

Adoption of Partially Automated Vehicle Technology Features and Impacts on Vehicle Miles of Travel (VMT)

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ABSTRACT

In this paper, we examine vehicle owners' adoption of five different types of partially automated features (PAFs); lane keeping system, backup camera (BUC), adaptive cruise control (ACC), automatic braking system (ABS), and blind spot monitoring; as well as PAF effects on vehicle miles of travel (VMT). The joint modeling of PAF adoption and VMT is achieved using both individual demographic characteristics as well as psycho-social characteristics. A Generalized Heterogeneous Data Model (GHDM) is estimated, which controls for possible self-selection effects in PAF adoption based on VMT, and thus is able to provide "true" PAF effects on VMT. Our analysis specifically indicates that ignoring this self-selection can lead to a significant underestimation of the VMT increase due to PAF adoption. The results also indicate that women and older individuals (65 years or older) appear to be more inclined to invest in assistive PAFs, because of a perception that these assistive features still leave the human driver in control. However, women are less likely than men to invest in the more active ABS PAF because of heightened safety concerns with technology. In terms of PAF effects on VMT, PAFs focusing on lateral movement assistance appear to have a smaller VMT effect than those that serve longitudinal movement assistance. The highest estimated VMT change of 2,462 miles (13.8% change) is for the case when the package of BUC, ACC, and ABS is installed for middle-aged men. The highest percentage VMT change (40%), though, is for the same package of BUC, ACC, and ABS for older women. Overall, there are considerable variations in VMT impact across demographic groupings, suggesting that a single aggregate percentage improvement in safety benefits may suffer from the well-known ecological fallacy.

Keywords: Partially automated vehicles, vehicle automation, safety offsets, vehicle miles of travel (VMT), psycho-social constructs.

1. INTRODUCTION

Automated vehicles (AVs) are likely to alter individual activity-travel behavior and mobility patterns, thanks to technologies that, in some future, will not require the human to pay attention to the road. However, while fully automated vehicles (or FAVs; that is, vehicles that do not need any human intervention in the driving task) were hailed as the wave of the very immediate future even five years back, such aggressive predictions of the availability and use of FAVs have simply not materialized. Thus, investigating the potential activity-travel behavior impacts of FAVs (designated as Level 4/5 automation on the Society of Automotive Engineers or SAE scale; see SAE, 2018) is typically undertaken through stated preference or SP surveys (that is, asking individuals how they may change their mobility patterns in a hypothetical environment with a Level 4/5 vehicle). The use of such SP surveys may be defended based on the notion that attitudes and stated intentions about the use of a new product do correlate with future actual behavioral action. Indeed, studies in the information sciences literature (see, for example, Leung et al., 2018 and Marikyan et al., 2019) point to the value of prediction models of future behavioral action based on earlier stated preferences and intentions, a concept that also has strong support from the Theory of Planned Behavior (TPB; Ajzen, 1991) and the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh and Davis, 2000). At the same time, there have been legitimate concerns raised about the level of ecological validity and reliability of stated responses to technologies that may still feel to many as “rocket science”, as in the case of FAVs. After all, FAVs continue to remain abstract and *psychologically distant*, and can conjure up different images for different people.

While the stated timeline for the introduction of FAVs has now been pushed back, there has been considerable progress in testing, refining, standardizing, and implementing lower levels (SAE levels 0, 1, and 2) of automated technology in vehicles. SAE Level 0 (or no automation) corresponds to the driver controlling all aspects of driving, though vehicles with Level 0 may be equipped with warning and related convenience systems, such as backup camera or lane departure warning. SAE Level 1 (or driver assistance) automation corresponds to a vehicle being able to “control steering or acceleration/deceleration using information from the external environment”, while SAE Level 2 (or partial automation) corresponds to a vehicle being able to “control both steering and acceleration/deceleration using information from the external environment”. Basically, Levels 0, 1, and 2 automation features represent driver support or assistance features, where the human driver still has full responsibility for driving. Examples of SAE Level 1 automation include adaptive cruise control or lane keeping, while an example of SAE Level 2 automation would be a vehicle that not only has adaptive cruise control, but also hands-free lane changing and self-parking capabilities. Level 2 automation is the highest level of automation in vehicles on the road today, and include technology packages such as the Tesla Autopilot, Cadillac Super Cruise, Mercedes-Benz Drive Pilot, and Volvo Pilot Assist. For ease in presentation, in this paper, we will refer to Level 0, 1, and 2 automation together as partial automation, and vehicles with partial automation as partially automated vehicles or PAVs. SAE Level 3 automation corresponds to the vehicle being able to “control all driving tasks and monitoring the environment”, with the driver still needing to stay alert all the time and being readily available to

back up when called upon (also referred to as conditional automation). Level 3 automation was available as the *Traffic Jam Pilot* in the Audi A8, but was cancelled in 2019 due to legal considerations. Even so, Audi and other companies such as Hyundai Motor Co., Kia Motors Corp., BMW, and Mercedes-Benz hope to have Level 3 technology (basically, a hands-off, legs-off, eyes-off, but brains-on situation) on the roads within a span of a couple of years or so. However, the highest two levels of SAE automation -- Levels 4 and 5, or FAVs -- corresponding to high/full automation (that is, “brains-off” too from the standpoint of the driver) are *temporally distant* (7-10 years from now or well beyond from a marketplace availability standpoint; IEEE, 2020).¹

The *psychological* and *temporal* distantness of FAVs, as just discussed above, suggest that there is value in examining activity-travel behavior responses to the currently existing (and, therefore, psychologically and temporally “there right now”) situation of PAVs, both in terms of enhanced reliability/validity of findings as well as the more practical issue of understanding activity-travel behavior impacts in the short-to-medium term future. Indeed, in the latter context, most households will go through at least two vehicle turnover events before FAVs may become available for purchase at the marketplace, given that households, on average, purchase a new vehicle every six years (Demuro, 2019). This is likely to have the result of further delaying any substantial FAV penetration in household vehicle holdings to well beyond a decade (even if FAVs become available in the marketplace before then). At the same time, during new car purchase occasions in the coming decade, families are likely to increasingly embrace affordable PAV safety features, and upgrade to the most up-to-date PAV convenience technology as part of their dashboard, entertainment system, navigation system, and engine or software capability. Even if families are hesitant to pay up for new PAV features, safety regulations will make at least some PAV features standard for new vehicles, as in the case of a federal law requiring backup cameras in all new vehicles after 2018 (Bomey, 2018).

The research in this paper is motivated by the discussion above. Specifically, there are two main objectives of our effort. The first is to examine the factors that affect the uptake of existing partial automation features (PAFs). After all, the rate at which PAFs penetrate the market depends on customer preferences. To effectively forecast and plan for the adoption and penetration of these technologies and options by consumers, a greater understanding of consumer preferences for PAFs is needed. The second is to investigate the impact of PAFs on vehicle miles of travel (VMT). Such an analysis is important to forecast travel demand in the short-to-medium future, especially as consumers purchase new and progressively higher levels of automation in their next purchased vehicle. At the same time, because of the potentially higher reliability through actual observations of VMT change in response to PAFs, an investigation of PAF effects on VMT can also provide

¹ The different levels of automation and the types of automated features have their own set of benefits and drawbacks. For example, Cicchino (2018a) found a decrease in rates of fatal crashes by 86% in PAVs with lane-keeping technology, while Winkle (2016) suggests that there is likely to be a drop of 27% in the total number of injuries due to the presence of any driver assistance system. On the other hand, Hardman et al. (2021) explain that, due to the potential for PAVs to increase VMT, there are likely to be negative implications for the U.S.’s goals to reduce greenhouse emissions. A detailed discussion of the benefits and drawbacks of automated features and automation levels is beyond the scope of this current study.

added insights on how FAVs may impact VMT in a longer-term future. As importantly, it is critical to enjoin the first analysis of PAF adoption with the second analysis of VMT effects, to account for possible self-selection effects. That is, to estimate the “true” effects of PAFs on VMT, the analyst needs to control for the potential endogeneity of PAF choice when assessing the effect of PAF choices on VMT, because people who may want to drive more (higher VMT) may be more likely to invest in PAFs in the first place, or, alternatively, people who currently drive less (lower VMT) may be those who are intrinsically safety conscious and thus are the ones more likely to invest in PAFs. In this paper, we formulate and estimate a joint model of PAF adoption and VMT. Our model employs individual and household socio-demographics, as well as psycho-social variables (in the form of latent psychological constructs), as determinant variables. The study uses data from a 2019 Austin-based survey on emerging technology and mobility service adoption and use.

The rest of this paper is organized as follows. Section 2 provides a brief overview of the PAFs considered as well as the importance of analyzing PAF effects on VMT, along with associated literature and a positioning of the current study. Section 3 describes the data collection design, sample characteristics and the modeling methodology. Section 4 presents the model results and goodness of fit measures. Section 5 discusses policy and safety implications. Finally, Section 6 concludes the paper with a summary discussion of the important findings, along with an identification of future research directions.

2. PA FEATURES AND VMT

2.1. PA Features (PAFs)

The five PAFs considered in this study are: (1) lane keeping system (LKS), (2) backup (rear-view) camera (BUC), (3) adaptive cruise control (ACC), (4) automatic braking system (ABS), and (5) blind spot monitoring (BSM).² The survey asked the respondent to identify the vehicle most often used by the respondent (hereafter referred to as the individual’s “primary vehicle”), and solicited information from the respondent on whether each of the five PAFs above were available or not in the vehicle. These responses were binary (yes/no), leading to five binary choices for the full set of PAFs.

Over the past decade, there has been an explosive body of literature devoted to the study of awareness levels of, attitudes toward, and adoption and use of FAVs. Some recent illustrative examples, almost exclusively based on stated preference surveys (but occasionally also based on exposure to simulated journeys in a virtual reality FAV), include Ghasri and Vij, 2021, Sharma and Misra, 2020, Xiao et al., 2020, Asmussen et al., 2020, Voinescu et al., 2020, Rahimi et al., 2020, Asgari and Jin, 2019, Spurlock et al., 2019, Jiang et al., 2019, Souris et al., 2019, Sweet and Laidlaw, 2020, Sener et al., 2019, Berliner et al., 2019, Hardman et al., 2019, Charness et al., 2018,

² The PAFs selected and included in the survey were based on ensuring adequate penetration and familiarity of the PAF in the consumer vehicle market, as well as the distinctiveness of each PAF in terms of the functional assistance offered. Note that the five PAFs listed here are the five most common PAFs in vehicles today, with Back-up Camera (BUC) now being standard in all vehicle models, and the other four PAFs now available in at least 80% of new vehicle models in each of the midsize, large, and SUV vehicle segments (see AAA, 2019).

Leung et al., 2018, Nair et al., 2018, Liljamo, 2018, and Lavieri et al., 2017a. Gkartzonikas and Gkritza, 2019 and Narayanan et al., 2020 are two recent sources for reviews of such studies. As indicated earlier, while these studies do provide important insights, their reliability/validity may be somewhat compromised because of the psychological and temporal distantness of FAVs.

In contrast to the substantial literature on FAV adoption and use, there is a surprising dearth of studies on the adoption and use of PAFs, even though currently available revealed preference behavioral choices regarding the choice of PAFs can provide reliable insights on those who are likely to embrace (as opposed to not embrace) current and future automation. Four studies focusing on consumer preferences and adoption of PAFs are Wali et al. (2021), Abraham et al. (2017), Shin et al. (2015), and Owens et al. (2015). These are briefly discussed in turn in the next four paragraphs.

The study by Wali et al. (2021) analyzes how consumer preferences for partially (level 3 or 4 connected) automated vehicles and FAVs are impacted by different vehicle attributes, electric vehicle ownership, safety concerns and sustainable travel behavior. For the analysis, a joint bivariate ordered discrete outcome modeling framework for PAV and FAV preferences is used to accommodate possible jointness, while also recognizing preference heterogeneity at household and regional levels. However, this study does not differentiate between different types of PAFs and is limited in the nature of psycho-social motivational factors considered. It also investigates higher levels of partial automation along with full automation, using questions based on stated intentions for adoption rather than revealed preferences.

The study by Abraham et al. (2017) reviews the extent to which consumers are happy with the technology in their current vehicle, evaluates how they have learned to use the advancing technology they currently have, and if they are willing to upgrade to more advanced autonomous technology in the future. As in the Wali et al. study, the Abraham et al. study also does not identify the specific partial automation technologies existing in the current vehicle owned, and so is unable to analyze the differences among individuals in actual PAF adoption. An important result from the Abraham et al. (2017) study, though, is that customers feel most comfortable using safety-oriented technologies (safety from crashes) relative to speed control or steering-oriented (such as lane keeping) automation technologies.

