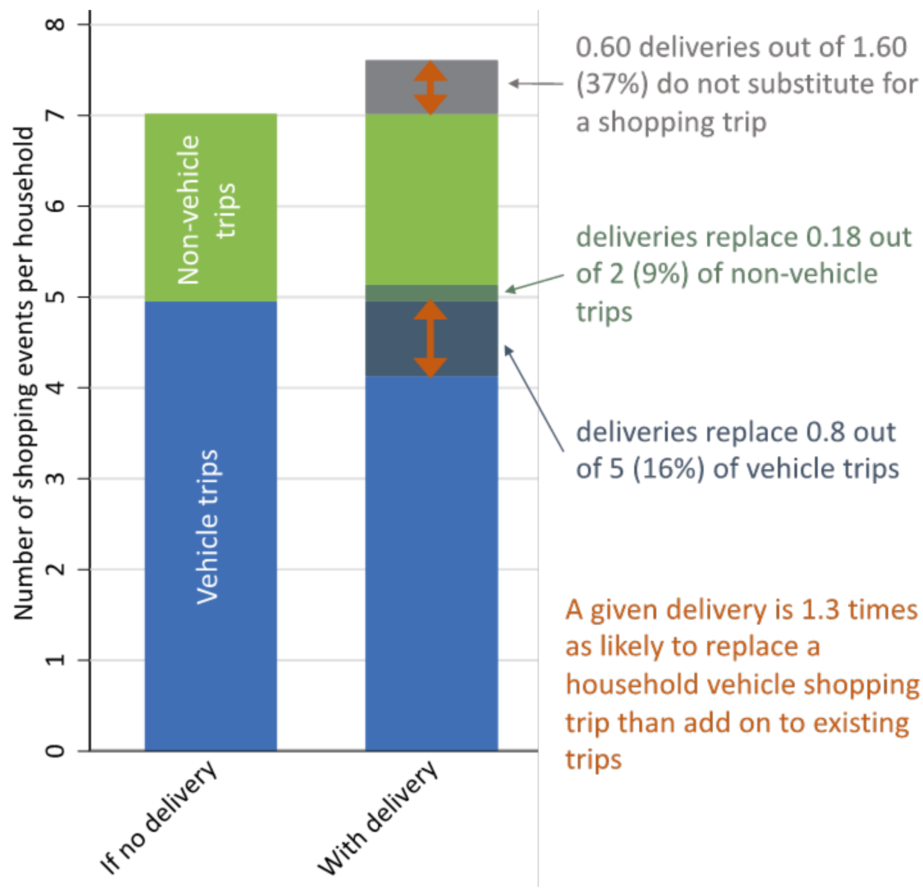

Figure ES-3. Overall degree of substitution and supplementation of delivery for household shopping trips

These two results suggest that e-commerce could increase the energy efficiency of the transportation system as a whole. However, there is significant heterogeneity in the population regarding these use patterns. For WholeTraveler respondents, many households receive either all or none of their purchases via delivery for certain types of goods. This all or nothing pattern holds with respect to how often those deliveries substitute for or supplement shopping trips as well. For a large proportion of the sample, deliveries either fully substitute for (55% to 70% of households) or fully supplement (20% to 35% of households) shopping trips, depending on the product type (groceries; prepared meals; clothing, shoes or accessories; or household items). In analyzing this underlying heterogeneity, MDS researchers found that WholeTraveler respondents from households with high incomes are motivated to engage in e-commerce due to time savings and these households are more likely to order items for delivery than others. Households with children are similarly motivated by time-saving and convenience and are more likely to order household items and clothes via delivery relative to those without children. However, the time-saving motivation does not result in a higher number of trips replaced by delivery. In particular, households with children are more likely to have deliveries supplement existing shopping trips (rather than replace them) in the case of household items and prepared meals. And households with higher incomes are more likely to supplement trips for prepared meals with delivery, rather than replace those trips. This indicates that the marginal time-consuming activity replaced by delivery is more likely to be cooking at home, in the case of ordering prepared meal delivery, rather than a trip to a restaurant. These nuances underscore the importance of understanding the underlying motivations for certain types of behaviors to gain a full picture of how increased reliance on delivery will impact the transportation system.

Increased vehicle automation, especially use of privately-owned driverless vehicles, could increase system-wide vehicle miles traveled (VMT) in part because automation could enable passengers to engage in other activities while travelling which could make people more willing to travel farther. Value of travel time (VOTT) is the key parameter related to this effect. MDS research underscored the fact that estimates of VOTT vary widely by study, data source, and across subpopulations and contexts. No clear, systematic understanding of what drives this variation exists. This lack of understanding remains an important gap. MDS researchers used the POLARIS agent-based model to demonstrate that VMT, congestion, and energy outcomes are highly sensitive to VOTT. Researchers also identified some trends with regard to VOTT impacts. For example, a Chicago-based POLARIS simulation demonstrated that individuals living in downtown and other urban core areas already have high accessibility to large numbers of work and recreational activities and do not tend to engage in substantial extra travel regardless of VOTT changes. This suggests that, if people have access to what they need, driverless vehicles may have no impact on their travel, implying that there may be an optimal level of accessibility in the system.

People make choices based on constraints, needs, and preferences that differ across the population and can depend on fundamental choices regarding lifestyle, values, and identity. As people progress through different phases of their lifecycles, their values and goals may evolve in response to life choices, such as attending school, forming careers, finding a partner, or having children. The solutions people adopt to achieve their goals also evolve over their lifetime, and the adoption of emerging technologies and services depends on whether they contribute to those solutions. These adoption trends shape the transportation system, with impacts on access to technologies and services, population mobility patterns, and system energy intensity and performance. With results such as those summarized here, MDS Pillar filled gaps in existing knowledge about how lifecycle patterns change over time; how these changes influence transportation-relevant choices such as where people live, whether or not they own a car, what modes they use, how they shop, and how they engage in shopping travel; and how the emergence and expansion of innovative technologies and services will affect these patterns. The objective was to study how underlying preferences, needs, and contextual factors might constrain or hasten future transportation system scenarios.

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1 Introduction

Dramatic technological changes—from electrified and automated vehicles to communication technology that enables shared mobility, e-commerce, and telecommuting—are transforming the transportation system. Existing vehicle-level models can estimate the potential energy savings from specific vehicle technologies, such as new powertrains, in individual vehicles, however, assessing the system-wide impact of multiple simultaneous changes in vehicle technologies, and how people use them, produces large uncertainties. A U.S. Department of Energy (DOE) study estimated that the potential energy impacts of connected and automated vehicles (CAVs) could range from a 60% reduction in energy use to a 200% increase. Much of the uncertainty stems from a lack of understanding about how people will use CAVs if they are broadly accessible and affordable [1].

People make choices based on constraints, needs, and preferences that differ across the population and can depend on fundamental choices regarding lifestyle, values, and identity. As people progress through different phases of their lifecycles, their values and goals may evolve in response to life choices, such as attending school, forming careers, finding a partner, or having children. The solutions people adopt to achieve their goals also evolve over their lifetime, and the adoption of emerging technologies and services depends on whether they contribute to those solutions. These adoption trends shape the transportation system, with impacts on access to technologies and services, population mobility patterns, and system energy intensity and performance.

To study and understand the impacts of behavior and decision making on the transportation system DOE formed the Mobility Decision Science pillar of research under the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium. The SMART Mobility Consortium is a multi-year, multi-laboratory collaborative dedicated to further understanding the energy implications and opportunities of advanced mobility technologies and services. The SMART Mobility Consortium consists of five pillars of research:

- Mobility Decision Science (MDS): Understanding the human role in the mobility system including travel decision-making and technology adoption in the context of future mobility.
- Connected and Automated Vehicles (CAVs): Identifying the energy, technology, and usage implications of connectivity and automation and identifying efficient CAV solutions.
- Multi-Modal Freight (MMF): Evaluating the evolution of freight movement and understanding the impacts of new modes for long-distance goods transport and last-mile package delivery.
- Urban Science (US): Understanding the linkages between transportation networks and the built environment and identifying the potential to enhance access to economic opportunity.
- Advanced Fueling Infrastructure (AFI): Understanding the costs, benefits, and requirements for fueling/charging infrastructure to support energy efficient future mobility systems.

The SMART Mobility Consortium creates tools and generates knowledge about how future mobility systems may evolve while identifying ways to improve their mobility energy productivity. The consortium also identifies R&D gaps that the DOE Energy Efficient Mobility Systems (EEMS) Program may address through its advanced research portfolio and generates insights that will be shared with mobility stakeholders. This report details the results from the MDS pillar of the consortium with a focus on the barriers and drivers faced by different subpopulations when considering adoption and use of emerging transportation, and related, technologies and services and the resulting system-level energy implications.

1.1 The Mobility Decision Science Pillar

People make choices based on constraints, needs, and preferences that differ significantly across the population. Assumptions about how people will adopt or use emerging technologies vary widely. For example, Arbib and Seba [2] forecast that, within 10 years of regulatory approval of automated vehicles (AV), 95% of all person-miles-traveled will be via automated ride-hailing fleets as opposed to privately owned vehicles, though privately-owned vehicles will still comprise 40% of the vehicle fleet. Similarly, Johnson and Walker [3] project that the United States will hit peak car ownership rates in 2020 and the rate of car ownership will be more than cut in half by 2035. In contrast, Gao et al. [4] project that only up to 10% of the cars sold in 2030 could be a shared vehicle and up to only 15% of new cars sold that year could be fully automated.

The MDS Pillar sought to fill gaps in existing knowledge about how lifecycle patterns change over time; how these changes influence transportation-relevant choices such as where people live, whether or not they own a car, what modes they use, how they shop, and how they engage in shopping travel; and how the emergence and expansion of innovative technologies and services will affect these patterns. The objective was to study how underlying preferences, needs, and contextual factors might constrain or hasten future transportation system scenarios.

Several studies prior to the advent of SMART Mobility examined the characteristics of current or likely adopters of new technologies. Belk [5] found younger generations moving away from car ownership in favor of ride-hailing and on-demand mobility, and McDonald [6] found millennials traveling less in general and less by privately owned vehicle in particular, compared to previous generations. However, it is unclear whether these trends are permanent societal shifts or merely the result of millennials' tendency to start careers, marry, and have children later in life. Rayle et al. [7] and Smith [8] both found that ride-hailing users tend to be younger, higher income, higher educated, and urban residents. Some studies indicated that plug-in electric vehicle (PEV) owners tend to be disproportionately male, younger, college educated, with higher income, and fewer or no children at home [9]–[11]. In contrast, Ziefle et al. [12] found that women and older generations tend to be more interested in adopting PEVs. Potential adopters of partially and fully automated vehicles tend to be male, technology savvy, and higher income [13], [14]. The relationship between age and technology adoption in the literature is mixed. Abraham et al. [15] found that older adults may be interested in fully automated vehicles for increased mobility, while Krueger, Rashidi and Rose [16] found that those aged 65 and older were less likely to be interested in using a shared AV relative to younger survey respondents.

Several of these previous efforts have attempted to contribute to an understanding of *why* these patterns across subpopulations exist. For example, Plötz et al. [11] included several attitudinal factors in their survey (e.g., agreement or disagreement with the statement "I like to give technical innovations a try even if they are not widely used yet") to demonstrate that a portion of the variation in electric vehicle (EV)[1] adoption is driven by differing values and preferences for comfort, sustainability, and innovative technology. Caperello and Kurani [9] conducted in-home interviews with plug-in hybrid electric vehicle (PHEV) trial households to explore participants understanding of vehicle technologies, driving habits, and prior expectations of PHEV alongside demographic variables. Rayle et al. [7] also considered the potential impact of technological familiarity, noting that smartphone fluency was a key coexisting factor for the young population they identified as ride-hailing

[1] Terms for electrified vehicle technology, such as electric vehicle, plug-in electric vehicle, plug-in hybrid electric vehicle, are not always consistently from publication to publication. Wherever possible references to different technologies in this report are as specific as possible, but in some cases the term "electric vehicle" is used as an umbrella category that may refer to more than one type of electrified vehicle technology.

users. On the topic of automated vehicles, Payre et al. [14] collected data that allowed them to assess the roles of "driving related sensation seeking" (e.g., pleasure from the act of driving itself) and "interest in impaired driving" (e.g., solutions for those with disabilities limiting their ability to drive) alongside demographics when analyzing interest in fully automated vehicles. However, all of these studies used cross-sectional data obtained through a single snap-shot collection, which necessitates a static approach in contrast to one in which dynamics over time are modeled or otherwise considered. Van Acker, Goodwin, and Witlox [17] reviewed studies of the relationship among contextual factors, life events, and travel behaviors concluding that the literature has not adequately captured the dynamics over individuals' life histories nor integrated analyses of decisions over the different temporal scales relevant to transportation choices previously identified in the literature [18]–[20]: (1) short-term decisions on daily activities, (2) mid-term decisions on vehicle ownership, residence, and employment, and (3) long-term decisions on "lifestyles."

Based on gaps in the existing literature, MDS Researchers outlined the following research questions to identify likely adopters of emerging transportation technologies and services and determine why people make different transportation choices at different life stages.

1. What sociodemographic, locational, preference/attitudinal, and personality/psychological characteristics influence the adoption of emerging transportation technologies and services, and how do these characteristics differ between current adoption and interest in future adoption?
2. What impact do lifecycle events (attending school, being employed, living with a partner, and having children at home) have on transportation behavior, and how do these impacts evolve over time and vary across people with different lifecycle trajectories and timing of these events?
3. To what extent does e-commerce with home delivery replace or add to household shopping trips? How does this relationship vary across different shopping travel modes, product categories, and household characteristics?

MDS researchers also focused on behavioral factors directly relevant to the energy implications of these emerging technologies and services. A review of the literature prior to SMART Mobility identified only one published study of the empty or "deadheading" miles (miles with no passengers) current ride-hailing vehicle drivers were accumulating. Cramer and Krueger [21] estimated that 45% of vehicle miles traveled (VMT) by ride-hailing vehicles were without passengers. In addition, at the beginning of SMART Mobility, only one known published academic paper empirically analyzed the impact of ride-hailing on public transit. Rayle et al. [7] found that 33% of ride-hailing users would have taken public transit if they had not taken ride-hailing. Based on the sparse research on these topics, MDS researchers developed the following questions:

4. How might significant declines in the cost of using ride-hailing impact use of mass transit?
5. What are the system-level energy implications of emerging mobility services, such as ride-hailing provided by transportation network companies (TNCs)?
6. What is the relationship between the entrance of TNC services into a city and personal vehicle registrations, vehicle fleet makeup (fuel economy and percent electric vehicles), VMT, and transit use?

One of the key parameters used in modeling transportation behavior is the value of travel time (VOTT), which can be described as the amount a traveler is willing to pay to reduce their travel time by an hour. VOTT influences mode choice, such as whether a traveler chooses ride-hailing or transit, and could influence whether driverless automated vehicles will cause people to travel more. VOTT varies across individuals and varies across travel contexts. Small [22] offers a number of observations on existing travel time estimates. The estimated values vary widely by trip purpose, tending to be highest for business travel and lowest for discretionary or leisure travel [23]. Estimated values also vary with income [23] and across different travel types and travel conditions, tending to be higher under congested conditions than free-flow conditions, by ~25% to 55% [24], [25], and can vary by time of day [26]. There is also significant "unobserved heterogeneity," which is not explainable by observed travel attributes [27]. VOTT is linked to travel conditions, many of which are expected to be affected by connectivity, which when coupled with automation in connected and automated vehicles (CAVs), could ease congestion and improve traffic flow. Fagnant and Kockelman [28] estimated the induced VMT effects of CAVs in a high CAV penetration scenario, accounting for two factors: (1) additional unoccupied VMT of shared CAVs when traveling to pick up riders, and (2) VMT induced by reduced costs and congestion. They estimated an increase in VMT of approximately 10% from the former and from the latter, using VOTT estimates by Cervero [29], they estimated a 26% increase in VMT. The magnitude of the impact of VOTT assumptions, such as those of Fagnant and Kockelman [28], in the context of these emerging technologies led MDS researchers to focus on the following question:

7. How does VOTT affect mode choice, VMT, system energy use, and other transportation system outcomes with the advent of AV technologies and other new mobility technologies and services?

The next section (Section 2) details the research and results from the MDS pillar. Section 2.1 describes three key methodological components underpinning much of the MDS research: the WholeTraveler Transportation Behavior Study survey and two transportation system simulation models. Section 2.2 summarizes findings on the transportation system implications of ride-hailing. Section 2.3 summarizes findings regarding transportation behaviors and life context from the WholeTraveler survey. Section 2.4 summarizes results regarding e-commerce use and impacts on the transportation system. Section 2.5 highlights several additional findings regarding the importance of psychological, personality, and identity factors, including VOTT, on transportation preferences and outcomes. Finally, Section 3 summarizes the key takeaways and concludes.

2 Research and Results

2.1 Data Collection and Transportation System Modeling

Research conducted in the MDS Pillar included a wide variety of methodological approaches, data (including original data collection), and model development and application. In this report, the methodological approaches, data, and models used are described in detail to contextualize each set of results as they are presented. There are three overarching efforts under MDS that underpin much of the work described here: (1) the WholeTraveler survey, (2) the POLARIS Model, and (3) the Behavior, Energy, Autonomy, Mobility (BEAM) Model. Figure 1 shows how projects under MDS relate to these three efforts and in turn how they map to the results sections of this report. Because the WholeTraveler survey, BEAM, and POLARIS interconnect across result topic areas, the overview of these efforts is provided in this section, while specifics about the analyses conducted (applying the data, using specific implementations of the models, etc.) are provided in the discussion of the results themselves in later sections of this report.

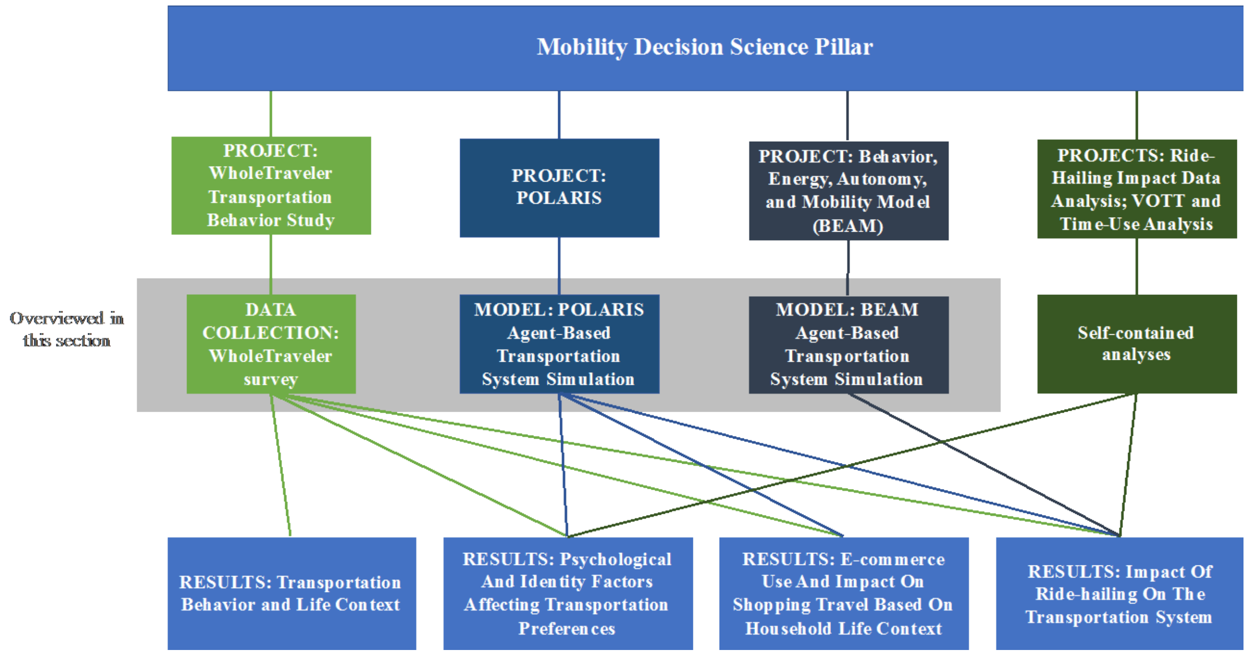


Figure 1. MDS Projects Mapped to Results

2.1.1 The WholeTraveler Survey

MDS researchers launched the WholeTraveler Transportation Behavior Study to identify likely adopters of emerging transportation technologies and services and to determine adopter motivations across life stages. The foundation of this study was the WholeTraveler survey, which captured data on three categories of observable variation in the population relevant to transpiration decisions. First, the survey collected traditional demographic data such as age, gender, income, ethnicity/race, and education level. Second, it collected data across personality, psychological, and preference categories. This included: (1) the "Big Five" inventory personality traits: openness to new experience, conscientiousness, extroversion, agreeableness, and neuroticism. These traits were captured using the Rammstedt & John [30] measure made up of 10 questions responded to on a scale of 1 (strongly disagree) to 5 (strongly agree); (2) risk and time preferences elicited based on the certainty equivalent and multiple price list approach (for examples see [31], [32]) in which the respondent indicates whether they would prefer an immediate (certain) payment amount in the case of time (risk) preferences to a delayed (uncertain) payment amount. A series of questions of this form are asked in which the relative payoff of the alternative payments is varied; and (3) green or environmental preferences captured using the New Ecological Paradigm (NEP) Scale [33]. NEP is a scale constructed from responses to 15 statements that measure agreement or disagreement to determine if an individual supports a "pro-ecological" world view. Third, the survey collected data on historical behavior patterns including: (1) adoption of (as well as interest in) new technologies or innovations (e.g., smartphones, PEVs, solar panels, adaptive cruise control [ACC]); (2) car ownership history and current car ownership status; (3) recent mode use across different time scales (e.g., previous week, previous month, previous year); and (4) timing of major life events such as starting a family as well as overall lifecycle trajectory patterns.

Lifecycle trajectory patterns were assessed using a Life History Calendar, which facilitates recollection of retrospective information. This method has been used in several transportation behavior studies in Europe and Japan [34]–[37], but it has not been used previously to study transportation behaviors in the United States. The

Life History Calendar portion of the WholeTraveler survey asked respondents to provide information on household composition (e.g., living with a partner, having at least one young child, overall household size), employment and school enrollment status, numbers of vehicles owned, timing of moving residence or work location, and regularly used transportation modes. Respondents were asked to indicate the occurrence of key life events and household contexts on an annual basis starting at age 20 and through age 50. Respondents less than 20 years of age were not asked to answer Life History Calendar questions.

The WholeTraveler survey was conducted in two sequential phases. Phase 1 consisted of an online-only survey covering the categories of data described above. Of note is that many of the questions surrounding travel patterns, mode use, and mode preferences were asked in the context of the commute that person made to their reported primary destination. However, the nature of that primary destination was up to the respondent. For many this destination was work or school, but for some it was a grocery store, adult child's home, or doctor's office, for example. Phase 2 consisted of global positioning system (GPS) data collection. Phase 2 started immediately after the completion of the Phase 1 survey for any respondent who opted into Phase 2.

The WholeTraveler survey was administered to a random sample of 60,000 active addresses in the nine core counties of the San Francisco Bay Area (Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma). An invitation letter to the Phase 1 survey and follow-up reminder postcard were mailed to this sample. The survey could be completed online, in English only, using a laptop or desktop computer only. Compensation in the form of a $10 Amazon gift card was provided to those who completed the required questions in the Phase 1 survey. To ensure as much balance as possible across age and gender, the invitation asked that the household member over 18 with the most recent birthday fill out the survey.

Data collection took place between March 2018 and June 2018. The number of complete responses to the Phase 1 survey was 997, and an additional 48 people completed everything but the Life History Calendar, for a response rate of 1.7%. This response rate is consistent with other transportation-related surveys in this region using similar unsolicited mailings to recruit and similar incentive payment amounts. For example, the 2015–2017 California Vehicles Survey had a 1.5% response rate [38]. Of those who completed the Phase 1 survey, 301 also completed Phase 2 and submitted seven days' worth of GPS data from Google location history.

The final set of 1,045 respondents were more highly educated than the general population, with 83% reporting a college degree or higher. According to the American Community Survey (ACS), 30% of the U.S. population and 45% of the Bay Area population reported a college education or higher. Median income levels tended to be commensurate with the ACS for Alameda, Contra Costa, Marin, San Mateo, Santa Clara, and Sonoma counties. However, Solano County respondents tended to have slightly lower median incomes than indicated by the ACS, and San Francisco and Napa County respondents tended to have higher median incomes. Of the ACS sampled households, 11% nationwide and 24% in the Bay Area earned greater than $150,000 per year, compared with 39% in the WholeTraveler sample, indicating a bias overall in the WholeTraveler responses toward higher-income households.

