Modeling Ridesharing and Carsharing Adoption and Use Patterns: Deciphering the Substitutive and Complementary Impacts of Built Environment, Transit Accessibility, & Active Travel.

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A Joint Demand Model for Ridesharing and Carsharing Use: Deciphering the Substitutive and Complementary Impacts of Built Environment, Transit Accessibility, & Active Travel.

ABSTRACT

Disruptive shared mobility services, including carsharing and ridesharing, impart transformative impacts on transportation systems. We present a behavioral framework to jointly model individuals' carsharing and ridesharing use with a focus on deciphering the substitutive vs. complementary roles of the built environment, active travel, and transit accessibility. Based on a sample of over 3,200 individuals from the 2019 Puget Sound Travel Survey, detailed travel behavior data are spatially integrated with objectively assessed neighborhood-level data on the built environment and transit accessibility. Joint heterogeneity-based multivariate ordered discrete choice models are developed to simultaneously account for random (unobserved) and systematic (observed) heterogeneity. The use patterns of carsharing and ridesharing services exhibited a strong positive dependence. Reflecting complementary impacts, neighborhood walkability, pedestrian-oriented urban design, and transit accessibility exhibited positive associations with individuals' use of carsharing and ridesharing services. Active travel behaviors (walking, biking, and transit use) also exhibited synergistic relationships with carsharing and ridesharing use. While transit accessibility and active travel independently complemented shared mobility services, our findings indicate that the interaction between the two could substitute ridesharing services. Significant random and systematic heterogeneity in the behavioral, environmental, and demographic determinants of shared mobility services was also revealed. We discuss the relevance and implications of the new findings considering scenario planning and travel demand modeling needs.

Keywords: Ridesharing, carsharing, built environment, active transportation, bivariate ordered probit model, random parameters, complementary vs. substitutive effects.

1. INTRODUCTION

The heavy reliance on personal vehicle ownership has led to major transportation externalities, including the use of carbon fuels, urban congestion, climate change, urban sprawl, and community disconnectedness (Garfinkel-Castro and Ewing 2022, Kondor et al. 2022, Vermeiren et al. 2022). With a surge in collaborative consumption and rapid advancements in Information and Communication Technology (ICT), the shared economy-based mobility model has emerged as a competitive alternative to the personal vehicle ownership model (Castellanos et al. 2022, Mattia et al. 2022). Shared urban mobility has the potential to enhance equity and community embeddedness, distributed consumption, and reduce climate change and urban congestion (Martin et al. 2010; Martin and Shaheen 2011b; Li et al. 2016; Handke and Jonuschat 2012). In this regard, ridesharing and the latest smartphone-based forms of carsharing have lately received wide attention and constitute the broader suite of technological innovations constituting emerging shared mobility services (Liao and Correia 2022, Sun et al. 2022, Yao et al. 2022). Compared to automobile and transit-based urban mobility, ridesharing and carsharing programs provide more accessible, flexible, and convenient mobility (Harmony 2022, Sun et al. 2022)(Shaheen et al. 2015; Barbour et al. 2020). On-demand ride services (ridesharing) harness smartphone-based applications to connect passengers (buyers) with drivers (sellers) who use their vehicles to offer ridesharing services. As one indicator of user acceptance of the technology, Uber's revenues increased around 22-fold between 2014 and 2020 ($0.4 billion and $11.1 billion in 2014 and 2020, respectively) (Iqbal 2020). On the other hand, carsharing services are tailored to provide short-term car rental services providing the benefits of private vehicle use without the costs and responsibilities of private vehicle ownership (Shaheen et al. 1998). While introduced as early as 1948 (Shaheen et al. 2020), carsharing service providers initially struggled to find a large enough consumer base in the pre-ICT era. However, the advent of digital smartphones and telematics has revitalized the utility and accessibility of carsharing services. According to industry estimates, worldwide carsharing membership reached 50.4 million in 2018 and will grow to 227 million by 2023 with a carsharing fleet size of around 1.2 million vehicles (Berg Insight 2018).

The surge in the growth of carsharing and ridesharing has led to an increased interest among researchers and practitioners in understanding their behavioral adoption (Aguilera-García et al. 2022, Baumgarte et al. 2022, Esfandabadi et al. 2022). However, very little is known about the adoption, use patterns, and potential impacts of such shared mobility options. Long-range transportation planning and demand models are currently limited by their inability to adequately reflect the use patterns of these services and capture the behavioral and environmental/infrastructural determinants of ridesharing and carsharing use. This study focuses on analyzing the current use patterns of ridesharing and carsharing technologies and how demographic, behavioral, and physical environment factors correlate with the adoption of these services. *From a conceptual standpoint*, the present study goes beyond the sociodemographic determinants of carsharing and ridesharing adoption – and examines how neighborhood-level objectively assessed built environment features, active transportation behaviors, and the interactions between the two, correlate with the use of on-demand mobility services while controlling for individuals' residential choices. *Methodologically*, we account for the stochastic dependence between the use of carsharing and ridesharing services arising due to complex interactions that influence how users adopt the two on-demand mobility services. In a joint modeling framework, we also account for unobserved and observed heterogeneity in the determinants of carsharing and ridesharing adoption characterized by systematic variations in unobserved/latent factors. To this end, the present study analyzes individual-level travel behavior data complemented with objectively assessed neighborhood built environment features. A novel simulation-assisted heterogeneity-based joint discrete outcome modeling framework is developed capturing the stochastic dependence between carsharing/ridesharing use and the underlying unobserved (random) as well as observed (systematic) heterogeneity in the determinants of carsharing/ridesharing use.

The rest of the paper is structured as follows. Section 2 synthesizes the existing body of knowledge. Research gaps along with study objectives and contributions are identified. The different data sources and the methodological framework used are introduced in sections 3 and 4, respectively. Distributions of ridesharing and carsharing use, built environment features, and estimation results are presented in section 5. We discuss the key findings, highlight the policy implications, and study limitations in Section 6. We conclude the study in section 7.

2. EXISTING KNOWLEDGE

The popularity of smartphone-based ridesharing and carsharing mobility-on-demand services has led to an increasing number of studies examining the potential impacts of these technologies on transportation systems. Earlier scholarly efforts examining carsharing impacts have documented the potential of the technology to enable more efficient mobility (Baptista et al. 2014), and reduce vehicular emissions (Namazu and Dowlatabadi 2015; Luna et al. 2020; María Arbeláez Vélez et al. 2021; Nijland and van Meerkerk 2017), vehicle ownership (Martin and Shaheen 2011a; Kim et al. 2019; Namazu and Dowlatabadi 2018; Kent 2014), and vehicle miles traveled (VMT) (Lane 2005; Nijland and van Meerkerk 2017; Kent 2014). Likewise, previous studies demonstrate the potential of on-demand ridesharing services in mitigating the carbon footprint of urban transportation (Tikoudis et al. 2021; B. Yu et al. 2017), enabling energy savings (B. Yu et al. 2017), enhancing urban mobility (Stiglic et al. 2018), and lowering VMT (Fiedler et al. 2018). Studies have also documented the potential of ridesharing services in reducing congestion (Diao et al. 2021) and improving road safety (Blazquez et al. 2021; Graf 2017). Compared to the positive impacts above, some studies have also documented the negative impacts of ridesharing on urban transportation systems with the potential to increase VMT (Tirachini 2020; Tirachini and Gomez-Lobo 2020), congestion and energy use (Kondor et al. 2022)(Wenzel et al. 2019; Tirachini and Gomez-Lobo 2020), and lower public transportation use (Diao et al. 2021; Gehrke et al. 2019).