Shin et al. (2015) examine consumer preferences for PAFs. As these options had not yet made their way into the marketplace in a significant way at the time this study was conducted, a stated preference survey is undertaken to elicit consumer preferences. Shin et al.'s results show that, among the PAFs and related technologies considered (broadly, these were vehicle connectivity bundles for entertainment, voice command technologies, and lane keeping), individuals are not too interested in lane keeping technology, which is consistent with the finding by Abraham et al. (2017). Again, though, Shin's study does not focus on the more expansive range of PAFs considered in this study. It was also based on a stated preference study rather than a revealed preference study, and was undertaken using a sample of consumers from a different geographical context than the current paper (specifically, South Korean consumers rather than a sample from a city in the U.S.).

The Owens et al. (2015) study, like the Shin et al. (2015) study, also focuses on eliciting the comfort levels and ownership of in-vehicle integrated partial automation technologies (backup camera, collision warning system, navigation system, and internet communication system), and examines cross-generational differences. The study, based on a sample of 1,000 respondents across the U.S., observes that there are no statistically significant differences in PAV ownership across generational cohorts, except for backup cameras that are more prevalent in vehicles owned by older generations than millennials (18-31 years of age). The study is exploratory and descriptive in nature, and focuses exclusively on age effects rather than a larger set of demographic and psychometric latent constructs.

2.2. Effect of PAFs on VMT

As in the case of adoption and use of technology features, a large body of literature in the past decade has focused on the potential effects of FAVs on (a) medium term mobility and urban structure decisions (including residential location, work location, recreation location, vehicle ownership, roadway element design, parking configurations/controls, and pedestrian/bicycle infrastructure; see, for example, Milakes et al., 2017, Duarte and Ratti, 2018, Fraedrich et al., 2019, Krueger et al., 2019, Cugurullo et al., 2021, Moore et al., 2020, Kim et al., 2020, and Acheampong et al., 2021 for recent studies on these longer-term effects) and (b) shorter-term activity-travel behavior decisions (see, for example, Dannemiller et al., 2021 and the extensive review therein of descriptive, model-based modification, and stated survey-based investigations of FAV effects; another good review may be found in Soteropoulos et al., 2019). Most of the studies in the second group examine FAV effects on vehicle miles of travel (VMT) or vehicle kilometers of travel (VKT), as may be observed from Table 4 of the review article by Gkartzonikas and Gkritza (2019). The focus on VMT (or VKT) as the travel outcome variable is not surprising, because VMT changes provide important macro-level repercussions on overall intensity of travel and traffic congestion levels. Earlier studies generally indicate a positive effect of FAV adoption/use on VMT, attributable to a reduction in the value (burden) of travel time due to increased comfort, less stress, the ability to pursue other activities during travel, and sending vehicles on errands, though the extent of the VMT change varies considerably in these studies (see Harb et al., 2018 and Hardman et al., 2019).

Similar to the case of automation adoption and use, the literature on FAV effects on VMT dwarfs the number of studies focusing on PAF effects on VMT.³ Two earlier studies that we are aware of that examine PAF effects on travel are Hardman et al. (2019) and Hardman (2020), which we briefly discuss below. To be noted is that both these studies focus on the specific class of Tesla battery electric vehicles and on a composite PAF corresponding to the Tesla autopilot (rather than a broader sample of owners of all vehicle types and no/multiple PAFs). In particular, the Tesla

³ To be sure, there have been studies related to (a) trust and comfort in the use of partial automation technology (see Lee et al., 2019, Abraham et al., 2017), (b) PAF effectiveness in avoiding crashes on different roadway facilities (Chan, 2017; Yue et al., 2020), and (c) older drivers' opinions on the ease of use of PAF features and older drivers' cognitive and physical health/sensory considerations (Fernandes et al., 2017 and Gish et al., 2017). But none of these studies examine PAV effects on travel behavior.

autopilot feature effectively represents the combined functionality of all the five PAFs considered in the current paper, given it is claimed to “match speed to traffic conditions, keep within a lane, automatically change lanes without requiring driver input, transition from one freeway to another, exit the freeway when your destination is near, self-park when near a parking spot, and be summoned to and from your garage”. That is, the autopilot feature corresponds to an affirmative decision along each of the five PAFs, while our study recognizes that many respondents may choose only one or a limited set of PAFs (in fact, only 8.4% of our sample had all the five PAFs in their vehicles).

Hardman et al.’s (2019) investigation revolves around usage patterns of the Tesla autopilot by 424 battery electric vehicle owners, upwards of 90% of whom had the autopilot feature installed in their vehicles. The study clusters respondents using a latent class approach into five groupings based on the frequency of use of the autopilot feature (including a “no use” category corresponding to the less than 10% of respondents without the feature) and examines the effect of demographic characteristics, psycho-social factors (frustrated commuter, technophobe, and driving enthusiast), and VMT on the frequency of use of the autopilot. The results show important differences across the five frequency use clusters, with VMT and technophobia being the most important determinants of frequency of use. The study is of an exploratory and associative nature, and does not address the issue of whether autopilot use causes VMT changes. The study is focused on PAF use conditional on a positive PAF adoption decision, rather than on the PAF adoption decision per se or PAF effects on VMT.

Another paper by Hardman (2020) is based on a qualitative semi-structured interview process with 36 autopilot-equipped Tesla battery electric vehicle owners. The study examines the benefits of autopilot as perceived by the respondents (less stressed, less tired, more relaxed, increased feeling of safety), activities undertaken when using autopilot (mobile phone use, observe the surroundings, sleep, and other), and reported changes to travel after acquiring the autopilot-equipped Tesla. None of the 36 respondents indicated a reduction in travel (relative to travel in their earlier vehicle), with about 45% indicating “no change”, and 33% indicating a definite increase (the remaining 22% were evenly split between “small increase”, “maybe increase”, and “no response”).

Another third independent study, just as we were completing our current study, is Hardman et al. (2021). This insightful Hardman et al. study descriptively examines the frequency of use of PAFs, and the driving scenarios that make drivers more likely to use PAFs. Three PAF packages are considered: (1) only adaptive cruise control (ACC), (2) only ACC and lateral lane keeping systems (LKS), and (3) the Tesla autopilot that combines all the five PAFs in this study. The first two packages are based on an analysis of non-Tesla vehicle owners, with 340 users with only ACC in their vehicles, and 312 with both ACC and LKS. The last package is based on data from 628 Tesla owners. Overall, the results indicate that, for both commute and long-distance travel, Tesla autopilot owners are more likely to use PAFs when driving than other respondents, and those with vehicles equipped with only ACC use PAFs the least. Additional descriptive analysis is undertaken to examine PAF use on different roadway types, distinct weather conditions, and varying traffic

conditions. In addition, and more relevant to this study, the study observes that PAFs appear to increase driving during congested times of the day and on congested roads, and for long distance trips more so than for local trips. These results are based on the self-reported behavioral change of users. A further analysis of long distance travel among respondents who have both LKS and ACC, as well as those with Tesla autopilot, suggests that those who are younger, have lower household incomes, and those who use PAFs in a wide variety of roadway, weather, and traffic conditions are more likely to report an increase in long-distance travel. Finally, the authors use a propensity score matching (PSM) approach that compares the VMT of Tesla autopilot owners with Tesla non-autopilot owners, and suggest an increase annually of 4,680 miles due to the presence of Tesla autopilot.

2.3. The Current Study

The current study uses a sample of 978 respondents drawn from across the spectrum of vehicle owners, and models both the dimensions of PAF choice in vehicles as well as VMT in a joint causal framework. As discussed earlier, disentangling the “causal” effect of PAFs on VMT from “spurious” associative effects due to self-selection considerations is important to better understand PAF effects on travel patterns. We use VMT as the travel outcome of interest because it has immediate implications for traffic volumes, congestion levels, and mobile-source emissions.

Our focus on VMT is also driven by the fact that VMT has been shown to be an effective exposure measure to assess safety. In fact, researchers typically normalize the absolute crash frequencies by VMT to characterize and compare crash risks across different types of drivers and driving conditions. For example, men report driving more miles and hours per year than women (Ding et al., 2017; Shen et al., 2020). With more miles on the roads, this puts men at greater exposure for wrecks and crashes. While the current crash risks due to increased VMT exposure, and the variations across drivers, may not exactly hold as increasing automation is implemented in our vehicles (because of progressively reduced human involvement in the driving task), it is only logical and reasonable to believe that increased VMT exposure will continue to lead to a heightened risk of crashes.⁴ This then brings in the issue of the *offsetting hypothesis*. The offsetting hypothesis (Peltzman, 1975) suggests that regulatory attempts to improve automotive safety through technological advancements and product design may at least be partially offset by driver behavioral changes. Researchers have been investigating this hypothesis since the early 1990s (see Traynor, 1993 for his revisit of the original Peltzman hypothesis and Chirinko and Harper, 1993 for their assessment of human behavior offset of the safety impacts of seatbelts and speed limits). Similarly, Peterson et al.’s (1995) study supports the offsetting hypothesis by showing the

⁴ There has been some debate in the literature regarding whether VMT is the best exposure measure for assessing crash risk, or if some other measure such as number of trips or time spent on the road is the more appropriate exposure measure. Mindell et al. (2012) and Santamarina-Rubio et al. (2014) argue that length of traveling time is a more valid measure of exposure than VMT; however, both these studies are in the context of pedestrian and bicyclist safety, rather than motorist crash risk. The preponderance of studies reach the conclusion that VMT is at least as good of a motorist crash risk exposure measure, if not better, than other measures (see Massie et al., 1997, Li et al., 2003, Beck et al., 2007, Pei et al., 2012, Papadimitriou et al., 2013, and most recently, Shen et al., 2020).

increased accident reports after the air bag system was adopted in 1993. They attribute this offset to more aggressive driving on the part of the driver, recognizing the additional protection offered by the airbag system. The offsetting hypothesis has been addressed in many other automotive safety scenarios as well (see Sen, 2001, Benedettini and Nicita, 2012, Winston et al., 2006); however, it has yet to be addressed in the context of advancing automated vehicle features. The key question here is how much will VMT change due to the introduction of automation in vehicles, and how will this VMT change caused by automation vary across different demographic groups? As we address this seemingly simple question, we also need to accommodate for the self-selection of individuals to tease out the “true” causal effects of increasing automation on VMT and not conflate this “true” effect with intrinsic unobserved characteristics that may make specific individuals more or less likely to own a PAV as well as put in more VMT.

In summary, there are several salient aspects of the paper. First, we examine PAF uptake (or adoption) using a joint model based on actual revealed choice data that examines multiple technologies individually and at once. We achieve this through a multi-dimensional econometric model using actual revealed preference data of technology ownership. This is in contrast to earlier studies that primarily use descriptive analysis techniques based on stated preference data. Second, we go beyond consumer acceptance and ownership of PAFs to also examine how the presence of PAFs affects annual vehicle miles of travel (VMT) In doing so, we recognize the endogeneity of VMT in the choice of PAFs by jointly modeling PAF uptake and VMT (that is, we account for possible self-selection effects in PAF adoption based on VMT). Such an analysis not only provides insights regarding the “true” effects of automation technology on VMT, but also can offer insights regarding any offset of safety benefits (of PAFs). As importantly, by considering vehicles with no automation at all as well as different levels of automation, we are able to obtain a more accurate assessment of PAF effects on VMT, relative to earlier studies that have considered only vehicles that are already equipped with PAFs. In this context, while the recent independent Hardman et al. (2021) study does use a propensity score approach to control for possible self-selection, the study does so based on observed individual/household characteristics and lifestyle attributes, but does not account for unobserved self-selection effects.⁵ Third, the foundational basis for our joint model

