

1 **Shared use travel behavior for improving rural mobility: A case study of Greene County,**  
2 **Pennsylvania**

3

4

5

6

7 **Zulqarnain H. Khattak, Ph.D.**

8 Civil and Environmental Engineering,

9 Carnegie Mellon University

10 5000 Forbes Ave, Pittsburgh, PA

11 [zkhattak@cmu.edu](mailto:zkhattak@cmu.edu)

12

13

14

15

16 **Sean Qian, Ph.D.**

17 Civil and Environmental Engineering,

18 Carnegie Mellon University,

19 5000 Forbes Ave, Pittsburgh, PA

20 [seanqian@cmu.edu](mailto:seanqian@cmu.edu)

21

22

23

24

25

26

27

28

29

30

31

32

33

34 **Abstract**

35 Rural communities are considered disadvantaged communities as they suffer from a lack of  
36 transport options. Thus, rural regions provide less accessibility for commuters to reach their  
37 destination as opposed to urban regions. However, the issues of transport disadvantage and  
38 shared use mobility in rural areas within the United States (U.S.) have not been well investigated.  
39 Furthermore, transport disadvantage differs between communities and regions across the globe;  
40 thus, there is a need to study the behavioral choices of rural commuters within the U.S. context.  
41 This study contributes by analyzing the behavioral choices of rural communities within the U.S.  
42 through a case study site of Waynesburg, Pennsylvania for adopting a shared use shuttle service.  
43 K-mean clusters showed that trips from the survey data were a good representation of real trips  
44 from Ecolane. Furthermore, random parameter - based binary logit models were calibrated using  
45 data collected from students, faculty and residents in Waynesburg, Greene County to study the  
46 behavioral choices of commuters. The findings for the faculty and students group revealed that  
47 prior experience with shared services increases the likelihood of using a shared shuttle. An  
48 important personal characteristic of inconvenience showed a higher propensity toward using  
49 existing modes as opposed to a shared shuttle. Such commuters value personal vehicles as more  
50 convenient, have childcare responsibilities, and varying schedules for work that require them to  
51 move back and forth across locations. Thus, making a shared shuttle less attractive for them. The  
52 socioeconomic factors of age and gender show a higher propensity for using shared shuttle. The  
53 findings from this study could be helpful for agencies in improving rural mobility and  
54 considering such shared mobility services for rural communities.

55 **Keywords:**

56 Rural mobility, shared use mobility, travel choices,

**58 Introduction**

59 Rural America, representing 97% of the U.S., is home to 15% of total U.S. population. Rural  
60 trips for commuting, shopping, health care and community-based services have been  
61 increasingly longer in the past few decades (Rosenbloom 2003). Unfortunately, mobility services  
62 in rural areas are insufficient, inefficient, unaffordable, and inaccessible, with highly limited  
63 resources. Often, rural trips are made by solo-driving in private vehicles with low fuel economy  
64 (Rosenbloom 2003). Public transit or shared mobility options are rarely utilized. Those rural trips  
65 are likely to be expensive, long, with a single trip purpose, and thus energy inefficient. More  
66 importantly rural trips are extra burdensome to households both financially and physically. Thus,  
67 resources, facilities and communities are becoming more inaccessible to rural populations, which  
68 in turn worsens the mobility services, health care service, and rural economy. Rural communities  
69 are therefore considered disadvantaged communities as they suffer from a lack of transport  
70 options.

71 Rural regions provide less accessibility for commuters to reach their destination as opposed to  
72 urban regions. The lower densities and resulting distances between residences, activity centers  
73 and job sites makes it harder for residents to reach their destinations. However, shared use  
74 mobility options such as ridesharing, vanpooling, and public transit may connect regions  
75 between rural communities and villages (Chan and Shaheen 2012)(Contreras and Paz 2017). The  
76 travel habits differ between rural and urban areas such as short distance trips in urban areas as  
77 opposed to rural areas, more car-dependent trips in rural areas due to presence of older people as  
78 opposed to urban areas, and higher travel distance in rural areas. Although the perception of  
79 certain travelers and value of car pride makes them less likely to share their ride with strangers,

80 rural car dependence can be reduced with shared use mobility that provides coverage for longer  
81 trips. However, the issue of transport disadvantage and shared use mobility in rural areas within  
82 the U.S. has not been well investigated. This study fills this gap by studying the behavioral  
83 choices of rural communities within the U.S. using a case study of Greene County, Pennsylvania  
84 for adopting a shared-use shuttle service, which is a special form of public transit.