2.1.Sociodemographic Factors

From a travel demand standpoint, a broad spectrum of studies has examined the preferences and characteristics of ridesharing and carsharing users. Broadly, the literature on demand estimation of mobility-on-demand services is based on two different approaches, including the use of individual-level stated/revealed preference survey instruments (Lavieri and Bhat 2019; Gomez et al. 2021; Rayle et al. 2016; Zhang and Zhang 2018a; Sioui et al. 2013; Costain et al. 2012; Dias et al. 2017; Ceccato and Diana 2021; Ye et al. 2019) and aggregate spatiotemporal trip data collected by on-demand service providers (Lavieri et al. 2018; H. Yu and Peng 2020; Marquet 2020; Ghaffar et al. 2020; Xu et al. 2021; Wali et al. 2022). The use of trip data aggregated to specific geographies provides invaluable insights into the spatiotemporal distribution of mobility-on-demand services and enables an empirical basis for resource planning and prioritization. However, as aggregate data mask the individual-level heterogeneity in travel behaviors (Wali et al. 2022; Dean and Kockelman 2021), they are not ideal to examine the objectives outlined in this study including the interactive effects of individual-level active travel behavior and built environment on the demand for shared mobility services. For this reason, we base the forthcoming synthesis of existing knowledge mainly on studies using individual-level data. Ridesharing users are reported to be young (Zhang and Zhang 2018b; Lavieri and Bhat 2019; Gomez et al. 2021; Rayle et al. 2016), higher income (Hyun et al. 2021)(Soltani et al. 2021), and more educated (Gomez et al. 2021; Dias et al. 2017). Personal innovativeness and technological savviness is also associated with higher ridesharing services (Wang et al. 2018). Regarding participation in carsharing programs, males and younger individuals are reported to be frequent users (Habib et al. 2012; Dias et al. 2017; Ceccato and Diana 2021)(Amirnazmiafshar and Diana 2022). Likewise, high-income and more educated individuals are more likely to use carsharing services (Costain et al. 2012; Ye et al. 2019). The household structure is also reported to be an important predictor of carsharing use with mixed findings in the literature. Sioui et al (2013) reported greater carsharing use for households with greater number of children (Sioui et al. 2013). Contrarily, Ceccato and Diana (2021) found a negative relationship between number of household members and carsharing use (Ceccato and Diana 2021). Except for Dias et al. (2017), the aforementioned studies did not simultaneously analyze the demand for ridesharing or carsharing services.

2.2.Active Travel & Built Environment

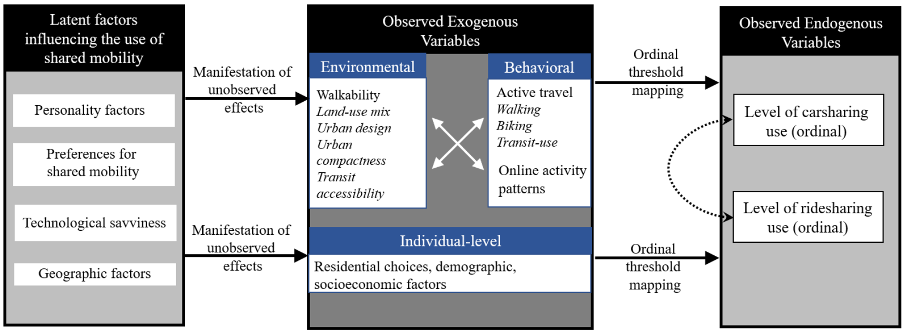
Compared to the broad literature on demographic determinants, evidence on the role of individual-level active transportation behaviors and built environment is extremely limited. From a travel behavior and demand perspective, the relationships of ridesharing and carsharing demand with traditional active transportation modes (including walking, biking, and public transit) are of high interest. Mixed findings are reported in the literature in this regard. A substitutive effect of carsharing on walking and biking was not found in adjusted models, whereas a complementary relationship was observed between carsharing and public transit use (Ceccato and Diana 2021). Likewise, mainly used for long-distance trips, carsharing exhibited a cooperative relationship with nonmotorized travel and public transit (Ye et al. 2021). On the other hand, results from a stated choice experiment in a university setting suggested a strong substitutive (competitive) effect of carsharing on public transportation and biking (Carrone et al. 2020). Only a handful of studies have examined the role of the built environment in facilitating (or hindering) the adoption of ridesharing services reporting mixed findings. Greater land use mix and auto-oriented accessibility were correlated with higher ridesharing demand (Alemi et al. 2018). Another study reported an inverse relationship between land use mix and the frequency of ride-hailing (Alemi et al. 2019). Population density was positively correlated with ridesharing use (Soltani et al. 2021; Alemi et al. 2019; Conway et al. 2018). Regarding carsharing services, studies using aggregate trip/transaction data have reported a higher carsharing demand in areas with greater building floor area (Kang et al. 2016) and light rail availability (Stillwater et al. 2009).

2.3.Research Gaps

Previous studies have provided invaluable insights into the determinants of ridesharing and carsharing demand with implications for long-range transportation planning and travel demand modeling. However, important methodological and substantive knowledge gaps remain.

Methodologically, existing studies are limited by analyzing either ridesharing or carsharing demand and did not account for the stochastic dependence between the use of carsharing and ridesharing services (Figure 1). The joint dependence between the two on-demand mobility services is an outgrowth of synergistic and competing relationships between carsharing and ridesharing services marked by both similarities and intrinsic differences between the two emerging mobility services (Shaheen and Chan 2016; Hyun et al. 2021)(Burghard and Scherrer 2022). Second, previous studies did not account for unobserved heterogeneity in the determinants of carsharing and ridesharing demand (Figure 1). It is unlikely that information on all key factors influencing the demand for the two services be available for analysis even with the availability of comprehensive behavioral data used in this and prior studies (Figure 1). The potential effects of such unobserved factors can get manifested through observed variables (such as built environment) confounding the interpretation of empirical results. An adequate understanding of the stochastic dependence patterns between the two on-demand mobility services and the underlying heterogeneous impacts of behavioral, demographic, and environmental factors is imperative to enhance existing transportation planning and demand models (Figure 1).

From a substantive standpoint, large gaps exist in our knowledge of the links between the built environment and active travel behaviors with individuals' use of carsharing and ridesharing services (Figure 1). The physical environment remains a key planning and policy lever to retrofit cities for providing active and healthy infrastructure (Sallis 2009, Crist et al. 2022). However, empirical evidence on the role of compact and more walkable neighborhoods in facilitating (or hindering) individual-level carsharing and ridesharing adoption is extremely limited. Few studies examining the role of the built environment are limited by the use of coarser or subjectively assessed built environment features. The need to harness more detailed built-environment variables in analyzing relationships between the built environment and individual-level on-demand mobility use is documented in the literature (Lavieri and Bhat 2019). Related to examining the impacts of built environment features, it is important to control for the potential role of residential choices. Likewise, despite the many potential benefits of carsharing and ridesharing services discussed above, the broader effect of on-demand mobility services on urban transportation and public health is still unclear. For example, there is a paucity of literature on individuals' participation in active transportation and their adoption of ridesharing/carsharing services, and whether the relationships between the two are complementary or substitutive (Figure 1). In addition, little to no information exists about how the interactions between the built environment and active travel behavior influence carsharing/ridesharing use (Figure 1). Enabling greater consistency between policy and action, evidence-based answers to such questions can guide resource allocation and the development of regulations to harness the benefits of ridesharing/carsharing services while minimizing its negative societal impacts (especially those related to public health).



The bidirectional solid arrows indicate potential interactive (substitutive vs. complementary) effects.
The bidirectional dotted curved arrow indicates stochastic dependence between individuals' level of carsharing & ridesharing use.

