

**E-Scooter Sharing and Bikesharing Systems: An Individual-level Analysis of
Factors Affecting First-use and Use Frequency**

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ABSTRACT

Shared micromobility modes have increasingly penetrated the mobility environment of cities in the U.S. and the world over. At the same time, to best integrate these emerging modes within the fabric of the existing (and larger) transportation ecosystem, it is critical to understand how individuals may respond and “who” the likely users of these relatively new modes may be. In this paper, we develop a model to analyze first-use and use frequency of two micromobility modes: E-scooter sharing systems (ESS) and Bike sharing systems (BSS). The model employs psycho-social constructs, built environment attributes, as well as individual-level demographics as determinants. In doing so, we explicitly recognize the role played by awareness/first-use of new technologies as a cognitive antecedent to subsequent frequency decisions. The main data source for this analysis is drawn from a 2019 survey of Austin, Texas area residents. Our results highlight the importance of considering psycho-social attitudes to both gain better insights into the behavioral process leading up to ESS/BSS adoption/use as well as ensure an accurate data fit. In particular, there are distinctive pathways of adoption/use frequency for each of the ESS and BSS modes, but also complementary processes and behavioral spillover effects at play that warrant a joint modeling of the ESS and BSS modes. Our results suggest that addressing safety concerns of micromobility modes should be the top priority of providers and public agencies. Efforts solely directed toward extolling the “green” virtues of micromobility modes is likely to have limited returns.

Keywords: Micromobility, electric scooters, bike share systems, active mobility, shared mobility, transportation equity

1. INTRODUCTION

Electric scooter sharing systems (ESS) and Bike sharing systems (BSS) have become increasingly popular within the past decade (Fishman et al., 2013; Ricci, 2015). These new modes of travel are integrated with personal technology, can provide tailored and flexible mobility services, and are typically powered by electricity (while some BSSs may still require manual peddling, electric-powered boosts make the physical effort easier). The ESS/BSS equipment is smaller in size and lighter than traditional transportation modes, and the modes are particularly suited for short trips or for last-mile trips such as access to a transit transfer point (Abduljabbar et al., 2021; Baek et al., 2021). The compactness of the physical and travel-related attributes of the modes have earned them the moniker of “micro-mobility” (see Sheller, 2011; Populus, 2018).

The most common micromobility modes today correspond to dockless ESSs and dockless BSSs. While docked BSSs have been available for over a decade, dockless ESSs and BSSs have dominated the micromobility market since their introduction in U.S. cities (including in 2018 in Austin, Texas, the city of focus in this paper). These dockless systems are viewed as positive accessibility “tools” that facilitate participation in out-of-home activities because of the ease of returning the equipment after use at proximal and conveniently located places (Chen et al., 2020a). Besides, these systems (a) are notably faster than walking and can be faster than public transportation, (b) can be less expensive and less stressful than the car mode, especially for travel around downtown and other dense city areas where car parking fees can be quite high and driving in congested traffic can create angst, (c) offer the convenience of quick unlocking and electronic payment through a single application on a smartphone, and (d) do not require any fixed commitment of ownership and maintenance (Teixeira et al., 2020; Sanders et al., 2020; City of Austin, 2019; Populus, 2018).¹ Environmentally conscious individuals may also view these systems as less polluting relative to other motorized vehicles, and as facilitators for pursuing activities using public transportation (Portland Bureau of Transportation, 2018; Kille, 2015).

Of course, some negative externalities of ESSs and BSSs have also been identified, the most important of which relate to safety, both with the actual equipment itself as well as in the context of broader traffic crash considerations (see Azad, 2018). This is particularly so because many users of ESS/BSS (66% of users according to the Portland Bureau of Transportation, 2018) are not aware of their obligations when sharing the road with other vehicles and pedestrians. The deregulated nature of dockless ESS/BSS systems and irregular parking behavior has also contributed to an increase in pedestrian/bicycle crashes, primarily due to hastily abandoned dockless BSS/ESS equipment on sidewalks and associated off-road infrastructure. In addition, earlier research does suggest that micromobility services, in general, appear to leave specific segments of the population behind, such as low-income groups, minorities, unemployed individuals, the not-so-well-educated, and senior individuals, potentially intensifying inequity considerations in mobility service offerings (see Teixeira et al., 2020; Buck et al., 2013; Goodman

¹ In a poll across 11 major U.S. cities conducted by Populus Groundtruth (Populus, 2018), 70% of respondents perceived ESSs as a positive addition to mobility options. In another study, 48% of visitors to a city used ESS instead of a car, taxi, or other ridesharing systems for recreational activities (Portland Bureau of Transportation, 2018).

and Cheshire, 2014; Ursaki and Aultman-Hall, 2015; and Fishman et al., 2015). Another concern is that these systems may draw away from current walk and solely manual bicycling trips, resulting in adverse impacts on active travel intensity with concomitant physical health repercussions: trips taken by walking or manual biking provide valuable exercise for the user and reduce many health risks and diseases (Buehler et al., 2016).

The preceding discussion highlights the benefits of ESS and BSS modes as being convenient, quick, easy, and accessible to many, but also point to the potentially unsafe, unregulated, and inequitable nature of these systems. However, many of the micromobility insights above on ESS/BSS systems are based on the vast literature on docked bicycle-sharing systems, and not on dockless systems. At the same time, the explosion of dockless systems in recent years has raised new safety, regulatory, and planning questions. Should the use of these dockless systems be restricted to specific areas or specific facility types? Where should rental and return facilities (even if dockless) be situated from a demand and safety perspective? Who are the current users of these dockless ESS and BSS systems? Are there specific social groups who are being left behind, and, if so how can planning and policy instruments be crafted to bring more equity? In particular, how can dockless ESS and BSS services be structured to bring these systems into the cognitive, consideration, and actual use zone of already-mobility-disadvantaged social groups?

At the heart of the questions posed above is a need to understand and characterize demographic and psycho-social factors that affect whether an individual will use these systems or not, and, if they do, the intensity of use. Further, since ESS and BSS modes have similarities, it is of interest to jointly consider both these systems to understand if they are complements or substitutes as mode choices. Accordingly, in this paper, we focus on an analysis of first-use (or not) as well as the intensity of use dimensions associated with both dockless ESS and BSS systems (note that the ESS system in Austin is entirely electric-powered, while the BSS system equipment may be completely manual or electric-assisted in the sense that the electric-assist kicks in only when riders manually pedal). By first-use above, we refer to the event of an individual using an ESS or a BSS for the first time (that is, the event through which the individual transitions from being a non-user to becoming a user), while intensity of use refers to how frequently an individual uses the micromobility alternative **given** that the individual has already used it at least once.

Individual socio-demographics, as well as psycho-social variables (in the form of latent psychological constructs) and built environment (BE) variables are used as determinant variables. Possible endogeneities among the first-use/use frequency outcome variables for ESS/BSS are modeled efficiently and in a behaviorally realistic manner by mediating socio-demographic effects through stochastic latent psychological constructs. Based on the model results, we propose policy measures that would address the safety and equity considerations identified earlier. The data source for our analysis is an Austin area survey undertaken between July 2019 and October 2019.

2. LITERATURE OVERVIEW AND THE CURRENT STUDY

Much of the literature related to micromobility studies has focused on docked bikesharing, with comparatively little research on dockless BSS and even scarcer investigations into ESS systems.

An extensive review of the docked and dockless BSS literature is available in Fishman (2016), Poveda-Reyes et al. (2021) and Chen et al. (2020a), with an earlier international review of BSS users being provided by Fishman et al. (2013). Some of the earlier studies have examined the system-wide considerations of docked BSSs and dockless BSSs, such as bicycle availability at docking stations, concentration of bicycles in specific zones, station locations, optimal rebalancing strategies, dynamic management frameworks, and helmet supply (see, for example, Fishman et al., 2013, Ricci, 2015, Romero et al., 2012, Li and Shan, 2016, Kabak et al., 2018, Ban and Hyun, 2019, Chen et al., 2019, Dong et al., 2019, Cheng et al., 2020, and Caggiani et al., 2018; Eren and Uz, 2020, provide a good review of these system wide considerations). Not surprisingly, relatively little research exists related to ESS and management considerations, given e-scooters entered the mobility market relatively recently.

For our current research, however, it is the consumer-level considerations (which focus on the “who” and “why” of ESS/BSS users) that are more relevant than the system-wide considerations just discussed (after all, as stated by Shaheen and Cohen, 2019, and Chen et al., 2020b, few research studies focus on the demand-side consumer-related factors influencing ESS/BSS use). Even within this consumer-side literature, most studies have focused on docked BSS, with relatively few studies investigating dockless ESS/BSS systems. Some of the studies examine ESS/BSS demand at an aggregate spatial level of analysis (either at a station-level or a zone-level, or a city-level, focusing on identifying the nature of spatial demand hotspots within a region or comparing use across different cities) to investigate the effects of weather, topography, bike infrastructure and equipment characteristics, and land-use attributes (see, for example, Wang et al., 2016, El-Assi et al., 2017, Noland et al., 2019, Scott and Ciuro, 2019, He et al., 2020, Guo and He, 2020, Wu et al., 2021, and Poveda-Reyes et al., 2021 in the context of docked and dockless BSS; and Lee et al., 2021 and Younes et al., 2020 in the context of ESS). While certainly providing insightful results on the effects of aggregate spatial-level features on ESS/BSS use, these are not at the individual decision-making level that is the focus in the current paper. Even within an individual-level decision-making context, our emphasis is on investigating individual-level factors, rather than trip-level and or travel pattern-level factors, such as trip time-of-day, trip purpose, trip distance, price for trip, battery charge level vis-a-vis trip distance, bike availability relative to trip origin, and current frequency of travel by other modes (see Caspi et al., 2020, Lee et al., 2021, Baek et al., 2021, and Reck et al., 2021 that place more emphasis on such trip-level and travel-level attributes impacting ESS/BSS use).

In the rest of this section, we confine attention to earlier individual-level studies of ESS/BSS use that consider socio-demographic and psychosocial variables. Further, we narrow the review to the most relevant precursor studies that examine ESS/BSS use as obtained from revealed choice data, rather than on studies that examine stated intentions to use ESS/BSS (see, for example, Eccarius and Lu, 2020, Said et al., 2021, Lee et al., 2021, and Biehl et al., 2019 for studies using stated intentions). While we acknowledge the potential value of stated intention-based analyses, these are potentially subject to various kinds of biases in terms of a mismatch in stated intentions and actual manifested behaviors, while our analysis focuses directly on the latter.