Ancillary data were collected and merged with the survey data from publicly available sources to augment the information from the survey itself. These ancillary data included information from the following sources:

- **U.S. Census Bureau:** The locations of residence and primary destination were matched with census block shapefiles to retrieve census-block-level information on total population from the 2012-2016 ACS 5-year estimates. Current land area information for each block was retrieved from TIGER/Line Shapefiles. Dividing the total population by current land area provided a calculation of population density for each census block.

- **Walk Score:** Walk Score is a number between 0 and 100 that measures the walkability of any address, constructed by a private company. These data were manually collected directly from their partner site, Redfin.com, an online real estate brokerage website, using the residential address of the respondent.
- **Google Map Platform API:** The Distance Matrix application programming interface (API) is a service of the Google Maps Platform that provides travel distance and time for a set of origins and destinations. The API returns information based on the recommended route between start and end points. The Distance Matrix API queries were run for four modes (drive, public transit, walk, and bike), two departure times (8 am and 5 pm), three sets of segments (residence to primary destination, residence to nearest Bay Area Rapid Transit [BART] station, primary destination to nearest BART station), and two directions ("leave" and "return").
- **All Bay Area Mass Transit:** Location of all Bay Area mass transit service stations (including BART, as well as other mass transit systems) and direct line distances were calculated between residential addresses and primary destination locations from each of these station locations.
- **EPA Fuel Economy**: FuelEconomy.gov provides information to help consumers make informed fuel economy choices. It is maintained by DOE's Office of Energy Efficiency and Renewable Energy with data provided by the U.S. Environmental Protection Agency (EPA). The year, make, model, and fuel type of the vehicle that is driven most frequently by the respondent's household was matched to the FuelEconomy.gov database to retrieve miles-per-gallon (MPG) fuel-economy metrics.
- **Kelley Blue Book:** The National Highway Traffic Safety Administration vehicle safety ratings of primary vehicles reported by survey respondents were assembled from Kelley Blue Book [39] and averaged across all test ratings for the make-model-year.
- **Consumer Reports:** The number of seats in and cargo capacity for the respondent's primary vehicle were collected from Consumer Reports [40] by make, model, and year.

A fully anonymized version of all of the phase 1 and phase 2 data, including merged and documented ancillary data, can be accessed at https://livewire.energy.gov/ds/wholetraveler/. At this site you can also view a more detailed description of the survey design and implementation. In addition, the complete set of survey instruments for phase 1 and 2 are included in the material on this site.

MDS researchers analyzed the WholeTraveler survey results and developed insights related to mode-use choices, openness to and adoption of emerging technologies and services, vehicle ownership and use patterns, and shopping travel and e-commerce behavior, with an emphasis on situating these patterns into the life contexts of the respondents. These results are summarized in sections 2.2 through 2.5.

2.1.2 Agent-Based Mesoscopic Transportation System Simulation Models

POLARIS and BEAM are both largescale mesoscopic agent-based models developed to assess the transportation system impacts of scenario assumptions regarding transportation behaviors, technologies, and services. These models were expanded to conduct analyses for MDS, but also to improve the overall modeling capabilities in SMART Mobility. Work across the SMART Mobility Consortium hinges on the development and use of tools and simulation models of varying scale and fidelity to analyze different elements of the transportation system. For example, component- and vehicle-level models represent powertrain technologies and individual vehicle control algorithms, while traffic micro-simulation tools are used to model traffic flow involving multiple vehicles in a traffic network. At a larger scale, mesoscopic transportation system models consider travel behavior at a city or regional level, but lose fidelity. Evaluating the impact of new transportation technologies and services, such as connectivity, automation, electrification, and shared mobility, requires many integrated models spanning multiple scales.

The SMART Mobility Modeling Workflow was developed by the SMART Mobility Consortium to provide a mechanism for connecting models using outputs from one model as inputs to other models at different scales. Linking these models in a consistent workflow represents a comprehensive approach to answering complex transportation system-level questions. The models utilized in the Modeling Workflow are not fixed—models can be substituted with others that provide similar functionality. This ensures that different tools with different levels of fidelity and capability can be used depending on the research questions being answered. To demonstrate the capabilities of the Modeling Workflow, three SMART Mobility Common Scenarios were implemented, representing several potential mobility futures. (For more detail on the Common Scenarios, see the Modeling Workflow Capstone Report.) These Common Scenarios were each modeled using two implementations of the Workflow (i.e., different sets of models were used on two different cities). This effort provided a way to compare the results across different models, from individual vehicles to the entire metropolitan transportation system.

BEAM and POLARIS were foundational components of the two Workflow implementations. The following two subsections provide detail on the design and function of these two models and highlight the expansions implemented in these models through the MDS Pillar.

2.1.2.1 POLARIS Transportation System Simulator

POLARIS is an agent-based modeling platform designed to simulate large-scale transportation systems. POLARIS features integrated travel demand, network flow, and a traffic assignment model to simulate multiple aspects of travel decisions (activity planning, route choice, and driving decisions) simultaneously and in a continuous, fully integrated manner. Mid-term and within-day travel behavior decisions are captured in a computational process model representation of decision making, which also includes the process of individual activity episode planning and engagement [41]. These decisions are constrained by long-term choices of home/workplace and household vehicle ownership. The network model includes a mesoscopic representation of vehicle movements based on Newell's kinematic wave model [42] with updates representing interactions with traffic-control infrastructure. The traveler agents in the model can react in real time to changing or unexpected network conditions based on either direct observation or information provision using an en-route rerouting and re-planning model. The Workflow implementation of POLARIS has so far been exercised for the Chicago Metropolitan area.

For long-term choices, the composition of the vehicle fleet within POLARIS can either come from external market penetration forecasts or from household-level choice modeling [43]. An additional CAV technology choice process is implemented using models based on stated-preference survey data collected by researchers at the University of Chicago in December 2016 [44] to determine the willingness to pay for various levels of CAV technology for each household vehicle. This transportation simulation framework connects to the Autonomie vehicle-level energy simulation model through the SVTrip stochastic trip reconstruction process. For more detail on the POLARIS framework, see Auld et al. [41].

Several key features were added to POLARIS through MDS research to integrate traveler behavior relating to future mobility technologies, including the following:

- Activity time-of-day and duration modeling has been made sensitive to changes in network performance and travel time variability as well as to changes in VOTT and time use [45].
- The transit (bus, rail, commuter rail) and active (walking and biking) mode models on a multilayered

network were improved to allow for fully intermodal movements such as walk-to-transit and park-and-ride. The model has been expanded to allow travelers to walk or drive to a transit stop, wait for a transit trip, board, sit, stand, disembark, transfer, get rejected to board and reroute [46].

- An intra-household automated vehicle sharing optimization model was developed to optimally assign household AVs to household member trips in order to minimize total household travel cost, and allows for empty travel to pick up or drop off household members [47].
- A flexible activity scheduling conflict resolution model has been developed to determine how time-use conflicts in the activity-based portion of the model are resolved. This is especially important if in-vehicle multitasking and telecommuting become more prevalent, since these both tend to make the scheduling behaviors more complex [48].
- The mode-choice model has been updated to include nested choices for various drive, transit, shared ride, and active modes.

2.1.2.2 Behavior, Energy, Autonomy, and Mobility (BEAM) Model

The BEAM model is also an integrated, agent-based travel demand model. BEAM models a set of spatially resolved resource markets, including the road network, parking and charging infrastructure, and the transit system. BEAM also models a synthetic population, with different household characteristics, home and work locations, vehicle ownership, and valuations of travel time. Travelers choose to consume these resources by taking trips on different modes based on characteristics such as travel times and crowding. Mobility providers, such as TNCs, dynamically operate their fleets to maximize service and productivity. The behavioral factors studied in the MDS Pillar directly impact transportation system performance primarily through mode choice—travelers choose which mode to take based on how they value travel time spent in different contexts (such as in a shared ride-hailing vehicle with another passenger or driving in a partially automated vehicle). Behavioral factors also implicitly impact the transportation system in terms of how different modes adjust their service to accommodate this demand (such as allocating ride-hailing requests between solo and pooled rides) and how households choose their commutes based on their valuation of travel time.

BEAM is an extension to the MATSim (Multi-Agent Transportation Simulation) model [49] in which agents employ reinforcement learning across successive simulated days to maximize their personal utility through plan mutation (exploration) and selecting between previously executed plans (exploitation). The utility of these plans considers both the performance of the transportation network and individual preferences. To model the road network, BEAM uses the JDEQSim (Java Deterministic Event-Driven Queue-Based Traffic Flow Micro-Simulation) event-based traffic simulation model [50] that captures the impact of personal car and ride-hailing vehicle use on congestion and travel times. In addition, BEAM shifts some of the behavioral emphasis in MATSim from across-day planning to within-day planning, where agents dynamically respond to the state of the system during the mobility simulation. BEAM also extends MATSim to incorporate more nuanced behavior in mode choice. The modal options available to agents include walk, bike, drive alone, ride-hailing, and three different variations on public transit (walk to transit, drive to transit, take ride-hailing to/from transit). These multimodal routes are generated by a modification of the RAPTOR algorithm [51], [52] to better capture the true space of modal options available to travelers. BEAM can tune how unattractive travelers find time spent in different situations, such as driving a car in traffic or at free-flow speeds, sitting in a ride-hailing vehicle with or without another traveler, or waiting while transferring between modes. BEAM's emphasis on within-day planning also involves simulating the operation of TNC fleets in detail, enabling determination of an equilibrium between TNC supply and demand that is sensitive to variations in traveler value of time, ride-hailing fleet automation and charging requirements, road network speeds, and the spatial distribution of travel demand. In BEAM, energy modeling is performed through integrated RouteE models to estimate road-link-level energy consumption for each vehicle in the BEAM simulation. Vehicles are assigned to agents in the BEAM simulation according to scenario assumptions about the vehicle fleet makeup.

Several extensions to BEAM have used work performed under the MDS Pillar:

- The process of travelers choosing modes has been updated to allow travelers to assign different values to travel time in different contexts.
- Different valuation of travel time has been modeled in such a way that it can also influence household and workplace location choice and long-term development patterns when BEAM is coupled with a land-use model.
- Ride-hailing fleet operations have been further developed, informed by data from RideAustin.

2.2 RESULTS: Impact of Ride-Hailing on the Transportation System

A focus of SMART Mobility is the impact emerging transportation technologies and services are having and will have on the transportation system. One of these transportation innovations is ride-hailing. Ride-hailing, unlike connected and automated vehicles, for example, represents a near-term innovation currently impacting the transportation system and therefore provides an opportunity to gain insight into the transportation system implications of new mobility options.

MDS researchers conducted multiple analyses to study the impact of ride-hailing on transportation system energy, VMT, vehicle ownership, and transit ridership. The MDS research on this topic included analyses of data from the WholeTraveler survey, transportation system simulations done by both POLARIS and BEAM, and stand-alone analyses of other relevant data sources.

2.2.1 The Relationship Between Ride-Hailing and Transit

2.2.1.1 Ride-Hailing and Transit Based on the WholeTraveler Survey

MDS researchers used results from a ride-hailing cost experiment in the WholeTraveler survey to assess how ride-hailing can both complement and substitute for mass transit based on relative costs and user distance to transit stations. This study focused on the impact of lower ride-hailing prices, which may result from AV technology. Respondents to the WholeTraveler survey were randomized into four groups that were each provided with a different prompt and then asked to respond to a survey question. This analysis focuses on three of these groups.[2] All three groups were asked which transportation modes they would use (either singly or in combination) for their regular commute to their self-reported primary destination. One group was asked to answer this question after being told that they should consider a case in which ride-hailing cost $1.20/mile in providing their answer. This was meant to represent a proxy for baseline ride-hailing prices (though it is somewhat lower than current day ride-hailing prices). The other two groups were each asked to consider a different—much lower—ride-hailing price: $0.70/mile and $0.20/mile, respectively. In all three cases the survey calculated and reported to the respondent the cost of their full commute if they took the whole trip using ride-hailing.

The results show that, specifically for respondents with commutes of at least 8 miles, if the price of ride-hailing is $0.20/mile, the probability of using mass transit declines statistically significantly relative to a

[2] The survey randomized respondents into four groups, each assigned a different hypothetical ride-hailing cost scenario: (1) $0.20/mile; (2) $0.70/mile; (3) $1.20/mile; and (4) 50/50 change the price would be either $0.50/mile or $0.90/mile. The first three randomized groups were used in the analysis described here. The fourth group was compared to the 2nd group in a separate analysis to identify any risk-related differences in mode choice comparing a certain to an uncertain price. There were no conclusive findings from that analysis due to lack of statistical power.

reference price of $1.20/mile. For people living between 0.5 and 1 mile from the nearest transit station, the probability decreased by about 30 percentage points, and for people living between 1 and 2.5 miles of the nearest mass transit station it declined by about 11 percentage points (green line in Figure 2), because at $0.20/mile travelers would shift from transit to ride-hailing. However, if the ride-hailing price is $0.70/mile—moderately lower than the reference price—the probability of using mass transit increases statistically significantly by about 31 percentage points for people living 0.25 to 0.50 miles from their nearest mass transit station (blue line in Figure 2).

The magnitude of these marginal effects suggests that the complementarity effect at $0.70/mile ride-hailing price is stronger than the substitution effect at $0.20/mile ride-hailing. However, those effects are the change in the probability of using mass transit per person. Because the population living 0.5 to 2.5 of stations is much larger (almost 57% of the sample) than the population living 0.25 to 0.50 miles from a mass transit station (less than 13% of the sample), the sample population-weighted effect of substitution results in a larger impact on mass transit. In particular, if ride-hailing prices are $0.20/mile, there is a statistically significant 10 percentage point overall reduction in mass-transit ridership across the full sample of people with commutes of at least 8 miles. In contrast, the complementarity effect at $0.70/mile, while relatively large per person living within 0.25 to 0.50 miles of a mass transit stations, does not result in a statistically significant overall increase in mass transit ridership. Therefore, the impact of lower ride-hailing prices in the future may vary significantly by how much the cost of ride-hailing changes and by the relative benefits of ride-hailing as a method for accessing mass transit, here examined based on how far away individuals live from a mass transit station.

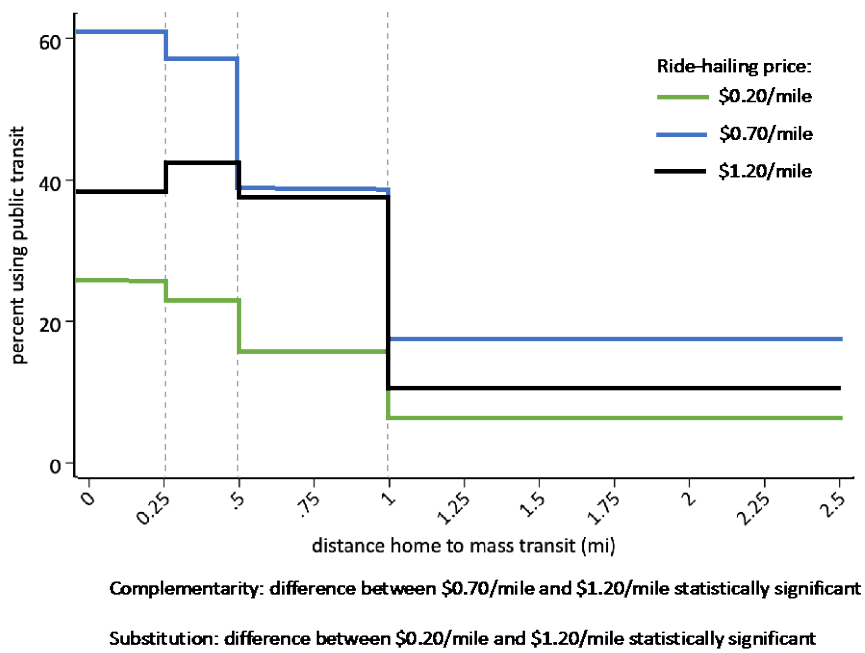


Figure 2. Change in the probability of using mass transit when ride-hailing is less expensive based on distance to mass transit station

2.2.1.2 BEAM Simulation Study of Ride-hailing Impact on Transit

Although the analysis of WholeTraveler data described previously indicated there was some risk of ride-hailing pulling ridership away from mass transit, there were mixed effects based on residential distance to mass transit stations and the cost of ride-hailing. Two forces of substitution and complementarity influence the effect of ride-hailing on mass transit (as both a substitute mode and as a mode enabling access or egress), so the overall net impact of increased ride-hailing use on the transportation system is unclear. BEAM conducted simulation analyses that shed light on the net system-level energy impact of ride-hailing, taking into account people who substitute ride-hailing for transit and people who use ride-hailing to access transit.

BEAM was used to simulate the impact that different levels of openness to ride-hailing use had on mode choice and transportation system outcomes under a series of scenarios in the San Francisco Bay Area. The motivation for this analysis was to assess the impacts if assumptions about who would use ride-hailing are made more conservative—relative to assuming everyone would be open to using ride-hailing under the right conditions—to reflect the fact that not everyone is willing to use ride-hailing. Using data from WholeTraveler on the percent of the respondents who expressed interest in using ride-hailing or AVs[3], two alternative scenarios were developed, a conservative scenario and a less conservative scenarios. The analysis assessed the impact on the transportation system if all those who do not express interest in using ride-hailing and/or AVs would not use ride-hailing under any conditions. Interest levels of both ride-hailing and AVs were used to define the two alternative scenarios for this analysis because the reported level of interest in ride-hailing was only 26% while the reported level of interest in AVs was 47%. The scenario definition for this analysis used the level of interest in ride-hailing as the most conservative scenario and, in-part motivated by the possibility that future ride-hailing service may be provided by AVs, the level of interest in AVs as a less conservative scenario.

In the BEAM simulation, each agent considers all possible mode alternatives and their attributes (cost and travel time) when making the choice of which mode to use. In these alternative scenarios, for a portion of agents, ride-hailing as an alternative mode did not even enter their choice set, as if they wouldn’t consider using it regardless of price or travel time. These scenarios are summarized in Table 1. In all scenarios, BEAM simulates an ample ride-hailing fleet that can serve traveler demand. In the “Base” scenario, an ample ride-hailing fleet is provided and considered by all travelers and is priced at $0.75 per minute of in-vehicle travel time. In the less conservative of the alternative scenarios, the “AV Interest” scenario, 47% of travelers consider using ride-hailing as a mode they would potentially choose. As described above, this number was taken from the percent of the WholeTraveler sample who expressed interest in using AV technology. In the most conservative scenario, the “Ride-hail Use/Interest” scenario, only 26% of the population considers the ride-hailing mode alternative—again, representing the proportion of WholeTraveler survey respondents who already use or are interested in using ride-hailing.

The BEAM results demonstrate that assuming a more restricted set of travelers would be open to considering ride-hailing in their mode choice set results in lower use of transit and higher use of personal vehicles (Figure 3). This results in an increase in system energy consumption by 6.6% in the most conservative “Ride-hail Use/Interest” scenario. Although ride-hailing trips can produce more VMT than car trips do, reducing ride-hailing use by limiting the number of people who would be willing to consider using it increases energy consumption mostly due to reduced use of ride-hail-to-transit (see the lower share of ride-hail-to-transit trips and the increased share of car trips in the top panel of Figure 3).

[3] Interest is defined as those who responded “Yes” to “I have used/experienced this technology (service)” or “I currently own/have owned (regularly use) this technology (service)” or “I am interested in owning or using (using) this technology (service) in the future”.

Table 1. Ride-Hailing Scenarios Studied in BEAM

Scenario	Description	Rationale
Base Scenario	Ample ride-hailing fleet is provided and considered by all travelers and is priced at $0.75 per minute of in-vehicle travel time.	Common assumption made in transportation mode choice modeling.
AV Interest	In total, 47% of the population considers ride-hailing as a mode they would possibly choose.	Serves as a more conservative scenario based on the limits of expressed interest in AV technology. Based on WholeTraveler respondents who expressed interest in adopting AV technology when available.
Ride-hail Use/Interest	In total, only 26% of the population considers ride-hailing as a mode in this scenario. Still ample ride-hailing fleet provided and priced at $0.75 per minute of in-vehicle travel time.	Serves the most conservative scenario due to a modified application of parameters from WholeTraveler (without county fixed effects). Based on WholeTraveler respondents who either use ride-hailing or are interested in using ride-hailing.

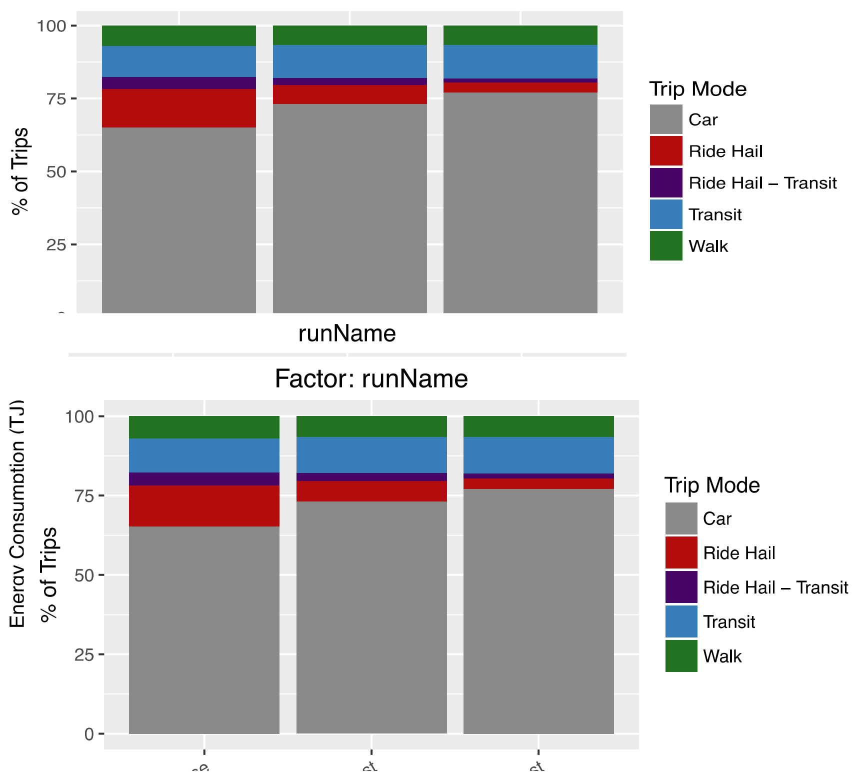


Figure 3. Trip mode-share (top) and energy consumption (bottom) predicted in BEAM across three scenarios

2.2.1.3 POLARIS Simulation Study of Ride-hailing Impact on Transit

Using POLARIS, MDS researchers also conducted simulations to examine the impact of ride-hailing on public transit. POLARIS simulations were conducted in Bloomington, Illinois, which is a representative small city (population 140,000) with relatively limited, bus-only transit service, where the majority of trips taken are by private automobile. The analysis in POLARIS included a baseline scenario as well as a scenario in which access to and from transit by TNCs was provided at no cost to the traveler. The only difference between these scenario runs is that, in the TNC access scenario, the cost of the TNC access portion of any ride-hailing-to-transit trip is set to $0 in the mode choice model; all other parameters and scenario settings use the POLARIS default values. Table 2 shows the results of the scenario analysis.

Table 2. Bloomington Transit Access Scenario Results

	Total VMT	Privately owned vehicle/Taxi/TNC VMT	TNC-to-transit VMT	Bus VMT	SOV / Taxi/ TNC trip mode %	Walk to Transit Trip mode %	TNC to Transit trip mode %	Overall Transit trip mode %	Total fuel consumed (kg)
Baseline	2,265,786	2,260,504	1,805	3,477	72.60%	1.30%	0.10%	1.30%	232,320
TNC access	2,232,961	2,223,746	5,737	3,477	72.40%	1.20%	0.30%	1.50%	229,669
% change	-1.40%	-1.63%	217.80%	0.00%	-0.30%	-6.30%	226.60%	10.90%	-1.1%

This analysis shows that subsidizing ride-hailing to access transit in the Bloomington, Illinois, metropolitan area would reduce VMT from privately owned vehicle and taxi/TNC trips by 1.6% and increase transit use 10.9% —resulting in a system-wide energy use decrease of 1.1%. This increase in transit use resulted from subsidizing 5,737 miles of ride-hailing access for about 2,000 new transit riders (individuals who were not using transit in the baseline) and these subsidized miles remove more than 33,000 vehicle (private, taxi or TNC) miles traveled from the network.

Figure 4 shows the geographic distribution of transit use in the baseline (left-hand figure) and the change in transit use under the TNC access scenario (right-hand figure). Overall, providing no-cost access to transit increased overall transit ridership by increasing the area around transit routes from which riders have easy access to transit and extending potential transit use to riders outside of walking distance from the nearest stop. There is an additional compounding effect, as once a rider chooses to use transit initially, they are more likely to do so on their homeward bound return trip.