FIGURE 1. Conceptual Framework - A Joint Travel Demand Model for Individuals' Carsharing & Ridesharing Use Programs

2.4.Research Objectives and Contribution

Considering the above research gaps, the present study makes methodological and substantive contributions. We present a joint heterogeneity-based multivariate ordered probit model capturing random (unobserved) and systematic (observed) heterogeneity in the demographic, behavioral, and environmental determinants of ridesharing and carsharing use. The study adds to the existing body of literature by exemplifying the role (substitutive vs. complementary) of active travel behaviors as it relates to the demand for on-demand mobility services. In addition, the study focuses on how the built environment and its interactions with active travel patterns may influence the demand for ridesharing and carsharing services.

3. DATA SOURCES

To achieve the study objectives, we harness comprehensive travel behavior data from the 2019 Puget Sound Travel Survey (PSTS) (PSRC 2019). These data are spatially joined with detailed objectively assessed neighborhood-level built environment data.

The 2019 PSTS is part of a six-year program by the Puget Sound Regional Council (PSRC) with an overarching objective of providing an up-to-date profile of the sociodemographic fabric, activity patterns, preferences, and attitudinal predispositions towards emerging transportation modes including ridesharing and carsharing services (PSRC 2019). Individuals under the age of 18 years were excluded from the sample to explicitly focus on the travel behavior and preferences of adults. This study harnesses the RSurvey group of the two survey groups (RSurvey and RMove) included in the 2019 PSTS (PSRC 2019, Wali and Khattak 2022). The dependent variables are collected at a person level and data on a wide variety of other relevant variables are pulled from the trip and household-level survey files. The final sample used in this study comprised 3,271 individuals belonging to 1,997 households in 465 census tracts. The survey is reasonably representative of the study area and the sociodemographic profiles are reported to be representative of larger urban areas in the US. For details, see (Wali and Khattak 2022).

3.1.Dependent Variables

The two dependent variables include the respondents' use of carsharing and ridesharing services in the past 30 days. Precisely, the 2019 PSTS asked survey respondents *"In the past 30 days, how often have you traveled in each of the following ways?"* – with the five travel mode options including "carshare (e.g., Car2Go, Turo, ZipCar, ReachNow, Getaround" and "Rideshare (Uber, Lyft, or other smartphone-app car service". The survey respondents provided data on the use of carsharing and ridesharing services on a seven-point categorical ordinal scale including: "*I never do this*", "*I do this, but not in the past 30 days*", "*1-3 times in the past 30 days*", "*1 day/week*", "*2-4 days/week*", "*5 days/week*", and "*6-7 days/week*". Given fewer responses, we collapsed the last three categories into one category as "2 or more days/week" – leading to a five-point ordinal scale for each of the two mobility services.

3.2. Independent Variables: Behavioral, Attitudinal, & Demographic Data

Detailed behavioral data on mode-specific active transportation (bike, walk, and public transit) use and online activity patterns (package deliveries, food deliveries, and grocery deliveries) were harnessed. Information on residential choices was also used to incorporate households' most important factors in choosing their current residential neighborhoods. These attitudinal variables help control for residential self-selection to the extent possible in any cross-sectional study. Demographic and socioeconomic data included information on household income, respondents' age, employment status, gender, education, and race.

3.3. Independent Variables: Objectively Assessed Walkability, Built Environment, Transit Accessibility

The PSRC survey is a unique source of public information since it provides census tract-level geographic identifiers that enable a detailed investigation of the impacts of neighborhood-level environmental features on travel demand for emerging modes. The environmental data are derived from the most recent 2020 Smart Location Database (SLD) by the U.S. Environmental Protection Agency (https://www.epa.gov/smartgrowth/smart-location-mapping). The most recent SLD version enhances the previous versions by expanding the set of environmental variables and using a more rigorous methodology for the creation of environmental variables (Wali et al. 2022). The physical and built aspects of the environment are key modifiable features that engineers and planners can alter to influence the travel demand of emerging mobility services (Wali et al. 2022). We harness objective data on measures of neighborhood walkability, built environment, and transit accessibility that previous studies have shown to predict travel demand and overall health outcomes (Cervero and Kockelman 1997, Frank et al. 2003, Saelens and Handy 2008, Wali and Frank 2021). These measures include urban design (pedestrian-oriented street connectivity, pedestrian-oriented facility miles), land use diversity (residential and employment land use mix), and transit accessibility (proximity to nearest transit stops). The measures of urban design, land-use diversity, and transit accessibility are combined in a composite walkability index (ranging from 1 to 20) to circumvent the multicollinearity issue that arises due to the strong dependencies among multiple built environment features (Frank et al. 2010). Additionally, objectively assessed measures of urban compactness (residential density) and worker transit accessibility (employment concentrations within ½ mile of fixed-guideway transit) are also harnessed. For more details on the environmental measures used, see (Wali and Frank 2021, Wali et al. 2022).

4. MODELING FRAMEWORK

The two dependent variables of interest in this study are individuals' use of carsharing and ridesharing programs. An ordinal modeling framework is appropriate as the response outcomes are measured on an ordinal scale. This study develops heterogeneity-based random parameter bivariate ordered probit models to simultaneously account for the stochastic dependence between individuals' use of carsharing and ridesharing services and unobserved heterogeneity in the effects of exogenous factors on carsharing and ridesharing use. The formulation and mathematical exposition are briefly presented next.

Consider b as an index indicating an individual i $[i = 1,2, \ldots, I]$ use of carsharing $(b = 1)$ and ridesharing $(b = 2)$ services. Let l_b represent the use of carsharing and ridesharing services taking the following values: *I never do this* [$l_b = 1$], *I do this, but not in the past 30 days* [$l_b = 2$], *1-3 times in the past 30 days* [$l_b = 3$], *1 day/week* [$l_b = 4$], and *2 or more days/week* [$l_b = 5$]. The observed and latent use levels of carsharing and ridesharing services are indicated by y_b and y_b^*, respectively. With an outcome-specific vector of thresholds φ_{l_b}, the latent carsharing and ridesharing use levels are modeled as a function of observed exogenous factors and unobserved factors (Greene and Hensher 2010):

$$y_{Ib}{}^* = \beta_b{}' x_{I_b} + \tau_{I_b} \tag{1}$$

Where: β_b indicates the vector of estimable parameters corresponding to each outcome b and τ_{I_b} are vectors of person-level error terms associated with carsharing and ridesharing use. The modeled latent carsharing and ridesharing use can be mapped to the observed use levels y_{Ib} using the vector of thresholds φ_{l_b} as (Greene and Hensher 2010):

$$y_{Ib} = l_b \text{ if } \varphi_{l_b-1} < y_{Ib}{}^* < \varphi_{l_b} \tag{2}$$

To obtain a formulation of observed carsharing and ridesharing use levels in terms of the linear-in-parameters utility functions, Eq. (2) can be substituted in Eq. (1) as (Greene and Hensher 2010):

$$y_{Ib} = l_b \text{ if } \varphi_{l_b-1} < \beta_b{}' x_{I_b} + \tau_{Ib} < \varphi_{l_b} \tag{3}$$

$$y_{Ib} = l_b \text{ if } \left(\varphi_{l_b-1} - \beta_b{}' x_{Ib}\right) < \tau_{I_b} < (\varphi_{l_b} - \beta_b{}' x_{I_b}) \tag{4}$$

The ordered probit framework is arrived at by assuming independent and identically distributed normal marginal distributions for the vector of errors for carsharing (τ_{I_1}) and ridesharing (τ_{I_2}) services (Greene and Hensher 2010).