2.1. Docked/Dockless BSS Studies

Studies of docked BSS consistently indicate that BSS users tend to be young men with high incomes (see, for example, Shaheen et al., 2013 and Heinen et al., 2018). BSS users are more likely to be employed and with a high level of education. The effects of car ownership and bicycle ownership is more ambiguous, with some studies suggesting that car/bicycle ownership increases BSS usage (Shaheen et al., 2011, Fishman et al., 2014), and others suggesting the opposite (Chen et al., 2020b, Bachand-Marleau et al., 2012). The presence of children in the household has also been associated with lower use of docked BSS (Poveda-Reyes et al., 2021, Grasso et al., 2020, and Ketchman, 2015).

Chen et al. (2020b) further study the differences in user characteristics between docked and dockless BSS systems, by classifying users into three categories of “hardly use” (almost don’t use), “occasionally use” (use several times a month), and “frequently use” (use several times a week). Their model results suggest that the overall user demographic effects are similar across both BSS systems. Interestingly, though, in their model analysis, gender and age did not turn out to be statistically significant impactors for both docked and dockless BSS frequency of use. Link et al. (2020) use a sample of 408 individuals at hotspots of parked BSS in Vienna to examine the factors that impact membership in both docked and dockless BSS programs. Similar to earlier studies, they find that young men are most likely to be part of a BSS program. Further they use a number of indicators of attitudes and observe that those who are fitness- and health-conscious are more likely to be BSS users. Dockless BSS users appear to have lower incomes, value time less, and are more cost-sensitive than docked BSS users.

2.2. ESS Studies

Sanders et al. (2020) investigate the individual-level characteristics of ESS users, using data collected from a 2019 survey of Arizona State University staff in Tempe, Arizona. They classify respondents into one of four categories: non-riders, past riders (used ESS, but not in the past month), occasional riders (ridden in past month, but less than once a week), and regular or frequent riders (ridden at least once a week in the past month). The primary purpose of their study was to understand the facilitators and deterrents to ESS use. Among their results, they observe that, while all ESS riders value (a) travel quickness relative to walking, (b) the lack of a need to drive, (c) environmental-friendliness, and (d) physical comfort in hot weather, frequent ESS riders value these benefits more so than other riders. Safety concerns in the use of ESS is identified as the single most important and consistent barrier (across all respondents and rider groups) to ESS use, especially for women (and this gender difference is particularly the case for non-riders). The researchers also consider the effect of race, though no statistically significant differences are noticed. A similar result of the lack of any race effect is observed in Poveda-Reyes et al. (2021).²

² While most individual-level analyses have not used or did not find any race/ethnicity impact on docked BSS use, some studies at a more aggregate spatial level do suggest disparities in docked BSS uptake. For instance, Goodman and Cheshire (2014) note that, in London, many of the economically poorer minority areas did not have any access to docked BSS, and also observe that many people in such areas also do not own smartphones to be able to rent the scooters. Within the U.S., Ursaki and Aultman-Hall (2015) point out that, African Americans have a generally lower

Aguilera-García et al. (2020) investigate the key drivers of individuals' use of ESS in Spain. Using a survey-based sample of 430 individuals from different Spanish cities who were aware of the existence of ESS, they employ a generalized ordered-response model to investigate the factors affecting use as characterized in a three-level ordered categorization of “never used”, “occasionally used” (less than once per week), and “frequently used” (once per week or more frequently). Their study confirms the importance of age (individuals below the age of 35 years are more frequent users, while those above 50 years of age use ESS less frequently), student status (students are more frequent users), education level (highly educated individuals are more frequent users), income level (high income increases the probability of never using ESS), and vehicle ownership (one or more vehicles in the household increases the propensity to occasionally use ESS). The researchers also consider indicators of personal attitudes (willingness to download new apps, share personal data, and share bank account information) and the travel priority of respondents (such as importance of travel time, travel cost, and travel time reliability). These indicators were captured in the survey on a five-point Likert scale and are directly used as explanatory variables. The results suggest that those more willing to share bank account information and those who have a high concern for environmental issues are the most frequent ESS users.

2.3. Joint BSS and ESS Studies

Two studies that most closely relate to the current study are those by Bielinski and Wazna, 2020 and Reck and Axhausen, 2021. The Bielinski and Wazna (2020) study uses data collected from a survey of 633 respondents of Tricity in Poland to examine the differences between the users of ESS and BSS. Using descriptive statistics, they observe that, while both ESS and BSS users tend to be young, ESS users are even younger, on average, than BSS users. They did not find any difference in income between BSS and ESS users, though ESS users are less likely to hold a car driving license than BSS users. The main barriers to ESS use are cost, lack of ESS scooters in the right locations, and safety concerns. Access to public transportation is identified as one of the primary reasons for the use of BSS/ESS modes, especially for the BSS modes.

The second study by Reck and Axhausen (2021), undertaken in Zurich, Switzerland, surveyed individuals to obtain information on their usage frequency of three sharing systems (docked BSS, dockless BSS, and dockless ESS programs), along with person-specific and household-specific demographics. The travel priority of respondents, in the form of priority for the environment, travel time, and travel flexibility, obtained on a four-point Likert scale spanning the range from “not important” to “important”, was also obtained and used directly to examine impacts on whether a respondent was a user of each of the three shared systems. The researchers define a respondent as a user if each service is used at least “several times a month”, resulting in a sample size of 207 docked BSS users, 73 dockless BSS users, and 178 ESS users. Next, using the binary outcome (user or not) for each of the three sharing systems, they estimate independent binary

access to docked BSS, based on their analysis of data from seven different U.S. cities. Buck et al., 2013 and Fishman, 2016 similarly note that, in Washington D.C., minorities are severely underrepresented in docked BSS programs.

probits and then a joint multivariate binary probit. The results indicate that women are less likely to use all three forms of sharing systems, especially so for ESS service. On the other hand, age and income have no effect on ESS service use but have a statistically significant effect on both docked and dockless BSS service. In particular, younger individuals and high-income individuals are more likely than their peers to use docked/dockless BSS. Individuals with children in the household are less likely to use ESS. Interestingly, a high priority for the environment negatively impacts all forms of ESS and BSS use (especially so for ESS), perhaps because walking is considered more environmentally friendly by individuals in Zurich. Individuals with high priority for time and flexibility, as well as those with public transport season ticket ownership, are also more likely to be ESS users, again perhaps because of the prevalence of walking as the immediate competing mode to ESS/BSS (a situation that is likely to be quite different from the situation in U.S. cities).

2.4. The Current Paper

There has obviously been a surge recently in ESS/BSS studies, which have provided insights from different vantage points. In the current study, we add to this literature by expressly considering awareness/first-use of sharing systems as a cognitive dimension separate from the manifested behavior of use frequency given a person has been brought to the point of being aware and has experienced the use of the system (while also recognizing the potential jointness across the first-use and use frequency dimensions). In addition, we consider psycho-social variables (in the form of latent psychological constructs) and go beyond simply presenting the model results to computing treatment effects of each variable, which facilitates the identification of effective policy strategies to promote the uptake of ESS/BSS systems and enable more equity in service provision.

Overall, there are at least six salient aspects of this research. First, we expressly recognize the importance of differentiating awareness/first-use from use frequency. The socio-technical literature clearly underscores the critical role played by awareness/first-use of new technologies as a cognitive antecedent to subsequent frequency of use, through a greater sense of transparency and downstream knowledge of the technology (see Piao et al., 2016, Ward et al., 2017 and Marikyan et al., 2019). These relatively recent studies in consumer behavior, drawing also from the awareness-knowledge transition from diffusion of innovation theory (see Rogers, 2002), point to the fact that awareness/first-use is not adequately considered even in the widely used Theory of Planned Behavior (TPB; Ajzen, 1991) and the Technology Acceptance Model (TAM) (Davis, 1989, and Venkatesh and Davis, 2000). In modeling awareness/first-use, we also implicitly draw on behavioral change theory based on delineating stage-specific determinants of readiness to change, as considered by Biehl et al. (2019), Eccarius and Lu (2020), and Said et al. (2021).³

³ This behavioral change theory, originating from the Transtheoretical Model (TTM) in health psychology, is still in its infancy in the transportation field (see Prochaska et al., 2008 and Biehl et al., 2019 for additional details). TTM basically views behavioral change as comprising five distinct stages of change: precontemplation, contemplation, preparation, action, and continuation. Of course, from the standpoint of a new technology uptake, an individual will also need to be aware of the new technology to even begin the pre-contemplation stage. Also, to be sure, there is considerable debate among psychologists about the value of the TTM, especially on the definitions and validity of the thresholds that constitute the change points between different stages. Essentially, while retaining the spirit of the TTM, studies use different numbers of stages and definitions for change points. In this study, to avoid the inevitable

Specifically, we recognize that individual-level factors may impact the first-use dimension differently from the subsequent frequency of use dimension.

Second, we consider not only demographic and built environment variables, but also psycho-social attitudinal variables in our analysis. The importance of including such attitudinal variables has been recognized in the field for some time now but has not been adequately recognized in the BSS/ESS field. As identified by Chen et al. (2020a) in a recent review of BSS, “What effects the social environment and attitude attributes have on usage of dockless shared bikes remain under-researched” (see also the works of Biehl et al., 2019, Eccarius and Lu, 2020, and Said et al., 2021, who find that pro-environmental and a sense of community do impact intentions to use BSS/ESS, though these papers are based on stated intentions rather than actual use behavior). Additionally, unlike the studies of Aguilera-García et al. (2020) and Reck and Axhausen (2021), which include indicators of attitudes (such as those related to environmental concerns, travel time priority, and travel cost) directly as explanatory variables, we recognize that the indicators are manifestations of underlying (but unobserved to the analyst) latent attitudes. Doing so is important from both a methodological and policy standpoint.⁴

Third, we identify the magnitude of different pathway effects of observed individual demographics, by partitioning the influence of an exogenous variable into a direct effect and indirect mediating effects through the psycho-social constructs. This exercise provides important policy insights to identify effective targeting and positioning strategies, customized to each socio-demographic group of the population.

Fourth, we model all the four main outcomes of interest; ESS first-use, BSS first-use, ESS use frequency, and BSS frequency; as a joint package choice. In addition to the gains that accrue from an econometric efficiency standpoint in estimating covariate effects, especially from the small samples of ESS and BSS users (given the relative novelty of these as mobility options), recognizing jointness allows the ability to answer intrinsically multivariate questions such as the effect of a covariate on a multidimensional outcome (Teixeira-Pinto and Harezlak, 2013). In this context, unlike earlier studies that simply estimate joint models, we show the value of doing so from both an intuitive data fit perspective as well as from a policy standpoint. From the latter standpoint, there may be complementary or competitive forces in ESS and BSS uptake/use due to

ambiguity arising in the definition of the change points, we simply consider a two-stage empirical framework for adoption and use frequency: bringing individuals to the point of first-use of BSS/ESS, followed by a separate process dictating frequency of use after first-use.