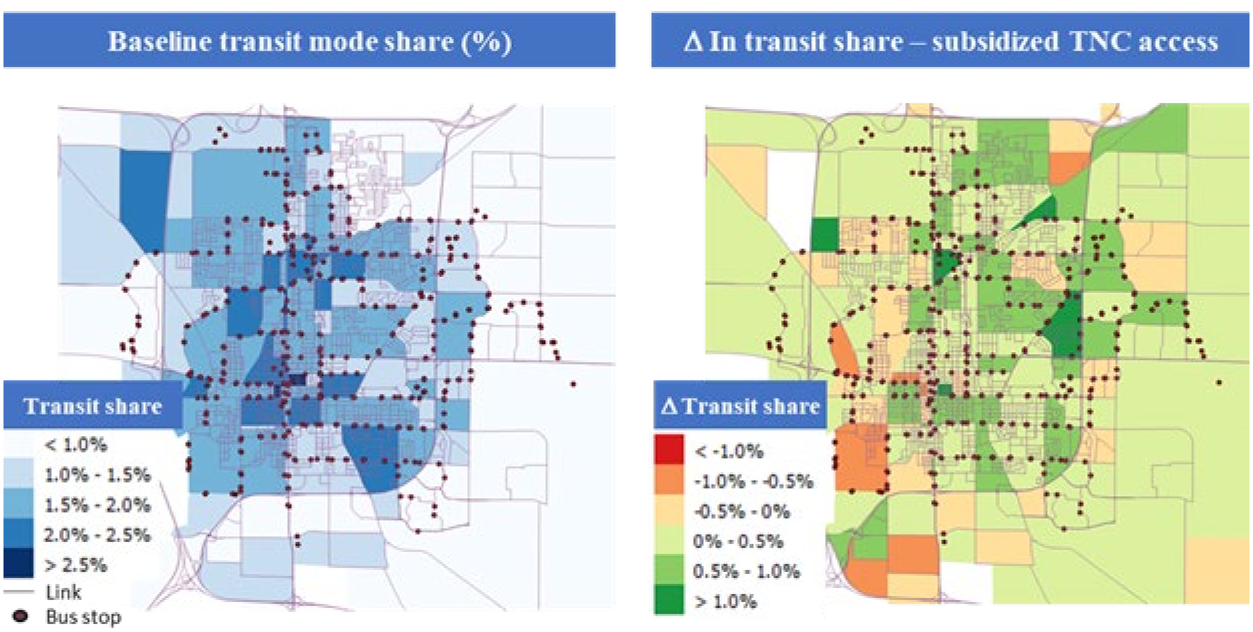


Figure 4. Change in transit mode share from baseline to subsidized TNC access scenario

Taken together, the WholeTraveler experiment in which the hypothetical price of ride-hailing was randomized and the two sets of simulation results demonstrate that ride-hailing can both complement and substitute for transit. Lower-priced ride-hailing can cause people living close to mass transit stations to substitute away from mass transit. However, moderately less expensive ride-hailing can enable mass transit use for people not otherwise easily able to access it. The BEAM simulation, which allows agents choosing between modes to choose ride-hailing instead of transit or to choose ride-hailing-to-transit and thereby models underlying patterns of both complementarity and substitution between ride-hailing and transit, suggests that this tradeoff between complementarity and substitution of ride-hailing for mass transit results in overall increased use of mass transit for the whole San Francisco Bay Area system, resulting in net energy savings. They showed this by mechanically reducing the amount of people willing to use ride-hailing, and demonstrating that there was a net reduction in transit ridership as a result, an implication of which is that the inverse is also true: increasing ride-hailing as a mode option has a net-positive effect on transit ridership. However, to maximize the benefits to the system, the POLARIS simulation underscores that a targeted cost reduction of ride-hailing, geared specifically for transit access rather than across the board for all ride-hailing use, would maximize benefits from complementarity while avoiding the increased energy consumption costs associated with the substitution effects.

2.2.2 The Drivers of Ride-Hailing Vehicles and Their Contribution to System Impacts

Results in this section were derived from stand-alone analyses that did not rely on WholeTraveler, BEAM, or POLARIS and demonstrate the system-level impacts of ride-hailing that result in-part from the individuals driving the ride-hailing vehicles. The choices drivers make regarding whether, where, and when to drive for a ride-hailing service can affect the energy impact on the transportation system. MDS researchers studied transportation system impacts of ride-hailing affected, in part, by the choices of those driving the ride-hailing vehicles.

2.2.2.1 Ride-hailing Impact on Overall Number of Vehicle Registrations

MDS researchers evaluated how the timing of ride-hailing service entry in a market area impacted vehicle ownership and used this to determine in what kinds of cities ride-hailing is likely to cause vehicle ownership to increase or decrease. Data used includes vehicle registration data for all U.S. Census-defined Urban Areas (UAs), along with the dates that Uber and/or Lyft were operating in those UAs. A difference-in-differences regression analysis related the timing of ride-hailing service entry to the overall number of vehicle registrations, controlling for total population, population over 16 years of age, population over 65 years of age, unemployment rate, average income, transit commuter percentage, UA fixed effect, year fixed effect, and UA fixed effect interacted with a linear time trend. The UA fixed effects control for everything about each UA that does not change over time (e.g., geographic characteristics) while the year fixed effects control for everything that impacts all UAs in the same year (e.g., macroeconomic shocks). In addition, the analysis included inverse probability of treatment weighting to control for the conflation of ride-hailing providing service in a UA with other factors, as the choice of a ride-hailing service to enter a given UA market is not independent of characteristics of that UA that might also affect vehicle registrations.

Given evidence of a possible trend toward younger generations moving away from car ownership in favor of ride-hailing and on-demand mobility [5], the researchers initially hypothesized that ride-hailing would reduce vehicle ownership if people rely on ride-hailing services in lieu of owning their own vehicles. However, results indicate that ride-hailing services entering UAs increased vehicle registrations by 0.7% on average (with a 95% confidence interval of 0.1% to 1.3%). In order to understand the variation across UAs underlying this average effect, two additional analyses were done: (1) UA-specific treatment effects were estimated and (2) hierarchical clustering analysis was conducted to group UAs and thereby estimate effects across clusters with different characteristics. The urban-area-specific estimates vary from a statistically significant increase of 15% to a statistically significant decline of 10%, shown in Figure 5. There is a statistically significant increase in per-capita vehicle ownership in 17% of UAs and a statistically significant decrease in 26% of UAs. Comparing cities exhibiting an increase with those exhibiting a decrease, both city-by-city and across clusters in the clustering analysis, a consistent trend emerges: cities with increases in per-capita vehicle registrations after ride-hailing services enter tend to have started with lower per-capita vehicle ownership and faster economic growth relative to those with a decrease in per-capita vehicle ownership. A possible explanation for increased vehicle registrations is that drivers who otherwise could not afford to, or otherwise chose not to, own a vehicle acquire one for the purpose of providing the service, outweighing the number of riders who shed a vehicle or suppress a planned vehicle purchase because of the service. This hypothesis would need to be tested, however, which is not currently possible with available data.

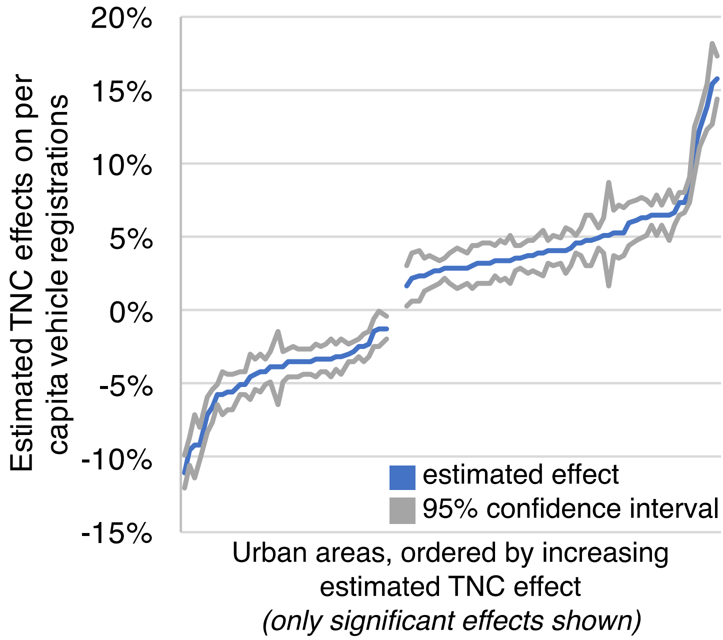


Figure 5. Urban-area-specific effects of ride-hailing on per-capital vehicle registration

2.2.2.2 Ride-hailing Impact on System Energy Use Using Observed Ride-Hailing Data

MDS researchers also evaluated the impact of a ride-hailing service in Austin, Texas, called RideAustin, on net energy use by analyzing detailed individual ride data from this service. Prior to the start of SMART Mobility, only one published paper estimated the share of VMT by ride-hailing fleets without passengers (also known as deadheading) at about 45% [21]. However, this study did not account for driver commuting miles accumulated by ride-hailing vehicles.

The RideAustin data provide the start and end location and time of more than 1.5 million trips over an 11-month period including the measured distance of the actual routes taken for segments of each trip (i.e., between the driver accepting the ride request and reaching the rider and between the trip start and end). Unique identifiers were assigned to each driver and rider, so the behavior of individual drivers and riders can be examined over time. The year, make, and model of each vehicle used was recorded and used to translate VMT to energy use. Researchers quantified deadheading miles resulting from travel between rides, and they estimated the empty miles driven as commutes before and after each driver's shift. This latter focus was motivated by anecdotal evidence suggesting that some drivers drive long distances without passengers before and after their driving shifts.

Two energy impact estimates were generated, a low and a high, relative to baseline pre-ride-hailing travel. The low-energy estimate assumes 66% of ride-hailing trips replaced driving/carpool/taxi trips and 19% replaced bike/walk/other trips based on estimates from Feigon and Murphy [53]. In addition, as the data do not include exactly what share of ride-hailing rides are shared nor what portion of a shared trip includes more than one rider, the low-energy estimate assumes 30% of all ride-hailing rides are shared [54] and that the two rides that are shared each have the same origin and destination, replacing all of the VMT of the second, shared ride.[4] In contrast, the high-energy estimate assumes 40% of ride-hailing trips replaced driving/carpool/taxi trips and 45% replaced bike/walk/other trips [55] and that only 15% of ride-hailing rides are shared that only half of the VMT of the second, shared ride is replaced (i.e. shared with the initial rider).[5] With regard to the mode-shift assumptions, both the low- and high-energy estimates assume that 15% of ride-hailing trips replaced rides on public transit. With regard to the sharing assumptions, the net effect of the sharing assumptions is that person-miles of travel are reduced by 30% in the low-energy case and by 7.5% in the high-energy case. For more information on the data and analysis see Wenzel at al. [56].

The estimated net impact of ride-hailing on energy use, shown in Figure 6, is a 41%–90% increase in energy use from ride-hailing compared with baseline pre-ride-hailing personal travel, with the 41% increase estimate resulting from the low-energy assumptions and the 90% increase resulting from the high-energy assumptions described above. The results indicate that ride-hail driver commuting accounted for 19% of total VMT, and empty miles between rides accounted for another 26%—thus deadheading constituted almost half of total VMT for this service. As shown in Figure 6, the large shares of VMT from empty operation (commute and between-ride deadheading) account for a large increase in energy use associated with ride-hailing, with commute deadheading and between-ride deadheading together accounting for 70 percentage points of increase in system energy with ride-hailing compared to without. As the figure shows, mitigating factors offset some of this increase, including the fact that RideAustin's ride-hailing vehicles averaged 3.2 mpg higher fuel efficiency compared with the city's overall fleet average.

[4] A shared TNC ride was assumed to reduce the VMT of two separate 10-mile trips from a total of 20 miles to a total of 10 miles (rider A and B share the full 10-mile distance of the trip).

[5] A shared TNC ride was assumed to reduce the VMT of two separate 10-mile trips from a total of 20 miles to a total of 15 miles (5 miles for rider A alone, 5 miles shared, 5 miles for rider B alone).

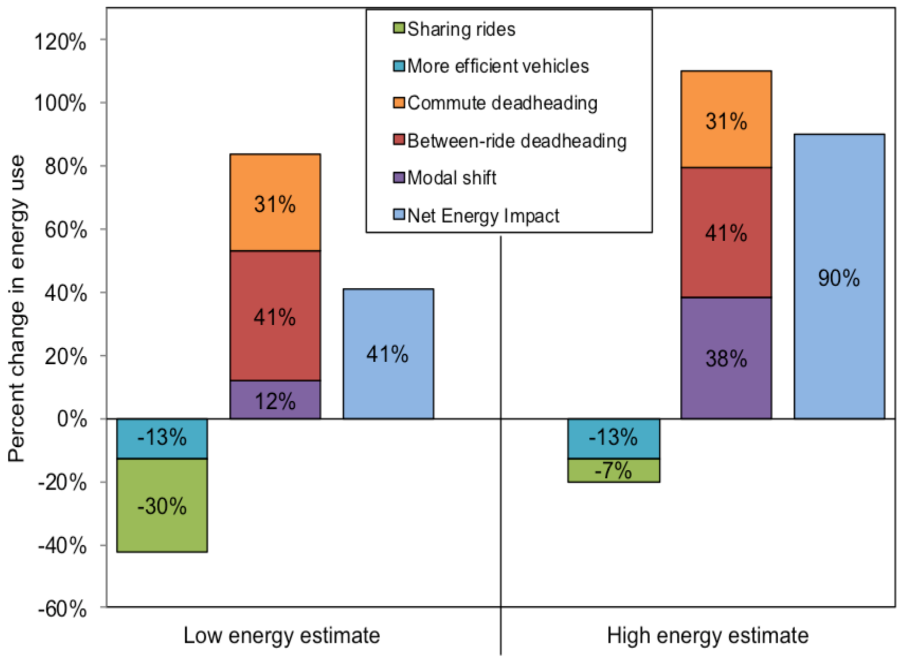


Figure 6. Low and high estimates of net energy impact of ride-hailing service in Austin

These results are specific to the context of the RideAustin service operating in Austin, Texas. However, they suggest that behaviors like deadheading, which are functions of driver behavior, can have sizeable impacts on transportation system energy use.

2.3 RESULTS: Transportation Behaviors and Life Context in the WholeTraveler Survey

As articulated in the introduction to this report, people make choices based on constraints, needs, and preferences that differ across the population and can depend on fundamental choices regarding lifestyle, values, and identity. The adoption of emerging transportation technologies and services is influenced by the extent to which those options provide solutions for different types of people throughout their lives. The resulting adoption trends shape the transportation system. Using data from the WholeTraveler survey, MDS researchers conducted a series of analyses focused on the relationship between life context and transportation technology adoption and mode choice.

2.3.1 Transportation Technologies Across the Generations

One of the fundamental forces influencing preferences, needs, and constraints, and in part defining the context in which we all make choices, is aging. Results have been mixed regarding how age correlates with adoption and use of some emerging transportation innovations. While studies have found that users of ride-hailing have generally tended to be younger [8], [55], [57]–[61], results with respect to age and openness to AV and EVs are inconclusive. Haboucha et al. [62] found that older adults may be interested in fully automated vehicles for increased mobility, whereas Bansal and Kockelman [63] found that older individuals express less interest, due in part to concerns about learning to use the new technology and losing the pleasure of driving. With respect to EVs, findings have largely suggested that EV owners tend to be younger [9]–[11], [64], although Ziefle et al. [12] found older generations to be more interested in electric vehicles.

MDS researchers used WholeTraveler survey data to clarify AV and, hybrid vehicle, and PEV[6] preferences by age and distinguish interest in future adoption from current ownership or regular use. This same distinction was explored for ride-hailing to determine if patterns in these data were consistent with previous findings. For simplicity, the survey's age cohorts are discussed below using the following terminology: baby boomers were born in the 1940s and 1950s, Generation X (Gen X) were born in the 1960s and 1970s, and millennials were born in the 1980s and 1990s. Figure 7 summarizes the data underlying this analysis.

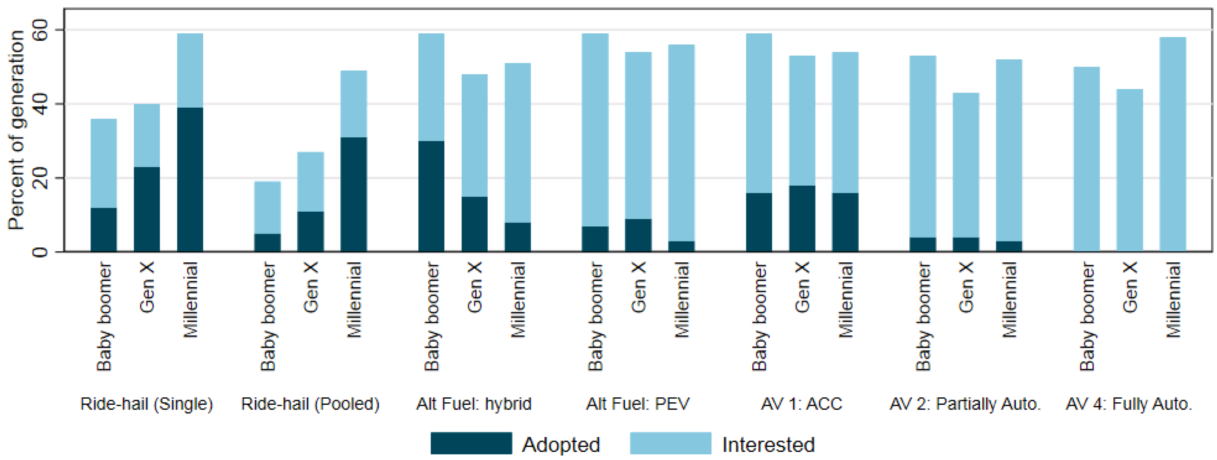


Figure 7. Transportation technology adoption and interest by generation

Multivariate regressions were conducted to ascertain correlations between key descriptive characteristics and current adoption as well as interest in future adoption of different transportation technologies. Results indicate that younger generations drive both current adoption and interest in future adoption of ride-hailing. Adoption is defined as regularly using the service. Nearly 60% of millennials are interested in using or already regularly use single-rider ride-hailing (e.g., UberX or Lyft). Millennials are 70% more likely to have adopted single-rider ride-hailing and almost 200% more likely to have adopted pooled ride-hailing (e.g., Uber Pool or Lyft Shared) relative to Gen X—differences that are both large and statistically significant after controlling for other factors including socioeconomic and household characteristics, residence and primary commute destination locations, preferences for different travel mode attributes, personality characteristics, and risk preferences [65]. This same pattern holds for interest in the service by those who had not yet adopted. About 30% of millennials who have not yet adopted single-rider or pooled ride-hailing are interested in the service, which is 50% higher relative to Gen X for both services, and the differences are statistically significant. Variations between Gen X and baby boomers tend not to be statistically significant. Interest in and adoption of both forms of ride-hailing are higher among millennials than among all previous generations.

MDS researchers analyzed adoption of and interest in three levels of vehicle automation: (1) ACC as a representation of widely available driver-assistance technologies; (2) partially automated vehicle technologies, defined as those with ACC and lane-keeping but require the driver to be alert and ready to take over control (e.g. Tesla Autopilot and General Motors SuperCruise); and (3) fully automated, or driverless, vehicles that can take the rider from an origin to a destination without any need for driver attention or intervention.

[6] The WholeTraveler survey asked respondents to report on their use of or interest in two types of alternative fuel vehicles: plug-in electric vehicles, and hybrid electric vehicles. It was recognized after the fact that these two categories as described lacked specificity, as plug-in hybrid electric vehicles did exist at the time of the survey and respondents may not have known how to categorize them. For the purposes of the analysis the two categories were analyzed separately, but interpretation needs to take into account that respondents may have categorized PHEVs into either category.

Adoption of or interest in ACC was similar across all generations. Adoption rates of partially automated vehicle technologies were low in general (about 4%), however, among those who have not yet adopted these technologies, the rate of interest tends to be bimodal. Interest was highest for the youngest and oldest respondents in the analyzed sample (those born in the 1990s and those born in the 1940s). Millennials and baby boomers are equally interested, with about 50% of respondents in these generations indicating interest. This interest is about 25% higher than for Gen X. The differences in interest among these respondents relative to Gen X are statistically significant and robust when controlling for the same variables summarized above in the ride-hailing analysis. This pattern holds for interest in fully automated vehicles as well. Millennials are 58% more likely and baby boomers are 50% more likely to express interest in fully automated vehicles compared to Gen X, 44% of whom expressed interest in fully automated vehicles, though the difference is only statistically significant for the youngest millennials (those born in the 1990s) when compared to younger Gen X (those born in the 1960s). These results help explain why some previous studies found a negative correlation for automated vehicle technology interest with age while others found a positive correlation with age. Both younger and older generations are more interested in AV technologies compared with Gen X. However, given the survey response method (online only), baby boomers who responded likely were more open to technology than those who did not respond. Therefore, the survey results may overestimate baby boomer interest in AV technologies.

MDS researchers analyzed two types of vehicle electrification via WholeTraveler data: hybrid vehicles and PEVs. The results show that millennials are statistically significantly less likely to own hybrids or PEVs relative to older generations. Baby boomers have the highest hybrid vehicle ownership with almost 30% of respondents reporting that they already own a hybrid vehicle. Baby boomer hybrid vehicle ownership is twice as high as the next-highest group, Gen X. Interest in hybrid vehicles among those who do not already own one is highest among millennials and is about 38% higher among the youngest millennials (born in the 1990s) relative to Gen X, a difference that is statistically significant. The differences in interest in hybrid ownership among those that don't yet own a hybrid vehicle between Gen X and baby boomers are not statistically significant. For PEVs, the 9% ownership rate among Gen X is almost 200% higher than ownership among millennials, a difference that is statistically significant. Interest in owning a PEV is 50% or higher across all generations, but highest among the oldest baby boomers (those born in the 1940s). Baby boomers born in the 1940s were about 14 percentage points more likely to be interested in owning a PEV compared to young Gen Xers born in the 1960s, a difference that is marginally statistically significant. Therefore, with respect to electrified vehicle technologies, results do not follow previous findings indicating that ownership is driven by youth. In this sample, current adoption of both PEVs and hybrid vehicles is driven by older generations. While interest in owning a hybrid is significantly higher among younger millennials, interest in owning PEVs tends to be marginally highest among older baby boomers.

2.3.2 Transportation Mode Use and Age

Analysis of data from the WholeTraveler survey reveals a strong relationship between mode use and age. Figure 9 shows the average overall mode use as respondents age. The vertical axis captures the share of respondents that indicated "regular use," defined as two or more times per week for the respondents' regular commute, of each indicated mode. Modes in this figure are not mutually exclusive so an increase in regular use of one mode may result from shifting between modes, or may result from adding an additional mode. This figure is generated using data from the Life History Calendar portion of the WholeTraveler survey, which means this pattern is captured from tracking a set of individuals across time, not based on a cross-sectional snapshot of multiple people at different ages. This means the data capture a more complete picture of patterns across time. Across all respondents, the percentage of people driving regularly increases with age, while the percentage of people regularly using public transportation and walking/biking decreases with age. In particular, between the ages of 20 and 33, the percent of people frequently driving increases from 40% to 70% and remains above 70% persistently thereafter. The relationship between ride-hailing use and age is less clear. This is in part because ride-hailing was only available for a short time near the end of the time series captured by the Life History Calendar, which ends in 2018, and in part because the question focused on "regular use" for commute travel while ride-hailing is often used for leisure activities [55].

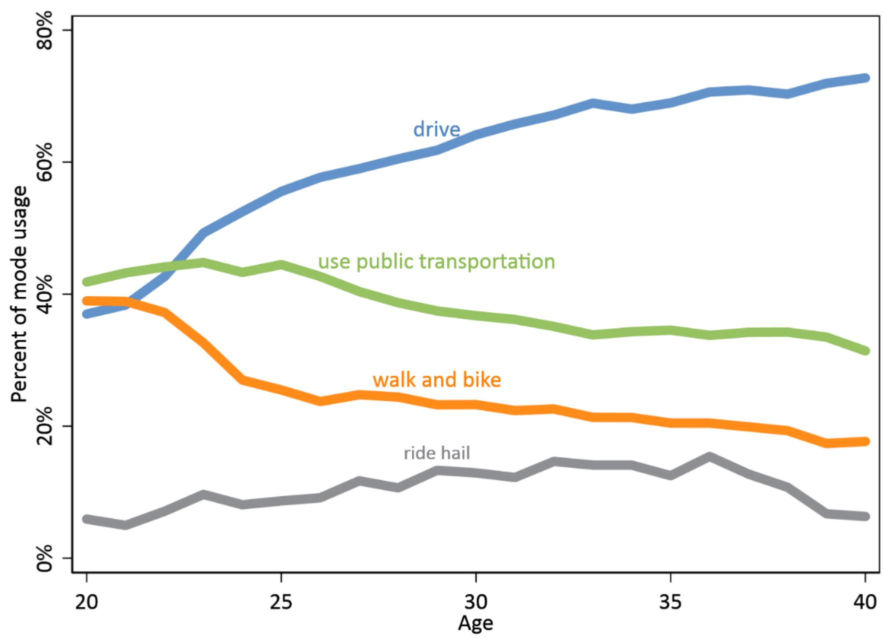


Figure 8. Overall patterns in mode use across age

These results demonstrate the extent to which people depend on their private vehicles, especially later in life. The extent to which technological, service, or policy changes could affect this trend to meet forecasts of minimal person-miles-traveled being via privately owned vehicle, for example, is uncertain. However, Figure 9 depicts some of the results from the previous section showing that people become more likely to own PEVs as they become older (especially starting at age 40), and older respondents (especially those over 60) remain highly interested in owning a PEV. If this technological trend with age continues into the future, this could influence the energy impact of increased private vehicle use with age.