4.1.Joint Bivariate Ordered Probit Model

The independent ordered probit models do not consider the latent/unobserved factors that can potentially influence the use of carsharing and ridesharing services. These unobserved factors could include factors such as technological savviness, personality-related factors, preferences, and geographic factors – inducing correlations between the unobserved components of utility associated with carsharing and ridesharing use (Figure 1). Incorporating the potential dependence among the unobserved factors leads to more efficient parameter estimates (Asmussen et al. 2022, Deepa et al. 2022). To account for the simultaneous correlations, the expression in Eq. (4) can be expanded as:

$$y_{I1} = l_1 \text{ if } \left(\varphi_{l_1-1} - \beta_{b=1}{}' x_{I1}\right) < \tau_{I_{b=1}} < (\varphi_{l_1} - \beta_{b=1}{}' x_1) \tag{5}$$

$$y_{I2} = l_3 \text{ if } \left(\varphi_{l_3-1} - \beta_{b=2}{}' x_{I2}\right) < \tau_{I_{b=2}} < (\varphi_{l_2} - \beta_{b=2}{}' x_{I_2}) \tag{6}$$

A joint distribution must be specified for $\tau_{I_{b=1}}$ and $\tau_{I_{b=2}}$ to tie Eq. (5) and Eq. (6). We assume a bivariate normal distribution to tie the two vectors as: $\begin{pmatrix}\tau_{I_{b=1}} \\ \tau_{I_{b=2}}\end{pmatrix} \sim N\left[\begin{pmatrix}0 \\ 0\end{pmatrix}, \begin{pmatrix}1 & \rho \\ \rho & 1\end{pmatrix}\right]$ with means of zero and variance-covariance matrix as shown – leading to a bivariate ordered probit model. The joint probability that an individual uses carsharing and ridesharing services with certain use levels becomes (Wali et al. 2021):

$$P\left(y_{I_1} = l_1, y_{I_2} = l_2\right) \tag{7}$$

$$= P\left(\left[\left(\varphi_{l_1-1} - \beta_{b=1}{}'x_{I1}\right) < \tau_{I_1} < \left(\varphi_{l_1} - \beta_{b=1}{}'x_{I1}\right)\right], \left(\varphi_{l_2-1} - \beta_{b=2}{}'x_{I2}\right) < \tau_{P_2} < \left(\varphi_{l_2} - \beta_{b=2}{}'x_{I2}\right)\right)$$

$$= P\left[\tau_{I_1} < \left(\varphi_{l_1} - \beta_{b=1}{}'x_{I1}\right), \tau_{l_2} < \left(\varphi_{l_2} - \beta_{b=2}{}'x_{I2}\right)\right] - P\left[\tau_{l_1} < \left(\varphi_{l_1} - \beta_{b=1}{}'x_{I1}\right), \tau_{l_2} < \left(\varphi_{l_2-1} - \beta_{b=2}{}'x_{I2}\right)\right] - P\left[\tau_{l_1} < \left(\varphi_{l_1-1} - \beta_{b=1}{}'x_{I1}\right), \tau_{l_2} < \left(\varphi_{l_2} - \beta_{b=2}{}'x_{I2}\right)\right] + P\left[\tau_{l_1} < \left(\varphi_{l_1-1} - \beta_{b=1}{}'x_{I1}\right), \tau_{l_2} < \left(\varphi_{l_2-1} - \beta_{b=2}{}'x_{I2}\right)\right]$$

4.2.Joint Random Parameter Bivariate Ordered Probit Model

A key restriction placed by the fixed parameter bivariate ordered probit model is the assumption of homogeneous effects of exogenous factors on the use of carsharing and ridesharing services. This is a very restrictive assumption since individual behaviors are largely determined by contextual and time-space factors that are often unobserved in the data. The effects of such unobserved factors shown in Figure 1 can be manifested through the observed exogenous variables leading to variations in the effects of independent variables on the use of carsharing and ridesharing services (Washington et al. 2020, Guo et al. 2021, Wali et al. 2021, Yang et al. 2021, Wali et al. 2022). To account for unobserved heterogeneity, we allow the estimable parameters to vary across the individuals $[i = 1,2, \dots, I]$ for carsharing $[\beta_{b=11}, \beta_{b=12}, \dots, \beta_{b=1I}]$ and ridesharing $[\beta_{b=21}, \beta_{b=22}, \dots, \beta_{b=2I}]$ use (Wali et al. 2019, Intini et al. 2020, Lee et al. 2021):

$$y_{Ib}{}^* = \beta'_{Ib} x_{I_b} + \tau_{Ib} \quad (8)$$
$$\beta'_{Ib} = \beta'_b + \xi_{I_b} \quad (9)$$

Where: β'_{Ib} is a vector of size I containing the individual-specific estimable parameters in the (joint) models for carsharing $(b = 1)$ and ridesharing $(b = 1)$ use. ξ_{I_b} are normally distributed noise terms with zero mean and precision $(^1/_{\sigma^2})$. Maximum simulated likelihood (MSL) estimation methods were used to approximate the integrals over the densities of unobserved factors. Scrambled Halton draws (N = 200) were used in the MSL estimator (Train 2009). Estimable parameters for exogenous factors were considered random parameters if they exhibited statistically significant means and standard deviations (Washington et al. 2020).

4.2.1. Model Interpretation

The parameter estimates from discrete ordered choice models indicate the direction of association but do not readily quantify the magnitude of associations. To better interpret the findings, we compute the marginal/treatment effects of exogenous variables. For dummy indicators, the marginal effects show the % increase/decrease in the likelihood of observing specific carsharing or ridesharing use levels. For continuous covariates, the marginal effects show the % increase/decrease in the likelihood of observing specific carsharing or ridesharing use levels with a unit increase in the value of the covariate. Given the focus on the built environment, we also estimate the marginal effects of treatment scenarios where the existing neighborhood built environment features are altered by a discrete change, e.g., changing neighborhood walkability from the 25th (low) to the 75th (high) percentile of the distribution. The marginal effects are computed using the sample enumeration technique at the individual level and then averaged across the sample (Nair et al. 2018, Wali et al. 2021).

4.3. Model Evaluation

Two sets of procedures were used to evaluate the alternative models. Information Criterion-based model selection measure (Akaike Information Criterion) was used to evaluate competing models considering model complexity and predictive fit (Bozdogan 1987). Between two competing models, a difference of over five points provides strong support in favor of the model with the lowest AIC, whereas a difference of over ten points rules out the model with the higher AIC (Bozdogan 1987). To test for model significance, likelihood-ratio tests were also conducted (Bhat 2000, Koppelman and Bhat 2006). By comparing restricted (e.g., fixed-parameter univariate models) and unrestricted models (e.g., random parameter joint model), the LR test formally determines if the additional model complexity exhibited by the unrestricted models is statistically warranted (Koppelman and Bhat 2006, Wali et al. 2021).

5. RESULTS

5.1. Descriptive Statistics

Figure 2 illustrates the distribution of the two response outcomes. Around 2,767 (84.5% of the sample) and 1,455 (44%) individuals have never used carsharing and ridesharing services, respectively. Around 2.3% and 13.6% of the sample indicated using carsharing and ridesharing services regularly (1 day/week or more). Between the two disruptive mobility services, ridesharing use is significantly greater than carsharing use. The use levels of the two shared mobility services are positively correlated (with Kendall's $\tau_b = 0.302$) (Figure 2) – suggesting the presence of common observed and unobserved factors influencing the use levels of the two services.

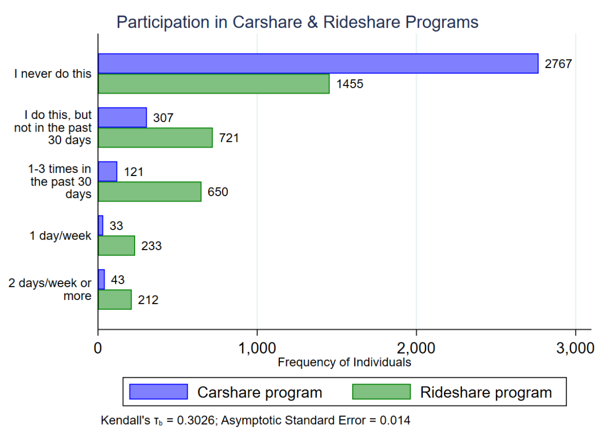


FIGURE 2. Distribution of User Participation Levels in Carshare and Rideshare Programs.