⁴ From a methodological standpoint, the indicators are proxies of attitudes captured with measurement error. This measurement error results in the stochasticity of the underlying latent construct, and this stochasticity engenders a correlation between the indicator and the outcome of interest. Thus, using an indicator variable directly as an exogenous variable invites the pitfalls of inconsistent model estimation (biased effects of the attitudinal effects, but also biased effects of other model coefficients; see Bhat and Dubey, 2014). In addition, the lack of a structural model to relate the attitudes to observed explanatory variables implies that the estimated model cannot be used in forecasting mode. From a policy standpoint, using attitudinal indicators directly does not provide insights regarding how informational campaigns can be appropriately directed and positioned to obtain a desired outcome. For example, if environmental consciousness is an important determinant of BSS/ESS, that by itself does not provide adequate insights for interventions, unless the relationship between observed individual characteristics and environmental consciousness is mapped out in a structural model.

unobserved correlation effects, as well as similar as well as distinct pathways by which a particular demographic variable may influence uptake/use. We show how the estimated model may be utilized to extract not only the marginal effects of exogenous variables individually on each of the ESS and BSS modes, but also the marginal effects on the combined use of the two modes. These insights can be harnessed appropriately by, for example, city agencies so that ESS and BSS do not cannibalize from each other as much as they work in tandem to promote the use of micro-mobility services in a safe and equitable manner.

Fifth, we employ Bhat's (2015) Generalized heterogeneous Data Model (GHDM) model to achieve the jointness just discussed. In particular, the stochasticity of the psycho-social latent constructs permeates into the four main outcomes of interest and generates the jointness in an econometrically efficient fashion as well provides a behaviorally grounded and insightful framework for policy interventions. The model includes 15 indicator variables as well as four main outcomes of interest, and results in an integral dimension of the order of 20 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).

Finally, our study focuses on a U.S. city, unlike the vast majority of earlier BSS/ESS studies that have either focused on a Chinese city or a European city (with questionable behavioral transferability to U.S. cities because of differing socio-political, cultural, existing transportation infrastructure, and typical travel norms). For example, the two studies closest in relevance to this study; Bielinski and Wazna, 2020 and Reck and Axhausen, 2021; were undertaken in a European city context, and travel behavior and motorized vehicle ownership levels in European cities are quite different from that in U.S. cities (see, for example, Gomez et al., 2021).

3. METHODOLOGY AND SAMPLE DESCRIPTION

3.1. The Survey

The data used in the analysis in this paper was collected as part of a larger “emerging mobility” on-line web survey conducted in the Austin metropolitan area in Texas in 2019 (see Asmussen et al., 2020, or Kang et al., 2021 for additional details). The survey, administered as an online survey and disseminated through a combination of a purchased list of 15,000+ e-mails, social media advertisements, and local area professional networks, resulted in a convenience sample of 1,141 respondents. This sample was reduced to a final size of 1,107 for the current analysis, after removing 34 respondents who did not provide adequate information.⁵ The survey sought information on individual and household socio-demographics (age, gender, race, employment status, student status, education level, driver's license holding, household annual income, household size, number of children in the household, and number of motorized vehicles currently

⁵ These 34 respondents either did not respond to the attitudinal questions or sociodemographic questions, or provided clearly inappropriate demographic values (such as stating that their age was less than a year or more than 115 years).

owned), attitudinal/life-style perspectives, and first-use/frequency of ESS and BSS services.⁶ The attitudinal perspectives were obtained by posing a series of attitudinal statements, and eliciting responses by asking respondents to choose the category that most closely matched their feelings; the attitudinal responses themselves were captured using a five-point Likert-scale from “strongly disagree” to “strongly agree”.

The four main outcomes in the current paper were obtained from questions related to familiarity and usage of ESS and BSS. For each of these modes, respondents were asked the following question: “How often do you generally use the following transportation services?” The response categories included the following:

- (1) I am not familiar with it
- (2) I am familiar with but never use the service
- (3) I am familiar with, but use it rarely (e.g. less than once a month)
- (4) I am familiar with, and use it monthly
- (5) I am familiar with, and use it weekly

We developed a binary variable of first-use with a value of “0” if the person selects response categories (1) or (2), and “1” if the person selects response categories (3) (4) or (5). Next, a use ordinal frequency variable was developed if first-use takes the value of “1” as follows: (1) rarely use (use rarely), (2) occasionally use (use monthly), and (3) regularly use (use weekly). As indicated earlier, any action to enhance the propensity to use ESS/BSS is contingent on first getting the individual to the point of first-use of the service.

3.2. Analytic Framework

A diagrammatic representation of the Generalized Heterogeneous Data Model (GHDM), as customized to the current paper, is shown in Figure 1. Individual-level variables (individual and household demographics), built environment (BE) variables, as well as attitudes/lifestyle factors (also referred to as psycho-social or latent constructs) are considered as determinants of the four main outcomes (the specific exogenous variables identified on the left side of Figure 1 were the ones that showed moderate to strong effects in our model). The psycho-social factors are not directly observed but are considered as latent stochastic constructs expressed through the responses to a suite of attitudinal statements (the responses to these statements are also referred to as indicators; to avoid clutter, these indicators are not shown in Figure 1, but are discussed later in Section 3.2.2). In the current study, three latent constructs (represented as ovals in the middle panel of the figure) are used: (1) safety concern (SC), (2) time consciousness (TC), and (3) green lifestyle

⁶ Technically speaking, BSS was not explicitly specified as being dockless, though that was the intent. In particular, respondents were asked to respond to their familiarity and use of bikesharing systems, with the bikeshare programs specific to dockless BSSs provided as examples (Jump, Grid, etc.). In Austin, Jump, which was acquired by Uber in April 2018, made its debut in July of 2018. Currently, as part of an Uber-led investment into Lime, dockless BSS in Austin is managed solely by Lime, which has about 5350 e-scooters and 500 e-bikes (“Shared Mobility Services, Austin, Texas”, n.d.). In any case, earlier studies do suggest that the behavioral correlates of dockless and docked BSS systems are very similar (see, for example, Chen et al., 2020b and Reck and Axhausen, 2021).

propensity (GLP).⁷ A traditional confirmatory factor analysis determined the most suitable indicators for each latent construct.

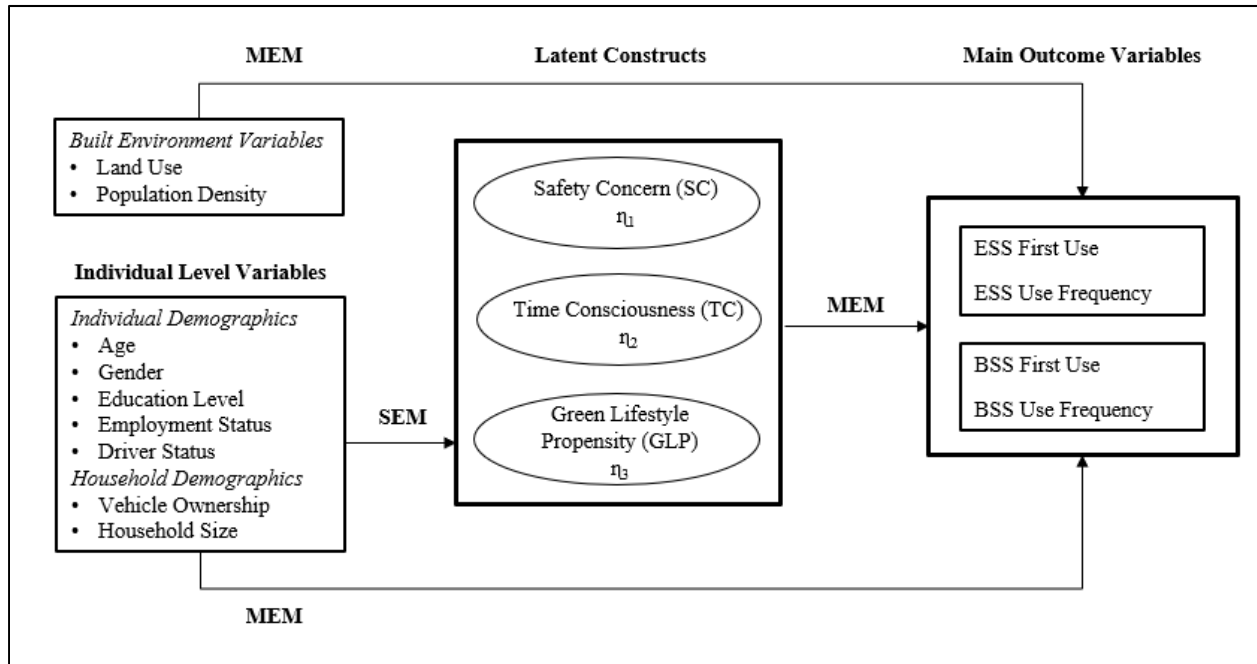


Figure 1: GHDM Model Framework

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. Each error term represents the effect of unobserved individual factors on a specific latent construct. Let these unobserved factors be denoted by η_1 , η_2 , and η_3 (corresponding to one of the three latent constructs in Figure 1) and collect them 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 $\boldsymbol{\Gamma}$ with three possible correlation elements (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 and the endogenous outcomes of interest (shown toward the right side of Figure 1). The exogenous socio-demographic variables, the latent constructs, and the built environment variables (and their interactions) all then serve as determinants of the underlying latent propensities of the observed ordinal/binomial outcomes characterizing the endogenous

⁷ These latent constructs are identified based on earlier studies, as discussed in the literature review section. Additional latent constructs, including those associated with variety-seeking lifestyle, security concern, and tech-savviness were also constructed and tested in the model, but did not turn out to be statistically significant in explaining any of the four main outcomes. This is because of correlation between these other constructs and the constructs already considered in this paper.

variables of interest and the indicator variables. This is represented by the MEM relationship in Figure 1.

The latent constructs of SC, TC, and GLP in Figure 1, in addition to capturing important attitudinal and lifestyle preference effects, also serve as vehicles to allow the parsimonious joint modeling of multiple outcomes of interest in the MEM component. Specifically, an advantage of using a framework with mediating stochastic latent constructs is that, in addition to capturing lifestyle/attitudinal effects and enabling better data fit, it allows us to parsimoniously parameterize the covariance matrix of the four main outcome variables of interest (listed in the right panel of Figure 1). For instance, if safety concern impacts ESS first-use as well as BSS first-use in the same direction, this generates a positive correlation (due to unobserved factors) between ESS first-use and BSS first-use propensities through the common η_1 term embedded in the safety concern stochastic latent construct. Similarly, if safety concern influences BSS first-use as well as BSS use frequency in the same direction (say negatively), this implies self-selection in use frequency based on BSS first-use. That is, individuals who are unlikely to be first-users due to safety concerns also intrinsically would be less likely to have a high use frequency; equivalently, those who are predisposed to be BSS first-users because of having trust in emerging technology and being comfortable riding a bicycle are also likely to have a high frequency of bicycle use. If this were the case, as is found in our empirical study, the implication would be that addressing safety concerns would not only elevate the possibility of BSS first-use, but also immediately increase BSS use frequency (if first-use materializes).