⁵ Two important points here. It could be argued that at least some consumers do not choose specific PAFs, but choose other vehicle features (such as leather seats or a sunroof) that are of importance to them and accept specific PAFs that come bundled with those desired features. But, of course, the reverse could also be true. Some consumers may desire specific PAFs, and find other not-particularly-important vehicle features to them (such as leather seats or a sunroof) bundled with their desired PAFs. Such a preference confounding due to bundling is, however, not specific to the current choice situation, and applies to most other choices studied in the literature. In any case, we will submit that examining an even more expansive set of vehicle attributes than the combination of the five PAFs examined in the current paper would be a worthwhile future research direction. Also, in this regard, it is only appropriate to interpret our use of the term “PAF adoption” with some healthy caution. A second point, and not unrelated to the first point, is that, in the current paper, we do not consider actual PAF use once a PAF is in the vehicle. That is, while we examine PAF adoption choice (with the caveat just mentioned and in the form of whether or not a vehicle is installed with a PAF), we do not examine the intensity of PAF use. If some consumers simply were thrust with specific PAFs in their quest to acquire other vehicle features, they may simply turn off the PAFs and not use them at all. In such a case, again, one would not obtain an accurate estimate of PAF effects on VMT. This second issue calls for a more comprehensive analysis of PAF use (and not simply PAF adoption), in addition to the bundling issue of the first point. At the same time, however, we will also note here that studies that investigate actual PAF use (once a PAF is already

is the use of stochastic latent attitudes/lifestyle constructs (also referred to as psycho-social latent constructs), along with a comprehensive set of observed individual variables, as the drivers of PAF adoption and VMT. We also examine the interaction effects of the psycho-social latent constructs with demographics on PAF adoption, as well as consider interaction effects among psycho-social constructs, demographics, and PAF in the VMT model. As importantly, we are able to examine VMT changes due to a variety of different PAF packages, and by different demographic groupings (Hardman et al., 2021 develop a single aggregate effect of Tesla autopilot presence across all demographic groupings). Fourth, methodologically, we adopt Bhat's (2015) generalized heterogeneous data model (GHDM) model to jointly model PAF adoption as well VMT (for recent studies using the GHDM framework, see Bhat et al., 2016, Lavieri et al., 2017a, Lavieri and Bhat, 2019, Dannemiller et al., 2021, Blazanin et al., 2021, and Gomez et al., 2021). In the GHDM model, jointness is achieved in an econometrically parsimonious manner through the stochasticity of the psycho-social latent constructs. The specific GHDM implementation in the current paper includes 11 indicator variables (allowing the estimation of the psycho-social latent constructs) as well as six main outcomes of interest (the five PAFs and VMT), and results in an integral dimension of the order of 17 in a maximum likelihood inference context. To estimate the model, we use a composite marginal likelihood approach that provides a consistent and asymptotically normal (CAN) estimator under the same regularity conditions needed for the CAN property of the maximum likelihood estimator (Bhat, 2014). The adoption of the five PAFs takes a binary choice form, while VMT information is elicited from respondents in bracketed categories and constitutes a grouped outcome variable. To our knowledge, this is the first formulation of such a mixed latent construct-based model with a grouped outcome variable in the broader econometric and transportation literature. Finally, we go beyond model estimation to estimate the VMT effect of PAFs by demographic groupings. These estimates can be used as part of a travel demand model framework to forecast the intensity of travel in the presence of PAVs, as well as can provide insights on safety offsets of PAFs. Moreover, this also provides a basis for car manufacturers to target specific sociodemographic groups and focus on specific PAF combinations that might be more popular than others.

3. METHODOLOGY

3.1. The Survey

The sample used for analysis in this paper was collected through an “emerging mobility” survey conducted in the Austin metropolitan area in Texas in 2019. The survey administration approach included an array of communication and information recruitment strategies, including purchasing

installed) suggest that owners of vehicles with PAF features, on average, tend to use them for about 70-75% of their trips, with some variation based on whether a trip is a local area trip or a long distance trip (see Crump et al., 2016 and Hardman et al., 2021). More specifically, Gorzelany (2020) state that the most often turned off PAF is Adaptive Cruise Control (ACC), with about 30% of vehicle owners turning the feature off. The second in terms of most often turned off PAF is Lane-Keeping Assist (LKA), with 25% turning the feature off. The other features sometimes turned off are Blind Spot Monitoring (BSM) at 9% and Back-up Camera at 6%. Overall, individual PAFs, once installed, are not very likely to be turned off.

a list of over 15,000 e-mails and “pushing” information through social media advertisements and local area professional network contacts. A financial incentive was offered in the form of a \$10 Amazon gift card to the first 250 respondents, followed by a lottery drawing from the remaining respondents to win one of one hundred additional \$10 Amazon gift cards. The recruiting effort resulted in a convenience sample of 1,127 respondents, which was reduced to a final size of 978 (149 respondents were removed either because they did not have a motorized vehicle available in their household or because they did not answer questions concerning their primary vehicle).⁶

The availability of each of the PAFs in the respondent’s primary vehicle, and the self-reported annual mileage driven (by all individuals in the household) in the primary vehicle, constitute the main (dependent) outcomes in the current analysis.⁷ The annual vehicle miles of travel (VMT) on the primary vehicle were sought in eight groupings, from less than 5,000 miles to 40,000 miles or more. In addition to information on these main outcomes, the survey sought information on individual and household demographics (age, gender, employment type, education level, household annual income, and number of children in a household), as well as respondents’ general attitudes and lifestyle preferences. These attitudinal perspectives were obtained through the responses, collected using a five-point Likert scale ranging from “strongly disagree” to “strongly agree”, to a battery of attitudinal statements.

3.2. Analytic Framework and Data Description

The analytic framework focuses on understanding the inter-relationship between the PAFs and VMT dimensions, while considering individual-level characteristics (individual and household demographics) as well as attitudes/lifestyle factors (also referred to as psycho-social factors). These psycho-social factors are not directly observed, and so are viewed as latent stochastic constructs manifested through a suite of observed indicators. In the current study, based on a combination of an exploratory factor analysis process and a subsequent confirmatory factor analysis, four such latent constructs (with their most suitable indicators) are identified: (1) (need for) driving control, (2) (need for) mobility control, (3) concerns with safety (safety concern), and

⁶ While a higher sample size would have been desired, our joint model structure is parsimonious in parameters, and makes efficient use of the available sample.

⁷ Note that the survey was targeted at individuals, while also obtaining demographic information at the individual’s household level (such as number of vehicles in the household, household income, household size, and household structure). However, information regarding PAFs and VMT was sought only for the individual respondent’s primary vehicle, defined as the vehicle used most often by the respondent. In this regard, because individuals are not likely to keep strict records of the use of their primary vehicle by the specific individual driving the vehicle, we sought the total annual VMT on that vehicle by all individuals in the household. Doing so, admittedly, does not capture the heterogeneity (across individuals within the household) in PAF effects on VMT. However, to be noted is that it is typical in the U.S. for non-zero vehicle households to own as many vehicles as the number of drivers, and each vehicle is almost strictly allocated for use by a single individual; that is, each vehicle in a household is driven quite exclusively by a single individual, as also evidenced in many activity-based models in the U.S. that assign a household vehicle to a single primary driver (see Goulias et al., 2013 and Lavieri et al., 2017b).

(4) an individual's interest in productive use of travel time (IPTT). Further discussion on these latent constructs is provided in Sections 3.2.2.⁸

Figure 1 provides a diagrammatic representation of the analytic framework, where we suppress the indicators of each latent construct to avoid clutter. There are two components to the GHDM model: (1) the latent variable structural equation model (SEM), and (2) the latent variable measurement equation model (MEM). The SEM component defines each latent construct as a function of exogenous socio-demographic variables and an unobserved error term. The error terms across the four latent constructs are collected in a vector $\boldsymbol{\eta}$. We assume $\boldsymbol{\eta}$ to be multivariate standard normal with a mean vector of $\mathbf{0}$ and a correlation matrix of $\boldsymbol{\Gamma}$ (due to identification considerations, the variances of the individual $\boldsymbol{\eta}$ elements need to be normalized to 1; see Bhat, 2015). The SEM model relationship between the socio-demographic variables and the latent constructs, as well as the correlation matrix elements of $\boldsymbol{\Gamma}$, are not directly estimable, but are estimated through observations on the latent construct indicators (not shown in Figure 1) and the main endogenous outcomes of interest (shown toward the right side of Figure 1). The exogenous socio-demographic variables, and the latent constructs (and their interactions) all then serve as determinants of the underlying latent propensities of the ordinal indicators, the binary PAFs, and the grouped VMT outcomes. This is represented by the MEM relationship in Figure 1. Note that, in the modeling, VMT is introduced as a dependent variable in a natural logarithm form, because VMT can only be positive. The logarithmic form is also well suited to account for the strong right skew of VMT.

The latent constructs in Figure 1, in addition to capturing important attitudinal and lifestyle preference effects, also serve as vehicles to allow the parsimonious joint modeling of the six main outcome variables of interest (listed in the right panel of Figure 1). For instance, if interest in the productive use of travel time leads to a higher PAF uptake but also reduces VMT, this generates a negative correlation (due to unobserved factors) between PAF uptake and VMT. That is, individuals who are intrinsically likely to be PAF adopters may also have a low VMT to begin with. As we discuss later, this unobserved self-selection needs to be accounted for when attempting to capture “true” PAF effects on VMT.

The GHDM framework, in its original form, supports the modeling of a mixture of different types of endogenous outcome variables, including continuous, nominal, ordinal, count, and multiple discrete-continuous variables. In our study, the framework is expanded to include grouped variables. The mathematical formulation of the GHDM framework is presented in an online supplement to this paper (see <https://www.cae.utexas.edu/prof/bhat/ABSTRACTS/PAF/OnlineSupp.pdf>).

⁸ We should note here that the psycho-social factors used in our study build upon traditional psychosocial frameworks, such as the Theory of Planned Behavior (TPB, Ajzen, 1991) and the traditional Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh and Davis, 2000). In particular, while retaining attitudinal and perceived usefulness factors (in the form of safety concerns and IPTT) that are accommodated within the TPB/TAM frameworks, we also consider the emotive factor of the need for control that has not been adequately considered in the TPB/TAM frameworks (see Piao et al., 2016, Ward et al., 2017 and Marikyan et al., 2019 for a discussion of this issue in the socio-technical literature).

Overall, the individual-level characteristics constitute the exogenous variables in our model system (see left side of Figure 1). On the other hand, the latent constructs, while also serving as determinant variables for the main outcomes, are affected themselves by the individual-level characteristics (so, these latent constructs are placed in the middle of Figure 1). Thus, the individual-level characteristics have both a direct effect on the main outcomes of interest, as well as an indirect mediating effect through the latent constructs. The right side of Figure 1 indicates the recursive effect of PAF choice on VMT. VMT is considered endogenous to PAF choice here, through the correlation between the PAF variables and VMT. That is, PAF choice and VMT decisions are modeled jointly, while accommodating the recursive effect of PAFs on VMT.⁹

The individual-level characteristics, the latent constructs, and the main outcomes are discussed next in turn in the subsequent sections.

3.2.1. Individual-Level Characteristics

The sample descriptive statistics of the convenience sample from the survey are presented in Table 1. To better characterize our sample, in the following discussion, we will provide the comparable Census population statistic for the Austin-Round Rock, TX Metro Area, as chronicled by the U.S. Census Bureau in 2018. This comparison is not technically appropriate, for the simple reason that our sample only includes respondents who have a vehicle in their household, while the Census corresponds to all households residing in the Austin area. Nonetheless, a comparison provides a sense of the nature of our sample.

The statistics in Table 1 represent an obvious over-representation of women in our sample, relative to the 50-50 gender split in the Census data for the Austin-Round Rock region. Our sample indicates an over-representation of young individuals, with about 56% of 18-29 year olds (far higher than the 18% of the Austin area population in this age group). This age bias is not surprising, as our survey dissemination efforts focused on social media outlets and on or near a college campus. The Census did not report on the number of students in the region, though our sample under-represents employment rates (61.9% in our sample compared to 73.3% in the Census; also, note the high number of individuals who are both students and employed, which is again quite characteristic of a University-biased sample). In terms of education levels, our sample shows a lower representation of individuals who have completed high school or less (13.9% compared to 29% in the Census) and those who have completed some college or technical school (34.7% compared to 25% from the Census). Again, since the survey was administered around a college campus, our sample shows a slight over-representation of individuals with an undergraduate or graduate degree (34.7% in our sample versus 30% from the Census for individuals with an undergraduate degree and 17.1% in our sample versus 17% with a graduate degree from the Census).

⁹ In joint limited-dependent variables systems in which one or more dependent variables are not observed on a continuous scale, such as the joint system considered in this paper that has binary PAF variables and the grouped VMT variable, the structural effects of one limited-dependent variable on another can only be in a single direction. See Maddala (1986) and Bhat (2015) for a more detailed explanation.