Table 1 shows the descriptive statistics of key exogenous variables. Significant variations are observed in neighborhood environmental features with a broad range of pedestrian-oriented intersection density (μ = 171.56 count / sq. km, SD = 99.10), employment land use diversity (μ = 0.6 on scale of 0 to 1, SD = 0.12), employment and residential land use diversity (μ = 0.53 on scale of 0 to 1, SD = 0.15), and distance to nearest transit stops (μ = 345.5 m, SD = 205.2). Considering the average walk speed of 3 mph, the average distance of 345.5 meters to the nearest transit stops translates to around 4.2 minutes of walking – which is lower than the preferred walk time of 5 to 10 minutes (El-Geneidy et al. 2014). On a scale of 1 to 20, the average neighborhood walkability index is 14.2 with significant variations across the sampled census tracts (Figure 3).

Regarding urban design, the study area exhibits a considerable provision of pedestrian-oriented links – with an average density of 22.18 facility miles of pedestrian-oriented links per sq. mi. Distributions for urban compactness (density) and workers' transit accessibility are shown. On average, the survey individuals made 0.1, 0.8, and 0.3 bike, walk, and transit trips per day. Related to online activities, the individuals received 0.18 package deliveries on the travel day. Nearly half (47.9%) of the survey individuals indicated the provision of walkable neighborhoods as an important factor in choosing their current home locations. Around 22% of the sample is comprised of elderly individuals (aged 65 years or more). Around three-fourths of the sample is comprised of white individuals and around 30% of the sample possess a post-graduate degree. Overall, the sociodemographic and behavioral characteristics of the sample seem reasonable as discussed elsewhere (Wali and Khattak 2022).

TABLE 1. Descriptive Statistics of Key Variables

Category	Variables	Mean (μ)	SD	Min	Max
Neighborhood Level Objectively-Assessed Built Environment	***Walkability Variables***				
	Urban Design: Pedestrian-oriented intersection density (connectivity)	171.565	99.108	0.50	521.17
	Diversity of land uses: Employment mix (employment entropy)	0.600	0.120	0.18	0.84
	Diversity of land uses: Mix of employment types & occupied housing	0.532	0.158	0.10	0.91
	Transit access: Proximity to transit stops (meters)[a]	345.506	205.244	63.04	1184.21
	Walkability Index [urban design, employment entropy, mix of employment types & occupied housing, access to transit)	14.270	3.816	2.75	19.42
	Other Built Environment Variables				
	Urban Design: Network density in terms of facility miles of pedestrian-oriented links per square mile	22.189	9.065	0.77	42.09
	Density: Gross residential density (HU/acre) on unprotected land	12.798	16.033	0.02	77.02
	Workers' transit access: Percent of CBG employment within ½ mile of fixed-guideway transit stop	21.854	36.129	0	99.99
Active Transportation	Number of bike trips	0.103	0.523	0	7
	Number of walk trips	0.812	1.532	0	9
	Number of public transit trips	0.305	0.764	0	7
Online Activity Patterns	Package deliveries received on travel day [1/0]	0.183	0.387	0	1
	Food/meal prep deliveries received on travel day [1/0]	0.013	0.114	0	1
	Number of grocery deliveries on travel day [1/0]	0.016	0.125	0	1
Residential Choices	***Important factors in choosing current home location…***				
	Being within a reasonably short commute to work [very important]	0.426	0.495	0	1
	Being close to the highway [very important]	0.093	0.290	0	1
	Being close to public transit [very important]	0.389	0.488	0	1
	Having a walkable neighborhood and being near local activities [very important]	0.479	0.500	0	1
Demographics	Annual Income: USD 75,000 - 99,999	0.138	0.345	0	1
	Annual Income: USD 100,000 or more	0.446	0.497	0	1
	Age: 65-74 years	0.146	0.354	0	1
	Age: 75 - 84 years	0.055	0.229	0	1
	Age: 85 years or older	0.014	0.118	0	1
	Gender: female	0.498	0.500	0	1
	Employed full time (35+ hours/week, paid)	0.535	0.499	0	1
	Education: Post-graduate degree	0.299	0.458	0	1
	Race: Black	0.033	0.178	0	1
	Race: White	0.756	0.429	0	1
	Race: American Indian or Alaskan Native	0.015	0.121	0	1

Race: Asian	0.116	0.320	0	1
Race: Hispanic	0.038	0.191	0	1
Race: Other	0.021	0.143	0	1

Notes: N = 3271 individuals; (*) indicate census-tract level variables derived from block group-level most recent (2020) US EPA Smart Location Database; (a) Transit access is measured in meters from population-weighted centroid of census-tract to nearest transit stop.

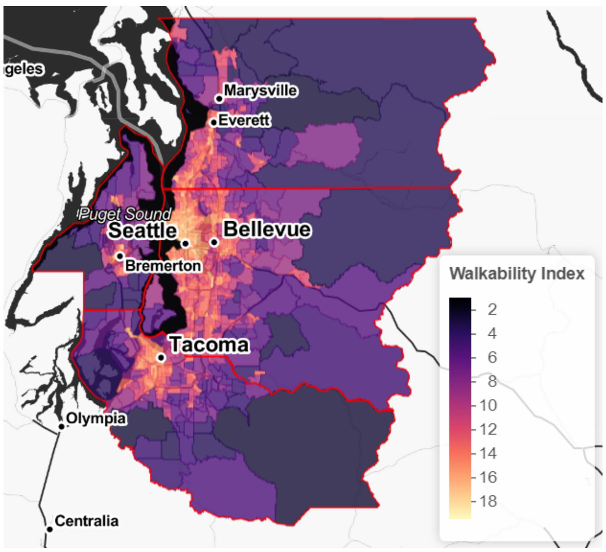


FIGURE 3. Distribution of Neighborhood Walkability in Four-County Puget Sound Regional Council

5.2.Estimation Results

Table 2 shows the goodness of fit statistics of the alternative model specifications. Compared to the two univariate ordered probit models, the AIC of the bivariate ordered probit (BOP) model was reduced by around 162 points indicating substantial improvements in model goodness of fit (Bozdogan 1987). Likewise, the LR statistic of 164.14 was significantly greater than critical χ^2 of 3.84 for 1 degree of freedom (representing the additional dependence parameter in the bivariate model). This marked improvement can be attributed to the ability of the BOP model in capturing the correlations among the unobserved factors underlying carsharing and ridesharing use. To account for unobserved heterogeneity in the effects of exogenous factors, a series of random parameter bivariate ordered probit models were developed. The AIC of the random parameter BOP model is lower than the fixed parameter counterpart and the results of the LR test conclude the statistical significance of the random parameter BOP over the fixed parameter BOP model (Table 2). Finally, to also account for potential systematic (observed) heterogeneity, the RP BOP framework was extended to also include multiple interaction effects. Doing so led to even further significant improvements in model goodness of fit and statistical significance. The AIC of the best-fit random parameter BOP model with systematic heterogeneity was lower than the AIC of the random parameter BOP model by around 16 points, whereas the LR statistic of 22.29 was significantly greater than critical χ^2 of 7.81 for 3 additional degrees of freedom (corresponding to the three additional interaction effects in the best-fit unrestricted model) (Table 2).

Collectively, these results suggest the presence of systematic variations in unobserved factors influencing the individuals' usage of carsharing and ridesharing services – leading to heterogeneity in the effects of exogenous factors. The effects of two variables in the carsharing and ridesharing equations were found to be random parameters. Additionally, independent of random unobserved heterogeneity, these results also demonstrate the presence of systematic heterogeneity in the effects of key exogenous factors on individuals' carsharing and ridesharing use. Table 3 shows the estimation results of the best fit random parameter BOP model with systematic heterogeneity.