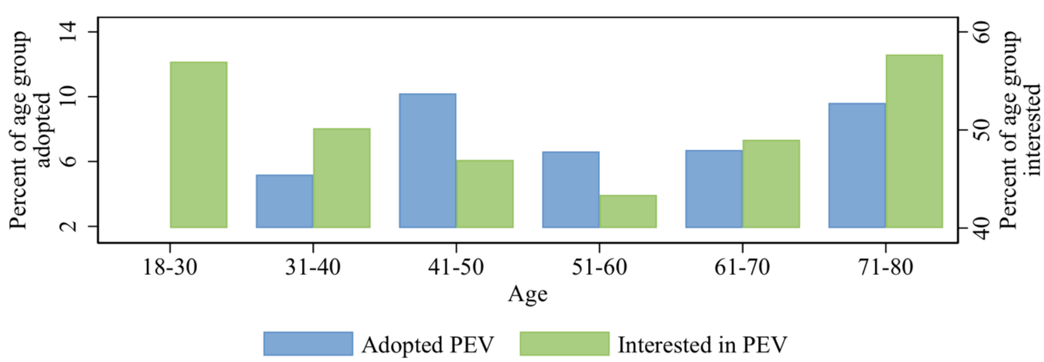


Figure 9. Overall patterns in PEV adoption across age

2.3.3 Impacts of Major Life Events on Transportation Choices

The drivers underlying mode-use shifts with age can reveal valuable information about how predictable, flexible, or potentially adaptable age-related patterns might be with regard to emerging transportation technologies or services.

2.3.3.1 Transportation Transitions Through Child Phases

MDS researchers built on an extensive body of literature studying how people change their travel choices when children enter the family, as children and parents age, and as children leave home [66]–[74]. MDS researchers focused on the effect of children in the home on adults' mode choices as this was identified as an important gap in the literature. For example, McCarthy et al. [75] states that the mode choices of families with young children (ages zero to four years) are relatively understudied.

In general, the literature has shown that car dependency tends to increase among families with children [76]–[80], although there are growing indications that families with children may increasingly rely on other modes in Europe and Canada [81]–[83]. McCarthy et al. [75] establish four primary factors important to child-related car dependence: (1) structural (relating to the built environment); (2) psychosocial (attitudes, social norms, etc.); (3) household characteristics (number of dependent children, prevalence of dual-earner families, etc.); and (4) features of young children's travel (the need to carry child-related equipment, the unpredictable nature of child behavior, etc.).

Some studies of structural factors have associated family car dependence with suburban environments characterized by relatively long travel distances for commutes and errands and low-density residential housing [84]–[86]. Structural studies have also identified cost as a barrier to family use of public transit, as purchasing multiple public transit tickets for a large family group on a regular basis can be cost-prohibitive in some cases [82], [87]–[91]. A psychosocial study by Dowling [92] demonstrates that, in auto-oriented cities, car use is perceived as a sign of good parenting, because cars are perceived as a safe way to transport children. Some household characteristics studies positively associate car use by families with children to a household's number of dependent children (e.g., [79], [80]). Other household studies find positive correlation between family car use and household income and car ownership [93] or between family car use and dual-earner households where demands on adult household members' time are constrained by both members being employed [68], [94]. Studies of family formation and earning potential complement the household characteristics literature. For example, Taniguchi [95] shows having a child at a relatively young (ages 20–27), especially for women, hinders career development and results in significantly lower lifetime earnings. Very few references specifically focus on the characteristics of young children's travel, as McCarthy et al. [75] note. A single exception is Dowling [94], who suggests that there is a barrier to family ride-hailing posed by a lack of car/booster seats in ride-hailing vehicles.

Using data from the Life History Calendar of the WholeTraveler survey, MDS researchers conducted a series of difference-in-differences panel regressions associating mode use, by mode, with the presence of children. These analyses estimated the average marginal change in mode use (defined in several ways, described in more detail below) across the population when people are in a given life state (e.g., employed, have children) relative to when they are not. The comparison is made relative to the same respondent when they are not in the given state, relative to other respondents when they are not in that state, and relative to those that never enter that state within the observed data.

The first analysis discussed here estimates the average impact that having children at different developmental stages in the home has on the use of different modes. The developmental stages assessed are: *nesting*, *children*, *children(≥5)*, and *children(>18)*. The term *nesting* is defined as zero for all years up until the two years prior to when a respondent has their first child, at which point it turns to one and remains one for all observations thereafter. *Children* is defined as zero for all years up until the year the respondent's first child entered the household and remains one for all observations thereafter. *Children(≥5)* is defined as zero for all years up until the year when all children in the household are at least five years old, at which point it turns to one and stays one for all observations thereafter. *Children(>18)* is defined as zero for all observations up until when all children in the household are over 18 years old, at which point it turns to one and remains one for all observations thereafter. Because of the definition of these variables, the estimated marginal effects are additive; the *nesting* effect is the marginal difference between being in the "nesting" phase relative to all other respondents of the same age not yet in the nesting phase, including those who never have children and those who are not yet in that phase. The *children* effect is then the marginal effect, on top of the *nesting* effect, of the first child being born or entering the household, and so on. This analysis separates the effect of children on mode use from the overall underlying effect of age by controlling for age flexibly with age fixed effects.

Results from this analysis are summarized in Table 3. The results show the marginal change in the probability that each mode is used regularly for travel to work, school, or other primary destination commuted to outside the home most frequently as children in the household transition through each of the defined developmental stages. On average, there is a statistically significant four percentage point increase in the probability a respondent reports regularly driving a personal vehicle for a commute when they are in the nesting phase relative to other respondents of the same age not in that phase (a 6% increase relative to the sample average). There is no statistically significant change in driving a personal vehicle for a commute at any of the subsequent transitions relative to other respondents of the same age. Use of public transit and walking or biking to commute both decline when a child enters the household by six and three percentage points, respectively. These changes represent a 17% and 13% decrease relative to the sample average, respectively. When all the children in the household reach school age (at least 5 years old*)*, there is a statistically significant, 5 percentage points, decrease in the probability that respondents use ride-hailing regularly to commute (a 55% drop relative to the sample average). This is in contrast to Dowling [94], who found that ride-hailing use was impacted by the need for a child safety seat, which is more relevant for the younger-child stage.

Table 3. Effect of Child Development Stages on Mode-Use Behavior

	Personal Vehicle	Public Transit	Ride-hailing†	Walk or Bike	# of Modes Used
nesting	0.0400+ (0.021)	-0.0093 (0.025)	0.010 (0.031)	-0.013 (0.019)	0.008 (0.031)
children	-0.0038 (0.017)	-0.0637** (0.022)	-0.0175 (0.027)	-0.0327* (0.016)	-0.0805** (0.028)
children (≥5yr)	-0.0077 (0.020)	-0.0062 (0.023)	-0.0519* (0.025)	0.002 (0.016)	-0.0543* (0.027)
children (>18yr)	0.0404 (0.051)	-0.0459 (0.057)	0.045 (0.071)	0.0198 (0.036)	0.0086 (0.051)
Average likelihood of mode use in sample:	0.62	0.36	0.09	0.24	

Standard errors in parentheses are clustered at the respondent level. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Notes: All regressions include respondent-specific fixed effects and age fixed effects, where age is the age of the adult respondent to the survey. Each of the first four columns presents results from a mode-specific regression where the dependent variable (listed at the head of the column) is equal to 1 if the survey respondent indicated that the mode was used at least two times per week to travel to their work, school, or other primary destination commuted to outside the home most frequently on average during that year, zero otherwise. The dependent variable for the regressions presented in the last column is a count variable indicating the number of different modes selected for that respondent in that year (taking values between 0 and 4). † The ride-hailing analysis was only conducted conditional on ride-hailing possibly being available (in 2008 or later).

The changes in mode use described above at these different developmental stages persist. Once people transition towards more private vehicle dependence and away from public transit, walking and biking, and ride-hailing, they tend to maintain this pattern. The decline in use of these modes to commute is reflected in a decrease in the overall number of modes a respondent reported regularly using (by 0.08 modes) at this same time. Even once children become more independent (older than 18 years), the influence they had on the family's transport choices may be sustained, in part because of parental habit formation [96], [97] and/or because of structural changes that happen concurrently with these transition points (e.g., moving to the suburbs or other more car-dependent environments).

The analysis presented in Table 4 assesses the mechanisms underlying the change in mode use presented in Table 3. The results, all of which are interpreted as relative to the same time step for people not in a given phase but of the same age, show that, both in the *nesting* phase and when the first child enters the home, there is a statistically significant increase in the number of vehicles owned. Because the effects are additive, when the household is in the *children* stage, about 0.48 more vehicles are owned relative to those of the same age not in this phase. While results in Table 4 show a decreased probability of experiencing a significant move in residence or primary commute destination during the nesting stage, there is a significant increase in the probability of this type of move when children enter the home. Respondents who have adult children are less likely to move residence or primary commute location than those that are the same age but did not have children. The survey design makes it impossible to identify transitions to or from different types of residence locations (i.e., urban, suburban, or rural) or to disentangle moving residence location from moving commute destination location.

Table 4. Effect of Child Development Stages on Vehicle Ownership and Moving

	Number of Vehicles in Household	Respondent Moved Location of Residence or Primary Commute Destination During Stage
nesting	0.294** (0.037)	-0.324** (0.034)
children	0.188** (0.028)	0.290** (0.034)
children (≥5yr)	0.0361 (0.037)	0.0289 (0.033)
children (>18yr)	0.0123 (0.104)	-0.382** (0.062)

Standard errors in parentheses are clustered at the respondent level. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Notes: All regressions include respondent-specific fixed effects and age fixed effects, where age is the age of the adult respondent to the survey. The dependent variable for the regressions presented in the first column is a count variable indicating the number of vehicles owned by the household for that respondent in that year (taking values between 0 and 5). The dependent variable in the second column is equal to zero if the respondent did not move during one of the years in that life stage, one otherwise.

2.3.3.2 Effects of Life Events on Mode Use by Lifecycle Pattern

In the previous sections the effect of age on mode use was shown averaged across the full sample. Similarly, the effect of having children at different developmental stages on mode use was estimated averaged across all people who had children relative to all those who didn't. However, people progress through lifecycles in different ways; people reach different lifecycle stages at different times than others. The following analysis uses Life History Calendar data from the WholeTraveler survey to characterize the lifecycle trajectory patterns of respondents, enabling a nuanced analysis of travel choices contextualized by lifecycle stage and overall trajectory.

Many studies have explored changes in travel choice associated with life events relying on short-term cross-sectional data, but fail to capture time-varying factors at household or personal levels associated with the dynamics of travel choices over the longer term [98]. Beige and Axhausen [34], [99] argue that the life course itself can be treated as a contextual system, because life events and their associated mobility-relevant choices are dynamically connected to individuals' past and future experiences and decisions. Failure to capture these dynamics obscures important insights regarding the underlying mechanisms for observed behaviors. Some studies investigating longer-term trends use static lifecycle stages to contextualize travel decisions [100], but these stages—as snapshots in time of a life course—are treated independently, without considering the dynamics, or interdependence over time, present in the longer life history. A recent set of studies using mobility biography and life-oriented approaches [35], [36], [101], including reviews by Rau and Manton [102] and Beige and Axhausen [99], recognize the interdependency of choices across various life domains and integrate the temporal dimensions into the analyses of long-term mobility in a comprehensive way. Although these emerging studies have begun to provide more of a life-course perspective on the influence of life events on mobility choices, more is known about aggregated changes associated with life events and general trends over age, such as those summarized in previous sections, whereas less is understood about differences that may exist across different types of individuals progressing through life stages in different ways.

MDS researchers contributed to the mobility-related life-course research by employing a data-driven approach to derive archetypal life-course cohorts and examine the effects of life events on mode use within each life trajectory. This was done by applying a machine-learning approach called joint social sequence clustering [103] to patterns and timing of events from the Life History Calendar data collected by the WholeTraveler survey. The clustering analysis was performed on yearly observations for each respondent in the sample of whether or not the respondent was in school, employed full time (at least 35 hours per week on average), living with a partner, or living with a child in the home. The clustering was performed on data from between the ages of 20 and 35, but the Life History Calendar data includes observations of respondents up through age 50, so patterns resulting from classifying people into these clusters can be observed for a longer period.

This analysis resulted in five distinct trajectories, referred to as "cohorts," described by distinct patterns in the timing of family and career formation: "Singles" (40% of sample) tend to finish school and enter the workforce early and delay or decline having a partner or children; "Couples" (27% of sample) tend to finish school, start work, and partner-up early, but delay or decline having children; "Have-it-alls" (18% of sample) tend to finish school and work early in life, partnering-up and having children concurrent with these other events or only slightly later; "Late Bloomers" (8% of sample) generally delay school, work, partner, and children or choose to forgo these events altogether; and "Family First" (7% of sample) tend to partner-up and have children early and delay or forgo school and/or career. These trends are presented in the top row of Figure 10. There is almost a perfect split between genders in the Singles and Couples cohorts, and, while Late Bloomers are slightly more likely to be men, the split between men and women in this cohort is relatively equal as well. The Family First cohort is 60% female, while the Have-it-alls is 60% male. The Singles, Late Bloomers, Couples, and Have-it-all cohorts tend to be made up of those in younger generations, with 60%, 60%, 46%, and 57%, respectively, born in or after 1965. The Family First cohort tends to be mostly made up of older generations, with 62% born prior to 1965.

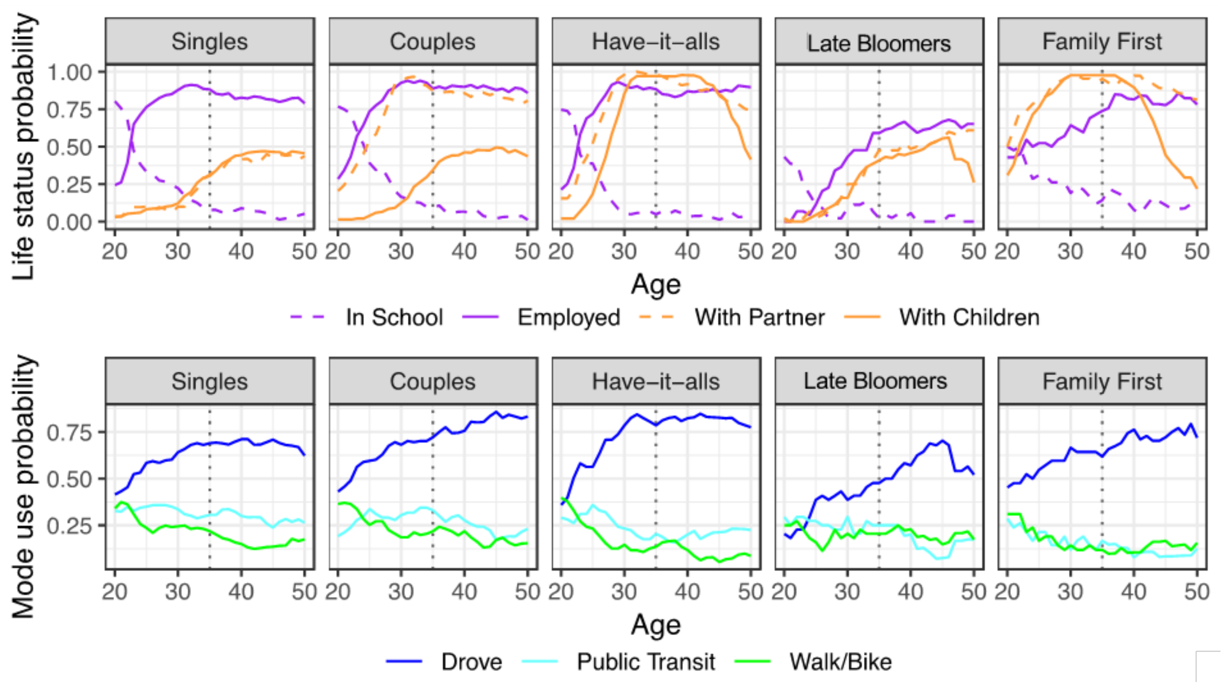


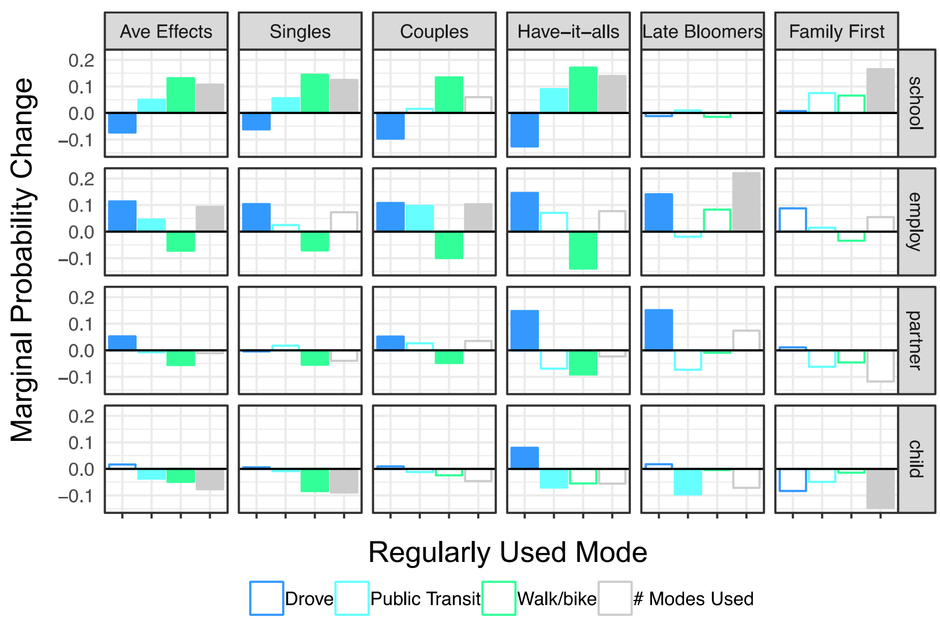
Figure 10. Five life-course patterns in the family and career formation

The bottom row of Figure 10 shows the patterns in regular mode use (two or more times per week on average) for trips to work, school, or other primary commute destination traveled to most frequently outside the home for these five cohorts. Modes included in this analysis are: driving one's own vehicle, using public transit, and walking/biking. A panel regression analysis was conducted to estimate the marginal effect of different life events on mode use, where the effect is allowed to differ across these five cohorts. To enable this differentiation, the effect of having a given life event status (in school, employed full time, living with a partner, or having a child) is estimated separately within each cohort. The analysis determines whether life events that occur at different times within different life-course trajectory patterns are likely to trigger different effects on mode use.

Figure 11 shows the estimated marginal effects of life events on mode use and number of modes regularly used, averaged across the entire sample (left hand column of results) and separated out by cohort.

This life-course perspective revealed that, events occurring relatively early in life are more strongly associated with changes in mode-use behavior compared with events that occur later. Couples, Singles, and Have-it-alls all finish school and start working relatively early in life, and for these cohorts these life events are associated with large and statistically significant transitions in mode-use. Similarly, Couples and Have-it-alls both partner up relatively early in life, and this life event is associated with statistically significant changes in mode-use patterns for these groups, an affect that is of large magnitude for the Have-it-alls cohort in particular.

In addition, mode use is affected by the relative order and proximity of life events. The Have-it-alls cohort finishes their education, starts working, partners up, and has children all in close proximity early in life, and increases personal vehicle use at each step after finishing school, resulting in the highest rate of personal vehicle use occurring the earliest of all the cohorts. This can be seen in the Have-it-alls graph in the bottom row in Figure 10. This demonstrates that the timing and order effect can have lasting implications for mode use aggregated over entire life cycles, as 80% of Have-it-alls are regularly driving a personal vehicle by age 30, and the rate of regularly driving for this cohort persists thereafter, in contrast to Couples, who don't reach this rate of personal vehicle reliance until over a decade later, or the remaining three cohorts who never reach this rate of regular personal vehicle use.

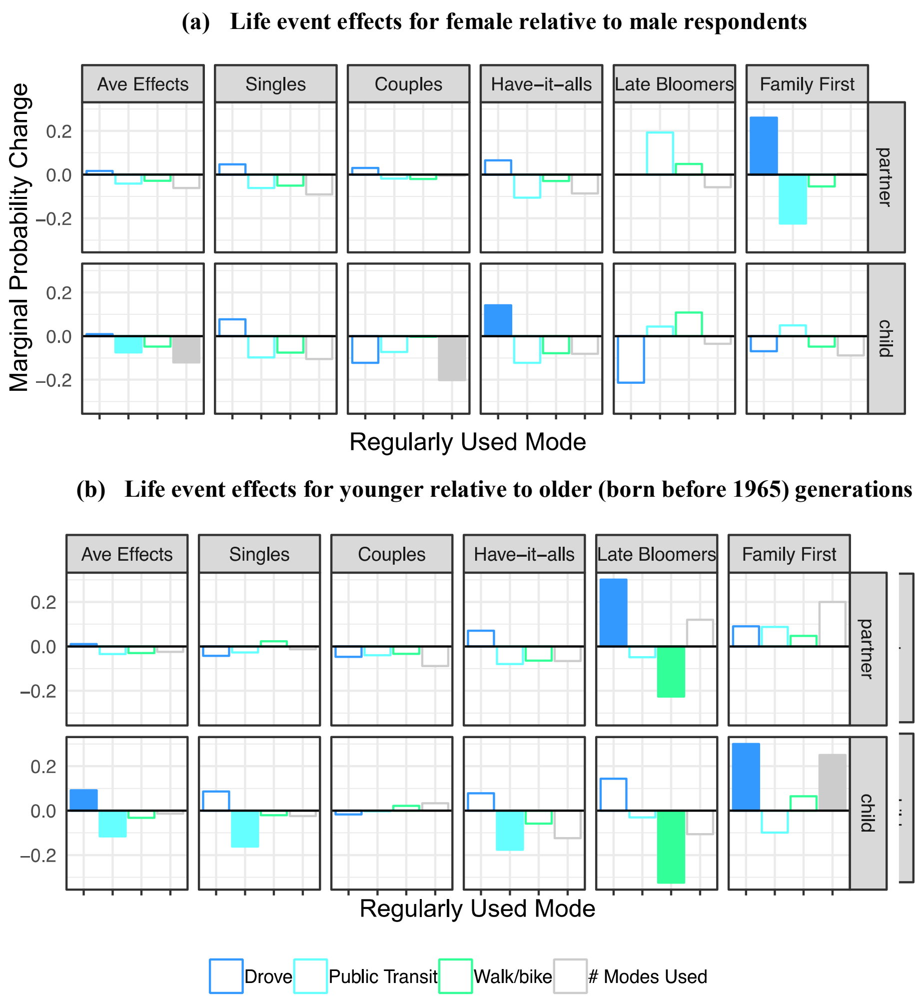


Note: Solid bars indicate values are statistically different from zero at the 10% level. The y-axis shows the estimated marginal effects, so a value of 0.1 reflects a 10-percentage point increase in the case of the three individual mode estimates (drove, public transit, walk/bike) and in the case of the number of modes used is interpretable as the level change in number of modes.

Figure 11. Marginal effects of life events (indicated by row facet) on mode use by cohorts (indicated by column facet) of overall population (first column, “Ave Effects”) and by cohorts (other five columns)

Figure 12 shows how the impact of life events on mode use by each cohort varies by gender and generation. These results show that women drive more relative to men when having children when their family formation and career formation happen in close proximity early in life (as is the case in the Have-it-alls cohort). In addition, younger generations rely relatively more on personal vehicle use and less on walking and biking during family formation when their careers have a later start (as is the case for the Late Bloomers and Family First cohorts).

These results demonstrate that the effect of life events on transportation choices, such as mode use, differ significantly depending on the timing of events and how they interrelate with different aspects of the lifecycle and can differ by gender and generation.



Note: Solid bars indicate values are statistically different from zero at the 10% level. The y-axis shows the estimated marginal effects, so a value of 0.1 reflects a 10-percentage point increase in the case of the three individual mode estimates (drove, public transit, walk/bike) and in the case of the number of modes used is interpretable as the level change in number of modes.