As for household characteristics (lower panel of Table 1), our sample is skewed toward low-income households. In particular, while 70% of our sample indicates an annual household income of less than \$100,000 (70%), the Census reports a significantly lower percentage (59%) of households making less than \$100,000. This may be attributed to the high fraction of students in our sample relative to the general population. The Census only reports average household size, which is 2.7 persons per household. This aligns well with our sample, which yields a three person per household average (the Census does not provide a distribution of the number of individuals in the household, and only provides an average household size value). The Census also does not provide information on the number of vehicles per household or household structure. Finally, our sample is remarkably representative of the Census data in terms of presence of children in the household (18.3% compared to 18.7% from the Census).

Obviously, our sample is not representative of the Austin-Round Rock population, particularly on the dimensions of gender and age distribution. This may be attributable to the high number of students who took our survey. Also, the Austin region is home to many colleges and universities, and students. If only renting property or living in Austin to attend school for nine months out of the year, students may not report themselves as Austin residents in the Census, leading to another reason for differences in individual/household characteristics between the Census and our sample. Thus, it is likely that both our sample as well as the Census may not represent the “true” Austin area living population at any given time. While this ambiguity makes it difficult to determine which of the descriptive statistics (from our sample or from the Census) would be closer to the “true” population characteristics, there is no reason to believe that the individual level causal relationships (how changes in exogenous individual-level characteristics impact the six endogenous outcomes of interest) estimated here would not be applicable to the larger “true” population of those with motorized vehicles in their households, because we are controlling for the exogenous demographic variables in our model specification. For example, safety concerns are likely to be different among different age groups, but we have included the “age” category variables as exogenous variables for the latent construct regression model as well as the main outcomes model to account for such demographic heterogeneity. In addition, our sample displays adequate variation across the range of values for each demographic variable, allowing us to test a variety of functional forms across different range values for the effects of these variables. Importantly, because our sampling strategy itself is not based on the endogenous variables (that is, our sample corresponds to the case of exogenous sampling where the sample collection process itself is not predicated on whether or not individuals have PAFs and is not based on VMT of individuals), an unweighted estimation approach provides consistent estimates as well as yields more efficient estimates relative to a weighted procedure (see Wooldridge, 1995 and Solon et al., 2015 for an extensive discussion of this point). Overall, the combination of our exogenous sampling approach, as well as the adequate variation in the sample to test demographic effects at a fine level of resolution, implies that there is no reason to believe that the individual level relationships estimated from disaggregate models developed in this paper are not applicable to the larger population of individuals with vehicle availability in their household.

3.2.2. *Stochastic Latent Constructs*

In the structural equations model component of the analytic framework, individual-level characteristics (left side of Figure 1) are used to explain the four latent constructs representing driving control, mobility control, safety concern, and interest in productive use of travel time (or IPTT). Other latent constructs such as security concern, green lifestyle, time sensitivity, privacy sensitivity, technology-savviness and variety-seeking were also considered based on theoretical and conceptual considerations. But our analysis of “within construct” and “between construct” variance (based on the battery of indicators), along with the testing of the larger set of developed constructs as they impacted the main outcomes, indicated that the most appropriate set were the ones finally used in the current paper. This is, of course, due to a similar set of indicators loading on the many theoretically-developed latent constructs. For example, frustration in the level of congestion during the daily commute turned out to be an important indicator that loaded rather heavily on both the IPTT and time sensitivity latent constructs. Similarly, “I will never ride in an AV” turned out to be an important indicator for both the “driving control” and “privacy-sensitivity” constructs. The resulting high correlations across the many developed latent constructs quickly led to the winnowing down to the four used here.

The first two latent constructs of driving and mobility control, while rarely used in transportation-related studies, encompass the concept of an individual’s sense of, and need for, control in life. The social-psychological literature (see, for example, Freeman and Muraven, 2010, McFarlane and Harvey, 2017, Elliot et al., 2018, Johnson et al., 2021, Chesters et al., 2019) suggests the pathways by which a sense of control can impact decisions and choices made by individuals, through its relation to individual’s level of overall life satisfaction, self-worth projections, risk-taking inclinations, personal agency in navigating/adapting to changes and trauma, and perception of power dynamics. For example, Freeman and Muraven (2010) indicate that individuals who report a high level of control over their life are less willing to engage in changes in their lifestyle, because they appreciate the sense of being in control and are averse to losing this sense. On the other hand, as Narisada and Schieman (2016) report, individuals who perceive less control over their lives are more likely to embrace new and “risky” situations because they anyway feel they have less to lose (because of their current low control). A related view reinforcing this reluctance to change among those with a strong need of control in their lives is that, for such individuals, having a stable (unchanging) environment serves as a coping mechanism to retain sanity in what may seem an out of-control external world (Laferton et al., 2018).

In the context of the current transportation study, control is characterized by driving control and mobility control. Individuals high in their need for driving control may be reluctant to embrace automation features that involuntarily wrest complete control away from them, even if only in specific emergency situations (such as automatic braking systems). Of course, it is also possible that older individuals, who may have progressively more physical challenges in driving themselves, invest in some of the PAFs as a means to preserve driving control and be independent in their travel needs. That is, the effect of driving control on PAFs may be dependent upon demographic variables such as age. We consider this and other similar moderation effects of

individual-level characteristics in the influence of latent constructs on PAFs through interacting individual-level characteristics with latent constructs.

The second latent construct, mobility control, is associated with a need for freedom to choose the “when, where, and the with whom” of travel. It may be expected that individuals with a high need for mobility control will not want to use other modes of travel other than their private vehicles, and, therefore, may be more willing to invest in PAFs that may make driving an easier and less tiring task (see Wu et al., 2020). This mobility control need is distinct from driving control in that it is not so much about wanting to be behind the wheel as it is about having movement flexibility and the ability to pursue activities spontaneously.

The third construct represents a general safety concern associated with automation technology (or, for short, simply safety concern from hereon). The indicators for this construct are based on responses about concern levels related to FAVs, but they are used in the current study to proxy a general safety-related mistrust about automated vehicle technology. Such individuals are less likely to trust their children, property, selves, or other items of value in or around PAFs and ultimately FAVs (see de Miguel et al., 2019; Moody et al., 2020; Nair and Bhat, 2021). As such, the expectation would be that those high on the scale of safety concern (with respect to automation) will be less likely to invest in PAFs. While this safety concern is specifically about automation technology, it is possible that these same individuals have a higher level of safety concerns about driving in general, and so may have low VMTs to keep exposure to crashes low.

The last latent construct is Interest in Productive use of Travel Time (in short, IPTT). PAFs obviously do not allow the same level of lack of need for attention to the driving task as would FAVs (in fact, drivers are supposed to be in full control of the vehicle at all times with PAFs, and doing otherwise is generally illegal). But the study by Hardman (2020) indicates that 50% of the respondents of Tesla autopilot users do in fact pursue activities such as texting or talking when driving, observing the scenery and surroundings and not looking forward, sleeping, and eating with both hands off the wheel. Without intending in any way to condone such activities or promote such activities, this study recognizes that some kinds of time-productive activities appear to be pursued in the presence of PAFs. So, we test whether a higher level of IPTT leads to more inclination to have PAFs need, and if IPTT has any impact on VMT.

The indicators used to extract information on each of the above four latent constructs are listed and presented in Figure 2. Each indicator is measured on the same five-point Likert scale of (1) Strongly disagree, (2) Somewhat disagree, (3) Neutral, (4) Somewhat agree, (5) Strongly agree. Descriptive statistics for each variable’s indicators are provided in Figure 2. The indicators for the first latent construct, driving control, show that, while individuals are generally positive toward yielding control to automation technologies, they also prefer to be a driver rather than a passenger. A similar range is observed within each of the indicators representing the second latent construct, mobility control. Individuals, overall, prefer keeping a private vehicle for their travel rather than completely sub-contracting their travel needs to ride-hailing services. In terms of the third latent construct, it is clear that there is concern related with safety associated with automation, with over 75% of respondents in somewhat or strong agreement that technology reliability is a concern, and

only about 20-25% stating they would be (somewhat or very) comfortable sleeping in a vehicle or having an AV pick up/drop off a child (the latter indicator may be associated with not only technology reliability in the context of whether a technology will function as intended in the regular course of use, but also related to safety concerns tied with cyber-security attacks by malicious agents). The final latent construct, IPTT, suggests a high degree of interest in productive use of time, as observed from the high percentage of individuals who report currently making good use of time when traveling, as well as high levels of frustration with traffic congestion levels and a stated inclination to drive more with automation.

3.2.3. Main Outcome Variables

There are six main outcome variables, five binary outcomes corresponding to each of the five PAF dimensions, and the grouped VMT dimension.

Table 2 presents the distribution of PAFs across respondents' primary vehicles. Just over half (50.5%) of respondents reported having backup cameras (BUCs) in their vehicles, clear evidence that BUCs have started becoming standard in new vehicles. Adaptive cruise control (ACC) and automatic braking systems (ABS) are also much sought after, while lane keeping systems (LKS) appear to have the lowest penetration (consistent with the findings of Abraham et al., 2017 and Shin et al., 2015). A significant fraction of respondents (close to 35.3%) report having no PAFs. Thus, household vehicle holdings continue to include older vehicles without any PAF. On the other side, only 8.4% of vehicles have all the five PAFs altogether. The most common technology package is only BUC (13.8%), followed by all PAFs (8.4%) and only BUC and ACC (8.3%). Additional popular technology packages are presented in the second row panel of Table 2.

The statistics related to the VMT dimension in Table 2 (the third row panel) show that most vehicles are driven between 10,000-14,999 miles, with less than 10% of vehicles driven more than 25,000 miles. These vehicle-specific annual VMT figures are quite consistent with U.S. national and Texas averages. The national average is 13,476 miles a year (Federal Highway Administration, 2018), while, in Texas, the average is a bit higher at 16,172 miles a year (Covington, 2021).

4. MODEL RESULTS

The final model specification was developed through a systematic process of analyzing alternate combinations of explanatory variables, while removing statistically insignificant ones. The individual-level characteristics are all obtained in the survey in either bracketed categories (age and income), or are naturally discrete (gender, household size, employment type, education, number of vehicles, household structure variables, and presence of a child). The effects of all these individual-level characteristics were tested as dummy variables in the most disaggregate form possible, and progressively combined based on statistical tests and intuitive reasoning to yield parsimonious specifications. Further, we examined interaction effects of latent constructs with individual-level characteristics as well as interactions of PAF effects with individual-level characteristics, but only the interaction effect of older individuals (≥ 65 years of age) with driving

control on lane keeping system (LKS) propensity turned out to be statistically significant, as discussed later.

In the final model specification, not all the included variables are statistically significant at a 95% level. This is to acknowledge the relatively small sample size of our estimation that may have led to the marginal significance of some of the variables, which nonetheless can help inform future investigations with larger sample sizes. As discussed earlier, our estimation proceeds by first identifying the most appropriate indicators for each of the four latent constructs based on a confirmatory factor analysis. The loadings of the latent constructs on the indicators are estimated jointly with other components of the model system, and are available in the online supplement (the entire model system was estimated using code written in the GAUSS programming language). Suffice it to say that the loadings were significant and had the expected sign. The other results are discussed next, starting first with the SEM results relating the individual-level characteristics to the latent constructs, and then proceeding to the results for the main outcomes.

4.1. Latent Constructs

The effects of individual-level characteristics (including individual and household demographics) on the four latent variables are presented in Table 3. As shown in the following section, the latent constructs have a strong impact on the main outcomes, implying that there is a significant mediating impact of individual-level characteristics (through the psycho-social constructs) on the PAF and VMT dimensions. Any cells marked "--" in Table 3 suggest that the corresponding row variable has no influence on the column latent construct. Further, while a host of individual-level characteristics (presented in Table 1) were tested in our specifications, only gender, presence of children, age, and household income turned out to be statistically significant determinants of the latent constructs.

The gender effects from Table 3 reveal that women, in general, have a stronger desire for driving control than men (see also Charness et al., 2018 for a similar result). One explanation from the social-psychological fields is that, in a rather asymmetric, male-dominated world in which women feel a lower sense of general life control, they are not willing to relinquish the feelings of free-spiritedness, independence, and empowerment they associate with driving (Skuladottir and Halldorsdottir, 2008; Leung et al., 2018). Table 3 also reveals that women are more likely than men to have safety concerns related with automation in vehicles, a result that is well established in the literature (see, for example, Acheampong and Cugurullo, 2019 and Asmussen et al., 2020). Women tend to be more risk-averse than men, since women experience feelings of nervousness and fear more so than men in anticipation of potentially negative outcomes (Meier-Pesti and Penz, 2008; Borghans et al., 2009). Thus, women are likely to shy away from any change in the travel environment, including automation, which is viewed as a risk. Not surprisingly, safety concern increases all the more for women in the presence of children in the household, given that women continue to shoulder much of the responsibility for transporting children (Ciciolla and Luthar, 2019). This result may also explain why women, in general, are less interested in productive use of travel time (IPTT). Though being time-poor (particularly mothers), the nature of non-travel

activities that women are typically responsible for (such as household chores and child-care responsibilities) cannot be performed inside a vehicle (Craig and Mullan, 2010). Moreover, earlier studies suggest that men and women engage in different types of activities when traveling (Keseru and Macharis, 2018). While men are more likely to engage in work-related activities (such as working on their laptop), women are more likely to engage in social activities (such as talking on the phone or interacting with other passengers), which they may not necessarily consider productive (see Moore et al., 2020 and Guo et al., 2015).