TABLE 2. Goodness of Fit Statistics for Fixed & Random Parameter Bivariate Ordered Probit Models with Systematic Heterogeneity

Model	N	$LL_{[NULL]}$	$LL_{[\beta]}$	DF	AIC	LR statistic (DF_{EFF}) $[\chi^2_{95\ CI}]$*
Univariate Ordered Probit Models						
Carsharing use	3271	-1926.255	-1778.891	18	3593.781	---
Ridesharing use	3271	-4514.937	-3928.084	19	7894.167	---
Total	*3271*	*-6441.192*	*-5706.975*	*37*	*11487.948*	---
Bivariate Ordered Probit (BOP) Models for Carsharing & Ridesharing Use						
Fixed parameter BOP model	3271	-6248.309	-5624.906	38	11325.81	164.14 (1) [3.84]
Random parameter BOP model	3271	-6248.309	-5618.344	40	11316.69	13.12 (2) [5.99]
Random parameter BOP model with systematic heterogeneity	3271	-6248.309	-5607.198	43	11300.4	22.29 (3) [7.81]

Notes: N is sample size. $LL_{[NULL]}$ is log-likelihood at zero. $LL_{[b]}$ is log-likelihood at convergence. AIC is Akaike Information Criterion. LR statistic is the likelihood ratio statistic. DF is degrees of freedom (number of estimable parameters). DF_{EFF} is effective degree of freedom indicating the difference between the degree of freedom between the restricted and unrestricted models. $[\chi^2_{95\ CI}]$ is the critical chi-square value corresponding to a 95% level of confidence for effective degrees of freedom shown. (*) The LR test values show the results of likelihood ratio tests comparing the unrestricted models with the restricted (immediately above) counterparts. (---) indicates not applicable. No LR test applies to the univariate ordered probit models since they are the simplest models and have no baseline models to be compared to.

6. DISCUSSION

The discussion of the key results is organized into the following categories: (1) Complementary Impacts of Built Environment, Transit Accessibility & Active Travel; (2) Interactive (Substitutive) Impacts of Transit Accessibility & Active Travel; and (3) Impacts of Online Activity Patterns, Residential Choices, & Sociodemographic Correlates. The substantive interpretations of the random and systematic heterogeneity impacts are also highlighted. Table 4 shows the average marginal/treatment effects associated with key exogenous factors.

The best-fit random parameter BOP model with systematic heterogeneity revealed a positive statistically significant correlation between the latent factors underlying the use of carsharing and ridesharing services even after controlling for the built environment, active travel behaviors, sociodemographic factors, and unobserved as well as systematic heterogeneity (Table 3). This finding highlights the presence of common observed and unobserved factors that simultaneously impacts the use levels of disruptive shared mobility services.

6.1. Complementary Impacts of Built Environment, Transit Accessibility & Active Travel

The built environment-related variables in the best-fit model capture key environment characteristics including urban design, urban compactness, land use mix, and transit accessibility. As a composite measure of these built environment characteristics, the neighborhood walkability index is positively correlated with the use of carsharing and ridesharing services (Table 3). A one-unit increase in neighborhood walkability was correlated with a 0.62% and 0.58% decrease in the chance of an individual never using carsharing and ridesharing services, respectively (Table 4). Likewise, if the neighborhood walkability was to be improved from low (< 25^{th} percentile) to high (≥ 75^{th} percentile), the chance of an individual never using carsharing and ridesharing would on-average decrease by 2.73% and 2.64%, respectively. Figure 4A shows the relationship between neighborhood walkability and carsharing/ridesharing use across the range of walkability levels. Independent of neighborhood walkability, pedestrian-oriented facility links and urban compactness (residential density) were also found to be correlated with greater carsharing and ridesharing use. A 10-unit increase in facility miles of pedestrian-oriented links was associated with a 2.08% and 8.14% reduction in an individual's chance of never using carsharing and ridesharing services, respectively. Similarly, the chances of an individual never using carsharing and ridesharing services were reduced by 1.27% and 2.22% if residential density was to be improved from low to high (Table 4). Worker transit accessibility was also positively correlated with the use of ridesharing use – with each 1% increase in the percent of neighborhood employment within ½ mile of fixed-guideway transit stop associated with a 0.11% reduction in the chance of never using ridesharing services (Table 4). However, the associations of this variable were found to be normally distributed random parameters. With a mean and standard deviation of 0.005 (Table 3), the associations were positive for around 84% of the population and negative for the rest.

The above findings on the complementary impacts of walkability and transit accessibility are intuitive keeping in view the accessibility-related benefits offered by more walkable neighborhoods characterized by a greater mix of activities, street connectivity, and urban compactness. Compared to the active travel-related benefits of such neighborhoods discussed elsewhere (Wali and Frank 2021, Yang et al. 2022, Zhang et al. 2022), more walkable neighborhoods with greater activity points and better street connectivity also tend to support disruptive mobility services (Mouratidis 2022). While recent studies have highlighted the supportive role of walkability and urban design (Dean and Kockelman 2021, Wali et al. 2022), the studies did not harness individual-level data and did not examine the use of carsharing services. Our findings extend the existing literature by analyzing objectively assessed neighborhood features with individual-level carsharing and ridesharing use. Our results demonstrate the benefits of improving neighborhood walkability, pedestrian-oriented design, and transit accessibility for accelerating the adoption of carsharing and ridesharing services.

TABLE 3. Estimation Results for Best-Fit Random Parameter Bivariate Ordered Probit Model with Systematic Heterogeneity

Category	Variables	Carsharing Outcome			Ridesharing Outcome		
		β	z-score	Sig.	β	z-score	Sig.
Neighborhood Level Objectively-Assessed Built Environment	***Walkability Variables***						
	Walkability Index [connectivity, employment entropy, mix of employment types & occupied housing, access to transit)	0.031	2.02	**	0.019	1.68	*
	Other Built Environment Variables						
	Urban Design: Network density in terms of facility miles of pedestrian-oriented links per square mile	0.011	1.69	*	0.026	5.43	***
	Density: Gross residential density (HU/acre) on unprotected land	0.006	2.96	***	0.006	2.7	***
	Workers' transit access	---	---	---	0.005	4.8	***
Active Transportation	Number of bike trips	0.142	3.52	***	---	---	---
	Number of walk trips	0.034	1.72	*	0.065	3.58	***
	Number of public transit trips	0.089	2.1	**	0.109	3.45	***
Online Activity Patterns	Package deliveries received on travel day [1/0]	0.178	2.52	**	0.187	3.58	***
	Food/meal prep deliveries received on travel day [1/0]	---	---	---	0.540	3.15	***
	Number of grocery deliveries on travel day [1/0]	0.309	1.67	*	0.405	2.54	**
Residential Choices	***Important factors in choosing current home location…***						
	Being within a reasonably short commute to work [very important]	---	---	---	0.052	1.25	ns
	Having a walkable neighborhood and being near local activities [very important]	---	---	---	0.122	2.77	***
Demographics	Annual Income: USD 75,000 - 99,999	0.139	1.47	ns	0.123	1.88	*
	Annual Income: USD 100,000 or more	0.302	4.69	***	0.507	10.92	***
	Age: 65-74 years	-0.514	-4.67	***	---	---	---
	Age: 75 - 84 years	-0.816	-3.68	***	---	---	---
	Gender: female	-0.327	-3.17	***	---	---	---
	Employed full time (35+ hours/week, paid)	---	---	---	0.605	14.05	***
	Education: Post-graduate degree	0.154	2.49	**	0.084	1.88	*
Systematic Heterogeneity	Number of walk trips × Number of transit trips	0.028	1.64	*	---	---	
	Workers' transit access × Number of walk trips	---	---	---	-0.001	-2.96	***
	Workers' transit access × Number of transit trips	---	---	---	-0.002	-3.36	***
Random Unobserved Heterogeneity	Female (scale parameter)	0.532	3.61	***	---	---	---
	Workers' transit access (scale parameter)	---	---	---	0.005	4.32	***
Joint Dependence	Estimated error correlation (z-score) [stat. significance]	0.406 (13.63) [***]					
Thresholds	Threshold 1	2.017	12.65	***	1.587	15.74	***
	Threshold 2	2.637	15.92	***	2.330	22.39	***
	Threshold 3	3.143	18.08	***	3.202	29.2	***
	Threshold 4	3.401	18.89	***	3.721	32.45	***

Notes: Sig. is statistical significance. (*, **, & ***) indicate statistical significance at 90%, 95%, and 99% levels of confidence, respectively. ns is statistically insignificant. (---) indicates not applicable.