Figure 12. Difference in the marginal effects of life events (indicated by row facets) by cohort on (a) women relative to men, and (b) on Gen X (born in and after 1965) relative to older generation (born before 1965)

2.3.3.3 Effect of Children on Transportation Choices of Parents Differentiated by Age at First Parenthood

In the previous section, results highlight the importance of accounting for life-event timing and order when determining the impact of events on mode use. However, the life-course trajectory clusters, derived using a data-driven machine-learning approach, slice the sample into small segments making it difficult to identify more specific effects—including effects of having a child on mode use—statistically. The previous section's results show that, for Have-it-alls, having children triggered a large and statistically significant increase in personal vehicle use on average. For the Family First cohort, who had children earlier, having children decreased personal vehicle use on average, though this effect was not statistically significant due to the relatively small size of the Family First cohort. The following analysis further explores how children affect mode use by splitting the sample by the age at which the respondent had their first child. This analysis is different from the analysis in section 2.3.3.1., where the effect of having a child was differentiated across child developmental stages, and different from that presented in 2.3.3.2, as the cohorts are defined only by the age at which they had their first child, and not by the other life event dimensions. Specifically, this analysis is estimating the average effect, across all child developmental stages when a child under 18 is in the home, differentiated across three different cohorts, defined by age at which parents had their first child.

Table 5. Effect of children on mode use differentiated by age cohort of parents

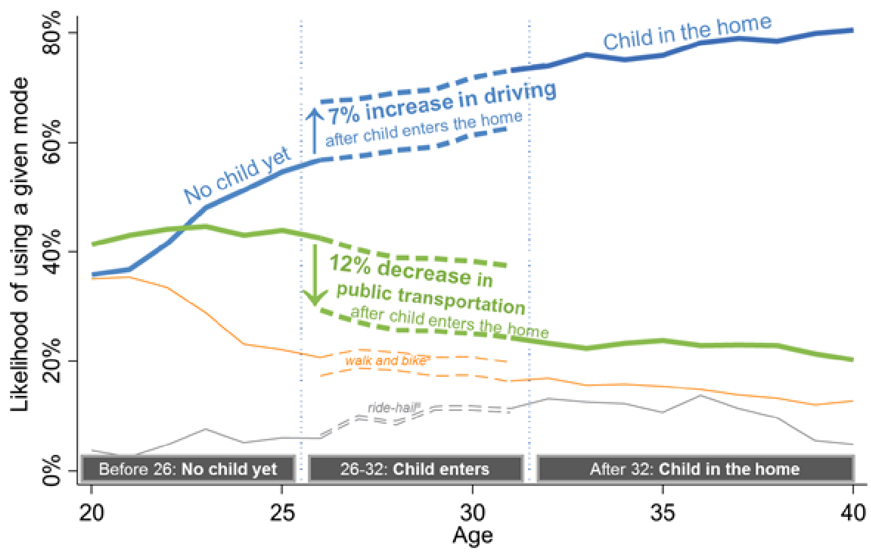
	Personal Vehicle	Public Transit	Walk or Bike
*children * cohort 20-25yr*	-0.104* (0.047)	0.0408 (0.045)	0.0089 (0.035)
*children * cohort 26-32yr*	0.0744* (0.029)	-0.122** (0.030)	-0.0401 (0.028)
*children * cohort 33-50yr*	-0.0144 (0.029)	-0.0125 (0.030)	-0.0545* (0.026)

Standard errors in parentheses are clustered at the respondent level. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Notes: All regressions include respondent-specific fixed effects and age fixed effects, where age is the age of the adult respondent to the survey. Each of the columns presents results from a mode-specific regression where the dependent variable (listed at the head of the column) is equal to 1 if the survey respondent indicated that the mode was used at least two times per week to travel to their work, school, or other primary destination commuted to outside the home most frequently on average during that year, zero otherwise.

In this analysis the effect of having a child in the home is estimated using the same approach as for the lifecycle cohorts in the previous section, only now the cohorts are defined by the age at which parents had their first child: between 20 and 25, between 26 and 32, or between 33 and 50.

The results presented in Table 5, all interpretable as relative to those of the same age not in that cohort and not in that life stage, show that different types of parents respond very differently to the introduction of a child into the household. The type of parents who have their first child when 26–32 years old are seven percentage points more likely to drive a personal vehicle regularly and 12 percentage points less likely to use public transit on average during the years when a child is in the home (approximately a 12% increase in driving and a 33% decrease in public transit use relative to the sample average) relative to those of the same age without children. Figure 13 shows mode-use effects for this type of parent. In contrast, younger parents (having their first child before age 26) reduce the probability they drive a personal vehicle regularly by 10 percentage points (a 16% decrease relative to the sample average), and parents having their first child after age 32 exhibit no statistically significant change in personal vehicle use, but are five percentage points less likely to walk or bike on average during the years when children are in the home (a 21% decrease relative to the sample average). Personal vehicle use changes statistically significantly for both groups having their first child prior to 33, but not for those having their first child later. This is likely because there is a general underlying increasing trend of vehicle use with age, as is shown in the blue lines of the top panel of Figure 9 and of Figure 13. Those having their first child after 32 have already transitioned to a more vehicle-dependent lifestyle, so there is no additional marginal effect on regularly using a vehicle when the child enters the home. In contrast, for those having their first child in the middle-range years, the child entering the home precipitates a more rapid increase in vehicle dependence. The reduction in vehicle use for those having their first child before 26 is likely related to a variety of other factors, several of which are explored below.



Notes: #For walking/biking and ride-hailing, the differences associated with a child entering the home are not statistically significant.

Figure 13. Impact of having a first child on mode use for parents who have their first child when they are between the ages of 26 and 32 years

Although the youngest cohort of parents experiences a reduced likelihood of driving regularly when a child enters the home, they are likely to acquire an additional vehicle at some point during the years when a child is in the home (Table 6). Those having children later in life have a greater increase in the likelihood of acquiring an additional vehicle during the years when a child is in the home. The younger parents are also significantly more likely to move or change the location of their primary commute destination during the years when a child is in the home compared to those of similar ages without a child and those having a child later in life.

Note that the types of moves and whether the moves are to more or less urban or suburban areas are not known. However, controlling for age, all respondents who had a child in the home at some point between the ages of 20 and 50 were less likely to live within two miles of a BART station at the time they filled out the WholeTraveler survey relative to those who did not have a child during these ages, suggestive of living outside of the main urban centers where these stations are mostly located. Those who had their first child later than 25 years old are 13–15 percentage points less likely to live within two miles of BART relative to those of the same age who did not have children. This difference is statistically significant. Those who had their first child at 25 years old or earlier are eight percentage points less likely to live within two miles of a BART station relative to those of the same age who never had a child, though this difference is not statistically significant.

It appears that the reduced driving by those having children young is most likely associated with the impact that having a child in the home has on full-time employment for this group of parents (third column of Table 6). Parents who have their children before age 26 are 20 percentage points less likely to be employed full time during the years when a child is in the home on average, compared to those of the same age who do not have children in the home. This effect is large in magnitude and statistically significant.

Table 6. Effect of having a child on vehicle ownership, moving, and employment by parent age cohort

	Number of Vehicles in Household	Respondent Moved Location of Residence or Primary Commute Destination During Stage	Respondent Employed Full Time
children * cohort 20-25yr	0.167* (0.081)	0.424** (0.070)	-0.213** (0.055)
children * cohort 26-32yr	0.424** (0.054)	0.169** (0.036)	-0.0456 (0.033)
children * cohort 33-50yr	0.343** (0.056)	-0.0762+ (0.044)	-0.0129 (0.032)

Standard errors in parentheses are clustered at the respondent level. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.
Notes: All regressions include respondent-specific fixed effects and age fixed effects, where age is the age of the adult respondent to the survey.

Research shows the significant negative impact having children can have on earning potential, especially for women and especially for those having a child relatively young (ages 20–27) [95]. Results from this analysis demonstrate how the behavior changes that affect that wage penalty (reducing working when having a child young) can translate through to significant changes in transportation behaviors, which can be masked if everyone with children is assumed to behave uniformly. The effect of having a child on the extent to which people are regularly driving differs significantly based on when a parent has a child relative to the parent's career formation. Although everyone is more likely to increase their vehicle ownership when having a child (to varying degrees), those having their first child between 26 and 32 years old increase the probability they regularly drive by almost the same magnitude as a result of a child joining the home as those who have a child between 20 and 25 decrease the probability they regularly drive as a result of this same event.

These underlying lifecycle behaviors can have lasting impacts. The WholeTraveler survey does not record income over the full life history of the respondents. However, controlling for age, those who had their first child young (between 20 and 26) were 25 percentage points more likely to be in the lowest income quartile at the time they took the survey relative to those of the same age who had their first child later in life (between 33 and 50). This group who had a child young have the highest probability of being in this lowest household income quartile and are the least likely to be in the highest income quartile, while those having their child between 33 and 50 are most likely to be in the highest income quartile, controlling for age.

2.4 RESULTS: E-Commerce Use and Impact on Shopping Travel

Similar to mode use and car ownership, as discussed in the previous section, shopping travel is another important transportation behavior influenced by underlying constraints and opportunities which are driven by individuals' life context. MDS researchers studied household shopping behavior and the relationship online shopping with delivery has on household shopping trips. Using data from the WholeTraveler survey, MDS researchers assessed this relationship among survey respondents and in particular analyzed the effect of having children in the home and household income on deliveries received and the extent to which those deliveries replaced shopping trips. Calibrating off of WholeTraveler data, researchers used POLARIS to assess the transportation system impacts of e-commerce.

2.4.1 E-Commerce Use and Impact on Shopping Travel Based on Household Life Context in the WholeTraveler Survey

E-commerce and delivery are growing quickly in the United States and across the world. As a percent of all U.S. retail sales, online sales almost doubled between 2012 and 2017 [104], [105]. As of June 2018, more than 95 million people in the U.S. (close to 40% of the U.S. adult population) were paying for Amazon Prime subscriptions, which provide benefits such as free two-day shipping [106]. Determining the impact of home delivery on overall system VMT and energy is complex. If a delivery trip substitutes for a personal vehicle trip, the delivery truck may consume more energy per mile than the vehicle replaced, but the total system energy use may decrease if a single truck delivers multiple items and replaced multiple shopping trips. However, home delivery may add to overall shopping-related VMT if deliveries do not replace personal shopping trips.

Empirical research on the impact of deliveries to date is mixed. Some studies suggest that e-commerce supplements in-store shopping, leading to an overall increase in shopping travel [107]–[110], while others suggest that it substitutes, leading to an overall decrease [111]–[114].

Many factors influence household shopping behavior and the use of e-commerce. For example, children in the home can constrain shopping time and flexibility [115], while having a higher income means a household is able to spend more but the earnings potential of their time, and therefore cost of time spent shopping, is higher than for lower income households. Empirical evidence relating time constraint to online shopping behavior is also mixed. Ferrell [116] finds a negative correlation between online and in-store shopping frequency, particularly for consumers with greater time constraints. However, Lee et al. [110] find that those who reported having increased time pressure were no more or less likely to shop online.

Motivated by these previous findings in the literature, MDS researchers used data from the WholeTraveler survey to study how the impact of delivery on household shopping trips differs based on household characteristics that are largely defined by time and financial constraints: household income and the presence of children in the home. The takeaways from this work are summarized here, with more information available in the published article [117].

As part of the WholeTraveler survey, respondents were asked to report how many times in a recent typical week they took a shopping trip via vehicle (e.g., personal vehicle, taxi, or ride-hailing) and non-vehicle (walking, biking, or public transit) modes and how many times they received deliveries. This was asked for each of four categories: (1) groceries (e.g., cereal, meat, produce, dairy, beans); (2) clothing, shoes, or accessories; (3) household items (e.g., paper towels, diapers, cleaning products, sunscreen); and (4) prepared meals (e.g., restaurant meals, take-out, meal delivery, cooking kit with prepared ingredients). They were then asked to report how many additional trips they would have taken (if any) if they could not have received the deliveries they reported in the first part of the question. They were also asked to report which aspects of online shopping with home delivery they liked most and least.

Results show that groceries are the most frequently purchased but the least frequently delivered in the San Francisco Bay Area, whereas a larger proportion of clothes and household items are purchased via delivery relative to other item types (Figure 14).

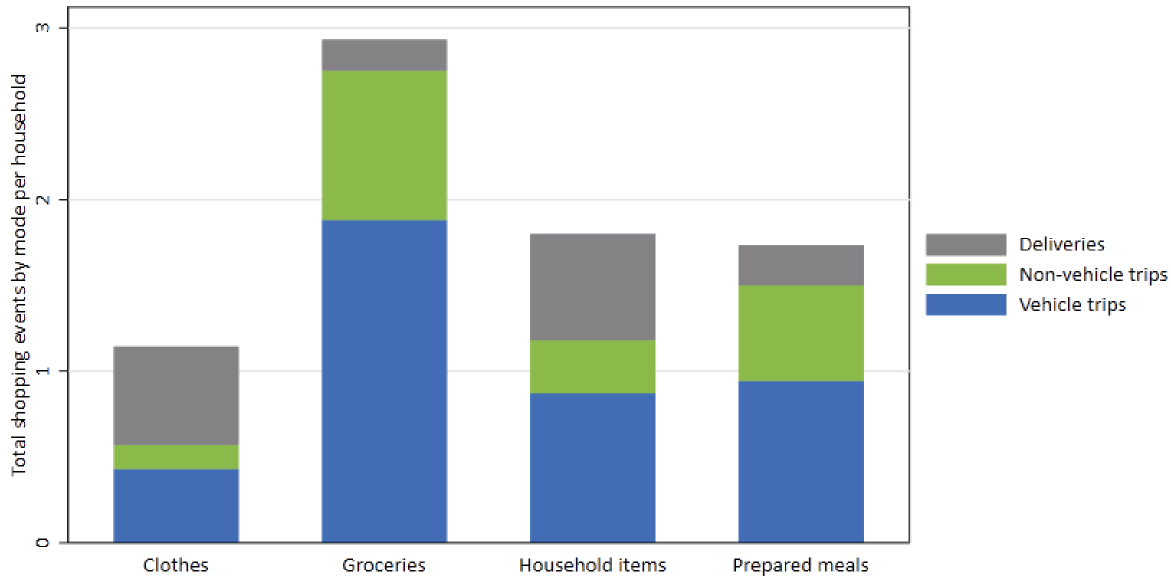


Figure 14. Shopping events per household in a typical week, by vehicle, non-vehicle, or delivery

As show in Figure 15, many people make no purchases at all via delivery, or no purchases of certain items via delivery. Groceries in particular are never purchased via delivery for many respondents. For those that do use delivery, there tends to be an all or nothing pattern. For example, for clothing, shoes, or accessories, bout 70% of respondents that made a purchase in a recent typical week bought these items either entirely or never via delivery, while only about 30% made some of their clothing purchases via delivery and some in a store.

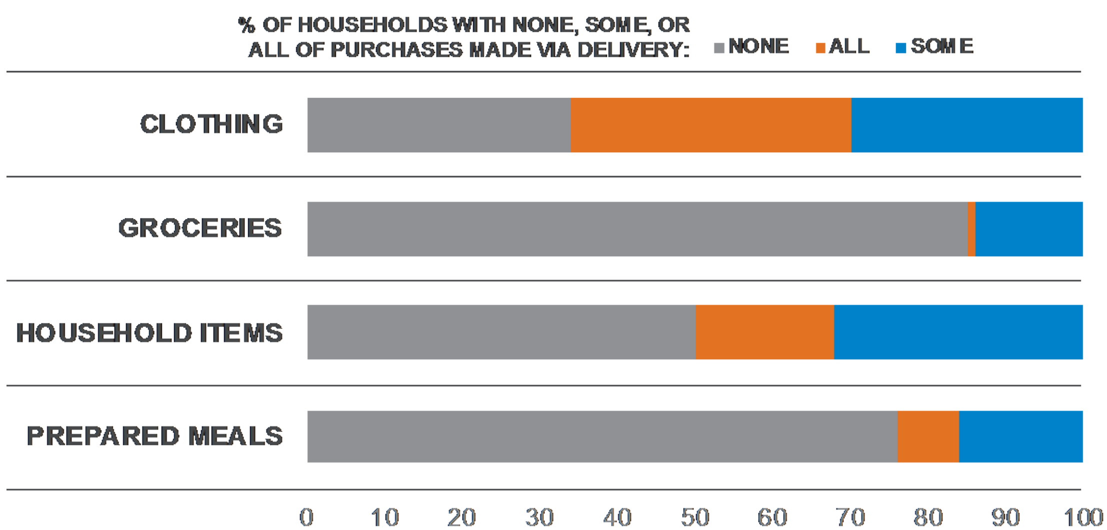


Figure 15. Binary Delivery Purchase Patterns

MDS researchers found that the impacts of increased online shopping and expanded goods delivery on household shopping trips are complex and nuanced. In aggregate, evidence from this analysis supports the subset of the literature [111]–[114] that has found more net substitution for vehicle trips than net supplementation. Figure 16 shows the degree of substitution and supplementation of delivery for household shopping trips from the WholeTraveler survey. Across all product types combined, delivery substitutes for 16% of vehicle trips and 9% of non-vehicle trips. Overall a given delivery is 1.67 times as likely to substitute for a trip than to supplement shopping trips, and in particular is 1.3 times as likely to substitute for a vehicle trip as adding to existing trips. A similar proportional relationship between substitution and supplementation exists across item types, though magnitudes differ based on the differing extent of delivery activity.

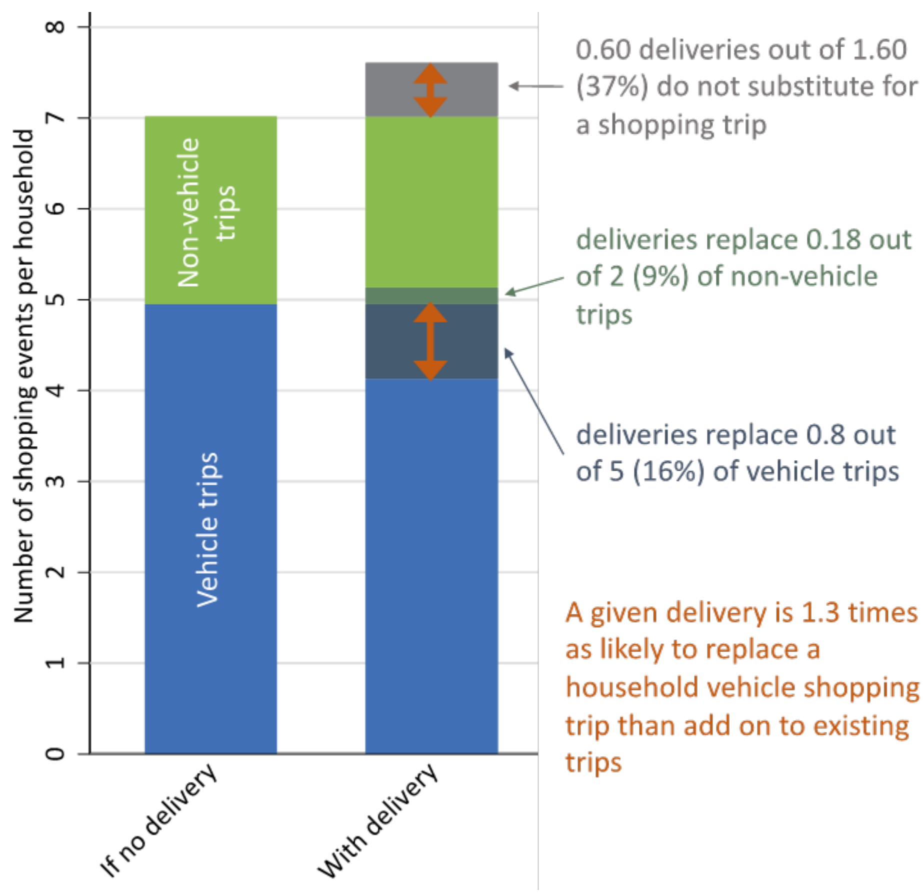


Figure 16. Overall degree of substitution and supplementation of delivery for household shopping trips

There is heterogeneity across households in shopping mode choice and in the degree to which engagement in e-commerce supplements or substitutes for shopping trips. For a large proportion of the sample, deliveries either fully substitute for (55% to 70%) or fully supplement (20% to 35%) shopping trips. This contrasts with all households using deliveries to supplement a few and substitute for a few of their shopping trips.

Consistent with previous literature [118]–[121], WholeTraveler results show that time savings and convenience, among other factors, are important to consumers when considering whether to make a purchase online. Specifically, time saving is more of a motivating factor for higher-income households and households with children relative to their counterparts. In addition, lower-income respondents are more likely to more heavily weight negative attitudes towards delivery charges.

The time-savings motivation of higher-income households and households with children has a mixed effect on delivery use and the degree to which these deliveries substitute for and supplement shopping trips. MDS researchers conducted multinomial logit analyses to assess whether households with children or higher incomes were more or less likely to have deliveries substitute for or supplement shopping trips to the store.

Higher-income households are more likely to receive deliveries overall across all item types compared to lower income households and are more likely to have at least some of their household item and clothes deliveries replace a trip, though there is no significant difference between low- and high-income households regarding the probability that at least one prepared meal or grocery delivery replaces a trip. Households with children are more likely to choose delivery for household items and clothing compared to households with no children, but are less likely to have a household item and prepared meal delivery substitute for a trip. With regard to household items, the intuition is that household items (such as diapers or paper goods for example) can be purchased in many grocery stores, and so could be purchased at the same time as a regular grocery shopping trip, but are convenient to purchase online and get delivered. Therefore, a delivery of diapers may be supplemental to an existing trip to the grocery store.

Prepared meal purchase behavior is an interesting case demonstrating significant distinctions between high- and low-income households and households with and without children. Households with children (by 15 percentage points) and higher-income households (by 12 percentage points) are significantly more likely to have prepared meal delivery supplement prepared meal trips (e.g., taking a trip to a restaurant) relative to their counterparts. These results are statistically significant. The convenience and time-saving aspects of meal delivery may actually substitute more for cooking at home, rather than for a trip to a restaurant. These results suggest that the marginal activity for those who are either more time constrained or have a higher opportunity cost of time is not necessarily the time it takes to make a shopping trip, but may be more so the time involved in other activities, such as preparing meals. This interpretation is not something that was possible to test given currently available data, but provides intuition for the finding that prepared meal delivery is more likely to supplement than substitute for shopping trips, especially for those with a high time-saving motivation to engage in online shopping.

2.4.2 E-commerce Impacts on the Transportation System through Simulation

The degree of substitution and supplementation is one important factor determining the extent to which e-commerce impacts the energy intensity of the transportation system. There is also a tradeoff between personal vehicle and delivery truck efficiency per mile. To test the impact of e-commerce at the system level, a household e-commerce demand module was developed and implemented in the POLARIS simulation framework. This demand model was developed using the e-commerce engagement data collected in the WholeTraveler survey. Using a joint-binary-ordered probit specification, the household e-commerce demand model evaluates households' decisions to participate in e-commerce and quantifies the delivery-to-retail-shopping trip ratio for the participating households.

The model indicates that among the households participating in e-commerce, number of adults, number of vehicles, household income, and walking accessibility are important determinants of delivery-to-retail trip ratio. Higher household income tends to increase the delivery-to-retail trip ratio, while high numbers of adults and vehicles tend to decrease this ratio. Households with higher walking accessibility (as measured by Walk Score and simulated walking access time within POLARIS) tend to have lower delivery-to-retail trip ratios. The household e-commerce demand model is implemented in POLARIS to simulate e-commerce demand and evaluate the related impact on the transportation system for the Chicago region. Three scenarios were evaluated using this implementation in POLARIS. In the baseline scenario, 50% of households participate in e-commerce and received 0.5 deliveries per person per week, calibrated using the WholeTraveler survey data. In a medium-term future scenario, household e-commerce participation is assumed to increase to 75% of households, who are assumed to receive 1.4 deliveries per person per week. In a longer-term future scenario, all households are assumed to participate in e-commerce and are assumed to receive about 2.5 deliveries per person per week, which is about the same frequency as most of the regular weekly shopping trips of the household.

Results from the simulation analysis suggest that higher e-commerce use in the medium and longer-term future scenarios may increase medium-duty delivery truck trips and reduce single-occupancy vehicle trips while reducing fuel consumption related to retail shopping in the Chicago area overall. Panel (a) of Figure 17 shows the distribution of the average delivery-to-retail trip ratio by traffic analysis zone (TAZ) for the Chicago region for the baseline, while panel (b) shows the percentage point change in the average delivery-to-retail trip ratio in the medium-term scenario compared to the baseline.