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 simplifies because all the outcomes are ordinal (some of the outcomes are binary, but such outcomes are but a special case of ordinal outcomes).⁸

Overall, the individual-level characteristics and the BE attributes constitute the exogenous variables in our model system. The latent constructs, while also serving as determinant variables for the main outcomes, are affected themselves by the individual-level variables. The exogenous variables and the latent constructs are each discussed in turn in the next two sections.

3.2.1. Exogenous Variables

The individual-level demographic attributes of the convenience sample collected in our survey show an over-representation of young individuals, women, and highly educated and low-income individuals (please see the online supplement for a detailed discussion and presentation of the sample demographic characteristics and comparison with the census population statistics of the Austin-Round Rock, TX Metro Area, as estimated by the U.S. Census Bureau, 2018). While the over-representation of women in our sample is interesting, the skew in the other variables is to be

⁸ The mathematical formulation of the simplified GHDM framework with only ordinal outcomes is presented in an online supplement to this paper (see <https://www.caee.utexas.edu/prof/bhat/ABSTRACTS/Micromobility/OnlineSupp.pdf>).

expected. The Austin region is home to many colleges and universities; students who study at these higher education institutions may not consider the area their main place of residence. 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. On the other hand, a high number of students responded to our survey (about 55% of the total respondent pool).

The descriptive statistics for the endogenous variables of interest in this paper cannot be generalized to the Austin area adult population, because of the sample skew. However, when estimating individual causal relationships from a sample based on exogenous sampling (that is, one not based on endogenous sampling as would be the case if our sample were collected at locations designated as BSS/ESS return stations), the unweighted approach is the more efficient estimation technique (provides more precise parameter estimates than a weighted approach). Thus, in our model estimations, we use the unweighted approach. The reader is referred to Wooldridge (1995) and Solon et al. (2015) for an extensive discussion of this point. In addition, our sample displays adequate variation across the range of values of each socio-demographic variable, allowing us to test a variety of functional forms for the effects of these variables. Overall, 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 Austin population.

The BE variables in this paper were constructed based off the home location of respondents. After geocoding the home locations and mapping to census block groups (CBG), the CBGs BE attributes, as obtained from the U.S. Environment Protection Agency (EPA) Smart Location Database (Ramsey and Bell, 2014), were bestowed on to the home locations of the respondents. These attributes included population density (people/acre), employment density (jobs/acre), retail density (retail jobs/acre), land use mix index (in the range of 0-1) based on five sectors of employment (retail, office, industrial, service, entertainment), street network density (links/acre), distance to nearest transit stop (meters from the centroid of CBG to the nearest transit stop), transit access (whether the distance to the nearest transit is less than/equal to 3/4 of a mile or over), and living environment (urban, suburban, or rural).⁹ All variables are continuous variables, except the transit access variable (dummy) and the living environment variable (categorical). Of these variables, only the living environment and population density variables turned out to be statistically significant in the GHDM model.

3.2.2. Latent Constructs

Our earlier literature review identified safety concerns with equipment and navigating the road with other road-users (see Beilinski and Wazna, 2020; Portland Bureau of Transportation, 2018; and Azad, 2018), time consciousness (Aguilera-García et al., 2020; Link et al., 2020; and Reck and Axhausen, 2021), and green life-style propensity (Biehl et al., 2019; Sanders et al., 2020; and Aguilera-García et al., 2020) as important considerations in BSS/ESS uptake. The indicators used to extract information on each of these latent constructs are listed and presented in Figure 2.

⁹ The living environment characterization is determined based on the density of jobs and dwelling units. Details are provided in Ramsey and Bell (2014).

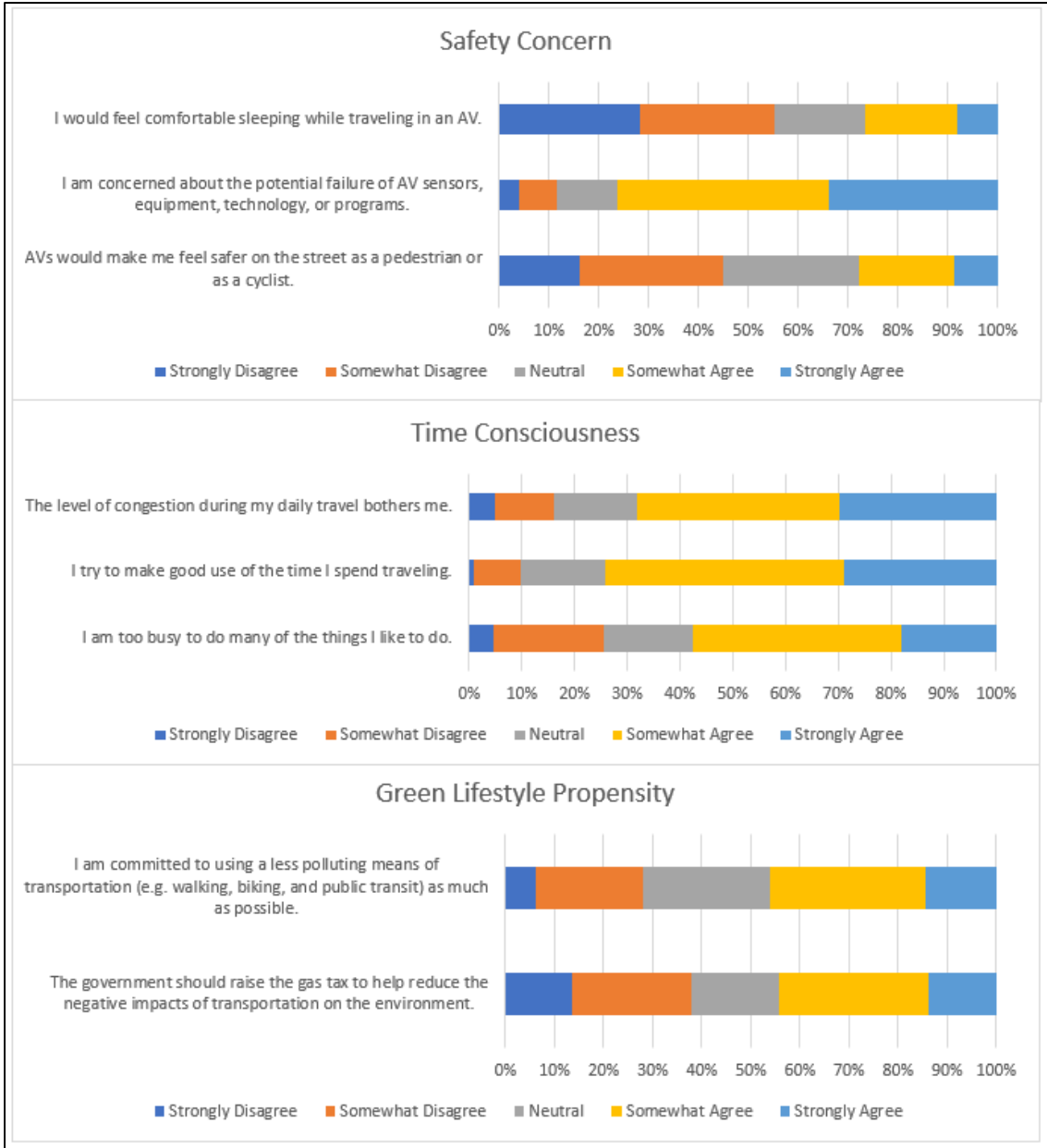


Figure 2: Latent Construct Indicators

The first latent construct, safety concern, is directly related to concerns about the malfunctioning of new mobility technologies, as well as concerns due to an unsafe riding environment. In the survey, respondents were presented with questions related to their discomfort/concerns with the new mobility technology of AVs (and not ESS/BSS), but responses to these AV-related questions can still provide a sense of overall distrust with new and emerging technology options. Figure 2 shows that over 75% of respondents are in somewhat or strong agreement that technology reliability is a concern (a measure of equipment distrust), while just over 25% state they would be (somewhat or very) comfortable sleeping in an AV or that AVs would make them feel safer as a pedestrian/cyclist (a measure of concern about safety in mixed

traffic conditions). The expectation is that safety-concerned individuals will be less likely to take up ESS/BSS modes and use them frequently.

The second latent construct, time consciousness, may be associated with how individuals value the opportunity cost of time. While not included as a latent construct in ESS/BSS studies, Aguilera-García et al. (2020) and Reck and Axhausen (2021) consider this attitude in terms of a single importance level indicator in their studies. Their results suggest that those who place a premium on the value of travel time (are time-conscious) are more likely to adopt and use ESS (though Reck and Axhausen's results suggest no effect on BSS). As discussed earlier, and again later, our results in a U.S. city context are likely to provide different results due to a much higher dependence on car travel in U.S. cities relative to European cities. The distribution of the indicators in Figure 2 show that our sample is relatively time conscious, with over 70% indicating that they try to make good use of travel time.

The final latent construct, green-lifestyle propensity (GLP), is the singular most-often used attitudinal variable in studies of walking and bicycling and combines notions of having a pro-environmental disposition and being socially altruistic. Figure 2 suggests a sample that is quite green.

3.2.3. *Main Outcome Variables*

The four main outcomes in this study correspond to ESS/BSS first-use and ESS/BSS use frequency for those who have experienced first-use. In terms of first-use, of the 1107 individuals, 73.2% of the sample has never used either of the services, 16.6% has used only ESS, 2.3% has used only BSS, and 8.0% has used both.¹⁰ 113 individuals have used BSS at least once, while the first-use of ESS is higher with 272 individuals having experienced ESS. Clearly, while both BSS and ESS were introduced about the same time in 2018 in Austin, there are more ESS first-users than BSS first-users.

In terms of frequency of use among those who have experienced first-use, the distributions are as follows: Rarely used: 68.3% for ESS (73.5% for BSS), Occasionally used (use monthly): 20.8% for ESS (18.3% for BSS), and Regularly used (use weekly): 10.9% for ESS (5.2% for BSS). As in the case of first-use, BSS is less often used relative to ESS. Of course, while these aggregate statistics provide a general comparison between ESS and BSS systems, they do not provide insights on demographics, psycho-social variables, and BE measures that may have similar or different effects across the four dimensions, which is the focus of this study.