TABLE 4. Marginal & Treatment Effects of Key Variables.

Variables	Level of participation in carshare programs					Level of participation in rideshare programs				
	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]
Walkability & Built Environment										
Walkability Index										
One-unit increase	-0.62	0.32	0.17	0.05	0.08	-0.58	0.05	0.22	0.13	0.18
Switch from low (25th percentile) to high (75th percentile)	-2.73	1.47	0.73	0.22	0.31	-2.64	0.23	1.03	0.60	0.79
Urban Design: Network density in terms of facility miles of pedestrian-oriented links per square mile (in 10s)										
10-unit increase in facility miles	-2.08	1.09	0.56	0.17	0.26	-8.14	0.66	3.08	1.85	2.55
Switch from low (25th percentile) to high (75th percentile)	-2.84	1.53	0.76	0.22	0.33	-12.02	1.16	4.98	2.72	3.16
Density: Gross residential density (HU/acre) on unprotected land (in 10s)										
10-unit increase in HU/acre	-1.10	0.57	0.30	0.09	0.14	-1.82	0.15	0.69	0.41	0.57
Switch from low (25th percentile) to high (75th percentile)	-1.27	0.69	0.34	0.10	0.14	-2.22	0.20	0.88	0.51	0.63
Workers' transit access	---	---	---	---	---	-0.11	0.02	0.04	0.02	0.02
Active Transportation										
Number of bike trips	-2.79	1.46	0.75	0.23	0.35	---	---	---	---	---
Number of walk trips	-0.90	0.45	0.25	0.08	0.12	-1.48	0.33	0.64	0.28	0.23
Number of public transit trips	-2.38	1.20	0.65	0.21	0.33	-2.01	0.70	0.97	0.30	0.04
Online Activity Patterns										
Package deliveries received on travel day [1/0]	-3.51	1.84	0.95	0.29	0.44	-5.84	0.48	2.21	1.33	1.83
Food/meal prep deliveries received on travel day [1/0]	---	---	---	---	---	-16.83	1.37	6.36	3.83	5.27
Number of grocery deliveries on travel day [1/0]	-6.10	3.19	1.64	0.50	0.76	-12.64	1.03	4.78	2.88	3.96
Residential Choices										
Important factors in choosing current home location…										
Being within a reasonably short commute to work [very important]	---	---	---	---	---	-1.62	0.13	0.61	0.37	0.51
Having a walkable neighborhood and being near local activities [very important]	---	---	---	---	---	-3.80	0.31	1.44	0.86	1.19

Notes: [1] is "I never do this". [2] is "I do this, but not in the past 30 days". [3] is "1-3 times in the past 30 days". [4] is "1 day/week". [5] is "2 days or more/week". (---) is Not Applicable.

TABLE 4. (Continued). Marginal Effects of Key Variables.

Variables	**Level of participation in carshare programs**					**Level of participation in rideshare programs**				
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**
Demographics										
Annual Income: USD 75,000 - 99,999	-2.73	1.43	0.74	0.22	0.34	-3.85	0.31	1.45	0.87	1.20
Annual Income: USD 100,000 or more	-5.96	3.12	1.61	0.49	0.74	-15.82	1.29	5.98	3.60	4.95
Age: 65-74 years	10.14	-5.31	-2.73	-0.83	-1.26	---	---	---	---	---
Age: 75 - 84 years	16.08	-8.42	-4.33	-1.32	-2.00	---	---	---	---	---
Gender: female	6.43	-3.37	-1.73	-0.53	-0.80	---	---	---	---	---
Employed full time (35+ hours/week, paid)	---	---	---	---	---	-18.88	1.54	7.13	4.29	5.91
Education: Post-graduate degree	-3.03	1.59	0.82	0.25	0.38	-2.63	0.21	0.99	0.60	0.82

Notes: [1] is "I never do this". [2] is "I do this, but not in the past 30 days". [3] is "1-3 times in the past 30 days". [4] is "1 day/week". [5] is "2 days or more/week". (---) is Not Applicable.

While walkable urban design complements the adoption of shared mobility services, the use of such services should not substitute active transportation given its proven health benefits (Martin and Shaheen 2011, Kent 2014, Göddeke et al. 2022). Our joint carsharing and ridesharing use model also provides insights into the complementary effects of active travel on shared mobility services. Each additional bike, walk, and public transit trip was correlated with a 2.79%, 0.90%, and 2.38% reduction in an individual never using carsharing services. Likewise, the chance of never using ridesharing services was reduced by 1.48% and 2.01% with each additional walk and transit trip, respectively. A statistically significant interactive complementary effect of walk and transit trips on carsharing use was also observed ($\beta = 0.028$; z-score = 1.64) (Table 3). Individuals who made greater transit and walk trips had a significantly greater chance of using carshare services two days or more per week (see Figure 4B which shows the predicted interactive complementary effect). The interactive impacts highlight the strong synergies between active transportation and shared mobility services and validate/extend the findings from previous studies that harnessed ecological study designs (Xu et al. 2021, Wali et al. 2022).

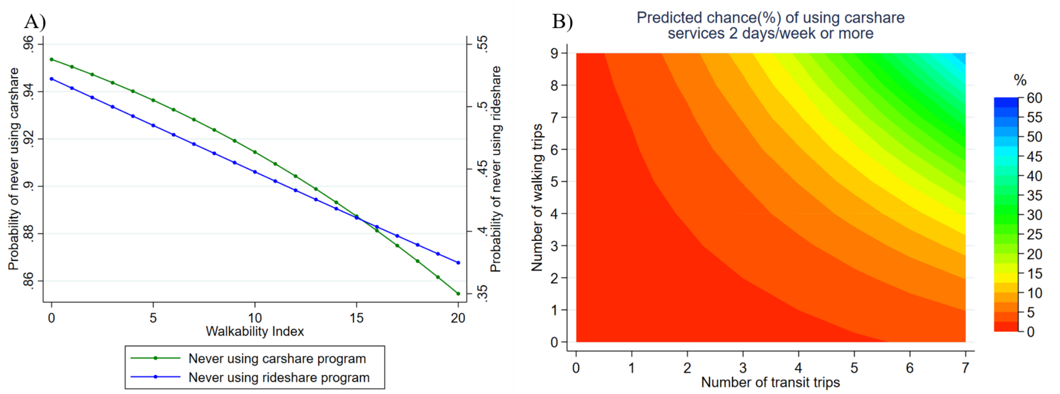


FIGURE 4. Predicted Effect of Built Environment & Active Travel on Carsharing/Ridesharing Use.

Notes: A shows the predicted effect of neighborhood walkability on never using carsharing and ridesharing programs. B shows the interactive complementary effect of walk and transit trips on carshare use.