In terms of age, older individuals (≥ 65 years of age) appear to have a stronger desire for both driving and mobility control. The need for driving control as one gets older may be traced to self-identity considerations. In particular, older individuals have driven on their own for much of their life, and a continuation of that lifestyle allows them to retain a sense of mental self-esteem at a time when their physical self-esteem may be flailing (Kessler, 2009; González Gutiérrez et al., 2005). Earlier studies have also clearly pointed to older individuals being less trusting of automation-based disruptors in general life as well as in vehicles (see Haboucha et al., 2017, Voinescu et al., 2020). The higher need for mobility control among the elderly may similarly be attributed to an unwillingness to let go of regular habits. In addition, the elderly, though they venture outside the home less than their younger peers, place a premium on mobility control because they have a habituated and rigid travel routine (with a regular spatial-temporal rhythm of activity participation; see Paillard-Borg et al., 2009, Bhat et al., 2020, Nikitas et al., 2018). The higher safety concern toward technology and lower IPTT among older individuals (as well as individuals between 30 and 64, for IPTT) may be associated, respectively, with the general distrust of technology in this population segment and a more relaxed way of life (see Oliveira and Baldi, 2019, Berkowsky et al., 2017, Rogers and Mitzner, 2017, and Nair and Bhat, 2021). The higher IPTT among younger individuals may also be associated with the higher technological ability and greater desire to undertake travel-based activities (see Dannemiller et al., 2021).

Alongside the age and gender effects, the results in Table 3 indicate a higher mobility control desire/ability, and a lower safety concern, among individuals from high income households. The mobility control result is consistent with higher income individuals being able to afford the ability to retain control over how they travel (see Veternik and Gogola, 2017, Brown, 2017, and Morris et al., 2020). The lower safety concern among high income individuals is corroborated by earlier literature on vehicle automation, attributable to such individuals being exposed earlier and more to new technological developments (see for example, Moody et al., 2020 and Asmussen et al., 2020).

The estimated correlations between the error terms of the latent constructs are presented at the bottom of Table 3. Unobserved factors that increase the need for driving control also increase the need for mobility control, while both of these constructs also positively correlate with safety concerns. The high positive correlation between driving control and safety concern toward automation is intuitive; those who intrinsically desire human control tend to have a deep mistrust of automotive technology. Interestingly, all of driving control, mobility control, and safety concern negatively correlate with IPTT; individuals who seek to be productive when driving are less

concerned about maintaining control and appear to have more safety trust in automated technology.

4.2. Main Outcomes

Table 4 presents the coefficients estimated for the PAF and VMT outcomes. These coefficients refer to the impact on the underlying propensities characterizing the outcomes. These propensities get mapped to the actual observed binary category responses (for the PAFs) and to the observed grouped category response (for the natural logarithm of VMT). Any cells marked “--” indicate that the corresponding row variable has no impact on the column outcome variable.

4.2.1. Latent Construct Effects

The latent construct effects in Table 4 reveal that individuals with a high driving control need are more likely to invest in lane keeping system (LKS), backup camera (BUC), and adaptive cruise control (ACC), but not automatic braking system (ABS) and blind spot monitoring (BSM). This is an interesting result, suggesting that those with driving control see the field-tested and passive nature of LKS, BUC, and ACC as not hampering or reducing their vehicle control need, but actually providing them a higher sense of driving control. For example, BUC and ACC have been available for some time now; BUC is standard in all vehicles since 2018, while ACC has been available in the form of cruise control, even if not adaptive cruise control, for at least a decade (Kamalanathsharma et al., 2015). All of LKS, BUC, and ACC are relatively passive, and do not have any substantial steering and swerving intervention longitudinally or laterally (though LKS and ACC aid in keeping to an appropriate lateral position, or assist in longitudinal slowing down based on the space/time headway with respect to the vehicle in front). Overall, it appears that LKS, BUC, and ACC are viewed as valuable assist features without eliminating the sense of driver control. In fact, these appear to bolster that sense by reinforcing driving exhilaration in a sensory-stimulating and rapid-moving environment, while also investing some in safety. This interpretation is strengthened by the supplementary positive effect of driving control for LKS. For the same level of driving control need, older individuals are more likely to invest in LKS, perhaps because these individuals particularly appreciate the lateral lane keeping assist as a feature that allows them to retain their driving control (especially in high speed driving environments) at a time when their cognitive and physical abilities are declining. To the contrary, ABS and BSM are relatively newer technologies with lower penetration in vehicles (see Table 2). ABS is also a much more active PAF than LKS, BUC, and ACC in that, in emergency situations, the feature involuntary and completely takes control away from the driver to stop the vehicle. In terms of the negative impact of driving control on VMT, this is again consistent with the notion that driving control is about a sense of “self-identity” and “empowerment” through retaining the ability to drive, much more so than associated with a need for driving more. Thus, for example, older individuals have a higher sense of driving control, though they drive less. But they do not want to give up driving for the limited traveling they undertake (Paleti et al., 2011; Harvey et al., 2011; FHWA, 2018).

Mobility control, on the other hand, does not impact adoption of LKS, BUC, and ACC, but positively affects the adoption of automatic braking system (ABS) and blind spot monitoring (BSM) features. Those desirous of mobility control may be the ones who chain activities routinely and are unwilling to (or cannot much afford to) compromise on their space-time movement freedom. These individuals will necessarily encounter different kinds of travel environments, including stop-and-go traffic in slow-moving as well as high-speed environments. Indeed, according to Hill and Boyle (2007), merging onto highways and having to abruptly stop in stop-and-go traffic and high-speed traffic are two of the most accident-prone driving maneuvers. Partially automated features such as ABS and BSM are particularly suited (among the 5 PAFs considered) to assist drivers in such high accident-prone situations. Thus, investment in these PAFs would be viewed as supporting individuals with high mobility control needs/desires as they scurry from one location to another. As in the case of driving control, the results suggest that individuals with high mobility control needs/desires generally drive less, which may be attributed to the types of chaining and short-distance activities that warrant high mobility control.

The sole effect of safety concern on ABS adoption supports our earlier observation that ABS is a more active PAF relative to the other four assistive PAFs. Specifically, the deployment of ABS entails the active non-human application of braking to prevent serious front-end collisions. For such potentially life-threatening situations, it is not uncommon for humans to be reluctant to yield control to a machine, because of a belief that machines just are not reliable as oneself. In fact, Shimazaki et al. (2018), in their study on the public's understanding of the functionality of automatic braking, state the following: "people enjoy a greater feeling of safety when they believe that driver intervention can readily disengage automatic braking, and this can be interpreted as a corollary to the anxiety drivers feel toward automated systems having primary control over driving". Also, the lower VMT among those who are safety-concerned related to technology is rather intuitive, given that such safety concerns may (a) permeate into a general concern for driving (given that miles driven is a well-established exposure measure for crashes and injuries) as well as (b) lead to an elevated crash risk perception because of other drivers using emerging technologies (Hardman et al., 2019). Another important point from our results is that the effect of psycho-social constructs (such as safety-concern) varies based on the specific PAF under consideration, and thus it is important to partition PAFs by specific functionality as opposed to grouping all of these under a single category, as undertaken in earlier studies (see, for example, Wali et al., 2021).

Finally, our results indicate that individuals interested in the productive use of travel time (IPTT) are more likely to invest in the lane keeping (LKS) feature. Although not a fully automated feature, LKS provides a safety margin for minor distractions or lapses from full driving concentration, thereby allowing drivers to engage in activities such as texting, making a phone call, distracted thinking about work place matters, or talking to fellow passengers. As reported by Hardman (2020), about 50% of individuals engage in one or more of these activities when driving in the presence of partially automated vehicles. IPTT reduces VMT, a direct consequence of a higher desire to use travel time for other activities.

4.2.2. *Effects of Individual-Level Characteristics*

The individual-level effects in Table 4 provide the direct effects of socio-demographics, beyond their indirect effects through the latent constructs. The results indicate that women in general are less likely to invest in BSM compared to men. That is, for a man and a woman with identical driving and mobility control desires/needs, the woman is less likely to invest in BSM. This may be a reflection of women being less prone to being distracted and less likely to make aggressive lane changes (see Schroeder et al., 2018 and Fountas et al., 2019), and thus not feeling as much need for BSM. Further, a woman's peripheral vision is effectively 180 degrees (Parnell, 2007), while a man's vision range is narrower. Thus, men are more likely to invest in BSM for their vehicles, as a way of supplementing their inherently tunnel vision to reduce blind spot problems. The positive effect of the "female" variable on the VMT equation indicates that, between a man and woman with identical values on the latent constructs, the woman drives more. However, when computing the net effect of the "female" variable (through both latent construct effects and the direct effect), women drive less (net "female" variable effect on VMT is -0.0431), supporting the findings from earlier literature (see, for example, Ding et al., 2017 and Shen et al., 2020).

Finally, individuals from high income households (annual income greater than \$100,000) put more mileage on their vehicles, after controlling for mobility control and safety concern. The net income effect (through both the latent construct effects and the direct effect) is also positive. This is consistent with earlier studies of trip generation and VMT that indicate that higher income households, because of their high consumption potential, generate more recreational and leisure trips, both within their area of residence and also long distance (for example, see Ke and McMullen, 2017 and Singh et al., 2018).

4.2.3. *PAF Effects on VMT*

The PAF effects provide the influence of each PAF's adoption on VMT, after controlling for the association between the PAFs and the VMT through the correlations engendered by the stochastic latent constructs. That is, these PAF effects represent the "cleansed" effects of the PAFs after accounting for spurious correlations among the PAFs and VMT. We first explain these spurious correlations before proceeding to a discussion of the cleansed PAF effects on VMT. To do so, note that, for example, the stochastic component embedded in driving control immediately permeates into the propensities for adoption of lane keeping (LKS), backup camera (BUC), and adaptive cruise control (ACC), and creates a positive correlation among these three dimensions (because the effect of driving control is uniformly positive on the three dimensions). At the same time, driving control also negatively impacts VMT, and engenders a negative covariance between VMT and each of the LKS, BUC, and ACC dimensions. Similar correlations are generated by the effect of other stochastic latent construct effects on PAFs and VMT.

The overall implied correlation matrix among the PAFs and VMT may be developed from the estimates in Table 4. These correlations are in the $+0.021$ to $+0.207$ range among the PAFs, with the highest correlation between the relatively higher level technology and more recent ABS and BSM entrants in the market. The positive correlations among the PAFs are to be expected,

indicating that complementary forces are at play in PAF adoption. As importantly, the generally positive effects of the stochastic latent constructs on PAF adoption and the simultaneous negative effects of these constructs on VMT imply a negative correlation between PAF adoption and VMT. That is, as discussed in the introduction section, individuals who intrinsically (after controlling for observed demographics) drive less (lower VMT) appear to be the ones more likely to invest in PAV features. Without controlling for this self-selection, any positive impact of the actual presence of the PAF on VMT would be underestimated. In our study, this correlation between PAFs and $\ln(\text{VMT})$ ranged between -0.001 to -0.130 . The lowest negative correlation is between BUC and $\ln(\text{VMT})$, while the highest negative correlation is between ABS and $\ln(\text{VMT})$. These results are intuitive. BUC is becoming standard today, and individuals who invest in BUC are intrinsically not much different in their VMT relative to those who do not invest in BUC. The high negative correlation between ABS and VMT is primarily driven by the intrinsic need for mobility control; those with a strong mobility control desire tend to drive less.