4. MODEL RESULTS

In the model specifications, we explored a range of alternative functional forms for the explanatory variables. These included a linear form, a dummy variable categorization, as well as piecewise

¹⁰ Interestingly, these percentages are not too different from those obtained in a larger (but less in-depth) survey of 9,263 Austin area respondents conducted by the City of Austin (CoA) in 2018, which revealed that 60% has never used either of the services, 25% has used only ESS, 3% has used only BSS, and 13% has used both. Relative to the CoA sample, our sample is skewed more toward non-users, especially ESS non-users. Of course, which of the samples is a better representation of ESS/BSS use is an open question.

spline forms for the continuous variables (respondent age and population/retail density). But the dummy variable specification turned up to consistently provide the best data fit in all cases and is the one adopted in the final model specification. In this dummy variable form, we tested many different finer categories, and progressively combined categories based on statistical tests and intuitive reasoning to yield parsimonious specifications.

The final model specification was obtained after a systematic process of testing alternative combinations (and interactions) of explanatory variables based on statistical fit and parsimony considerations. In this final model specification, a couple of variables that were only moderately statistically significant were retained. This is to acknowledge the relatively small size of ESS/ESS users in the larger estimation sample. Also, the loadings of each latent construct on the indicators are sub-components of the estimation process. These loadings are not of primary interest in this paper and are available in the online supplement.

4.1. Results for Latent Constructs

The structural relationships between the individual-level demographics and the latent constructs are presented in Table 1 and discussed below.

Table 1: Effect of Exogenous Variables on Latent Constructs

Variables (base category)	Safety Concern		Time Consciousness		Green Lifestyle Propensity	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
<i>Individual-Level Characteristics</i>						
Age (18 to 24 years)						
25 to 39	--		--		--	
40 to 54	0.258	8.78	--		-0.434	-10.83
55+	0.447	15.18	--		-0.631	-15.97
Gender (male)						
Female	0.658	26.98	0.377	9.77	--	
Education (< bachelor's degree)						
Higher Education	--		0.280	7.24	0.126	5.03
Employment Status (not a full or part time employee)						
Employed	--		0.364	7.79	--	
Correlations						
Safety Concern	1.000	--	-0.354	-5.30	-0.217	-3.08
Time Consciousness	--	--	1.000	--	0.639	6.88
Green Lifestyle Propensity	--	--	--	--	1.000	--

The results associated with age in Table 1 clearly reveals higher levels of safety concern, but lower levels of GLP among older adults. The former effect is consistent with several earlier studies related to trust in, and safety perceptions associated with, new mobility options. Older

individuals are typically less open to change and new experiences (Kessler, 2009; González Gutiérrez et al., 2005) and the gerontology, psychology, and neuroscience literature has established that ageing is associated with a decline in cognitive ability (such as memory, attention, and verbal and visual/spatial information retention), which makes older individuals more cautious, risk-averse, and concerned about travel safety in general (Albert and Duffy, 2012; Boot et al., 2013; Sample, 2016; Bossaerts and Murawski, 2016; Graham et al., 2017; and Asmussen et al., 2020). The lower GLP among older adults is consistent with the environmental sociology literature (see, for example, Liu et al., 2014 and Clements, 2012), which attributes this effect to young adults being increasingly exposed to environmental issues in the past decade through school curricula, social media, and actual extreme weather events. Also, a recent global study (Hassim, 2021) of opinions about sustainability confirms that the younger generation is greatly concerned with global challenges (such as climate change) and feels much more socially responsible to adopt environmentally friendly lifestyles.

In terms of gender effects, the results confirm the increased safety concern among women, as has been documented in multiple studies from different fields, including in the context of new emerging mobility options (see, for example, Kang et al., 2020; Sanders et al., 2020; Poveda-Reyes et al., 2021; and Sayfty, 2016). Table 1 also indicates a higher level of time consciousness among women, attributable perhaps to women continuing to be the person primarily responsible for household activities/caregiving, while also increasingly partaking in work outside home (see Mike et al., 2014 and Festini et al., 2019).

The positive relationship between high education and time consciousness in Table 1 is supported by earlier studies in the psychology and time-use literature that suggest a generally lower time availability for non-work activities among those highly educated (Festini et al., 2016). Also, highly educated individuals tend to be more aware of the need for, and are likely to partake in, green lifestyle choices, a finding that aligns with results in the social-psychological literature (McCright, 2010; Lo and Jim, 2012; Fisher et al., 2012; and Franzen and Vogl, 2013).

Finally, the results in Table 1 also show, not surprisingly, that employed individuals are more time conscious than their unemployed counterparts. In fact, Kalenkoski et al. (2011) and Bernardo et al. (2015), in their studies on time poverty, report that employed individuals, especially those with children, have substantially higher time poverty rates compared to unemployed individuals, attributable to the fixed, relatively non-flexible, and obligatory work hours.

4.1.1. Latent Construct Correlations

The lower panel in Table 1 provides the correlations between the unobserved components of the latent constructs. The safety concern construct is negatively correlated with time consciousness as well as the GLP constructs, while the time consciousness and green lifestyle constructs are positively correlated. While these correlations represent the aggregate of many unobserved factors and are not easily interpretable, the latter positive correlation between the time consciousness/GLP constructs may be a result of green lifestyle choices (such as walking and bicycling instead of

using motorized transportation means) leading to time becoming more of a scarce commodity and hence being valued more (see Chen et al., 2019 and Politis et al., 2020).

4.2. Results for Main Outcomes

As discussed earlier, within our joint framework, we modeled ESS/BSS first-use separately from ESS/BSS use frequency to tease out the possible dissimilar impacts of explanatory variables on the first-use and frequency dimensions. Aguilera-García et al. (2020) also consider first-use/use frequency as two separate dimensions, but focus only on the ESS mode and further consider the first-use/use frequency decisions as being independent of each other. On the other hand, through the use of stochastic latent constructs impacting all the four main outcomes, we accommodate full jointness across the first-use/frequency dimensions as well as across the two modes of ESS and BSS. The results, presented in Table 2, indicate the effects of variables on the propensity of first-use (for the first-use results) and use frequency beyond first-use (for the use frequency results).

4.2.1. Latent Construct Effects

Among the latent construct effects, safety concern negatively impacts first-use propensity for both the ESS and BSS modes, and additionally also has a negative effect on BSS use frequency. Safety concern in the use of micromobility modes (including equipment failure and feeling more physically “exposed” to fast-moving motorized traffic) has been identified in earlier literature (see, for example, Fishman et al., 2015, Sanders et al., 2020, and Bielinski and Wazna, 2020) as one of the most important barriers to the uptake of micromobility modes. Interestingly, while safety concern in the context of ESS use is not perceived differentially as a barrier across age groups by Sanders et al. (2020), our results show a substantially higher safety concern in ESS first-use among those 55 years or older relative to their younger peers. This difference between Sanders et al. and our study may be related to our distinction between first-use and subsequent use frequency conditional on first-use; indeed, a related observation from our study is that safety concern does not impact ESS use frequency in any way (regardless of age) among those who have already experienced first-use. This suggests that the safety concern associated with ESS is more technology-related; once a user becomes familiar with the use of this mode, there is a substantial reduction in their distrust or apprehension toward the use of ESS. On the other hand, safety concern not only has a higher negative impact on first-use propensity for BSS (relative to ESS), but also continues to affect BSS use frequency among those who have experienced first-use. Clearly, our results suggest that BSS-related safety concerns are quite distinct from ESS-related safety concerns: BSS-related concerns appear to be associated with both technology distrust as well as traffic safety considerations, the latter of which may be related to the higher speed variance between a BSS and a motorized vehicle relative to the speed variance between an ESS and a motorized vehicle.

Table 2: Main Outcome Results

Exogenous Variables (base category)	ESS First-use Propensity		BSS First-use Propensity		Propensity of ESS Use Frequency		Propensity of BSS Use Frequency	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
<i>Latent Constructs</i>								
Safety Concern	-0.295	-7.88	-0.570	-9.49	--		-0.379	-3.23
Safety Concern*Age 55+	-0.940	-4.79	--		--		--	
Time Consciousness	-0.707	-7.85	-0.753	-6.33	--		-0.655	-3.02
Time Consciousness*Employee	0.557	6.16	0.595	4.47	--		--	
Green Lifestyle Propensity	0.520	5.19	--		0.191	1.42	0.348	2.00
Green Lifestyle Propensity*Student	-1.049	-8.56	--		-0.455	-2.85	--	
<i>Individual-Level Characteristics</i>								
Gender (male)								
Female	--		--		-0.298	-5.88	--	
Education (< bachelor's degree)								
Higher education	-0.139	-3.70	--		--		--	
Student Status (not a full or part time student)								
Full or part time student	--		--		--		0.801	5.29
Employment Status (not a full or part time employee)								
Full or part time employee	--		--		--		0.415	3.04
Driver Status (does not have a license)								
Has a driver's license	--		--		0.388	5.34	-0.284	-1.87
<i>Household-Level Characteristics</i>								
Vehicle Ownership (no vehicles)								
At least one vehicle in HH	0.430	6.72	--		--		--	
Household Size (< 4 individuals in HH)								
4 or more individuals in HH	--		0.210	4.37	--		--	
<i>Built Environment Factors</i>								
Land Use (rural)								
Suburban location	0.402	6.44	0.337	3.42	--		--	
Urban location	0.730	10.58	0.739	7.15	--		--	
Population Density (low density)								
High population density	0.233	4.32	--		0.649	10.69	--	
Constant, User								
	-1.141	-12.91	-1.604	-14.57	--		--	
Threshold (rarely monthly)								
					1.580	21.33	2.078	8.89
Threshold (monthly weekly)								
					8.127	15.88	8.126	7.00

The latent construct of time-consciousness has a similar pattern of effect as safety concern. Specifically, time conscious individuals are less likely to be first-time users of both ESS and BSS modes, and also less likely to be repeat users of the BSS mode. This result is different from the European studies of Aguilera-García et al. (2020) and Reck and Axhausen (2021) in that Aguilera-García et al. does not find statistically significant effects of travel time and travel time reliability on ESS use, while Reck and Axhausen find that travel time priority positively affects ESS use but has no statistically significant effect on BSS use. The differing results do underscore the importance of the travel context in ESS/BSS uptake; as also alluded to earlier, while walking may be viewed as the immediate competing mode to ESS/BSS in European cities, individuals in the U.S. are more likely to evaluate ESS/BSS travel time relative to travel times by motorized modes such as driving or ride-hailing services. However, it appears that, even in the U.S., once individuals have experienced ESS first-use, they are better able to evaluate the ESS mode relative to motorized modes (as evidenced in the non-effect of time consciousness on ESS use frequency in Table 2). Unlike the case of ESS, time consciousness continues to influence BSS use frequency even beyond first-use, presumably because BSS has a distinct time disadvantage compared to other motorized modes. Interestingly, the impact of time consciousness on ESS/BSS first-use is tempered for employed individuals (although the net effect of time consciousness is still negative).