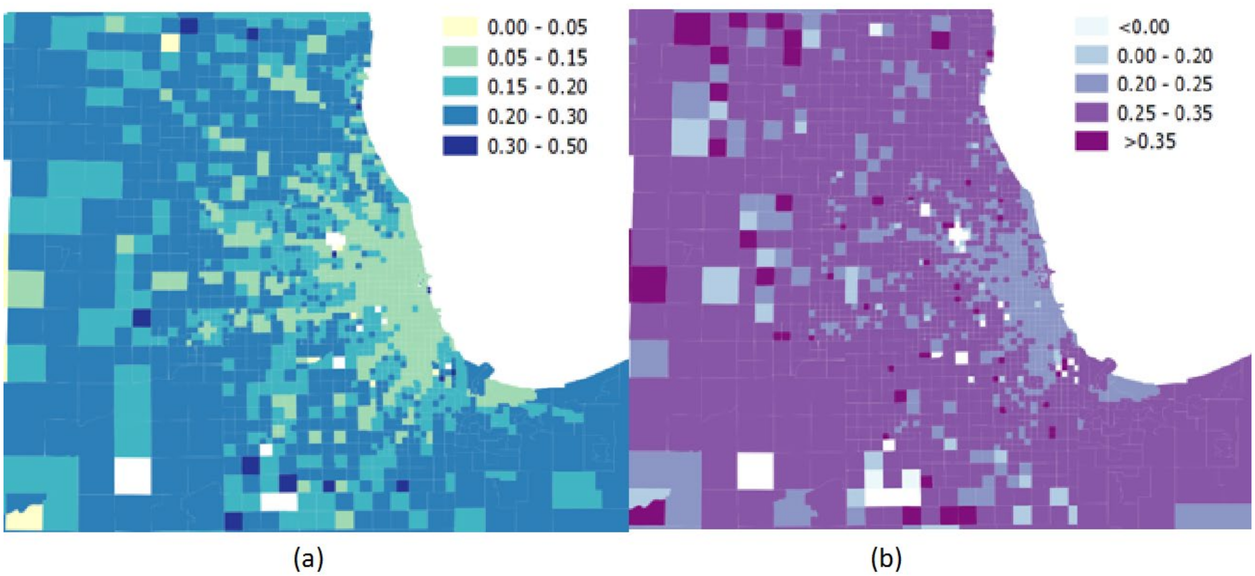


Figure 17. (a) Average delivery-to-retail ratio by TAZ, baseline; (b) percentage point increase (0.05=5 percentage points) in average delivery-to-retail ratio by TAZ, medium-term compared to baseline

In the urban core, in the baseline there are between 3.5 and 10 trips for each 0.50 deliveries (delivery-retail trip ratio of 0.05 to 0.15). Increasing e-commerce to 1.4 deliveries per person per week could drive a 20–25 percentage point increase in the delivery-to-retail trip ratio compared to the baseline scenario and would increase that ratio by more than 30 percentage points in some suburban regions. The differences in demographic distribution and network accessibility measures resulted in the non-uniform increase in the average delivery-to-retail trip ratio across regions in the future scenarios. This increase in delivery-to-retail trip ratio reflects increased delivery truck trips and subsequently increased delivery truck VMT. However, the decrease in VMT due to fewer shopping trips was greater than the delivery VMT increase, resulting in an overall 33 percentage point decrease in system-wide energy consumption in the medium-term scenario compared with the baseline. These results suggest that, at a system level, increasing e-commerce is likely to reduce transportation system energy use.

2.5 RESULTS: Psychological and Identity Factors Affecting Transportation Preferences

Section 2.1 presented results relating some location-based factors to transportation impacts, and Sections 2.2 through 2.4 presented results related to the life context of decision-makers with regard to personal and shopping transportation decisions. There are other contextual factors affecting transportation preferences and behaviors related to, but distinct from, those related to location and lifecycle. This section summarizes MDS findings related to psychological and identity factors affecting transportation preferences from the WholeTraveler survey, including personality characteristics and gender. In addition, stand-alone analyses using other data sources coupled with POLARIS simulation studies are presented assessing the importance of a key behavioral parameter in the context of transportation choices: VOTT.

2.5.1 Personality Characteristics

The BFI dimensions of personality are extraversion (vs. introversion), agreeableness (vs. antagonism), conscientiousness (vs. lack of direction), neuroticism (vs. emotional stability), and openness (vs. closedness to experience) [122]. Extraversion is associated with gregariousness, assertiveness, activity, excitement-seeking, positive emotions, and warmth; agreeableness with trust, straightforwardness, altruism, compliance, modesty, and tender-mindedness; conscientiousness with competence, order, dutifulness, achievement, self-discipline, and deliberation; neuroticism with anxiety, angry hostility, depression, self-consciousness, impulsiveness, and vulnerability; and openness with appreciation of unusual ideas, fantasy, aesthetics, emotions, and a variety of experiences. People possess all five dimensions and they vary in terms of what proportion of each that they have.

Findings from analyses of WholeTraveler data suggest that perceptions people tend to have about the personality characteristics of those who own and drive PEVs may not always perfectly align with reality. Skippon and Garwood [123] found that people tend to perceive the typical PEV driver as rating high on agreeableness, conscientiousness, and openness. However, WholeTraveler results revealed that while agreeableness is positively correlated with interest in PEV adoption interest, conscientiousness is negatively correlated with PEV adoption interest.

Greater extraversion has been found to relate to more willingness to engage in the sharing economy [124]. However, Roy [124] asked people to express their willingness to engage in a general concept of a sharing economy, described as “business concept that highlights the ability for individuals to rent or borrow unused resources or goods rather than buy or own them,” and while Uber is listed as an example of such a business concept, it is lumped in with others, such as Air BnB. Backer-Grøndahl et al. [125] found that those who rate highly on agreeableness worry less about unpleasant interpersonal incidents occurring across a wide range of transportation modes (e.g., bus, metro, taxi, tram) and those rating highly on neuroticism worry more about these incidents. This previous literature suggests extraversion and agreeableness likely correlates positively with shared mobility use, while neuroticism likely correlates negatively, but in neither case was this effect clearly isolated and identified. MDS research identified these effects in the WholeTraveler survey.

Findings from the WholeTraveler survey indicate that, while neuroticism did not have any significant correlation with ride-hailing use, extraversion and agreeableness both correlated significantly and positively with the use of pooled ride-hailing and extraversion with single-rider ride-hailing as well. Specifically, a one standard deviation increase in the extraversion scale is associated with a four percentage point higher adoption rate for both single-rider and pooled ride-hailing options and a one standard deviation increase in agreeableness is associated with a seven percentage point increase in interest in PEV adoption. The Big Five personality characteristics scales are between one and five for each trait, with a standard deviation of about one for each. These results suggest, therefore, that someone rating one on the extraversion scale is 16 percentage points less likely to have adopted ride-hailing compared to someone ranking five. Similarly, someone ranking one on the agreeableness scale is 28 percentage points less likely to be interested in PEV adoption relative to someone ranking five. These results are economically meaningful and statistically significant. This moves beyond the suggestive evidence from previous literature and demonstrates a clear correlation with actual ride-hailing use.

The significance of these findings is that fundamental personality characteristics, such as extraversion, correlate with traveler's use of shared modes, especially ride-hailing. This could have important implications for transitioning to a fully shared transportation paradigm—and realizing associated energy efficiency gains to the system—because people with introverted personality traits may be unlikely to transition to shared transportation modes, for example.

2.5.2 Gender

MDS researchers analyzed data from the WholeTraveler survey to explore gender differences in transportation preferences and behaviors. In the WholeTraveler survey gender was self-reported by the survey respondents. The question asked "What is your gender?" and the options to select from were male, female, other (with an option to specify if desired), or the respondent could indicate that they preferred not to answer. The question regarding gender was asked, along with all the other demographic and household characteristic questions, at the end of the survey so that reporting gender or other demographic information did not prime respondents to answer other survey questions differently. In the remaining discussion respondents who selected "female" are referred to as women, female, or female-identified.

MDS researchers analyzing WholeTraveler survey data found that women are less likely to adopt and/or be interested in adopting most new transportation technologies, with the exception of ride-hailing. In particular, women are three percentage points less likely to have adopted partially automated vehicles, 16–26 percentage points less likely to be interested in adopting vehicles with any level of automation, and 10 percentage points less likely to be interested in adopting PEVs, all differences that are statistically significant and robust to the inclusion of a variety of additional controls. Similar patterns have been found in other studies [11], [14], [64], [126]. On the other hand, it was found that identifying as female is associated with no significant difference in current use of or future interest in ride-hailing. This finding is consistent with Smith [8], whereas Alemi et al. [57] and Kooti et al. [59] both found that women were more likely to use ride-hailing services. These findings suggest that ride-hailing may be a context to better understand the types of transportation innovations that appeal to women.

Additional analyses explored explanations for why women in the WholeTraveler sample are less interested in adopting PEVs relative to men. Researchers used WholeTraveler survey data on the make, model, and year of the primary vehicle used in respondent households merged with additional vehicle characteristics regarding vehicle fuel economy, cargo capacity, and safety ratings from FuelEconomy.gov, Kelley Blue Book, and Consumer Reports (see Section 2.1.1) to test four possible drivers of the observed gender gap: (1) risk and safety preferences (e.g., [127]–[129]), (2) personality factors (e.g., [11], [123]), (3) ability and willingness to pay (e.g., [129], [130]), and (4) differences in transportation-related tasks and requirements (e.g., [131], [132]). This fourth hypothesis stems from findings of Taylor, Ralph and Smart [131] and Shirgaokar and Lanyi-Bennett [133], indicating that the distribution of tasks related to family member transport and household maintenance is unequally divided by gender, with women taking on a greater share of travel associated with shopping and transporting other household members and belongings, a pattern that is exacerbated by the presence of children in a household [132]. These factors point to the desirability of passenger and cargo spaces, as well as any vehicle features that mesh well with multi-stop trips.

A method called mediation analysis was used to estimate the portion of the gender gap in PEV interest associated with the specific hypotheses summarized in Table 7. In mediation analysis, a factor can either mediate, meaning it can increase the magnitude of the relationship between two factors (in this case gender and interest in PEVs) or it can suppress, meaning it can suppress the magnitude of this relationship, bringing the correlation closer to zero. Mediating factors are referred to as consistent mediators and suppressing factors are referred to as inconsistent mediators or suppressors. The hypotheses specified for this analysis are described in terms of mediation and suppression.

Table 7. PEV Interest Gender Gap Hypotheses

Hypothesis Group	Hypothesis
H1: Risk	**H1a**: Monetary risk aversion mediates the gender gap (+)
	H1b: Concern for physical safety mediates the gender gap (+)
H2: Personality	**H2a**: Openness suppresses the gender gap (-)
	H2b: Neuroticism mediates the gender gap (+)
	H2c: Extraversion suppresses the gender gap (-)
	H2d: Agreeableness suppresses the gender gap (-)
	H2e: Conscientiousness mediates the gender gap (+)
H3: Willingness and/or ability to pay	**H3**: Willingness and/or ability to pay mediates the gender gap (+)
H4: Transportation Preferences	**H4a**: Factors related to household responsibility for transporting family members and household goods mediate the gender gap (+)
	H4b: Factors related to commute habits suppress the gender gap (-)

Results from this analysis are presented in Table 8 and visualized in Figure 18 and indicate that, when looking at the all consistent mediators and all suppressors, the variables included in the analysis mediate 35% of the gender gap, but also suppress 10% of the gender gap. Two hypotheses account for the largest share of the gender gap in this analysis: (1) factors associated with willingness or ability to pay (H3) taken together account for about 10% of the gender gap and (2) factors related to household responsibility for transporting family members and household goods (H4a) account for about 11% of the gender gap. The largest single consistent mediator is income, with findings indicating that if women respondents had the same household income level as men respondents on average, the gender gap could be 10% smaller. The largest single suppressor is agreeableness, indicating that if women had the same average rating on the agreeableness scale as men, the gender gap could be 5% larger.

Table 8. Gender Gap Mediation Analysis Results

Hypothesis Group	Hypothesis	Key Variable(s)	% mediated ($p<0.05$)	% suppressed ($p<0.05$)
H1: Risk	H1a: Monetary risk	Risk averse identifier		-2.38
	H1b: Safety	Safety importance index	3.23	
		Vehicle safety rating	0.41	
H2: Personality	H2a: Openness	BFI openness score		-1.2
	H2b: Neuroticism	BFI neuroticism score	0.81	
	H2c: Extraversion	BFI extraversion score		-0.39
	H2d: Agreeableness	BFI agreeableness score		-4.7
	H2e: Conscientiousness	BFI conscientiousness score	6.53	
H3: Willingness and/or Ability to Pay	H3: Willingness and/or Ability to Pay	Income level	10.28	
		Low cost index	0.74	
		Discount factor	0.24	
		Predictable cost index	1.66	
		Vehicle purchase price	0.12	
H4: Transportation Preferences	H4a: Moving people and stuff	Child(ren) in household	0.28	
		Child transport index	1.57	
		Vehicle seats (#)	3.17	
		Multiple stops index	7.28	
		Vehicle cargo capacity	3.05	
	H4b: Commute habits	Travel time importance	0.3	-1.12
		Primary commute distance		

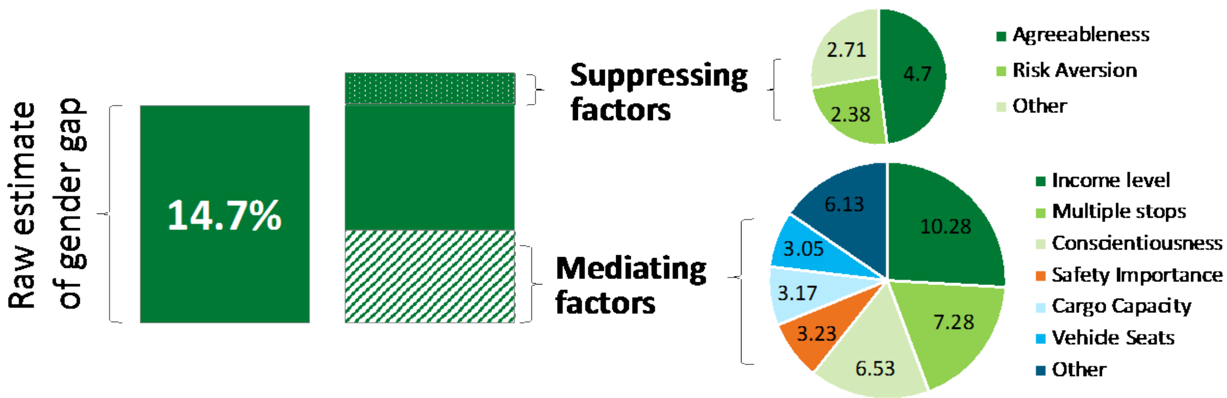


Figure 18. Gender Gap Mediation Analysis Result Visualized

The implications of the findings from this analysis are that the gender gap could be reduced if: (1) there is a reduction in the purchase price of PEVs, making ability to pay less of a differentiating factor and (2) PEV technology is incorporated into a wider array of vehicle types to enable PEVs to more readily accommodate the needs associated with the type of travel more likely to be done by women. To this latter point, several high seating and cargo capacity PEVs have entered the market (e.g., Chrysler Pacifica in 2017). These results suggest that such PEV models should better connect PEV use and transportation tasks associated with child and household care, which this analysis indicates would have the potential to shrink the gender gap in interest in PEVs. However, large PEVs carry a very high price point, which may mitigate the extent to which they can contribute to the reduction in the gender gap in PEV interest.

2.5.3 Value of Travel Time

Perceived VOTT or VOTT savings on the part of travelers represents the amount a traveler would theoretically be willing to pay to reduce travel time. VOTT is usually expressed in dollars per hour and relates to the perceived burden or disutility of time spent traveling. This value varies by individual, travel situation, travel mode, and a variety of other factors. Time spent on different portions of the same trip (e.g., walking to a train vs. waiting for a train vs. riding on the train) can have different associated values. VOTT, therefore, impacts not only the choice of mode when traveling, but also the choice of route, location, departure time, and many other mobility-related behaviors. Understanding how new mobility services alter time use and valuation is central to understanding how they may fundamentally alter travel behavior and demand and thereby alter travel energy use and emissions (e.g., [134]).

Depending on the traveler's preferences, time availability, and accessibility to activity locations, the ability to engage in multiple activities or uses of time while travelling with AVs could persuade individuals to travel more and perform activities like working, reading, sleeping, or other activity not possible to engage in while driving with the advent of AV technology [135]. However, it also could lead to less travel or congestion depending how the traveler uses their time in the AV and the timing of their travel (e.g., if the time in an AV can be spent ordering groceries, that can save a later shopping trip, or if work can be done in an AV one can commute later, thereby reducing peak time congestion) [136]. Thus, it is anticipated that people's lifestyles, how they use their time, and the activities they participate in are likely to change as a result of fully automated vehicles in the transportation system [137]. However, the extent of these changes is not clear. VOTT and its variability across people and contexts are typically estimated to be the single largest component of time- or distance-dependent travel cost (e.g., fuel consumption, fares, vehicle wear and tear, value of the time spent not engaged in other activities) accounting for about 45% [138]. A key conclusion of the large literature on this topic is that, despite extensive research and progress, the concept of VOTT remains in flux, both theoretically and empirically. Estimates of VOTT vary widely by study, data source, and across subpopulations and contexts. No clear, systematic understanding of the underlying logic behind these variations exists.

MDS researchers used multiple approaches to explore VOTT. First, three analyses were conducted using publicly-available data sources to generate estimates of VOTT and analyze time-use preferences during transit and ride-hailing travel. Second, simulation studies were conducted using the POLARIS agent-based model to assess the sensitivity of modeled transportation system impacts to variation in the VOTT parameter.

2.5.3.1 VOTT and Time-Use Estimation and Analysis

The first stand-alone analysis used a multiple discrete-continuous extreme value (MDCEV) model applied to data sources from which time-use information could be derived, including the American Time Use Survey (ATUS), the National Household Travel Survey (NHTS), and the Consumer Economic Survey (CES). It was observed that time-use patterns are highly inconsistent between the ATUS and NHTS analyses (i.e., the distribution of how people split their time across different activities, including travel, varied between the two data sources). Both data sets offer limited ability to compare time use to travel time in order to make VOTT estimates and neither includes information on multitasking—limiting their applicability to the context of fully automated vehicle availability and motivating the need for additional data collection. This approach was therefore deemed to be of limited value for generating VOTT estimates.

The second stand-alone analysis used multinomial logit mode-choice models applied to data from the Chicago Metropolitan Agency for Planning (CMAP) Travel Survey, deriving VOTT from the estimated travel time and travel cost parameters. The results again offer vastly different and inconsistent values of estimated parameters depending on context and subgroups. Specifically, the average VOTT of transit users ($7.6/hour, varying from $0.3–$35.3/hour depending on arrival/departure hours, location, trip purpose, and respondent demographics) is much lower than the average VOTT of auto users ($28.5/hour, varying from $2.1–$82.3/hour depending on arrival/departure hours, location, trip purpose, and respondent demographics). VOTT varies by arrival and departure time, showing higher magnitude in the peak hours and lower magnitude in the off-peak hours for auto and transit users. However, for the Chicago central business district (CBD) as a destination, the model results are nuanced: VOTT is higher for work-oriented auto trips than for non-mandatory trip purposes. This is expected, given the hypothesis that, when commuting to work, people would be willing to pay more to reduce travel time compared to leisure trips. Leisure trips may more likely include friends or family members and be potentially less subject to critical arrival or departure times. However, it was found that the opposite appears to be true for transit users. A modeling approach using direct VOTT estimation (as opposed to indirect estimation through mode-choice modeling) was also performed using the CMAP data set. Average VOTT was found to be approximately $25/hour across all trips, with CBD-based trips having substantially higher values. This was in line with the indirect estimation of VOTT, with the highest values obtained for working-age and high-income travelers and for commute trips and trips on weekdays.

A third stand-alone analysis studied time-use and multitasking based on a transit rider intercept survey collected for a Federal Transit Administration study on transit disruptions [139]. This intercept survey, while limited to a transit-riding population, obtained data not available elsewhere including time use during travel during the intercepted trip and historically during general transit and TNC vehicle trips. Because time use during travel has been identified as one of the key drivers of VOTT change [135], it was important to explore this effect in a public transit context, as that can provide insight into other modes which don't require vehicle operation by the traveler, such as AVs. To explain the preferences for multitasking while traveling in different contexts, multiple linear regression and rank-ordered logit models were formulated. The findings reveal substantial heterogeneity in time-use preferences for different activities across population subgroups. For example, younger adults are more likely than older adults to use an electronic device for entertainment during travel while older adults are comparatively more likely to read paper-based media while traveling. In addition, the results show that travelers are comparatively more likely to socialize or talk with others when using ride-hailing services compared to transit.

2.5.3.2 Impact of VOTT in Transportation System Simulation

A sensitivity analysis was conducted to assess the effect of VOTT on regional mobility using the Bloomington, Illinois, area implementation of the POLARIS model. The Bloomington model has the same underlying specifications, assumptions, and features of the Chicago POLARIS model, and includes approximately 150,000 travelers, representing a small city. In the first analysis, the impacts of VOTT on mode choice, destination choice, and departure time of day were explored by starting with baseline assumptions about VOTT, which allow VOTT to vary across travel and choice situation. The analysis then varied VOTT between +50% and -50% from these baseline values, so all baseline VOTT values were simultaneously changed by the same percent, but variation across travel and choice situation remained. The study revealed that there is a 2.5% reduction in miles traveled for every 10% increase in the travel time parameters, an average elasticity of approximately -0.25 (Figure 19). To contextualize the magnitude of this elasticity, a comparison can be made to the previously described analysis using CMAP data in which VOTT estimates ranged from less than $1/hour to $82/hour, depending on the mode, context, and traveler characteristics. If driverless vehicles are able to reduce VOTT from $29/hour (the average VOTT of auto users in the study using CMAP data) to $8/hour (the average VOTT of transit users in the studying using CMAP data), reflecting a 72% decrease in VOTT, the elasticity estimate from the POLARIS sensitivity analysis suggests there would likely be an 18% increase in miles traveled.

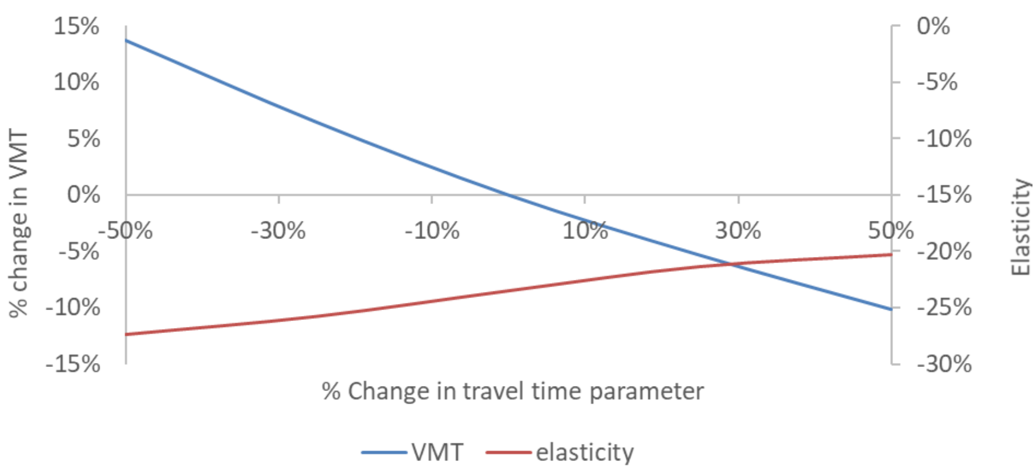


Figure 19. VMT sensitivity to change in VOTT captured by percent change in VMT (left axis) and elasticity of VMT to VOTT (right axis)

In a second simulation study of the impact of VOTT, the Chicago-area implementation of POLARIS was used. There was an initial baseline set of assumptions regarding VOTT, also varying across travel and choice situation, similar to the Bloomington sensitivity analysis. In the Chicago-based POLARIS analysis VOTT was reduced from 0% to 50% from the baseline specifically for travel in a privately-owned AV, with analyses conducted over a range of AV penetration levels to explore potential impacts of partially automated vehicles. The results demonstrate that reducing the VOTT by 50% for travelers in privately owned AVs with very high penetration (over 75%) of privately owned partially automated vehicles would increase VMT by 45%, vehicle hours traveled (VHT) by 46%, and fuel consumption by 46%, while also increasing congestion. These effects reflect comparing the last row in Table 9 to the baseline, which is the first row. Reducing VOTT shows a fairly uniform increase in energy and travel across the region, with the exception of the high-density employment and downtown areas. Those living in downtown and other urban core areas already have immediate access to a diverse range of employment and recreation activities and do not tend to engage in substantial extra travel regardless of VOTT changes. Most of the VMT changes stem from travelers in outlying areas.