6.2. Interactive (Substitutive) Impacts of Transit Accessibility & Active Travel

As discussed above, both transit accessibility and active travel measures were independently associated with greater ridesharing use. Besides these independent associations, we also found interactive (substitutive) impacts of transit accessibility and active travel on individuals' use of ridesharing services. A statistically significant interaction effect of transit accessibility and walk trips on ridesharing use was observed ($\beta = -0.001$; z-score = -2.96) – suggesting that the interaction between accessibility to transit and walk trips could substitute ridesharing use. To elaborate further, Figure 5A shows the predicted chance of using rideshare services 2 days/week or more as a function of walk trips and transit accessibility. Individuals making a greater number of walk trips living in neighborhoods with lower transit accessibility had a relatively greater chance of using rideshare services. On the other hand, the chance of using rideshare services was significantly lower for individuals who made more walk trips and lived in high transit accessibility neighborhoods. A statistically significant substitutive effect of transit accessibility and transit trips on ridesharing use was also observed ($\beta = -0.002$; z-score = -3.36). Referring to Figure 5B, those individuals who made a greater number of transit trips and lived in high transit accessibility neighborhoods had a significantly lower chance of using ridesharing services. We tested interactions of other walkability characteristics with active travel but none of them were statistically significant. Collectively, these findings suggest that individuals living in high transit accessibility neighborhoods may substitute ridesharing for walking and transit. While active travel and transit accessibility independently complement on-demand mobility services, the interaction between the two could substitute ridesharing services. Recent studies have found significant complementary and substitutive impacts of transit accessibility on ride-sourcing and/or dynamic ridesharing demand (Wali et al. 2022, Zhang et al. 2022). Our findings extend the previous results by providing new insights into the potential substitutive impacts of active travel and transit accessibility on shared mobility services.

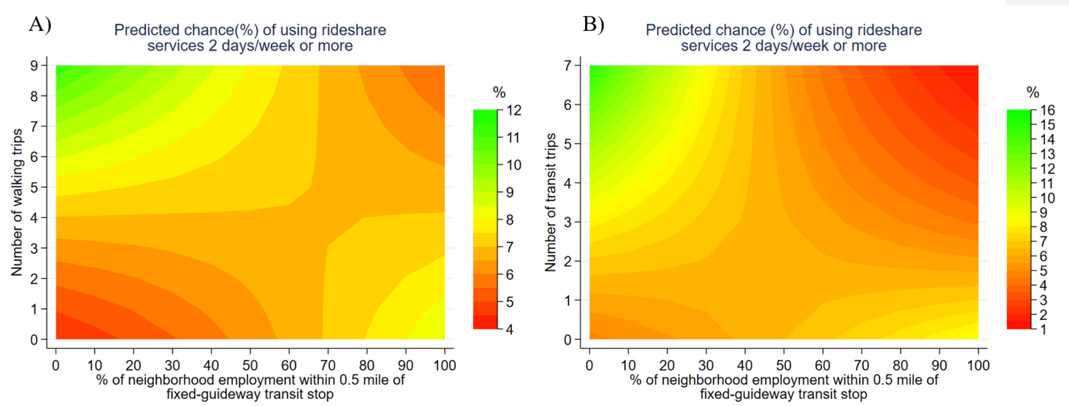


FIGURE 5. Predicted Interactive Effects of Built Environment & Active Travel on Ridesharing Use.

Notes: A shows the substitutive effect of workers' transit access and walk trips. B shows the substitutive effect of workers' transit access and transit trips.

6.3. Impacts of Online Activity Patterns, Residential Choices, & Sociodemographic Correlates

Factors related to individuals' online activity patterns, residential choices, and sociodemographic characteristics were found to predict carsharing and ridesharing use. A greater number of package, food, and grocery deliveries were positively correlated with individuals' use of carsharing and ridesharing services. Referring to Table 4, the marginal effects for online activity-related variables are considerably significant in magnitude. These findings are intuitive and could be capturing individuals' technological savviness and the resulting disposition to availing technology-enabled travel mobility options (Asmussen et al. 2022, Sharma and Mishra 2022, Wali and Khattak 2022). Capturing potential self-selection effects, residential choices also meaningfully influenced the use of carsharing and ridesharing services (see Table 4). In agreement with previous studies (Dias et al. 2017, Soltani et al. 2021, Aguilera-García et al. 2022), high-income, employed, and highly educated individuals were more likely to use carsharing/ridesharing services, whereas the reverse was true for older individuals and females. However, the associations between the female indicator and carsharing use were found to be heterogeneous across the sample. With a mean β of -0.327 and standard deviation of 0.532, the associations were negative for 73% of the population and positive for 27% of the population.

7.3. Limitations

The study harnessed detailed data from a comprehensive survey in Washington conducted using standardized protocols over decades. While the sociodemographic characteristics of the study area are reported to be reasonably representative of larger urban areas in the U.S. (Wali and Khattak 2022), caution must be made in generalizing the study findings to other localities. Significant complementary and substitutive associations of the built environment, active travel, and transit accessibility were found. There is a need to validate the cross-sectional associations in a longitudinal study design, ideally in a natural experiment setting. A broad spectrum of high-resolution objectively assessed built environment features was harnessed. Future research may create and harness buffer-based parcel-level built environment data that could provide richer insights. Applicable to all relevant studies, recall bias may influence our results given the use of self-reported data on ridesharing and carsharing use.

7. CONCLUSIONS

This study presented a behavioral framework for modeling carsharing and ridesharing use with a focus on exemplifying the role (substitutive vs. complementary) of the built environment, active travel behaviors, and transit accessibility. Methodologically, the study contributed by developing a joint heterogeneity-based multivariate ordered discrete choice model accounting for random (unobserved) and systematic (observed) heterogeneity. Comprehensive travel behavior data from the 2019 Puget Sound Travel Survey were spatially integrated with high-resolution objectively assessed data on the built environment fabric. The joint modeling framework demonstrated the presence of strong positive dependencies between the demand for carsharing and ridesharing services. Significant random and systematic heterogeneity in the behavioral, environmental, and demographic determinants of shared mobility services was also revealed.

The present study provided new insights into the important role of neighborhood-built environments, transit accessibility, and active travel behaviors. Reflecting complementary impacts, measures related to neighborhood walkability, pedestrian-oriented urban design, and transit accessibility exhibited positive associations with individuals' use of carsharing and ridesharing services. Active travel behavior was also found to exhibit synergistic relationships with the use of carsharing and ridesharing services. Individuals making a greater number of walk, bike, and transit trips were more likely to use carsharing and ridesharing services. While active travel and transit accessibility independently complemented on-demand mobility services, our findings indicate that the interaction between the two could substitute ridesharing services. The chance of using ridesharing services was significantly lower for individuals who made more walk and transit trips and lived in high transit accessibility neighborhoods. These findings suggest that individuals living in neighborhoods with high transit accessibility may substitute ridesharing for walking and transit.

The findings of this study have important implications both from the perspectives of scenario planning and travel demand modeling. From a scenario planning standpoint, the findings demonstrate the benefits of improving neighborhood walkability, pedestrian-oriented design, and transit accessibility for accelerating the adoption of carsharing and ridesharing services. Land use and built environment interventions have been known to provide significant health benefits in the form of supporting active travel and lowering chronic disease. Our findings show that continuing to invest in the development of more compact and walkable neighborhoods can also help achieve sustainable mobility-related goals. Ultimately, the empirical results from this study can serve as a basis for scenario planning tools to paint the impacts of contrasting built environment investments. From a travel demand perspective, the steady increase in the demand for shared mobility services will likely lead to significant impacts on travel demand and transportation system performance over time. Existing travel demand models are limited with respect to incorporating the impacts of key behavioral and environmental factors that are becoming increasingly known to influence the use of disruptive mobility services. By reflecting the role of environmental and behavioral factors, the joint behavioral model presented in this study can help enable better travel demand forecasts for shared mobility services.

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