The final latent construct effect in Table 2, corresponding to green lifestyle propensity (GLP), indicates that individuals with an eco-friendly lifestyle are more likely to use ESS and more frequently so, while such individuals, if brought to the point of first-use of BSS, also are more likely to be repeat BSS users. This result is to be expected, since ESS and BSS modes are typically positioned as being eco-friendly and good for the environment (Fishman et al., 2014). Interestingly though, the impact of GLP on both ESS first-use propensity and ESS use frequency turns negative within the segment of students. This is possibly because a few recent studies (see Temple, 2019, Hollingsworth et al., 2019, and Moreau et al., 2020) argue that ESS mode use may actually result in substantially higher life-cycle greenhouse gas emissions relative to BSS systems and public transport, attributable to production processes and rebalancing needs of ESS equipment. Students in higher education institutions are likely to be better aware of various aspects of mobility options and technology; they may not be simply swayed by an “environmental-friendly” label associated with ESS.

4.2.2. Effects of Individual and Household Level Characteristics

Education status (Bachelor’s degree or higher relative to less than Bachelor’s degree), after controlling for time consciousness and green lifestyle propensity effects, has a *direct* negative effect on ESS first-use. This *direct* negative effect may be ascribed to highly educated individuals being more health conscious (Kriwy and Mecking, 2012; Jaafar et al., 2017), and perceiving electric ESS systems as a competing mode to active forms of travel (such as walking and manual bicycle pedaling). The second demographic variable affecting ESS first-use corresponds to the positive effect of the respondent’s household owning at least one motorized vehicle, a result also found in Aguilera-García et al. (2020). However, this is different from the negative finding of car

ownership on ESS use as observed in Reck and Axhausen (2021), highlighting again the importance of local context in micromobility adoption and use. Households with at least one vehicle constitute a much higher fraction of households in Austin relative to many European cities. When combined with the warm weather throughout the year in Austin, it is possible that individuals in at least one-car households view the ESS mode as an appealing (even if only occasional) power-driven mobility option to experience the outdoors without manual effort. Finally, in the context of demographic effects on first-use, individuals belonging to households with more than four members are likely to have limited private mobility options (since the number of household members are likely to be greater than self-owned cars) and may be more embracing of the relatively inexpensive BSS option. Such individuals often have a desire to travel together (especially for leisure/recreational purposes) and therefore may opt for the traditional “bicycling” option that every household member would be comfortable with.

In terms of use frequency results, women are less likely to use ESS frequently relative to men (within the group of individuals that has experienced ESS use), while students and employed individuals are found to have a high underlying propensity for BSS usage. The first result related to gender falls within the general pattern established in most earlier studies of ESS use. Further, education-centric and dense employment zones (that is, the University of Austin and downtown Austin) are locations particularly well served by BSS pick-up/return points, and already have well-established bicycling infrastructure (in terms of lane designation, parking allotments and ease of access), which may explain the student/employed status effects. Finally, within the group of individual/household characteristics, the possession of a driver’s license leads to a higher underlying propensity for ESS use frequency, but a negative effect on BSS use frequency, reinforcing our earlier interpretation for the vehicle ownership effect that motorized mode use may make ESS appealing, but not the manual pedal-based BSS mode.

4.2.3. Built Environment Factors

Individuals dwelling in urban and suburban neighborhoods exhibit a higher propensity for the first-time use of both ESS and BSS. These modes are more likely to be available in urban and suburban regions compared to rural areas where there is little to no demand. Even from an operator’s financial viability aspect, the micromobility mode market is “pro-urban”. For similar reasons, population density has a positive impact on ESS first-use and ESS use frequency, a result also observed by Jiao and Bai (2020).

The last set of rows in Table 2 present the constant for the first-use equations and the ordered-response thresholds for the frequency models. These do not have any substantive interpretations but serve the role of mapping underlying propensities to observed choices.

4.2.4. Implied Correlations Among Main Outcomes

The results in the previous sections underscore the foundational behavioral ties in the ESS-BSS mode through the similarity in the direction of several psycho-social, sociodemographic, and built environment factors. In addition to these effects, the linkage becomes even stronger through the

positive correlations engendered by the safety concern, time consciousness, and green lifestyle propensity stochastic latent constructs. One can compute the implied correlation for each of eight demographic groups, based on combinations of the three dimensions of age (age 55+ versus less than 55 years of age), employment status, and student status. To conserve on space, we present, in Table 3, the estimated correlation matrix for the specific combination of a young individual (age <55 years) who is not employed and is not a student.

Table 3: Implied Correlations Between Main Outcomes (Pertaining to a Combination of Less than 55 Years Old, Not a Student, and Not an Employee)

	ESS First-Use	BSS First-Use	ESS Frequency of Use	BSS Frequency of Use
ESS First-Use	1.000	0.192	-0.060	0.205
BSS First-Use	0.192	1.000	0.026	0.262
ESS Frequency of Use	-0.060	0.026	1.000	0.003
BSS Frequency of Use	0.205	0.262	0.003	1.000

The table above reveals positive pairwise correlations across the four dimensions, except for the negligible correlation between ESS use frequency and BSS use frequency. Thus, while exogenous factors and psycho-social considerations influence ESS/BSS first-use/frequency in different ways and to different extents, our results clarify that the ESS-BSS mode-dyad may be simultaneously promoted.

4.3. Model Goodness of Fit

The GHDM model used in the joint modeling of ESS/BSS first-use and use frequency provides important insights on the joint, yet different, nature of the factors influencing the two modes. 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 four dimensions of ESS first-use, BSS first-use, ESS use frequency and BSS use frequency. 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 four main outcomes of the paper independently in the form of two binary outcomes (for the first-use outcomes) and two ordered-response outcomes conditional on first-use (for the frequency outcomes). This independent model takes the form of an independent ordered probit (or IOP) model. For each of the four endogenous outcomes in the IOP 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 IOP models is whether

jointness in the four outcomes is considered or not). The GHDM model and the IOP 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 IOP models, we compute the predictive likelihood at convergence for only the four 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 with respect to the log-likelihood with only the constants in the four 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 $\bar{\rho}_{IOP}^2$. If the difference in the indices is $(\bar{\rho}_{GHDM}^2 - \bar{\rho}_{IOP}^2) = \tau$, then the probability that this difference could have occurred by chance is no larger than $\Phi\{-[-2\tau L(c) + (M_{GHDM} - M_{IOP})]^{0.5}\}$, 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 both the disaggregate and aggregate levels. To do so, we compute multivariate predictions for each of the 16 multivariate combinations of possible outcomes for ESS/BSS first-use and use frequency.¹¹ At the disaggregate level, for the joint model, we compute an average (across individuals) probability of correct prediction at this 16-dimensional level. A similar disaggregate measure is computed for the independent model. At the aggregate level, we design a heuristic diagnostic check of model fit by computing the predicted aggregate share of individuals for each of the 16 combinations. These shares are then compared with the actual shares, and the absolute percentage error (APE) statistic is computed.

The results of the disaggregate data fit evaluation are provided in Table 4. 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 IOP model. In terms of aggregate data fit too, for each of the 16 possible combinations, the shares predicted by the joint model are better than those predicted by the independent model. Overall, across all the combinations, the weighted average (weighted

¹¹ For each of BSS and ESS, there are four possible outcomes from the combined model system of first-use and frequency – (1) Not used, (2) Rarely used, (3) Occasionally used, and (4) Regularly used. Then, across the BSS and ESS modes, there are a total of $4^2=16$ combinations.

by the share of each combination) of the absolute percentage error is 13.93% for the joint model, compared to 25.27% for the independent model.

Table 4: Disaggregate Data Fit Measures

Summary Statistics	Model	
	Joint (GHDM) Model	Independent (IOP) Model
Predictive log-likelihood at convergence	-3727.32	-4251.54
Number of parameters	48	34
Bayesian Information Criterion (BIC)	3895.55	4370.70
Constants-only predictive log-likelihood	-4432.04	-4432.04
Predictive adjusted likelihood ratio index	0.162	0.0742
Informal non-nested adjusted likelihood ratio test: Joint model versus Independent model	$\Phi[-28.485] \approx 0.000$	
Average probability of correct prediction	0.147	0.103

5. IMPLICATIONS

5.1. Analysis Preparation

The results in Section 4.3 provide the effects of variables on underlying propensities of first-use and frequency given first-use, and provide important insights by themselves. However, they do not provide information on actual effects of the variables on first-use and frequency (note also that, in ordered-response models, even the directionality of effect of a variable on the underlying propensity does not provide a sense of how the variable may actually impact individual ordered-response categories). To determine directionality and magnitude effects, the estimates need to be translated to actual outcome effects, which however will vary across individuals because of the non-linear nature of our model. But an average effect can be computed by taking the mean (across individuals) of the effect of a variable, which can then provide valuable insights for policy actions. In the context of the current paper, a specified goal may be to increase the uptake/frequency of each of the ESS and BSS modes. The procedure to estimate the relevant effects of variables is discussed next.