After accommodating for the self-selection discussed above, the “true” impacts of PAFs on $\ln(\text{VMT})$ are shown toward the bottom of Table 4.¹⁰ We considered the effect of all the popular individual and packaged PAFs identified in Table 2; the ones reported in Table 4 are those that turned out to be statistically significant. As can be observed, every PAF, either in isolation or as part of a technology package, has a positive effect on VMT. This implies that, once invested in, PAFs generally increase VMT. Though these VMT shifts vary across both sociodemographic groups and PAF packages, the increase in VMT due to the presence of automation in vehicles aligns with similar findings in Harb et al. (2018), Hardman et al. (2019), Hardman (2020), and Hardman et al. (2021). The magnitude of these VMT increases may be obtained using the parameter values from Table 4. To do so, we first estimate, at the individual-level, the expected value of $\ln(\text{VMT})$ with a specific PAF/PAF combination relative to without any PAF. The corresponding expected VMT (EVMT) may be obtained by exponentiating and adding the square of half of the variance estimated for $\ln(\text{VMT})$. Then, the EVMT change may be computed for each PAF bundle for each individual, and then averaged by demographic group or averaged over the entire sample. In common econometric terminology, this refers to the average treatment effect (ATE), which corresponds to the case of moving all individuals to vehicles equipped with each specific PAF/PAF combination. In our analysis, we present the results by gender and age-specific combinations, so that our sample bias on these two important determinant sociodemographic variables of VMT (through direct as well as latent construct-mediated indirect effects) do not much affect our conclusions. We then use the distributions of annual VMT by each of these combination groups in the larger population, as obtained from FHWA (2018), to compute a percentage change (that is, the percentage ATE or PATE) for each demographic group combination. Finally, we

¹⁰ The constants and the standard deviations at the bottom of Table 4 do not have any substantive interpretations. The constants simply adjust for the range of the continuous latent constructs. However, the magnitudes of the constants are consistent with the overall PAF uptake rates presented in the first row panel of Table 2, with the lowest negative value for backup camera and the highest negative value for lane keeping systems.

estimate an overall weighted (by VMT of each group) ATE and PATE attributable to each specific PAF/PAF combination.¹¹

The results of the above analysis are presented in Table 5. Thus, the presence of only a backup camera (BUC), according to our analysis, would lead to an average increase of 1,350 miles on an annual basis in the group of men under the age of 30. This corresponds to an increase of 8.2% over the mileage without any PAFs installed (see first numeric cell of Table 5). The last two columns for the BUC row provide the estimated population-wide changes in miles and percentage mileage increase due to BUC presence (relative to no PAF presence at all). Other figures in Table 5 may be similarly interpreted.

A number of interesting insights may be obtained from the table. First, the PAF associated with the smallest VMT increase corresponds to only automatic braking system (ABS) being installed in the vehicle (third numeric row in Table 5), while the largest VMT increase is associated with the combination of BUC, adaptive cruise control (ACC) and ABS in the vehicle (fourth numeric row of Table 5). The former result is consistent with ABS being the most active PAF of all the PAFs, and being primarily considered a safety PAF when installed solely in the vehicle. On the other hand, the latter result suggests that when ABS is linked up with BUC and ACC, the combination appears to provide an extra sense of convenience/comfort in longitudinal vehicle maneuvering and assistance that encourages more driving. BUC and ACC, alone by themselves too, lead to a relatively high (and about an equal) amount of additional driving, perhaps given the extra ease people find in driving once these PAFs are mounted (see first two rows of Table 5). Second, when the PAFs that assist in lateral guidance (that is, lane keeping and blind spot monitoring) are mounted (these are almost always exclusively packaged with BUC), there is but only a VMT small increase (over and above when only BUC is installed; see the first and last numeric rows of Table 5), suggesting that PAFs focusing more on lateral movement assistance do not increase VMT as much as those that serve the functionality of providing longitudinal movement assistance. Third, the PAF combination of “all five PAFs” does not appear in Table 5. That is, our analysis indicates that the combination of all five PAFs at the same time, rather surprisingly, did not lead to any statistically significant change in VMT from the base case of no PAFs at all. Note that this cannot be attributed to the PAF preference of individuals, since that is modeled jointly with VMT decisions. What this implies is that, if all five PAFs are installed, individuals do not increase their driving VMT. One possible explanation is that, after purchasing a vehicle with many PAFs packed in, it is not uncommon to turn all features off because of false alarms, annoyance, unreliable technology, and the jerky movements (see Edmonds, 2020, Gorzelany, 2020). That is, when the entire suite of lateral as well as longitudinal assist features are in place, it is possible that individuals turn off all features *en masse*, and get back to a situation of essentially not activating any feature. On the other hand, specific packages of exclusively lateral or exclusively longitudinal movement assists may not have the same figurative and literal “turn-off” effect. But certainly this result warrants some additional investigation in future studies.

¹¹ Of course, an assumption here is that driver travel behavior shifts from the absence of PAFs to the presence of PAFs would be similar between Austin drivers and the larger U.S. population of drivers.

Fourth, middle-aged individuals (30-64 years of age) put in the most miles if equipped with PAFs, even more so than young individuals (<30 years of age), attributable to a lower IPTT in the middle-aged relative to the very young. However, the difference in additional mileage is rather small between these two age groups. As would be expected, the absolute value change in VMT is lowest for older individuals. But, from the standpoint of percentage change, the highest change is among this group of older drivers, with an estimated VMT percentage increase of 19.4% for men and 40% for women for the PAF combination that produces the highest absolute VMT change (corresponding to the package of BUC, ACC, and ABS). Fifth, and related to the previous point, while the absolute VMT change after PAF installation is higher among men relative to women, the difference is not substantial. But the percentage change is much higher among women than men because women drive less than men in general.

The last two columns provide the overall (weighted) average of the VMT increase (that is, weighted ATE) and percentage VMT increase (that is, weighted PATE) across all demographic groupings. The highest VMT change of 2,297 miles (18.9% change) is for the case when the package of BUC, ACC, and ABS is installed, while the lowest VMT change of 607 miles (5.0% change) corresponds to the case when only ABS is in the vehicle. This is consistent with the notion that sole active driving assistance systems are more intended for safety applications, while the other PAF combinations are viewed as being more assistive in nature. Interestingly, even our highest estimation of VMT change for the PAF package of BUC, ACC, and ABS, is only half as much as predicted by Hardman et al. (2021) (where they suggested an annual increase of 4,680 miles due to the presence of the composite Tesla autopilot PAF). This difference could be attributed to (a) variations in vehicle fuel type (Hardman et al.'s research was based on electric vehicles, while our study is based on all vehicles regardless of fuel type), or (b) additional features such as automatic steering in Tesla autopilot vehicles that are not part of the PAFs considered in our study, or (c) even contextual variations (Californian drivers versus Texan drivers, and differences in land-use patterns in the two states).

Another important note here. We also estimated the VMT changes for the case when PAF adoption is considered exogenous to VMT (that is, ignoring self-selection effects based on VMT in the adoption of PAFs). The corresponding full table is available in the online supplement. As expected, the VMT increases are generally underestimated when this self-selection is ignored, for reasons discussed earlier. For example, for the case of the package of BUC, ACC, and ABS, the overall population-wide VMT change is estimated at only 1,547 miles (12.6% increase) instead of our estimate of 2,297 miles (18.9% increase), a 33% underestimate in mileage. Further, the VMT change due to only ABS in the vehicle is negatively estimated at -193 miles (-1.6%), an estimate that is in the wrong direction and an underestimate in mileage by 132%. This underscores the importance of considering self-selection when examining the effects of PAFs on VMT and activity-travel behavior more generally. The finding, however, has broader applicability and highlights the importance of considering the adoption of all kinds of automation (including fully automated vehicles or FAVs) when examining activity-travel behavior impacts of that automation.

On the other hand, most studies of FAVs do not consider adoption preferences when investigating the potential activity-travel behavior impacts of FAVs.

4.3. Model Goodness of Fit

The GHDM model used in the joint modeling of PAFs and VMT provides important insights on the joint, yet different, nature of the factors influencing the five different PAFs and the VMT dimension. But to ensure that the insights gained from the joint modeling are valid and accurate, it is also important to consider the data fit provided by such a model relative to a naïve model that completely ignores jointness among the two dimensions of PAFs and VMT. For such an evaluation, the performance of the proposed GHDM model may be compared with that of a restricted model (that is, an independent model) that does not consider latent constructs (and consequently also ignores any type of dependency among the outcomes because of unobserved factors). In the restricted independent model, we model the main outcomes of the paper independently in the form of five independent binary outcomes (for the PAF outcomes) and one grouped outcome for $\ln(\text{VMT})$. This independent model takes the form of an independent binary-grouped (or IBG) model. For each of the six endogenous outcomes in the IBG model, we include all the determinants of the latent constructs (from the GHDM) as exogenous variables in the main outcome equations (so that the primary difference between the GHDM and IBG models is whether jointness in the six outcomes is considered or not). The GHDM model and the IBG model are not nested, as the latter model does not provide a mechanism to incorporate the latent constructs. Therefore, for a fair comparison between the GHDM and IBG models, we compute the predictive likelihood at convergence for only the six main outcome variables in the GHDM. Our joint model and the independent model may be then compared using a predictive Bayesian Information Criterion (BIC) statistic [$= -\mathcal{Z}(\hat{\theta}) + 0.5 (\# \text{ of model parameters}) \log(\text{sample size})$] ($\mathcal{Z}(\hat{\theta})$ is the predictive log-likelihood at convergence). The model with a lower BIC statistic is the preferred model. In addition to the comparison using the BIC value, an informal predictive non-nested likelihood ratio test may be used to compare the models. The adjusted likelihood ratio index of each model of the joint and independent models is first computed as follows with respect to the log-likelihood with only the constants in the six outcomes:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\theta}) - M}{L(c)} \quad (1)$$

where $L(\hat{\theta})$ and $L(c)$ are the predictive log-likelihood functions at convergence and at constants, respectively, and M is the number of parameters (excluding the constants) estimated in the model. Let the corresponding values be $\bar{\rho}_{GHDM}^2$ and $\bar{\rho}_{IBG}^2$. If the difference in the indices is $(\bar{\rho}_{GHDM}^2 - \bar{\rho}_{IBG}^2) = \tau$, then the probability that this difference could have occurred by chance is no larger than $\Phi\{-[-2\tau L(c) + (M_{GHDM} - M_{IBG})]^{0.5}\}$, with a small value for the probability of chance occurrence suggesting that the difference is statistically significant and the model with the higher value for the adjusted likelihood ratio index is preferred.

We also evaluate the data fit of the two models intuitively and informally at the disaggregate level. To do so, we first compute the multivariate predictions for each of the six outcomes (this will entail a total of $2^5 \times 8 = 256$ combinations). Then, for the joint model, we compute an average (across individuals) probability of correct prediction at this full dimensional level. A similar disaggregate measure is computed for the independent model. The results of the disaggregate data fit evaluations are provided in Table 6. The BIC values, predictive adjusted likelihood ratio indices, the corresponding informal non-nested likelihood ratio statistics, and the average probability of correct prediction from the joint model indicate the superior fit of the GHDM relative to the IBG model. These average probabilities reported in the table may appear low, but considering that the six outcome variables produce a total of 256 combinations, the probability of correct prediction due to random chance is $1/256 = 0.0039$; our probability values are several times better than this random chance probability of correct prediction.

5. IMPLICATIONS

Our results in Section 4 and the ATEs in Table 5 have several important policy implications and can be utilized in a multitude of ways. We identify some possibilities below.

Offsetting Hypothesis

As discussed earlier, the offsetting hypothesis suggests that the effect of improved automotive safety through technological advancements is often met with an offset effect through behavioral changes in drivers. Our analysis suggests that we could be walking a similar pathway in terms of PAFs as well. Thus, while there are suggestions that PAFs can lead to a reduction in crashes (20% reduction of head-on crashes due to LKS, 17% reduction in backing-up crashes due to BUC, 30% reduction in rear-end collisions due to ACC, 50% reduction in total crashes due to ABS, and 14% reduction in lane-change crashes due to BSM; see Utriainen et al., 2020, Cicchino, 2017, Li et al., 2017, Gorzelany, 2020, Cicchino, 2018a, Cicchino, 2018b), some of these percentage reductions are likely to be offset because of the higher VMT. Whether the increase in crashes would be closer to being linear or non-linear functions of VMT is an open question (depends on the level of automation and driver-intervention too). Nevertheless, what we can most certainly infer is that the *offsetting* effect that were observed during the introduction of seat-belts and air bag systems is also likely to be at play as automated features begin to penetrate the market. Therefore, studies and reports that provide numbers and figures about the safety improvements attributable to automation need to be viewed with caution. For example, BUC, based on our analysis, increases VMT by 10.6% in the overall, which can significantly offset the estimated 17% rear-end crash reduction attributed to BUC when VMT increase is ignored. As importantly, the 10.6% VMT increase can lead to additional rear-end as well as non-rear end crashes. That is, it is important to also consider the totality of crashes rather than the ability of an individual PAF or a combination of PAFs to reduce specific types of crashes. Further, our analysis strongly suggests that any crash reduction estimates of PAFs be examined in the context of specific demographic groups, because of the considerable variation across demographic groupings in PAF effects on VMT. For example, our estimates

indicate that BUC increases VMT by 22.6% for women older than 65 years, but only by 7.8% for men in their middle ages. Given variations in crash frequencies and injury consequences, a careful disaggregate analysis is needed in crash reduction estimates due to PAFs. Additionally, ignoring self-selection effects during estimation of automation impacts on VMT can underestimate VMT increase, and therefore also underestimate the safety offset effect.