Table 9. Impact on Mobility and Energy as VOTT Changes

Partially AV Penetration	VOTT Reduction	VMT (millions)	VHT (millions)	Avg. Travel Time (min)	Avg. Trip Length (mi)	Fuel Use (MM gallons)
0	**0%**	**268.0**	**8.17**	**23.4**	**11.79**	**4.85**
10.1%	30%	306.5	8.37	23.7	13.38	5.62
10.1%	50%	319.2	8.74	24.7	13.99	5.85
36.1%	0%	291.2	7.86	22.2	12.50	5.34
36.1%	30%	324.6	9.04	25.5	14.21	5.94
36.1%	50%	357.8	10.45	29.9	15.77	6.55
75.5%	0%	292.0	7.96	22.5	12.73	5.32
75.5%	30%	337.7	9.64	27.3	14.82	6.14
75.5%	**50%**	**387.4**	**11.92**	**34.5**	**17.40**	**7.05**

3 Conclusion

The MDS Pillar of the DOE SMART Mobility Consortium examined the underlying identity, preference, personality, lifecycle, geographical, and contextual factors that impact transportation behaviors. Of particular interest are factors that are, or could be, critical barriers to, or drivers of, adoption and use of emerging transportation technologies and services such as vehicle automation, vehicle electrification, ride-hailing, shared modes, and e-commerce.

Assumptions about how people will adopt or use emerging technologies vary widely. For example, Arbib and Seba [2] forecast that, within 10 years of regulatory approval of AV technologies, 95% of all person-miles-traveled will be via automated ride-hailing fleets as opposed to privately owned vehicles, though privately-owned vehicles will still comprise 40% of the vehicle fleet. Similarly, [3] project that the U.S. will hit peak car ownership rates in 2020, and the rate of car ownership will be more than cut in half by 2035. While in contrast Gao et al. [4] project that only up to 10% of the cars sold in 2030 could be a shared vehicle, and up to only 15% of new cars sold that year could be fully automated.

Results from MDS research provide significant new insights into potential behavioral impacts to the transportation system of emerging technologies and services and their integration, or not, with more traditional modes. In particular, factors pertaining to underlying needs of people based on their personality or psychological characteristics, lifecycle stages and context, identity, and socioeconomic status were examined to provide a deeper understanding that can inform assessments of how realistic projections, such as some of those cited above, might be.

Previous research has shown that age correlates strongly with adoption and use of several emerging modes. MDS research helped fill gaps in existing literature related to age with regard to both mode choice and technology adoption. In the WholeTraveler sample from the San Francisco Bay Area in 2018, younger generations drive both current adoption and interest in future adoption of ride-hailing. Most millennials are either interested in or already regularly use ride-hailing; they are 70% more likely to have adopted single-rider ride-hailing and almost 200% more likely to have adopted pooled ride-hailing, relative to Gen X. In addition, millennials who have not yet done so are 50% more likely to express interest in adopting both of these ride-hailing service types compared to Gen X travelers who have not yet adopted. Overall, interest in and adoption of ride-hailing is higher for millennials compared to all previous generations.

To resolve ambiguous findings in the literature regarding the correlation between interest in AV technologies and age [62], [63], MDS researchers found that both millennials and baby boomers are significantly more interested in AV technologies relative to Gen X. In the WholeTraveler sample, about half of millennials and baby boomers express interest in adopting partially automated vehicle technology, which is about 25% higher than for Gen X. Interest tends to be highest for the youngest and oldest respondents in the analyzed sample (those born in the 1990s and those born in the 1940s). This pattern holds for the case of interest in fully automated vehicles as well, with millennials (58%) and baby boomers (50%) both more likely to express interest in fully automated vehicles compared to Gen X (44%). In addition, with respect to electrified vehicle technologies, WholeTraveler findings contrast with most previous findings, which indicated that EV ownership is driven by youth [9]–[11], [64]. In the WholeTraveler sample, current adoption of both PEVs and hybrid vehicles is driven by older generations. Although interest in owning a hybrid is significantly higher among the youngest millennials, interest in owning PEVs tends to be marginally highest among baby boomers. However, due to the WholeTraveler being conducted online, it may be the case that the older WholeTraveler respondents are more likely be open to new technologies relative to the broader population of the same age.

Such age-related findings are relevant to underlying patterns in mode use. For example, using data from the WholeTraveler Life History Calendar, MDS researchers demonstrated that vehicle dependence increases with age, stabilizing at around 70% regularly driving a private vehicle (more than twice per week) by about age 33 and persisting at that level thereafter. This increase comes largely at the expense of public transit, walking, and biking. However, if interest in adopting PEVs continues to follow the patterns observed and described above with regard to age, this could influence the energy implications of this underlying trend toward increased vehicle dependence with age.

MDS researchers also examined why people tend to make particular mode choices and how these dynamics might manifest in the context of emerging transportation choices. This included using machine learning techniques to derive five cohorts defined by different archetypical life trajectory patterns. Analyses of these cohorts revealed that mode use is affected by the relative order of life events, and when certain key events occur earlier in life they are more strongly associated with changes in mode-use behavior compared with events occurring later. These timing and order effects can have lasting implications for mode use over entire life cycles. For example, the “Have-it-alls” cohort (almost 20% of the sample), finishes their education, starts working, partners up, and has children all in close proximity early in life, ramping up car use at each life transition after school. This results in the highest rate of car use occurring the earliest of all the cohorts (about 80% by age 30 as compared to about 70% by age 33 for the sample as a whole). The Have-it-alls cohort, which has high rates of living with a partner, having children, and early career formation concurrent with family formation, resemble what Dowling [94] referred to as time-poor dual-earning households. Dowling [94] and Fyhri et al.[68] showed these types of households are likely to have higher rates of vehicle dependence. The WholeTraveler results also show the extent to which, currently, this effect is permanent. Having children concurrent with career formation is a major driver of earlier transition to vehicle dependence for people in the “Have-it-all” life trajectory.

Women in the WholeTraveler sample are significantly less likely to be interested in adopting PEVs and vehicles with high levels of automation compared to men. The gender gap in PEV adoption interest is found to be largely driven by a lower ability or willingness to pay by women as well as a misalignment between women's vehicle needs and PEV characteristics, which tend not to have as much passenger or cargo capacity as conventional vehicle options, and are less likely to be preferred by women who place a high importance on the need to safely transport children or make multiple stops, such as would be needed to run household errands. The link between income, gender, and children also relates to the MDS finding that, when people have children relatively young (before age 26), they are less likely to drive regularly as a result, largely due to a lower probability that they work while having young children. Women in the WholeTraveler sample who had their children young had the highest probability of being in the lowest household income quartile and are the least likely to be in the highest income quartile relative to women who had their children later in life, or men overall. These findings are consistent with research that has shown a lifetime wage penalty of having a child before age 26 [95], especially for women, and they further illuminate the gender gap regarding interest in PEV adoption, because women survey respondents tended to have lower household incomes and income was a strong predictor of interest in PEV adoption.

These findings underscore the fact that people have needs and constraints when making transportation decisions. The tendency towards increased private vehicle dependence due to certain lifecycle factors suggests a need is being met by privately owned vehicles for much of the population. Those who have children in the WholeTraveler sample are less likely to live close to Bay Area Mass Transit (BART) stations compared to those without children, a finding consistent with a higher likelihood of moving to a more suburban environment when children are in the household. WholeTraveler results showed that owning more vehicles and moving to a new residential location when having children results in long-term impacts on mode use, because increased vehicle dependence tends to be permanent. In addition, other underlying characteristics of users can have implications for how much they are willing to rely on alternatives to private vehicles, such as shared modes like shared ride-hailing. For example, MDS researchers showed that introverts are less likely to currently use ride-hailing (either single-rider or pooled). This information can be used to assess the likelihood of outcomes, such as the projection of Arbib and Seba [2] and Johnson and Walker [3], of significantly reduced private vehicle ownership and primary reliance on automated ride-hailing fleets. The needs and preferences driving private vehicle dependence documented in MDS research (including personality characteristics, household management travel needs, and the presence of children) help to improve the understanding of how transportation decisions are made now and what may or may not change regarding these needs and preferences in the context of new mobility technologies and services.

Factors limiting use of public transit tend to be similar to factors limiting use of ride-hailing. Thus, if ride-hailing expands and becomes less expensive, it is likely to pull riders who otherwise do not have significant barriers to mass transit use (e.g., do not current have children and also live close to mass transit stations) away from mass transit, as these modes are currently tending to compete for a similar pool of riders. MDS research has shown that there is potential for ride-hailing to complement mass transit if priced low enough to enable increased mass transit access—but not so low as to make it more likely that people will take ride-hailing their full commute instead of coupling with transit. Simulations by MDS researchers using POLARIS have demonstrated that ride-hailing can be a meaningful mechanism to increase transit ridership if rides to or from transit stops are provided at low cost to incentivize the complementary relationships, but general ride-hailing costs are not changed.

Simulation studies by MDS researchers using BEAM have shown that ride-hailing can induce increased mass transit use and decrease system-wide energy use. However, empirical studies analyzing the real-world impact of ride-hailing also conducted by MDS researchers portray a less optimistic story, in part due to the behavior of ride-hailing drivers. Specifically, based on an analysis relating when ride-hailing first entered different urban areas to characteristics of those urban areas across the United States, MDS researchers found that, especially in urban areas with lower per-capita vehicle ownership and high rates of economic growth, ride-hailing entering the market has increased the number of vehicle registrations by 0.7% on average, though with notable heterogeneity between urban areas. The reason for this effect is not fully identified in the research to date, but one hypothesis is that ride-hailing induces drivers of the service, who otherwise may not own a car, to acquire one in order to drive for the ride-hailing company. Additionally, in the case of RideAustin, a ride-hailing service that had been in operation in Austin, Texas, drivers tend to commute relatively long distances (commute deadheading) and drive to reposition their vehicle between ride-hail trips (between-ride deadheading) enough to increase system-wide energy consumption by 41-90%, depending on assumptions about pooling and modal shift.

Increased e-commerce and delivery could also impact system wide energy use. A POLARIS simulation study of Chicago, using e-commerce engagement data from the WholeTraveler survey, showed that increasing per-capita weekly household deliveries from 0.5 to 1.4 results in a 33% decrease in transportation system-level energy consumption. This is consistent with WholeTraveler results that revealed, that in a typical week for survey respondents, a given delivery is about 1.7 times as likely to substitute for a shopping trip than not; of those that substitute, a given delivery is 300% more likely to substitute for a vehicle trip than a non-vehicle (walk, bike, public transit) trip. This overall pattern is relatively consistent in proportional terms across different product types studied (groceries; household items; clothing, shoes or accessories; and prepared meals), although the quantity of deliveries per household varies by product type.

These two results suggest that e-commerce could increase the energy efficiency of the transportation system as a whole. However, there is significant heterogeneity in the population regarding these use patterns. For WholeTraveler respondents, many households receive either all or none of their purchases via delivery for certain types of goods. This all or nothing pattern holds with respect to how often those deliveries substitute for or supplement shopping trips as well. For a large proportion of the sample, deliveries either fully substitute for (55% to 70% of households) or fully supplement (20% to 35% of households) shopping trips, depending on the product type (groceries; prepared meals; clothing, shoes or accessories; or household items). In analyzing this underlying heterogeneity, MDS researchers found that WholeTraveler respondents from households with high incomes are motivated to engage in e-commerce due to time savings and these households are more likely to order items for delivery than others. Households with children are similarly motivated by time-saving and convenience and are more likely to order household items and clothes via delivery relative to those without children. However, the time-saving motivation does not result in a higher number of trips replaced by delivery. In particular, households with children are more likely to have deliveries supplement existing shopping trips (rather than replace them) in the case of household items and prepared meals. And households with higher incomes are more likely to supplement trips for prepared meals with delivery, rather than replace those trips. This indicates that the marginal time-consuming activity replaced by delivery is more likely to be cooking at home, in the case of ordering prepared meal delivery, rather than a trip to a restaurant. These nuances underscore the importance of understanding the underlying motivations for certain types of behaviors to gain a full picture of how increased reliance on delivery will impact the transportation system.

Increased vehicle automation, especially use of privately-owned driverless vehicles, could increase system-wide vehicle miles traveled (VMT) in part because automation could enable passengers to engage in other activities while travelling which could make people more willing to travel farther. Value of travel time (VOTT) is the key parameter related to this effect. MDS research underscored the fact that estimates of VOTT vary widely by study, data source, and across subpopulations and contexts. No clear, systematic understanding of what is underlying this variation exists. This lack of understanding remains an important gap. MDS researchers used the POLARIS agent-based model to demonstrate that VMT, congestion, and energy outcomes are highly sensitive to VOTT. They also identified some trends with regard to VOTT impacts. For example, a Chicago-based POLARIS simulation demonstrated that individuals living in downtown and other urban core areas already have high accessibility to large numbers of work and recreational activities and do not tend to engage in substantial extra travel regardless of VOTT changes. This suggests that, if people have access to what they need, driverless vehicles may have no impact on their travel, implying that there may be an optimal level of accessibility in the system.

People make choices based on constraints, needs, and preferences that differ across the population and can depend on fundamental choices regarding lifestyle, values, and identity. As people progress through different phases of their lifecycles, their values and goals may evolve in response to life choices, such as attending school, forming careers, finding a partner, or having children. The solutions people adopt to achieve their goals also evolve over their lifetime, and the adoption of emerging technologies and services depends on whether they contribute to those solutions. These adoption trends shape the transportation system, with impacts on access to technologies and services, population mobility patterns, and system energy intensity and performance. With results such as those summarized here, MDS Pillar filled gaps in existing knowledge about how lifecycle patterns change over time; how these changes influence transportation-relevant choices such as where people live, whether or not they own a car, what modes they use, how they shop, and how they engage in shopping travel; and how the emergence and expansion of innovative technologies and services will affect these patterns. The objective was to study how underlying preferences, needs, and contextual factors might constrain or hasten future transportation system scenarios.

While research conducted by the MDS Pillar contributed to filling important gaps, the above-summarized results identified remaining research needs. Several key remaining gaps and recommendations for future research are summarized here.

First, the transportation system continues to diversify and the nature of innovations continues to expand. New services and business models have emerged since the beginning of SMART Mobility that need to be incorporated into analyses by researchers going forward, including micro-mobility services (dockless shared e-scooter and bike services, etc.). These services are likely to complicate the already nuanced relationship between emerging modes, including ride-hailing services, with conventional travel modes, and in particular with public transit. In addition, new e-commerce service models continue to emerge, including subscription services where items are sent automatically and unwanted items can be returned, for example. These new services continue to complicate the relationship between household shopping travel and e-commerce delivery. Taken together, increased e-commerce and the expansion and diversification of ride-hailing and micro-mobility service models mean that the flow of traffic in urban centers is becoming more complex. There is increased competition for curb space, as delivery vehicles and ride-hailing vehicles pull to the curb for short stops and e-scooters and bicycles often attempt to use those same spaces as they traverse alongside vehicle traffic. More traditional modes such as buses are being directly affected by this dynamic, as is the overall flow of traffic. These interactions and the behavioral factors underpinning them, as well as behavioral responses to them, are not well understood.

Second, as has been summarized in results from MDS research, assumptions regarding VOTT greatly affect simulation model results of transportation behavior. However, the nature of the heterogeneity in this parameter across individuals, within individuals across time and context, and interacting with other constraints such as demands on time outside of travel at work, home, or elsewhere, is not well understood. There is a significant need to better understand this variation to better model the impact of vehicle automation or alternative mode options.

Third, related to the concept of constraints on time use imposed by context, the lifecycle work conducted by MDS researchers made significant progress addressing gaps in the literature regarding the dynamics in transportation choices over lifecycle events. This work lays out a foundation that can be built on by the research community going forward. Building off of the work focused on mode use and vehicle ownership by MDS, a better connection needs to be made between lifecycle patterns, destination and residence location choice and the timing of those choices in the lifecycle, and dynamic changes in income. In addition, integrating the rich heterogeneity across the population articulated by these results into micro-simulation models with diverse agents can contribute to a better understanding of the distribution of outcomes across the population. In particular, are the constraints or choices made by certain subsets of the population imposing significant negative or positive externalities on other subsets of the population through transportation system dynamics?

Fourth, this latter point is related to a broader need for more focus on equity and access to transportation services and innovations by underserved communities. The WholeTraveler survey, for example, tended to have less representation of lower income and lower educated communities relative to the San Francisco Bay Area populations. Future work should include a more concerted focus than what MDS was able to accomplish to this point on those with lower incomes, those from disadvantaged communities and regions, and those with varied work and transportation needs (such as those in service sectors who travel to multiple work locations in a day, for example).

References

[1] T. S. Stephens, J. Gonder, Y. Chen, Z. Lin, C. Liu, and D. Gohlke, "Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles," *Tech. Rep. NREL/TP-5400-67216*, 2016.

[2] J. Arbib and T. Seba, "Rethinking Transportation 2020-2030: The Disruption of Transportation and the Collapse of the Internal-Combustion Vehicle and Oil Industries," *RethinkX Sector Disruption Report*, 2017. .

[3] C. Johnson and J. Walker, "Peak car ownership," *Rocky Mountain Institute*, 2016. .

[4] P. Gao, H.-W. Kaas, D. Mohr, and D. Wee, "Disruptive Trends That Will Transform the Auto Industry," *McKinsey & Company*, 2016. .

[5] R. Belk, "You are what you can access: Sharing and collaborative consumption online," *J. Bus. Res.*, vol. 67, no. 8, pp. 1595–1600, 2014, doi: 10.1016/j.jbusres.2013.10.001.

[6] N. C. McDonald, "Are millennials really the 'go-Nowhere' Generation?," *J. Am. Plan. Assoc.*, vol. 81, no. 2, pp. 90–103, 2015, doi: 10.1080/01944363.2015.1057196.

[7] L. Rayle, D. Dai, N. Chan, R. Cervero, and S. Shaheen, "Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco," *Transp. Policy*, vol. 45, pp. 168–178, 2016, doi: 10.1016/j.tranpol.2015.10.004.

[8] A. Smith, "Shared, collaborative and on demand: The new digital economy," *Pew Research Center*, 2016. .

[9] N. D. Caperello and K. S. Kurani, "Households' Stories of Their Encounters With a Plug-In Hybrid Electric Vehicle," *Environ. Behav.*, vol. 44, no. 4, pp. 493–508, Jul. 2012, doi: 10.1177/0013916511402057.

[10] A. Nayum, C. A. Klockner, and M. Mehmetoglu, "Comparison of socio-psychological characteristics of conventional and battery electric car buyers," *Travel Behav. Soc.*, vol. 3, pp. 8–20, Jan. 2016, doi: 10.1016/j.tbs.2015.03.005.

[11] P. Plötz, U. Schneider, J. Globisch, and E. Duetschke, "Who will buy electric vehicles? Identifying early adopters in Germany," *Transp. Res. Part A Policy Pract.*, vol. 67, pp. 96–109, Sep. 2014, doi: 10.1016/j.tra.2014.06.006.

[12] M. Ziefle, S. Beul-Leusmann, K. Kasugai, and M. Schwalm, "Public Perception and Acceptance of Electric Vehicles: Exploring Users' Perceived Benefits and Drawbacks," in *Design, User Experience, and Usability: User Experience for Every Day Life Applications and Services, PT III*, 2014, vol. 8519, pp. 628–639.

[13] P. Bansal, K. M. Kockelman, and A. Singh, "Assessing public opinions of and interest in new vehicle technologies: An Austin perspective," *Transp. Res. Part C Emerg. Technol.*, vol. 67, pp. 1–14, 2016, doi: 10.1016/j.trc.2016.01.019.

[14] W. Payre, J. Cestac, and P. Delhomme, "Intention to use a fully automated car: Attitudes and a priori acceptability," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 27, pp. 252–263, 2014, doi: 10.1016/j.trf.2014.04.009.

[15] H. Abraham *et al.*, "Autonomous Vehicles, Trust, and Driving Alternatives: A survey of consumer preferences," *Massachusetts Inst. Technol. AgeLab White Pap. 2016-6*, 2016.

[16] R. Krueger, T. H. Rashidi, and J. M. Rose, "Preferences for shared autonomous vehicles," *Transp. Res. PART C Emerg. Technol.*, vol. 69, pp. 343–355, Aug. 2016, doi: 10.1016/j.trc.2016.06.015.

[17] V. Van Acker, P. Goodwin, and F. Witlox, “Key research themes on travel behavior, lifestyle, and sustainable urban mobility,” *Int. J. Sustain. Transp.*, vol. 10, no. 1, pp. 25–32, Jan. 2016, doi: 10.1080/15568318.2013.821003.

[18] M. Ben-Akiva, “Structure of passenger travel demand models,” *Transp. Res. Rec.*, vol. 149, pp. 129–142, 1974.

[19] I. Salomon, “Life style as a factor in explaining travel behavior,” Doctoral Dissertation from Massachusetts Institute of Technology, 1980.

[20] I. Salomon and M. Ben-Akiva, “The use of the life-style concept in travel demand models.,” *Environ. Plan. A Plan. A*, vol. 15, no. 5, pp. 623–638, 1983, doi: 10.1068/a150623.

[21] J. Cramer and A. B. Krueger, “Disruptive change in the taxi business: The case of uber,” *Am. Econ. Rev.*, vol. 106, no. 5, pp. 177–182, 2016, doi: 10.1257/aer.p20161002.

[22] K. A. Small, “Valuation of travel time,” *Econ. Transp.*, vol. 1, no. 1–2, pp. 2–14, Dec. 2012, doi: 10.1016/j.ecotra.2012.09.002.

[23] C. A. Lave, “A behavioral approach to modal split forecasting,” *Transp. Res.*, vol. 3, no. 4, 1969, doi: 10.1016/0041-1647(69)90041-0.

[24] N. Saxena, T. H. Rashidi, V. V Dixit, and S. T. Waller, “Influence of Number of Stop-&-Gos on the Route Choice Behavior of Car Drivers in Urban Road Networks (No. 17-06690),” 2017.

[25] L. I. Rizzi, J. P. Limonado, and S. S. C. Steimetz, “The impact of traffic images on travel time valuation in stated-preference choice experiments,” *Transportmetrica*, vol. 8, no. 6, pp. 427–442, 2012, doi: 10.1080/18128602.2010.551524.

[26] W. Vickrey, “Pricing, metering, and efficiently using urban transportation facilities,” *Highw. Res. Rec.*, vol. 476, pp. 36–48, 1973.

[27] K. E. Train, *Discrete choice methods with simulation*. Cambridge University Press, 2009.

[28] D. J. Fagnant and K. Kockelman, “Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations,” *Transp. Res. Part A Policy Pract.*, vol. 77, pp. 167–181, 2015, doi: 10.1016/j.tra.2015.04.003.

[29] R. Cervero, “Induced Demand : An Urban and Metropolitan Perspective,” 2001.

[30] B. Rammstedt and O. P. John, “Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German,” *J. Res. Pers.*, vol. 41, no. 1, pp. 203–212, 2007, doi: 10.1016/j.jrp.2006.02.001.

[31] R. Bostic, R. J. Herrnstein, and R. D. Luce, “The effect on the preference-reversal phenomenon of using choice indifferences,” *J. Econ. Behav. Organ.*, vol. 13, no. 2, pp. 193–212, 1990, doi: 10.1016/0167-2681(90)90086-S.

[32] C. A. Holt and S. K. Laury, “Risk aversion and incentive effects,” *Am. Econ. Rev.*, vol. 92, no. 5, pp. 1644–1655, 2002.

[33] R. E. Dunlap, K. D. Van Liere, A. G. Mertig, and R. E. Jones, “Measuring endorsement of the new ecological paradigm: A revised NEP scale,” *J. Soc. Issues*, vol. 56, no. 3, pp. 425–442, 2000, doi: 10.1111/0022-4537.00176.

[34] S. Beige and K. W. Axhausen, “Interdependencies between turning points in life and long-term mobility

decisions," *Transportation (Amst).*, vol. 39, no. 4, pp. 857–872, 2012, doi: 10.1007/s11116-012-9404-y.

[35] A. T. M. Oakil, D. Ettema, T. Arentze, and H. Timmermans, "Changing household car ownership level and life cycle events: An action in anticipation or an action on occurrence," *Transportation (Amst).*, vol. 41, no. 4, pp. 889–904, 2014, doi: 10.1007/s11116-013-9507-0.

[36] J. Zhang, B. Yu, and M. Chikaraishi, "Interdependences between household residential and car ownership behavior: a life history analysis," *J. Transp. Geogr.*, vol. 34, pp. 165–174, Jan. 2014, doi: 10.1016/j.jtrangeo.2013.12.008.

[37] R. Schoenduwe, M. G. Mueller, A. Peters, and M. Lanzendorf, "Analysing mobility biographies with the life course calendar: A retrospective survey methodology for longitudinal data collection," *J. Transp. Geogr.*, vol. 42, pp. 98–109, Jan. 2015, doi: 10.1016/j.jtrangeo.2014.12.001.

[38] M. Fowler, T. Cherry, T. Adler, M. Bradley, and A. Richard, "2015–2017 California Vehicle Survey Consultant Report. CEC-200-2018-006," *California Energy Commission*, 2018. .