The model provides, for each individual, the four-variate probability of (suppressing the index for individual for presentation ease) $P(y_{ESS,FU} = i, y_{BSS,FU} = j, y_{ESS,FR} = k, y_{BSS,FR} = m)$, where $y_{ESS,FU}$ is the Boolean for ESS first-use ($i=0$ or $i=1$), $y_{BSS,FU}$ is the Boolean corresponding to BSS first-use ($j=0$ or $j=1$). $y_{ESS,FR} = k$ refers to ESS use frequency in the k th ordinal category (relevant only if $y_{ESS,FU} = 1$), and $y_{BSS,FR} = m$ refers to BSS use frequency in the m th ordinal category (relevant only if $y_{BSS,FU} = 1$). In the paper, both k and m may take one of three values of “rarely

use” ($k=1$ and $m=1$), “occasionally use” ($k=2$ and $m=2$), and “regularly use” ($k=3$ and $m=3$). From the above joint probability, we can further compute the following unconditional probabilities of use frequency (note that the unconditional use frequency f_{ESS} and g_{BSS} , which we will simply refer to as “use”) now refer to the combined first-use and “conditional on first-use” frequency, and can take on the values of 0, 1, 2, or 3):

$$\begin{aligned}
P(f_{ESS} = 0) &= P(y_{ESS,FU} = 0); P(f_{ESS} = k) = P(y_{ESS,FU} = 1, y_{ESS,FR} = k); k = 1, 2, 3 \\
P(g_{BSS} = 0) &= P(y_{BSS,FU} = 0); P(g_{BSS} = m) = P(y_{BSS,FU} = 1, y_{BSS,FR} = m); m = 1, 2, 3 \\
P(f_{ESS} = 0, g_{BSS} = 0) &= P(y_{ESS,FU} = 0, y_{BSS,FU} = 0) \\
P(f_{ESS} = k, g_{BSS} = m) &= P(y_{ESS,FU} = 1, y_{BSS,FU} = 1, y_{ESS,FR} = k, y_{BSS,FR} = m); k, m = 1, 2, 3
\end{aligned}$$

From the above suite of probabilities, one can examine the effect of each exogenous variable on the shift probability from one frequency state to another for each of ESS and BSS. But, for ease in presentation (because there are so many state transition pairings that can be considered) and also to facilitate an understanding of the order-of-magnitude effects of variables, cardinal values are assigned to the ordinal levels of ESS use ($l=0,1,2,3$) and BSS use ($n=0,1,2,3$) as follows: (1) No use = 0 instances per month, (2) Rarely use (less than once a month) = 0.5 instances per month, (3) Occasionally use (use once a month) = 1 instance per month, and (4) Regularly use (use once a week) = 4 instances per month. With these assignments, and using the notation c_l ($l = 0,1,2,3$) and d_n ($n = 0,1,2,3$) for the cardinal value assignments corresponding to ESS use level l and BSS use level n , respectively, the marginal expected value of ESS use (say \tilde{f}_{ESS}) and BSS use (\tilde{g}_{BSS}) (both on a per month basis) may be computed as follows:

$$\tilde{f}_{ESS} = \sum_{l=0}^3 c_l P(f_{ESS} = l); \tilde{g}_{BSS} = \sum_{n=0}^3 d_n P(g_{BSS} = n)$$

An additional challenge with the estimation results in the previous section is that they do not provide the relative magnitudes of the direct effects of exogenous variables and the indirect effects through the psycho-social constructs. This is important to develop effective policies aimed at specific demographic groups. For example, would campaigns directed toward increasing micromobility use among women be more effective if they addressed safety concerns or promote green lifestyle living? Would it be most effective to advocate for the micromobility’s time efficiency when it comes to employed and educated people? Would funds for safety campaigns be better focused on older age groups, or all age groups? This partitioning can be done using the Average Treatment Effect (or ATE effect; see Angrist and Imbens, 1991, and Heckman and Vytlačil, 2000), which is a metric that computes the impact on a downstream posterior variable of interest due to a treatment that changes the state of an antecedent variable from A to B. For example, if the intent is to estimate the treatment effect of densifying land-use on ESS usage frequency, A can be the state where the individual is in a rural area, and B can be the state where the individual is in an urban area. The impact of this change in state is measured in terms of the change in the expected (unconditional) use frequency of ESS and BSS. If an exogenous variable

impacts the expected frequency of use through one or more mediating latent variables (such as the effect of gender on ESS use through the safety concern and time consciousness latent constructs, and a direct effect on ESS use), one can use the estimates from Table 2 to partition out the ATE by its sub-effects. To do so, we ignore the directionality of the ATE effect and compute sub-effect percentages as a function of the sum of the absolute values of the different sub-effects. These percentages are provided as the relative contributions of each sub-effect in Table 5. For completeness, we also provide the overall effect of each variable, which would be the sum of the individual sub-effects (after considering the directionality of effect). Note also that, for presentation ease, in this paper, we only report the ATEs for a change between the two extreme categories for the antecedent variable (for example, we focus only on the change from the base age category of <40 years to 55+ years).

The ATE values (in the last column of Table 5) are to be interpreted as follows. Consider the ATE effect of age on ESS use frequency. The last column of the first numeric row corresponding to this variable shows a value of -0.1171. This implies that if 100 individuals younger than 40 years of age were replaced by 100 individuals 55+ years of age, there would be about 12 fewer instances of ESS use per month. Other ATE values may similarly be interpreted. The sub-effect categories are labeled in a way that a positive change in the sub-effect would lead to a positive increase in micromobility use. Thus, the sub-effects are labeled as “safety concern decrease”, “time consciousness decrease”, and “green lifestyle propensity decrease”. The “% contribution by mediation through...” columns are then to be interpreted as follows. The value of -70% in the column for “safety concern decrease” for the age variable indicates that, in terms of magnitude, 70% of the sum of the contributions of each sub-effect (ignoring directionality) to the ATE change in ESS use is due to the safety concern sub-effect. The negative sign on 70% reflects the fact that the change from the base “<40 years” age category to the “treatment” “55+ years” age category would lead to a reduction in the “safety concern decrease” effect (that is, this change leads to a decrease in ESS use because older individuals have higher safety concerns). Similarly, the “-8%” entry for this age “treatment” corresponding to the “green lifestyle propensity (GLP) increase” effect suggests that the GLP sub-effect contributes 8% to the overall ATE change, and the negative sign shows that the sub-effect leads to a decrease in the ATE effect. The entry of “-22%” for the direct effect (penultimate column of Table 5) reflects a 22% decrease in ESS use that is associated directly to age beyond the effects through the psycho-social constructs. Other entries may be similarly interpreted.

Table 5: Average Treatment Effect (ATE) for ESS and BSS

Variable	Base Level	Treatment Level	% Contribution by Mediation Through			% Direct or LC Interaction Effect	Overall ATE
			Safety Concern Decrease	Time Consciousness Decrease	Green Lifestyle Propensity Increase		
ESS Frequency of Use							
<i>Socio-Demographic</i>							
Age	Under 40	Over 55	-70	0	-8	-22	-0.1166
Gender	Male	Female	-36	-22	0	-42	-0.1671
Education Level	Less than a bachelor's degree	Bachelor's degree or more	0	-39	3	-58	-0.0662
Student Status	Non-student	Student	0	0	0	-100	-0.0033
Employment Status	Unemployed	Employed	0	-37	0	63	0.0110
Driver Status	Non-driver	Driver	0	0	0	100	0.0638
<i>Household and Built Environment Characteristics</i>							
Vehicle Ownership	No vehicles	At least 1 vehicle	0	0	0	100	0.1046
Household Size	< 4 people	4 or more people	0	0	0	0	0.0000
Land Use	Rural	Urban	0	0	0	100	0.1867
Population Density	Low	High	0	0	0	100	0.2453
BSS Frequency of Use							
<i>Socio-Demographic</i>							
Age	Under 40	Over 55	-93	0	-7	0	-0.0311
Gender	Male	Female	-62	-38	0	0	-0.0969
Education Level	Less than a bachelor's degree	Bachelor's degree or more	0	-98	2	0	-0.0224
Student Status	Non-student	Student	0	0	0	100	0.0368
Employment Status	Unemployed	Employed	0	-55	0	45	-0.0040
Driver Status	Non-driver	Driver	0	0	0	-100	-0.0178
<i>Household and Built Environment Characteristics</i>							
Vehicle Ownership	No vehicles	At least 1 vehicle	0	0	0	0	0.0000
Household Size	< 4 people	4 or more people	0	0	0	100	0.0236
Land Use	Rural	Urban	0	0	0	100	0.0783
Population Density	Low	High	0	0	0	100	0.0000

5.2. ATE Discussion and Policy Implications

The first row panel of Table 5 provides the ATE effects with respect to ESS use frequency and the second row panel with respect to BSS use frequency. In the next few sections, we discuss these ATE effects by each of the psycho-social constructs and the direct effects, and policy implications.

5.2.1. Addressing Safety Concerns

Age and gender (the first two rows of each panel) clearly have an important influence on ESS and BSS use frequency, with older individuals and women less likely to be BSS users and even more less likely to be ESS users (as may be observed by the lower magnitudes of the overall ATEs for these variables in the BSS row panel relative to the ESS row panel). These results are consistent with those of Bielinski and Wazna (2020) and Reck and Axhausen (2021). However, our analysis goes beyond these overall age/gender effects and indicates that higher safety concern and lower green lifestyle propensity drive the lower ESS/BSS use among older individuals, and higher safety concern and higher time consciousness underpin the lower ESS/BSS use among women. There is also a difference in the nature of these pathway effects across the ESS and BSS modes, with safety concern being less of an issue for both older individuals and women in the context of the ESS mode relative to the BSS mode (70% of total ATE for ESS relative to 93% of total ATE for BSS for older individuals, and 36% of total ATE for ESS relative to 62% of total ATE for BSS for women). These results reinforce the notion that, while safety concerns represent an important barrier for micromobility mode use among older individuals and women, there is also a generic reticence (resistance to change that is unrelated to safety concerns) on the part of older individuals and women to embrace newer mobility options (in this case, the ESS mode) relative to traditional modes (in this case, the BSS mode). This is also evidenced in the 22% direct negative sub-effect of age and 42% direct negative sub-effect of gender for the ESS mode, while the corresponding entries are zero for the BSS mode. But across both the ESS and BSS modes, safety concerns dominate over other sub-effects, as observed from the entries of 72% (for age) and 50% (for women) in the safety concern decrease column in the last row panel of Table 5 corresponding to overall micromobility use. Also, gender has the highest total ATE effect among all exogenous variables in the context of overall micromobility use.

The results above suggest that, while there are differences in the extent of safety concern effects between ESS and BSS systems, a general strategy to promote micromobility use (especially BSS use) among older individuals and women would be to address safety concerns through (a) actual safety improvements in the riding environment and the equipment themselves, (b) informational campaigns to enhance safety perceptions and provide roadway use guidelines, and (c) curbside management. For example, the riding environments can be greatly improved by introducing separate scooter/bicycle lanes, as well as keeping those lanes clear from debris and ESS/BSS equipment themselves (Shaheen and Cohen, 2019). Besides improving the riding environments, cities can help develop policies for safer systems overall. One such policy may be to require helmet use. This not only would benefit the older generations and women in their concern over safety, but also keep all users safe regardless of their personal level of safety concern. Helmet use is rarely required by cities or ESS/BSS providers, and most ESS/BSS providers do not

offer helmets as part of the service. In fact, a study on emergency room visits due to ESS use showed that none of the people admitted to the hospital were wearing helmets at the time of the accident (Badeau et al., 2019). Another policy in the context of equipment maintenance would be to conduct regular light and brake checks by the ESS/BSS companies and advertise/disseminate such efforts in public-facing campaigns. Roadway use guides would also greatly improve safety in an increasingly multi-modal traffic stream. In this regard, the worry of the “unknown” can by itself deter first-use of micromobility modes. Providing clear information on where micromobility users can ride and how fast they should be travelling and providing guidelines and even perhaps mandating a short training course (not different from what is done when acquiring a car driving license) may be beneficial. This may be achieved at the time of downloading the application, or through online and social media-based informational workshops. Curbside space management is another important issue that many cities are already paying close attention to. Managing curb space for shared mobility services is vital to continue to create a safe environment for users and would also greatly benefit the blocked bicycle lane issue that cities are facing.