Informing Governmental Policies

Our results suggest that, of all the PAFs, the PAF corresponding to only automatic braking systems (ABS) being installed in vehicles increases VMT the least. Thus, ABS appears to not only be effective in actually reducing crashes per mile of travel exposure, but also does not have as much offset effects by way of increasing VMT as do other PAFs. While it would obviously be impossible to mandate that only ABS be installed in the vehicle without other assistive PAFs, it does suggest that making ABS a standard feature in vehicles sooner rather than later should be a government priority. At the same time, there is a high reluctance and technology reliability concern associated with ABS systems, particularly among women and older individuals. Government-led information campaigns directed toward these demographic groups that, in a simple and clear manner, articulate the reliability and benefits of ABS should help. Of course, at a more fundamental level, it is imperative that car manufacturers undertake much more extensive testing in different driving environments before making ABS (and other PAFs) available on the market. While there is a race to include such features among auto manufacturers, ostensibly to obtain a competitive edge, a recent study by AAA automotive researchers concluded that PAFs are simply not as reliable as made out to be and had some type of a malfunction or unintended result about every eight miles of travel (Edmonds, 2020). Such experiences could, in fact, also hold back the acceptance of reliable future automation systems. In this regard, clear governmental regulations and metrics related to testing and performance quality control of all emerging automation technology would be beneficial.

More broadly speaking, the federal government and some states, such as California, have established (or are considering establishing) goals to reduce VMT, primarily to reduce mobile-source emissions. Our analysis suggests that the increased availability and standardization of PAFs in vehicles may work against such VMT reduction goals. There is also the issue of potentially increased traffic congestion due to the elevated levels of VMT. These results do point to the continued need to examine ways to hold consumers responsible for the full externality cost of their travel footprint, including potentially VMT-based fees.

Take Away for Car Manufacturers

From a marketing perspective, our analysis provides useful insights for car manufacturers regarding who among consumers are most likely to be drawn toward specific PAFs or PAF combinations. In general, women and older individuals (65 years or older) are likely to be more inclined to invest in LKS, BUC and ACC, primarily because of a perception that these assistive features contribute further to their driving control. Older individuals also have a higher propensity

to invest in ABS and BSM, because these are viewed as fostering their need for space-time mobility control (while older individuals also express safety reservations with ABS, the mobility control-based desire for ABS dominates over safety concerns in this demographic group; the net effect of being 65 years or older on ABS adoption propensity may be computed from Tables 3 and 4, and is $0.714*0.839 - 0.339*0.492 = +0.432$).¹²

Unlike the older generation, women are less likely than men to invest in the active ABS PAF (because of heightened safety concerns with technology), and are less predisposed to adopt BSM (presumably because of women's generally better peripheral vision than men). Importantly, by partitioning out the effects of demographics by psycho-social constructs, our analysis provides car manufacturers with a way to customize their advertising and media campaigns for maximum impact. Of particular note here is that, while women and older individuals appear to shy away from fully autonomous vehicles (FAVs) because of a perceived lack of driving/mobility control and safety concerns (see Asmussen et al., 2020), they appear to be much more receptive to PAFs because of a sense that they are retaining control. Strategies that play up the emotive control elements, thus, may be a good approach for car manufacturers to not only promote PAF adoption in the short-term, but also to establish a foundational affective pathway for the uptake of FAVs in the future. For example, as also identified in Asmussen et al. (2020), the new cohort of the elderly tend to be more physically active, and more open to "seeing the world" (Levy, 2020). This tendency can be exploited by positioning PAFs first, and subsequently FAVs, as the new "vehicle" for older adults to fulfill their bucket-list of travel desires and explorations, providing them a new perception of mobility control.

Travel Demand Shifts

The results of our analysis in Table 5 indicate that PAF adoption will increase VMT, well before driverless vehicles will arrive on the market and are predicted to increase VMT. This can have consequences for the urban structure of our cities, with (a) potential sprawl because of willingness to accept longer commutes and (b) an increase in urban and suburban traffic congestion due to increased trip-making and longer trips. In this regard, the likely VMT shift for several combinations of PAFs as presented in Table 5 can be directly used as inputs to travel demand models. Often, these travel models use VMT modifying factors to predict the future travel patterns under hypothetical scenarios related to automated or partially-automated vehicles. Our estimates from Table 5 can be directly used as modifying factors to forecast the intensity of travel in the presence of PAVs.

¹² The generational difference across PAF adoption in the current study is consistent with the findings of Abraham et al. (2017), though not entirely so with Owens et al.'s (2015) results that "current seniors may be more cautious with and hesitant to adopt new vehicle technology, but that they do not necessarily avoid it". The difference from Owens et al.'s conclusions may be attributed to the rapid change and maturation in PAF technology between 2015 and the dates of the more recent research of Abraham et al. and our study. In any case, our study, unlike earlier studies, "peels the onion" by partitioning demographic effects by psycho-social motivations. Overall, the efforts of Owens et al. (2015), Abraham et al. (2017) and the current study indicate that older individuals have the same, if not more, interest in lower level PAFs that will help them keep control over their driving.

6. CONCLUSIONS

In this paper, we have examined the adoption of five different types of PAFs; lane keeping system, backup camera, adaptive cruise control, automatic braking system, and blind spot monitoring; as well as PAF effects on VMT. Our focus on PAFs (rather than the extensive focus on fully automated vehicles in the earlier transportation literature) is driven by the fact that PAFs are available today in vehicles, and it is possible to investigate PAF automation preferences and PAF effects on travel using actual revealed data. In so doing, and unlike earlier PAF-related studies, we formulate a joint psycho-social latent construct-based model that examines multiple PAF technologies and investigates how the presence of PAFs affects annual vehicle miles of travel (VMT). This approach explicitly recognizes that PAF choice may be endogenous to VMT decisions (that is, we account for possible self-selection effects in PAF adoption based on VMT). As importantly, by considering vehicles with no automation at all as well as different levels of automation, we are able to obtain a more accurate assessment of PAF effects on VMT, relative to earlier studies that have considered only vehicles that are already equipped with PAFs.

The PAF dependent variables in our analysis takes the form of a binary variable. The VMT dimension takes the form of a grouped dependent variable, because annual mileage information is typically elicited from respondents in bracketed categories. The joint modeling of PAF adoption and VMT is accomplished using a behavioral framework that considers both individual demographic characteristics as well as psycho-social characteristics. The resulting GHDM model controls for possible self-selection effects in PAF adoption based on VMT, and thus is able to estimate “true” PAF effects on VMT. Our analysis specifically indicates that ignoring this self-selection can lead to an underestimate of VMT increase due to PAF adoption. The data used for the analysis is drawn from a 2019 “emerging mobility” survey conducted in the Austin metropolitan area in Texas,

The results underscore the importance of considering psycho-social variables, in addition to individual demographic characteristics, when modeling PAF adoption. For example, women and older individuals (65 years or older) appear to be more inclined to invest in assistive PAFs, because of a perception that these assistive features do not wrest control away from the human driving act. However, women are less likely than men to invest in the more active ABS PAF because of heightened safety concerns with technology. In terms of PAF effects on VMT, PAFs focusing more on lateral movement assistance appear to have a smaller VMT effect than those that serve the functionality of longitudinal movement assistance. The highest estimated VMT change of 2,462 miles (13.8% change) is for the case when the package of BUC, ACC, and ABS are installed and for middle-aged men. The highest percentage estimate VMT change (40%), though, is for the same package of BUC, ACC, and ABS for older women. Overall, there are variations in VMT impact across demographic groupings and PAF combinations, suggesting that a single aggregate percentage improvement in safety benefits across all demographic groupings may suffer from the well-known ecological fallacy.

Our study points to the need for much additional research related to PAF effects on VMT and activity-travel behavior. First, VMT is a rather aggregate dependent outcome, and a closer

examination of PAF effects on activity-travel behavior at a finer resolution would be valuable. Second, as discussed in Section 2.3, examining an expansive set of vehicle attributes (in addition to the PAFs examined in the current paper) as well as analyzing PAF usage (jointly with PAF adoption and VMT effects) would help in more accurately assessing PAF effects on VMT. Third, isolating PAF use and VMT driven (on each household vehicle) by each household member would better capture preference heterogeneity across different household members. Fourth, a larger sample size of respondents may identify additional determinant variables of PAF preferences and VMT. Fifth, there is a need to undertake more studies to develop a resource base to evaluate PAF benefits and offset effects by demographic groupings, given the repercussions of varying (across demographic groups) VMT impacts of PAFs for number of crashes and injury severity. Finally, policy studies that focus on how best to harness the safety benefits of assistive technologies, while also curtailing the consequent VMT growth, is needed.

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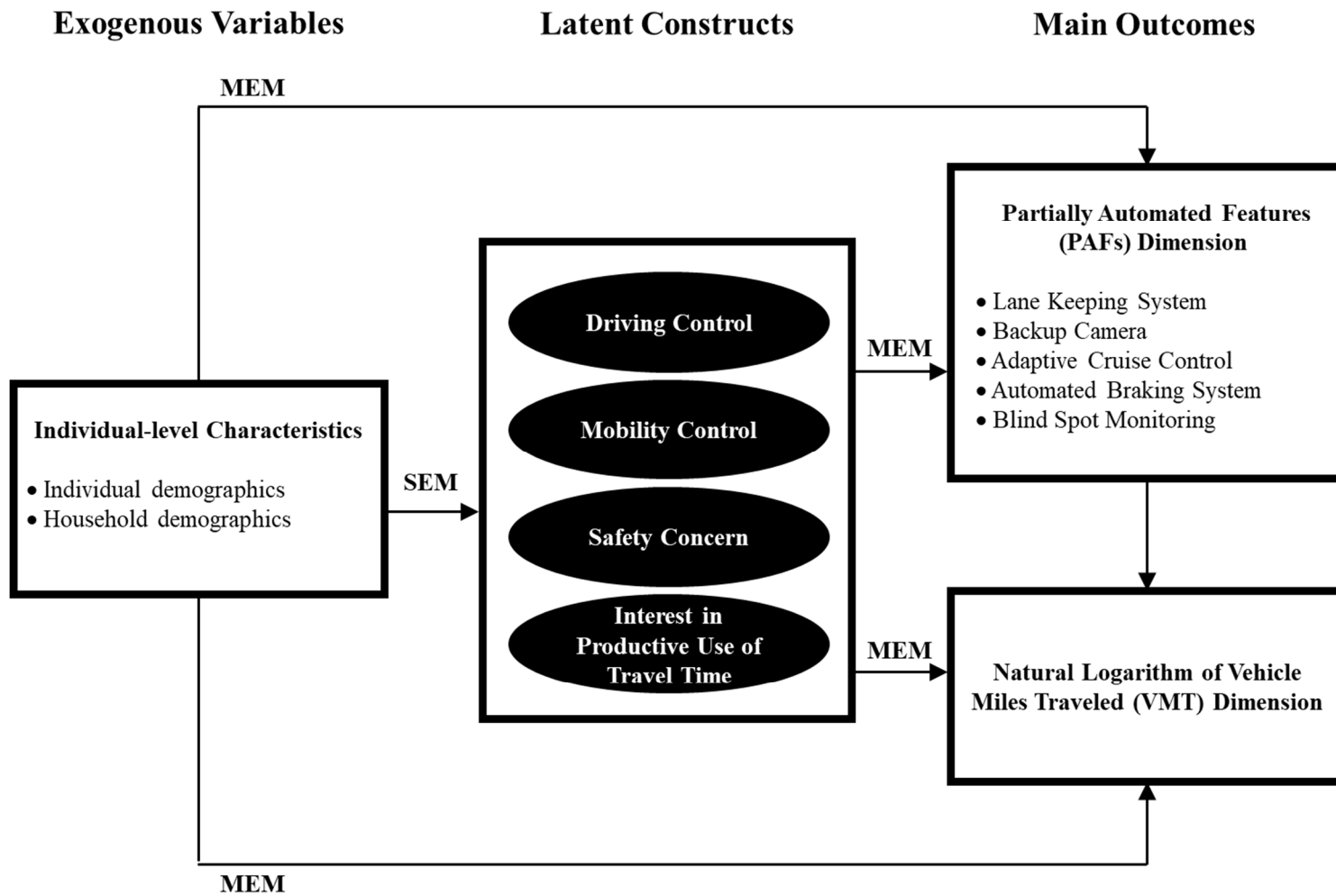