[39] "Kelley Blue Book: Car Reviews," *Kelley Blue Book*, 2019. .

[40] "Consumer Reports: Cars," *Consumer Reports*, 2019. .

[41] J. Auld, M. Hope, H. Ley, V. Sokolov, B. Xu, and K. Zhang, "POLARIS: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations," *Transp. Res. Part C Emerg. Technol.*, vol. 64, pp. 101–116, 2016, doi: 10.1016/j.trc.2015.07.017.

[42] G. F. Newell, "A simplified theory of kinematic waves in highway traffic, part I: General theory," *Transp. Res. Part B Methodol.*, vol. 27, no. 4, pp. 281–287, 1993, doi: 10.1016/0191-2615(93)90038-C.

[43] Y. Zhao and K. M. Kockelman, "Anticipating the Regional Impacts of Connected and Automated Vehicle Travel in Austin, Texas," *J. Urban Plan. Dev.*, vol. 144, no. 4, p. 04018032, Dec. 2018, doi: 10.1061/(ASCE)UP.1943-5444.0000463.

[44] R. Shabanpour, N. Golshani, A. Shamshiripour, and A. K. Mohammadian, "Eliciting preferences for adoption of fully automated vehicles using best-worst analysis," *Transp. Res. Part C Emerg. Technol.*, vol. 93, pp. 463–478, Aug. 2018, doi: 10.1016/j.trc.2018.06.014.

[45] N. Golshani, R. Shabanpour, J. Auld, and A. K. Mohammadian, "Activity start time and duration: incorporating regret theory into joint discrete–continuous models," *Transp. A Transp. Sci.*, vol. 14, no. 9, pp. 809–827, 2018, doi: 10.1080/23249935.2018.1440261.

[46] Ö. Verbas, J. Auld, H. Ley, R. Weimer, and S. Driscoll, "Time-Dependent Intermodal A* Algorithm: Methodology and Implementation on a Large-Scale Network," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2672, no. 47, pp. 219–230, Dec. 2018, doi: 10.1177/0361198118796402.

[47] M. Jayanmardi, J. Auld, and O. Verbas, "Intra-Household Fully Automated Vehicles Assignment Problem Model Development and Case Study," 2019.

[48] A. Shamshiripour, R. Shabanpour, N. Golshani, J. Auld, and A. Mohammadian, "A flexible activity scheduling conflict resolution framework," in *Mapping the Travel Behavior Genome*, K. G. Goulias and A. W. Davis, Eds. Elsevier, 2019, pp. 299–322.

[49] "The MATSim Book, MATSim.org," *Matsim.org*, 2018. .

[50] R. A. Waraich, D. Charypar, M. Balmer, and K. W. Axhausen, "Performance improvements for large-scale traffic simulation in MATSim," in *Computational Approaches for Urban Environments*, Springer International Publishing, 2015, pp. 211–233.

[51] D. Delling, T. Pajor, and R. F. Werneck, “Round-based public transit routing,” *Transp. Sci.*, vol. 49, no. 3, pp. 591–604, 2014, doi: 10.1287/trsc.2014.0534.

[52] M. W. Conway, A. Byrd, and M. Van Der Linden, “Evidence-based transit and land use sketch planning using interactive accessibility methods on combined schedule and headway-based networks,” *Transp. Res. Rec.*, vol. 2653, no. 1, pp. 45–53, 2017, doi: 10.3141/2653-06.

[53] S. Feigon and C. Murphy, “Shared mobility and the transformation of public transit TCRP J-11, Task 21,” *American Public Transportation Association*, 2016. .

[54] S. R. George and M. Zafar, “Electrifying the Ride-Sourcing Sector in California,” *California Public Utilities Commission*, 2018. .

[55] R. R. Clewlow and G. S. Mishra, “Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States Research Report – UCD-ITS-RR-17-07,” *University of California Davis, Institute of Transportation Studies*, 2017. .

[56] T. Wenzel, C. Rames, E. Kontou, and A. Henao, “Travel and energy implications of ridesourcing service in Austin, Texas,” *Transp. Res. Part D Transp. Environ.*, vol. 70, pp. 18–34, May 2019, doi: 10.1016/j.trd.2019.03.005.

[57] F. Alemi, G. Circella, S. Handy, and P. Mokhtarian, “What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California,” *Travel Behav. Soc.*, vol. 13, pp. 88–104, 2018, doi: 10.1016/j.tbs.2018.06.002.

[58] F. F. Dias, P. S. Lavieri, V. M. Garikapati, S. Astroza, R. M. Pendyala, and C. R. Bhat, “A behavioral choice model of the use of car-sharing and ride-sourcing services,” *Transportation (Amst).*, vol. 44, no. 6, pp. 1307–1323, 2017, doi: 10.1007/s11116-017-9797-8.

[59] F. Kooti, N. Djuric, M. Grbovic, V. Radosavljevic, L. M. Aiello, and K. Lerman, “Analyzing uber’s ride-sharing economy,” in *26th International World Wide Web Conference on World Wide Web Companion*, 2017, pp. 574–582, doi: 10.1145/3041021.3054194.

[60] R. Cervero, A. Golub, and B. Nee, “City CarShare longer-term travel demand and car ownership impacts,” *Transp. Res. Rec.*, vol. 1992, no. 1, pp. 70–80, 2007, doi: 10.3141/1992-09.

[61] M. Namazu and H. Dowlatabadi, “Vehicle ownership reduction: A comparison of one-way and two-way carsharing systems,” *Transp. Policy*, vol. 64, pp. 38–50, 2018, doi: 10.1016/j.tranpol.2017.11.001.

[62] C. J. Haboucha, R. Ishaq, and Y. Shiftan, “User preferences regarding autonomous vehicles,” *Transp. Res. Part C Emerg. Technol.*, vol. 78, pp. 37–49, 2017, doi: 10.1016/j.trc.2017.01.010.

[63] P. Bansal and K. M. Kockelman, “Are we ready to embrace connected and self-driving vehicles? A case study of Texans,” *Transportation (Amst).*, vol. 42, no. 2, pp. 641–675, 2018, doi: 10.1007/s11116-016-9745-z.

[64] J. H. M. Langbroek, J. P. Franklin, and Y. O. Susilo, “Electric vehicle users and their travel patterns in Greater Stockholm,” *Transp. Res. PART D Transp. Environ.*, vol. 52, no. A, pp. 98–111, May 2017, doi: 10.1016/j.trd.2017.02.015.

[65] C. A. Spurlock *et al.*, “Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area,” *Transp. Res. Part D Transp. Environ.*, vol. 71, pp. 283–301, 2019, doi: 10.1016/j.trd.2019.01.014.

[66] R. N. Buliung, R. Mitra, and G. Faulkner, “Active school transportation in the Greater Toronto Area, Canada: An exploration of trends in space and time (1986-2006),” *Prev. Med. (Baltim).*, vol. 48, no. 6, pp.

507–512, 2009, doi: 10.1016/j.ypmed.2009.03.001.

[67] G. E. J. Faulkner, R. N. Buliung, P. K. Flora, and C. Fusco, "Active school transport, physical activity levels and body weight of children and youth: A systematic review," *Prev. Med. (Baltim).*, vol. 48, no. 1, pp. 3–8, 2009, doi: 10.1016/j.ypmed.2008.10.017.

[68] A. Fyhri, R. Hjorthol, R. L. Mackett, T. N. Fotel, and M. Kyttä, "Children's active travel and independent mobility in four countries: Development, social contributing trends and measures," *Transp. Policy*, vol. 18, no. 5, pp. 703–710, 2011, doi: 10.1016/j.tranpol.2011.01.005.

[69] K. Larsen, J. Gilliland, P. Hess, P. Tucker, J. Irwin, and M. He, "The influence of the physical environment and sociodemographic characteristics on children's mode of travel to and from school," *Am. J. Public Health*, vol. 99, no. 3, pp. 520–526, 2009, doi: 10.2105/AJPH.2008.135319.

[70] N. C. McDonald, "Children's mode choice for the school trip: The role of distance and school location in walking to school," *Transportation (Amst).*, vol. 35, no. 1, pp. 90–103, 2007, doi: 10.1007/s11116-007-9135-7.

[71] T. E. McMillan, "The relative influence of urban form on a child's travel mode to school," *Transp. Res. Part A Policy Pract.*, vol. 41, no. 1, pp. 69–79, 2007, doi: 10.1016/j.tra.2006.05.011.

[72] Y. Sun, E. O. D. Waygood, K. Fukui, and R. Kitamura, "Built Environment or Household Life-Cycle Stages–-Which Explains Sustainable Travel More?," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2135, no. 1, pp. 123–129, Jan. 2009, doi: 10.3141/2135-15.

[73] E. O. D. Waygood, Y. Sun, and Y. O. Susilo, "Transportation carbon dioxide emissions by built environment and family lifecycle: Case study of the Osaka metropolitan area," *Transp. Res. Part D Transp. Environ.*, vol. 31, pp. 176–188, Aug. 2014, doi: 10.1016/j.trd.2014.06.001.

[74] E. Waygood, Y. Sun, and L. Letarte, "Active Travel by Built Environment and Lifecycle Stage: Case Study of Osaka Metropolitan Area," *Int. J. Environ. Res. Public Health*, vol. 12, no. 12, pp. 15900–15924, Dec. 2015, doi: 10.3390/ijerph121215027.

[75] L. McCarthy, A. Delbosc, G. Currie, and A. Molloy, "Factors influencing travel mode choice among families with young children (aged 0–4): a review of the literature," *Transp. Rev.*, vol. 37, no. 6, pp. 767–781, 2017, doi: 10.1080/01441647.2017.1354942.

[76] C. a Klöckner, "How single events change travel mode choice–a life span perspective," 2004.

[77] J. Prillwitz, S. Harms, and M. Lanzendorf, "Impact of life-course events on car ownership," *Transp. Res. Rec.*, vol. 1985, no. 1, pp. 71–77, 2006, doi: 10.3141/1985-08.

[78] T. Ryley, "Use of non-motorised modes and life stage in Edinburgh," *J. Transp. Geogr.*, vol. 14, no. 5, pp. 367–375, 2006, doi: 10.1016/j.jtrangeo.2005.10.001.

[79] J. Scheiner, "Gendered key events in the life course: Effects on changes in travel mode choice over time," *J. Transp. Geogr.*, vol. 37, pp. 47–60, 2014, doi: 10.1016/j.jtrangeo.2014.04.007.

[80] O. Taubman - Ben-Ari and A. Noy, "Does the transition to parenthood influence driving?," *Accid. Anal. Prev.*, vol. 43, no. 3, pp. 1022–1035, May 2011, doi: 10.1016/j.aap.2010.12.001.

[81] M. Lanzendorf, "Key Events and Their Effect on Mobility Biographies: The Case of Childbirth," *Int. J. Sustain. Transp.*, vol. 4, no. 5, pp. 272–292, 2010, doi: 10.1080/15568310903145188.

[82] A. T. McLaren, "Families and transportation: Moving towards multimodality and altermobility?," *J. Transp. Geogr.*, vol. 51, pp. 218–225, 2016, doi: 10.1016/j.jtrangeo.2016.01.006.

[83] T. Schwanen, “Car Use and Gender: The Case of Dual-Earner Families in Utrecht, The Netherlands,” in *Auto Motives*, K. Lucas, E. Blumenberg, and R. Weinberger, Eds. Bingley: Emerald Group Publishing Limited, 2011, pp. 151–171.

[84] F. J. Andrews, S. Rich, R. Stockdale, and J. Shelley, “Parents’ experiences of raising pre-school aged children in an outer-Melbourne growth corridor,” *Heal. Place*, vol. 27, pp. 220–228, 2014, doi: 10.1016/j.healthplace.2014.02.013.

[85] M. Caroli *et al.*, “Physical activity and play in kindergarten age children,” *Int. J. Pediatr. Obes.*, vol. 6, no. sup2, pp. 47–53, 2011, doi: 10.3109/17477166.2011.613671.

[86] L. Oxford and J. Pollock, “How actively do children travel to their pre-school setting?,” *J. Transp. Heal.*, vol. 2, no. 2, pp. 151–159, 2015, doi: 10.1016/j.jth.2015.02.002.

[87] J. Fritze, “You Might as Well Just Stay at Home: Young Mums and Transport in Victoria,” *Victorian Council of Social Services*, 2007. .

[88] T. M. McCray, “Delivering healthy babies: Transportation and healthcare access.,” *Plan. Pract. Res.*, vol. 15, no. 1–2, pp. 17–29, 2000.

[89] L. Price and B. Matthews, “Travel time as quality time: Parental attitudes to long distance travel with young children,” *J. Transp. Geogr.*, vol. 32, pp. 49–55, 2013, doi: 10.1016/j.jtrangeo.2013.08.001.

[90] O. Rubin, C. H. Mulder, and L. Bertolini, “The determinants of mode choice for family visits - evidence from Dutch panel data,” *J. Transp. Geogr.*, vol. 38, pp. 137–147, 2014, doi: 10.1016/j.jtrangeo.2014.06.004.

[91] L. Bostock, “Pathways of disadvantage? Walking as a mode of transport among low-income mothers,” *Heal. Soc. Care Community*, vol. 9, no. 1, pp. 11–18, 2001, doi: 10.1046/j.1365-2524.2001.00275.x.

[92] R. Dowling, “Cultures of mothering and car use in suburban Sydney: A preliminary investigation,” *Geoforum*, vol. 31, no. 3, pp. 345–353, 2000, doi: 10.1016/S0016-7185(99)00048-2.

[93] N. C. McDonald, “Exploratory analysis of children’s travel patterns,” *Transp. Res. Rec.*, vol. 1977, pp. 1–7, 2006.

[94] R. Dowling, “Parents, children and automobility: Trends, challenges and opportunities,” in *Handbook on Transport and Development*, R. Hickman, M. Givoni, and D. Banister, Eds. Cheltenham: Edward Elgar, 2015, pp. 526–538.

[95] H. Taniguchi, “The Timing of Childbearing and Women’s Wages,” *J. Marriage Fam.*, vol. 61, no. 4, p. 1008, Nov. 1999, doi: 10.2307/354020.

[96] T. J. Bungum, S. Clark, and B. Aguilar, “The Effect of an Active Transport to School Intervention at a Suburban Elementary School,” *Am. J. Heal. Educ.*, vol. 45, no. 4, pp. 205–209, 2014, doi: 10.1080/19325037.2014.916635.

[97] B. Verplanken and W. Wood, “Interventions to Break and Create Consumer Habits,” *J. Public Policy Mark.*, vol. 25, no. 1, pp. 90–103, Apr. 2006, doi: 10.1509/jppm.25.1.90.

[98] R. Kitamura, T. Yoshii, and T. Tamamoto, Eds., “The Expanding Sphere of Travel Behaviour Research: Selected Papers from the 11th International Conference on Travel Behaviour Research,” 2009.

[99] S. Beige and K. W. Axhausen, “The dynamics of commuting over the life course: Swiss experiences,” *Transp. Res. Part A Policy Pract.*, vol. 104, pp. 179–194, 2017, doi: 10.1016/j.tra.2017.01.015.

[100] Y. O. Susilo, C. Liu, and M. Börjesson, “The changes of activity-travel participation across gender, life-

cycle, and generations in Sweden over 30 years," *Transportation (Amst).*, vol. 46, no. 3, pp. 793–818, Jun. 2019, doi: 10.1007/s11116-018-9868-5.

[101] J. Zhang and V. Van Acker, "Life-oriented travel behavior research: An overview," *Transp. Res. Part A Policy Pract.*, vol. 104, pp. 167–178, Oct. 2017, doi: 10.1016/j.tra.2017.06.004.

[102] H. Rau and R. Manton, "Life events and mobility milestones: Advances in mobility biography theory and research," *J. Transp. Geogr.*, vol. 52, pp. 51–60, 2016, doi: 10.1016/j.jtrangeo.2016.02.010.

[103] G. Pollock, "Holistic trajectories: A study of combined employment, housing and family careers by using multiple-sequence analysis," *J. R. Stat. Soc. Ser. A Stat. Soc.*, vol. 170, no. 1, pp. 167–183, 2007, doi: 10.1111/j.1467-985X.2006.00450.x.

[104] "U.S. Census Bureau News: Quarterly Retail E-Commerce Sales 4th Quarter 2012 Publication CB13-24," *U.S. Census Bureau*, 2013. .

[105] "U.S. Census Bureau News: Quarterly Retail E-Commerce Sales 4th Quarter 2017 Publication CB18-21," *U.S. Census Bureau*, 2018. .

[106] Statista, "Number of Amazon Prime Members in the United States as of December 2018 (in Millions)," *Statista - The Statistics Portal*, 2019. .

[107] X. Cao, F. Douma, and F. Cleaveland, "Influence of E-Shopping on Shopping Travel Evidence from Minnesota's Twin Cities," *Transp. Res. Rec.*, no. 2157, pp. 147–154, 2010, doi: 10.3141/2157-18.

[108] Y. Zhou and X. C. Wang, "Explore the relationship between online shopping and shopping trips: An analysis with the 2009 NHTS data," *Transp. Res. Part A Policy Pract.*, vol. 70, pp. 1–9, Dec. 2014, doi: 10.1016/j.tra.2014.09.014.

[109] Y. Ding and H. Lu, "The interactions between online shopping and personal activity travel behavior: an analysis with a GPS-based activity travel diary," *Transportation (Amst).*, vol. 44, no. 2, pp. 311–324, Mar. 2017, doi: 10.1007/s11116-015-9639-5.

[110] R. J. Lee, I. N. Sener, P. L. Mokhtarian, and S. L. Handy, "Relationships between the online and in-store shopping frequency of Davis, California residents," *Transp. Res. Part A Policy Pract.*, vol. 100, pp. 40–52, Jun. 2017, doi: 10.1016/j.tra.2017.03.001.

[111] L. L. Sim and S. M. Koi, "Singapore's internet shoppers and their impact on traditional shopping patterns," *J. Retail. Consum. Serv.*, vol. 9, no. 2, pp. 115–124, 2002, doi: 10.1016/S0969-6989(01)00029-7.

[112] B. E. Tonn and A. Hemrick, "Impacts of the Use of E-Mail and the Internet on Personal Trip-Making Behavior," *Soc. Sci. Comput. Rev.*, vol. 22, pp. 270–280, 2004, doi: 10.1177/0894439303262581.

[113] J. W. J. Weltevreden and T. van Rietbergen, "E-shopping versus city centre shopping: The role of perceived city centre attractiveness," *Tijdschr. voor Econ. en Soc. Geogr.*, vol. 98, no. 1, pp. 68–85, 2007, doi: 10.1111/j.1467-9663.2007.00377.x.

[114] E. Suel and J. W. Polak, "Development of joint models for channel, store, and travel mode choice: Grocery shopping in London," *Transp. Res. Part A Policy Pract.*, vol. 99, pp. 147–162, May 2017, doi: 10.1016/j.tra.2017.03.009.

[115] M. P. Kwan, "Gender differences in space-time constraints," *Area*, vol. 32, no. 145–156, 2000, doi: 10.1111/j.1475-4762.2000.tb00125.x.

[116] C. E. Ferrell, "Home-Based Teleshopping and Shopping Travel: Where Do People Find the Time?," *Transp. Res. Rec.*, vol. 1926, no. 1, pp. 212–223, Jan. 2005, doi: 10.1177/0361198105192600125.

[117] C. A. Spurlock, A. Todd-Blick, G. Wong-Parodi, and V. Walker, “Children, Income, and the Impact of Home Delivery on Household Shopping Trips,” *Transp. Res. Rec. 0361198120935113*, 2020.

[118] J. C. Darian, “In-home shopping: Are there consumer segments?,” *J. Retail.*, vol. 63, no. 2, pp. 163–186, 1987.

[119] P. Harris, F. Dall’Olmo Riley, D. Riley, and C. Hand, “Online and store patronage: a typology of grocery shoppers,” *Int. J. Retail Distrib. Manag.*, vol. 45, no. 4, pp. 419–445, Jan. 2017, doi: 10.1108/IJRDM-06-2016-0103.

[120] F. Sabatini, “Can a click buy a little happiness? The impact of business-to-consumer e-commerce on subjective well-being (12/2011),” *Economics and Econometrics Research Institute (EERI) Research Paper Series*, 2011. .

[121] P. K. Chintagunta, J. Chu, and J. Cebollada, “Quantifying Transaction Costs in Online/Off-line Grocery Channel Choice,” *Mark. Sci.*, vol. 31, no. 1, pp. 96–114, Dec. 2012, doi: 10.1287/mksc.1110.0678.

[122] L. A. Pervin and O. P. John, Eds., *Handbook of Personality: Theory and Research*. Elsevier, 1999.

[123] S. Skippon and M. Garwood, “Responses to battery electric vehicles: UK consumer attitudes and attributions of symbolic meaning following direct experience to reduce psychological distance,” *Transp. Res. Part D Transp. Environ.*, vol. 16, no. 7, pp. 525–531, Oct. 2011, doi: 10.1016/j.trd.2011.05.005.

[124] S. Roy, “The impacts of gender, personality and previous use on attitude towards the sharing economy and future use of the services,” Doctoral Dissertation from Fresno State University, 2016.

[125] A. Backer-Grøndahl, A. Fyhri, P. Ulleberg, and A. H. Amundsen, “Accidents and unpleasant incidents: Worry in transport and prediction of travel behavior,” *Risk Anal.*, vol. 29, no. 9, pp. 1217–1226, 2009, doi: 10.1111/j.1539-6924.2009.01266.x.

[126] K. Zucchi, “What Drives Consumer Demand for Tesla?,” *Investopia.com*, 2015. .

[127] G. Charness, U. Gneezy, and M. A. Kuhn, “Experimental methods: Between-subject and within-subject design,” *J. Econ. Behav. Organ.*, vol. 81, no. 1, pp. 1–8, 2012, doi: 10.1016/j.jebo.2011.08.009.

[128] N. D. Caperello, J. Tyree-Hageman, and K. S. Kurani, “Engendering the Future of Electric Vehicles: Conversations with Men and Women (Research Report – UCD-ITS-WP-14-02),” *University of California, Davis Institute of Transportation Studies*, 2014. .

[129] A. K. Mohammadian, “Gender Differences in Automobile Choice Behavior,” 2014.

[130] S. Carley, R. M. Krause, B. W. Lane, and J. D. Graham, “Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites,” *Transp. Res. Part D Transp. Environ.*, vol. 18, pp. 39–45, 2013, doi: 10.1016/j.trd.2012.09.007.

[131] B. D. Taylor, K. Ralph, and M. Smart, “What Explains the Gender Gap in Schlepping? Testing Various Explanations for Gender Differences in Household-Serving Travel,” *Soc. Sci. Q.*, vol. 96, no. 5, pp. 1493–1510, Nov. 2015, doi: 10.1111/ssqu.12203.

[132] Y. Fan, “Household structure and gender differences in travel time: spouse/partner presence, parenthood, and breadwinner status,” *Transportation (Amst).*, vol. 44, pp. 271–291, 2017.

[133] M. Shirgaokar and K. Lanyi-Bennett, “I’ll have to drive there: How daily time constraints impact women’s car use differently than men’s,” *Transportation (Amst).*, pp. 1–28, Jan. 2019, doi: 10.1007/s11116-018-9969-1.

[134] Z. Wadud, D. MacKenzie, and P. Leiby, "Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles," *Transp. Res. Part A Policy Pract.*, vol. 86, pp. 1–18, Apr. 2016, doi: 10.1016/j.tra.2015.12.001.

[135] G. H. de Almeida Correia, E. Looff, S. van Cranenburgh, M. Snelder, and B. van Arem, "On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey," *Transp. Res. Part A Policy Pract.*, vol. 119, pp. 359–382, 2019, doi: 10.1016/j.tra.2018.11.016.

[136] B. Pudāne, E. J. E. Molin, T. A. Arentze, Y. Maknoon, and C. G. Chorus, "A Time-use Model for the Automated Vehicle-era," *Transp. Res. Part C Emerg. Technol.*, vol. 93, pp. 102–114, 2018, doi: 10.1016/j.trc.2018.05.022.

[137] G. Lyons, "Viewpoint: Transport's digital age transition," *J. Transp. Land Use*, vol. 8, no. 2, pp. 1–19, 2015, doi: 10.5198/jtlu.2015.751.

[138] P. L. Mokhtarian and I. Salomon, "How derived is the demand for travel? Some conceptual and measurement considerations," *Transp. Res. Part A Policy Pract.*, vol. 35, no. 8, pp. 695–719, 2001, doi: 10.1016/S0965-8564(00)00013-6.

[139] R. Krueger, T. H. Rashidi, and J. Auld, "Preferences for travel-based multitasking: Evidence from a survey among public transit users in the Chicago metropolitan area," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 65, pp. 334–343, 2019, doi: 10.1016/j.trf.2019.08.004.

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