5.2.2. Addressing Time Efficiency Concerns

Another key factor that appears to deter individuals’ use of micromobility modes is time consciousness. This is particularly relevant to women, highly educated individuals, and those employed, especially for the BSS mode. Women are less likely to use ESS and BSS modes, in part because of their time consciousness (22% contribution for ESS and 38% contribution for BSS). A similar pattern holds for those highly educated and employed, with the contribution of time consciousness being much higher in these groups than for women, though the net effect of time consciousness is still lower for these groups relative to women (given the much lower total ATE for the educated and employed compared to women). To promote micromobility in these population groups, it would be helpful for providers and cities to highlight the time efficiency of micromobility modes at least for certain kinds of trips. For example, this may entail emphasizing that micromobility trips can replace short car trips and can help people get from origin to destination even quicker than a drive-alone or taxi ride in congested urban centers (Sanders et al., 2020, and Fishman, 2016). Additionally, users can save time because they would not need to transfer or walk at the end of a trip. Also, city planners and administrators could work with employers to advocate for the use of ESS/BSS on lunch breaks or to run short errands. With encouragement from employers, employees may be more willing to substitute a drive alone lunch trip with a micromobility-based trip. Another possibility is for cities and communities to partner closely with micromobility providers to ensure good accessibility to ESS/BSS systems and associated return stations in dense city blocks and urban areas (areas that are common for employed individuals to travel to and from).

At a much broader level, the results also suggest that progressing our societies toward a more egalitarian gender-symmetric balance structure may not only be a basic equity issue, but also have benefits from the standpoint of moving away from a car-centric culture. Time-use studies repeatedly draw attention to the substantial gender asymmetry in maintenance-oriented household

activities, and the resulting time poverty of women relative to men (see, for example, Bernardo et al., 2015, Bernstein, 2015, Cerrato and Cifre, 2018, and Mondal and Bhat, 2021). These studies also point out that, while gender perceptions have changed considerably over the years in terms of universal support for women pursuing professional and political careers, perceptions regarding traditional gender roles dominate on the home front. In particular, while men have picked up a little over time in terms of household chores, there is still a significant gap, with women spending, on average, about an hour more than men (U.S. Bureau of Labor Statistics, 2018). And this gap exists even in the younger generation (18-30 years of age).

5.2.3. Promoting Greenness of Micromobility Systems

Our ATE analysis shows that green-lifestyle propensity has an effect on ESS and BSS usage based on age and education level. Older individuals and those with less than a bachelor's degree are less likely to consider green living, and this leads to a reduced use of micromobility modes. Admittedly, the GLP sub-effect is rather small compared to other sub-effects, indicating that other aspects of the travel environment take priority for many individuals in their micromobility usage decisions. This is particularly true for women, given that gender has no ATE impact on green lifestyle propensity, but has a substantial impact through the safety concern effect (see the row corresponding to gender in Table 5). Thus, policies to promote micromobility use (particularly BSS use) would be more effective if focused toward alleviating safety concerns among women relative to actions that emphasize the virtues of micromobility modes as being “green”. More broadly, it may be important to package the financial benefits with environmental considerations in micromobility promotion campaigns. For example, ESS/BSS providers may want to consider providing information on an estimate of how much gas would be saved by eschewing motorized vehicle rides, while also providing a “green rating” for different types of rides and different trip lengths (Theen, 2019). As each of the micromobility systems is used more frequently, the ratio of the cost (both financially and environmentally) of system production and rebalancing needs to the number of rides decreases, and these micromobility systems can become less expensive and also even further less polluting in a downward snowballing spiral. In other words, the more trips taken on a single device, the better micromobility systems become at reducing emissions and manufacturing waste.

There are three caveats to the above discussion. First, the “greenness” of electric ESS systems is still being studied, and while ESS trips by themselves may produce little emissions, some studies suggest that the overall life-cycle greenhouse gas emissions per ESS trip from equipment production and equipment collection/rebalancing efforts may be much more than for a public transportation trip (Moreau et al., 2020; de Bortoli and Christoforou, 2020; Hollingsworth et al., 2019; Cazzola and Crist, 2020). Second, micromobility modes may take away from the walking mode, which is by far the most sustainable and environmentally-friendly mode relative to any form of ESS or BSS systems. However, if micromobility modes are used for first mile/last mile access to public transportation, the consequent potential boost in public transportation share may have important benefits for cities and communities. These issues, and the many intricate and

nuanced inter-relationships in mode use within an increasingly multi-modal landscape, is an open area for additional research and investigation. Third, information campaigns focusing solely on promoting “greenness” appear to have limited impact on changing behaviors (see Lanzini and Thøgersen, 2014). As just discussed, it is important to package any appeals to social responsibility with a clear articulation of the financial and convenience benefits that would accrue from behavioral change.

6. CONCLUSIONS

In this paper, we have developed a model to analyze first-use and use frequency of ESS and BSS. The model uses a Generalized Heterogeneous Data Model (GHDM) and employs psycho-social constructs as mediators of the effects of demographic variables. In doing so, we explicitly recognize the role played by awareness/first-use of new technologies as a cognitive antecedent to subsequent frequency decisions based on the awareness-knowledge transition paradigm from diffusion of innovation theory (see Rogers, 2002) and behavioral change theory (see Prochaska et al., 2008). Specifically, we recognize that individual-level factors may impact the first-use dimension differently from the subsequent frequency of use dimension. Our modeling approach also captures important attitudinal and lifestyle preference effects, and enables the parsimonious joint modeling of ESS and BSS outcomes. The primary dataset is based on responses from a 2019 multi-city Transformative Technologies in Transportation (T4) Survey. The Austin, Texas component of this dataset was supplemented with a procedure that geocoded home locations of the individuals and provided additional built environment factors. To our knowledge, we are the first to use such a comprehensive joint framework for first-use and subsequent use frequency of ESS and BSS systems.

Our results may be summarized in the following general findings.

1. The influence of demographic variables on ESS/BSS use are not all direct effects but are strongly mediated through the psycho-social attitudes of safety concern (in technology and the travel environment), time consciousness, and green lifestyle propensity.
2. The process underlying first-use of micromobility modes is distinct from the process driving subsequent use frequency. Further, these process pathways vary by the specific micromobility mode. Thus, social-psychological effects dominate over demographic effects in determining ESS first-use, but demographic effects dominate over psychosocial factors in ESS use frequency once first-use has been experienced. However, for the BSS mode, safety concern and time consciousness affect both first-use and use frequency. From a policy action standpoint, the implication is that once an individual is brought to the point of ESS first-use, it is more important to offer incentives (such as a loyalty program) for ESS use rather than investments to ameliorate, for example, safety concerns of such individuals. But for the BSS mode, continual efforts to alleviate safety concerns (potentially in the form of actual bicycling infrastructure improvements and positive communication strategies), as well as actions to highlight the potential time savings/environmental benefits, appears to be needed to retain BSS users even after BSS first-use. Due to the differences between the outcomes of

ESS and BSS first-use and frequency, a “one approach fits both” strategy to promoting adoption and sustaining ESS and BSS use may not be the most effective.

3. There are distinctive pathways of adoption/use frequency for each of the ESS and BSS modes. At the same time, however, there are clear foundational ties between ESS and BSS, with complementary processes and behavioral spillover effects at play that warrant a joint modeling of both modes. From a policy standpoint, the implication is that both the ESS and BSS modes can be simultaneously promoted. Also, any efforts to bolster first-use of one of the ESS or BSS modes has a complementary spillover of promoting the other mode. This complementarity in first-use/use frequency and across the two modes also suggests the need for careful regulations in planning, operations, and regulations associated with both modes.
4. Addressing safety concerns of micromobility modes should be the top priority of providers and public agencies. Efforts solely directed toward extolling the “green” virtues of micromobility modes is likely to have limited returns.

Of course, there are many possibilities for future research, including an in-depth exploration of the decision-making process of individuals within the context of their specific household and travel environment contexts. Our results do reveal the important direct sub-effects of individual and household demographic variables. While many alternative interpretations may be provided to explain such direct sub-effects, the take-away message is that there is ample room for additional studies of micromobility mode adoption to further “peel the behavioral onion” and understand travel behaviors in a multi-modal travel environment. The fact that all the household variables show up as pure direct effects implies a particular need to drill down and examine modal availability, modal considerations, and the specific decision-making context of individuals as part of their households and their immediate travel environments. In this regard, our analysis is limited by the absence of the supply side of micromobility systems, which presumably is showing up as direct BE effects of residential locations and population density. In addition, finer resolutions of BE attributes (than the Census Block Group level used in the current paper) around each individual’s residence location would be valuable in gaining additional insights on how best to design our neighborhoods to promote ESS/BSS use in ways that draw more from motorized means of transport rather than walking. Overall, future research efforts need to focus on a more comprehensive capture of demand side constraints, supply side considerations, and rebalancing operations when modeling individual-level micromobility uptake and use behavior.

The issue of transportation equity related to micromobility modes is another important open area of research. Our research suggests that women and older individuals, in particular, are being left behind in the new mobility revolution, or at least that these new mobility options are benefitting men and younger individuals more so than women and older individuals. At the same time, it is well established that women and older individuals are more at risk of transport-related social exclusion (Lucas, 2012; Bernardo and Bhat, 2014). Further, while our analysis did not find any race-based differences in micromobility adoption (similar to Sanders et al., 2020 and Poveda-Reyes et al., 2021), minority groups traditionally have had less access to smartphones and credit

cards that play a critical role in renting micromobility modes. There is also a “double-edged sword” nature to these micromobility systems. While it can be legitimately argued that micromobility services (especially the dockless versions) relieve social exclusion from a spatial standpoint (in that providers can flexibly and relatively easily change operating areas to serve needs), market forces and business practices may slant this flexibility toward serving wealthier already travel-rich neighborhoods, while the already travel-poor continue to face limited mobility choices. City policy regulations can be promulgated to ensure good operating area coverage and repositioning strategies that ensure proximal and temporal availability even in traditionally underserved communities. More broadly, there is pressing need for further investigations into how cities/public agencies and providers can work together to integrate new mobility options within the fabric of traditional mobility options to actualize an equitable, reliable, sustainable, and resilient new mobility landscape.

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