### 85 **Study Contributions and Scope**

86 The issue of transport disadvantage and shared use mobility in rural areas within the U.S. has not  
87 been well investigated. While a few studies (Pucher and Renne 2005)(Rogalsky 2010) exist on  
88 this subject, they do not cover the needs of U.S. rural communities from the perspective of  
89 behavioral choices of travelers to adopt shared use mobility in rural areas. Further, transport  
90 disadvantages differ between communities and regions across the globe; thus, there is a need to  
91 study the behavioral choices of rural residents within the U.S. context. This study fills the  
92 literature gap by studying the behavioral choices of rural communities within U.S. using a case  
93 study of Greene County, Pennsylvania for adopting a shared-use shuttle service, which is a  
94 special form of public transit. The survey data collected for rural residents is processed using a  
95 random parameter-based binary logit formulation to account for unobserved heterogeneity within  
96 the behavioral choices of using a shared shuttle as opposed to other available modes of travel.

### 97 **Literature Review**

98 According to the American Community Survey, approximately one fifth of the country's  
99 population (Mattson 2017) lives in rural areas, that are less accessible. The reasons for lower  
100 accessibility in rural areas are lower population densities and longer commuting distances,  
101 making it difficult to provide reliable public transportation. Due to the above two factors, rural  
102 residents are highly reliant on personal vehicles and are unwilling to take public transportation.

103 Only 4% of the rural population does not have access to an automobile while the proportion for  
104 urban residents is 10% (Bureau 2015).

105 Although there are numerous research studies on factors affecting travel mode choice in urban  
106 areas, focus on rural areas is inadequate. A description of literature studies is provided in Table  
107 A1 while this section summarizes the factors studied in some rural transit mode choice research:  
108 socioeconomic factors and built environment. Shared mobility is a promising alternative that is a  
109 hybrid between public transportation and personal vehicles. Therefore, studies that focus on  
110 shared mobility (Shaheen et al. 2015) potential are also summarized.

### 111 *Socioeconomic factors*

112 Several studies have focused on the influence of socioeconomic factors on rural mobility. Studies  
113 have used data sources ranging from revealed and stated preference surveys to apply basic  
114 descriptive statistics, mixed logit, cluster analysis and interaction modeling with mostly common  
115 insights. They observed the choice to use available transportation modes in rural areas to be  
116 impacted by age, gender, educational level, and income. Schwanen et al., (2004) observed low-  
117 income households without car accessibility to be more inclined towards walking and cycling  
118 than urban areas (Sandow & Westin, 2010). Mattson et al., (2010) observed that low-income  
119 households choose public transit in response to higher gas prices. Zhou et al., (2017) observed  
120 income and car ownership to have negative relation with transit use.

### 121 *Built environment*

122 Several recent studies have shown the relation of built environment Ewing et al., (2008) with  
123 auto mode choice. Grue et al., (2020) found that the use of auto mode choice for commuting trips  
124 in the rural areas increases with maximum distance to an urban center. These findings are  
125 consistent with Chen et al., (2008) that indicates density and lower accessibility exert an

126 influence on auto mode choice. Additionally, Christiansen et al., (2017) observed parking lot  
127 availability at work to facilitate the use of car. Furthermore, Ao et al., (2020) proposed that aside  
128 from density, accessibility, and parking lot availability, people will not choose to drive a car if  
129 they consider residential areas as safe. Maeder, Stauffacher, and Knaus (2023) identified built  
130 environment and lack of availability of public transit in rural localities limit the resident to drive  
131 personal cars.