Figure 1. Model Framework

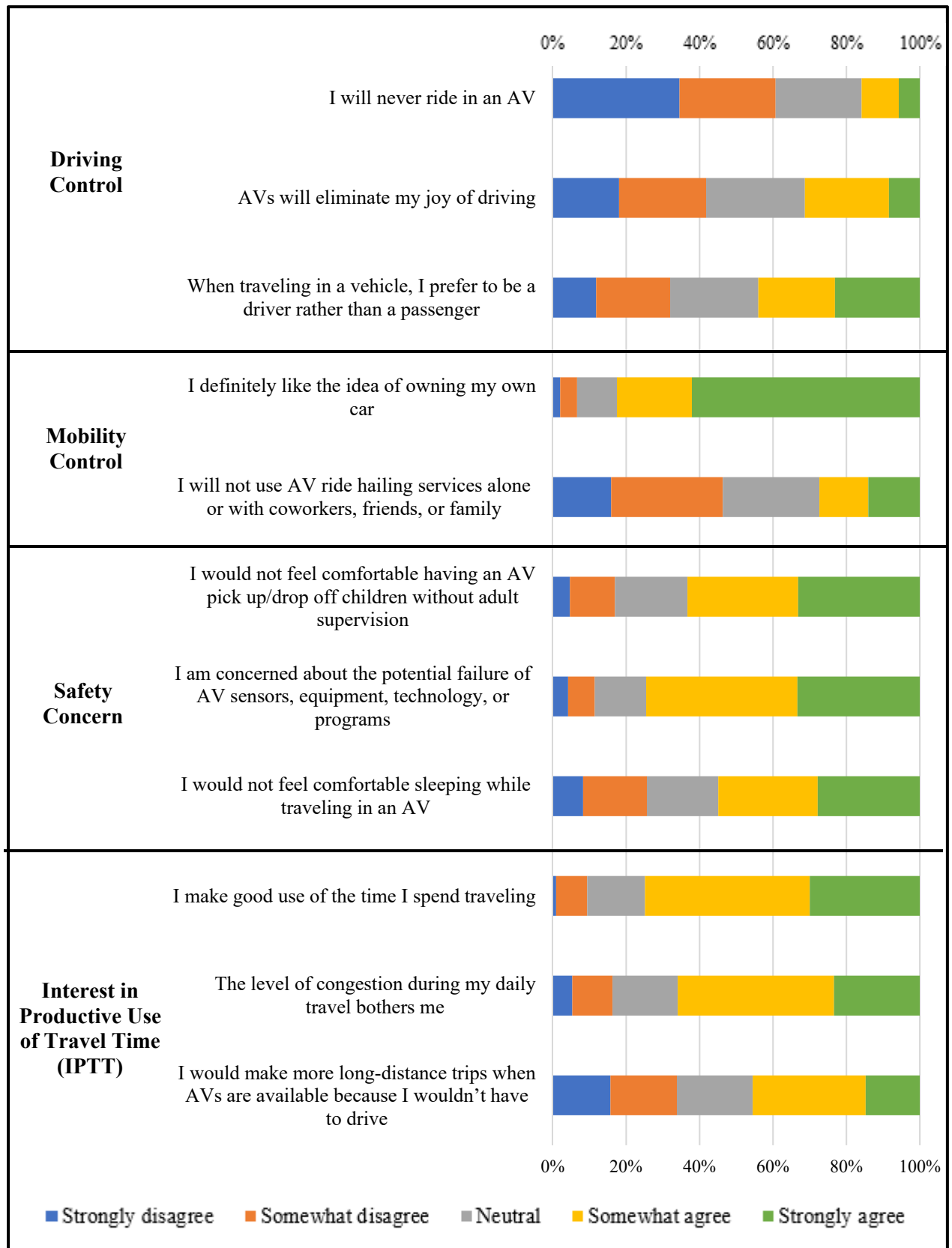


Figure 2. Distribution of Attitudinal Indicators

Table 1. Sample Distribution of Exogenous Variables: Socio-Demographic and Household Related Characteristics

Variable	Count	%
<i>Individual Demographics</i>		
Gender		
Female	634	64.8
Male	344	35.2
Age		
18 to 29	550	56.3
30 to 39	117	12.0
40 to 49	104	10.6
50 to 64	103	10.5
65 or older	104	10.6
Employment Type		
Student	*490	50.1
Employed	*605	61.9
Unemployed and not a student	113	11.6
Education		
Completed high-school or less	136	13.9
Completed some college or technical school	340	34.7
Completed undergraduate degree	335	34.3
Completed graduate degree	167	17.1
<i>Household Characteristics</i>		
Household Annual Income		
Less than \$24,999	205	20.9
\$25,000 to \$49,999	191	19.5
\$50,000 to \$74,999	158	16.2
\$75,000 to \$99,999	139	14.2
\$100,000 to \$149,999	155	15.9
\$150,000 to \$249,999	91	9.3
\$250,000 or more	39	4.0
Household Size		
1	210	21.5
2	278	28.4
3	152	15.5
4 or more	338	34.6
Number of Vehicles in Household		
1	265	27.1
2	353	36.1
3 or more	360	36.8
Household Structure		
Nuclear family	134	13.7
Single parent	45	4.6
Lives alone	210	21.5
Couple, no children	207	21.2
Multiple adults, no partner, no children	310	31.7
Other	72	7.3
Children (<18 years) in Household		
Yes	179	18.3
No	799	81.7

*230 respondents were both employed and students

Table 2. Sample Distribution of Outcome Variables

Variable	Count	%
Partially Automated Features		
Lane Keeping System (LKS)	151	15.4*
Backup Camera (BUC)	494	50.5
Adaptive Cruise Control (ACC)	352	36.0
Automatic Braking System (ABS)	272	27.8
Blind Spot Monitoring (BSM)	203	20.8
None	345	35.3
Popular “Technology Packages”		
No PAFs	345	35.3
Only Backup Camera	135	13.8
All PAFs	82	8.4
Only Backup Camera (BUC) and Adaptive Cruise Control	81	8.3
Only Adaptive Cruise Control	50	5.1
Only Automatic Braking System	41	4.2
Only Backup Camera, Adaptive Cruise Control and Automatic Braking System	34	3.5
Only Backup Camera and Automatic Braking System	31	3.2
Only Adaptive Cruise Control and Automatic Braking System	28	2.9
Only Lane Keeping System, Backup Camera and Blind Spot Monitoring	14	1.4
Household Annual Miles Traveled by Relevant Vehicle		
Less than 5,000	128	13.1
5,000 to 9,999	232	23.7
10,000 to 14,999	375	38.3
15,000 to 19,999	98	10.0
20,000 to 24,999	56	5.7
25,000 to 29,999	26	2.7
30,000 to 39,999	20	2.1
40,000 or more	43	4.4

*The sum of the percentages in this column for this first row panel do not add up to 100 because multiple PAFs can be installed at the same time.

Table 3. Determinants of Latent Variables

Variables (base category)	Structural Equations Model Component Results							
	Driving Control		Mobility Control		Safety Concern		IPTT	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Gender (male)								
Female	0.188	10.11	0.261	8.04	0.745	32.87	-0.094	-4.94
Female*Presence of children	--		--		0.151	5.45	--	
Age (younger than 30)								
34 to 64	--		--		--		-0.085	-4.80
65 or older	0.531	16.82	0.839	17.78	0.493	15.93	-0.367	-11.80
<i>Household Characteristics</i>								
Income (<\$100,000)								
≥\$100,000	--		0.274	10.11	-0.124	-6.50	--	

Table 4. Estimation Results of PAFs and VMT

Exogenous Variables (base category)	Vehicle Features										Vehicle Miles Traveled	
	Lane Keeping System (LKS)		Backup Camera (BUC)		Adaptive Cruise Control (ACC)		Automatic Braking System (ABS)		Blind Spot Monitoring (BSM)			
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Latent Construct Effects												
Driving Control	0.396	2.80	0.304	10.35	0.331	11.17	--	--	--	--	-0.131	-1.78
Driving Control*Age 65 or Older	0.419	7.25	--	--	--	--	--	--	--	--	--	--
Mobility Control	--	--	--	--	--	--	0.714	10.48	0.506	8.06	-0.227	-5.97
Safety Concern	--	--	--	--	--	--	-0.339	-6.93	--	--	-0.100	-1.22
IPTT	0.205	1.55	--	--	--	--	--	--	--	--	-0.364	-3.82
Individual-level Characteristics												
Gender (male)												
Female	--	--	--	--	--	--	--	--	-0.285	-8.84	0.081	1.47
Household Characteristics												
Income (<\$100,000)												
≥\$100,000	--	--	--	--	--	--	--	--	--	--	0.144	6.21
PAF Effects												
Only Backup Camera	NA		NA		NA		NA		NA		0.096	5.32
Only Adaptive Cruise Control	NA		NA		NA		NA		NA		0.088	3.90
Only Automatic Braking System	NA		NA		NA		NA		NA		0.046	1.83
Only BUC*ACC	NA		NA		NA		NA		NA		0.117	6.01
Only BUC*ACC*ABS	NA		NA		NA		NA		NA		0.164	5.48
Only ACC*ABS	NA		NA		NA		NA		NA		0.117	3.64
Only LKS*BUC*BSM	NA		NA		NA		NA		NA		0.099	2.42
Constant	-1.148	-39.67	-0.039	-3.22	-0.436	-30.59	-0.762	-24.41	-0.921	-28.61	0.064	5.52
Standard Deviation	NA		NA		NA		NA		NA		0.613	35.22

Table 5. VMT Change Estimates (ATE) (% Change Estimates or PATE) for each PAF Combination

PAF Combination	Gender and Age Group ATEs						Overall ATE for each PAF	Overall PATE
	18-29 Years		30-64 Years		65 Years or Older			
	Male	Female	Male	Female	Male	Female		
Only Backup Camera	1,350 (8.2%)	1,290 (11.6%)	1,392 (7.8%)	1,331 (12.7%)	1,132 (11.0%)	1,082 (22.6%)	1,299	10.6%
Only Adaptive Cruise Control	1,232 (7.5%)	1,178 (10.5%)	1,271 (7.1%)	1,215 (11.6%)	1,034 (10.0%)	988 (20.6%)	1,186	9.8%
Only Automatic Braking System	631 (3.9%)	603 (5.4%)	650 (3.6%)	622 (5.9%)	529 (5.1%)	506 (10.6%)	607	5.0%
Only Backup Camera and Adaptive Cruise Control	1,663 (10.2%)	1,590 (14.3%)	1,715 (9.6%)	1,640 (15.6%)	1,395 (13.5%)	1,333 (27.9%)	1,600	13.2%
Only Backup Camera, Adaptive Cruise Control and Automatic Braking System	2,387 (14.6%)	2,282 (20.5%)	2,462 (13.8%)	2,354 (22.4%)	2,003 (19.4%)	1,915 (40.0%)	2,297	18.9%
Only Adaptive Cruise Control and Automatic Braking System	1,663 (10.2%)	1,590 (14.3%)	1,715 (9.6%)	1,640 (15.6%)	1,395 (13.5%)	1,333 (27.9%)	1,600	13.2%
Only Backup Camera, Lane Keeping System, and Blind Spot Monitoring	1,394 (8.5%)	1,333 (12.0%)	1,438 (8.0%)	1,375 (13.1%)	1,169 (11.3%)	1,118 (23.4%)	1,341	11.0%

Table 6. Disaggregate Data Fit Measures

Summary Statistics	Model	
	Joint (GHDM) Model	Independent (IBG) Model
Predictive log-likelihood at convergence	-4381.98	-4645.49
Number of parameters	103	31
Bayesian Information Criterion (BIC)	4736.58	4752.21
Constants-only predictive log-likelihood	-4782.42	-4782.42
Predictive adjusted likelihood ratio index	0.0622	0.0221
Informal non-nested adjusted likelihood ratio test: Joint model versus Independent model	$\Phi[-16.241] \approx 0.000$	
Average probability of correct prediction	0.022	0.020