### 132 *Shared mobility potential in rural areas*

133 Shared mobility is a transportation mode that enables users to gain short-term access on an “as  
134 needed” basis, which includes transportation modes like ridesharing, carpooling, bicycle sharing,  
135 and demand -responsive transportation. Unlike traditional public transportation that operates on a  
136 fixed route, shared mobility not only accommodates travelers’ specific needs better but also  
137 incorporates the notion of vehicle sharing to reduce environmental impact. As traditional public  
138 transportation systems are often not cost-effective in rural areas, shared mobility is a solution of  
139 great potential to solve the rural mobility problem by bridging gaps in existing transportation  
140 networks.

141 Ridesharing, a transportation mode that involves the sharing of individual automobile trips, is a  
142 possible solution to improve the accessibility situation in rural areas. Delhomme and Gheorghiu,  
143 (2016) identified the lack of digital knowledge of older people to be likely reason of lesser ride  
144 share in rural areas. Furthermore, Tirachini & R o, (2019) and Neoh et al., (2017) indicated that  
145 female, people of higher income or people without access to cars have a higher chance of ride  
146 sharing. Furthermore, Rietveld et al., (1999) identified that travel time for ride sharers is 17%  
147 longer, which greatly affects people’s tendency to rideshare. People may avoid ridesharing if  
148 they feel it is unsafe. Lee et al. (2016) identified that younger individuals and females are more

149 likely to rideshare, but they would not participate in the programs that would match them to  
150 strangers. Madani et al. (2022) recognized some reasons for why rural residents do not choose  
151 ride sharing, which are car ownership, safety concerns, and no guarantee of a return.

152

### 153 *Demand responsive transit*

154 Demand responsive transportation (DRT) offers flexible (non-fixed route) mobility services in  
155 low -density areas, and it is an important segment of the Mobility as a Service (MaaS) concept.  
156 Some studies researched the intention of less mobile people to use DRT, and several determinant  
157 factors were found. Furthermore, Wang et al. (2015) indicated a negative correlation between  
158 population density and the frequency of DRT use in rural areas. (Knierim and Schlüter 2021)  
159 observed a clear modal shift from private cars to DRT minibuses and better accessibility of  
160 transport services. Eckhardt, Lauhkonen, and Aapaoja (2020) observed that rural residents in  
161 Germany would like to take a quarter of all trips people via DRT for medical purposes,  
162 demonstrating an urgent need for improving rural mobility.

163 For the Miocar carsharing pilot program, Rodier, Harold, and Zhang (2021) observed that 59%  
164 respondents would not have been able to travel to the primary destination without Miocar. Pike,  
165 Rodier, and Martinez (2018) used survey results to suggest a strong willingness to use ride  
166 sourcing and carsharing services for people living in rural California. Hult, Perjo, and Smith  
167 (2021) identified insufficient incentives and elderly population that are less tech-savvy to be  
168 detrimental to the adoption of demand responsive shared services. Mulley et al. (2006) also  
169 observed digital literacy to be a barrier to shared service adoption and the fact that MaaS services  
170 only offer integrated information, payment or booking, which is an infancy of MaaS. Coutinho et

171 al. (2020) observed DRT system to be well perceived by users due to consistency of the service  
172 but recognized digital literacy as a detriment to adoption of smart phone based shared services.

### 173 **Summary and research gaps**

174 The issue of transport disadvantage and shared use mobility in rural areas within the US has not  
175 been well investigated. While a few studies (Pucher and Renne 2005)(Rogalsky 2010) exist on this  
176 subject, they do not cover the needs of US rural communities from the perspective of behavioral  
177 choices of travelers to adopt shared use mobility in rural areas. A few past studies indicate that  
178 socioeconomic factors, built environment and income, influence travel mode choice for rural  
179 residents. Furthermore, transport disadvantages differ between communities and regions across  
180 the globe; thus, there is a need to study the behavioral choices of rural residents within the US.  
181 context. This study fills the literature gap by studying the behavioral choices of rural  
182 communities within U.S. using a case study Greene County, Pennsylvania for adopting a shared-  
183 use shuttle service, which is a special form of public transit.

### 184 **METHODOLOGY**

185 This section discusses the study methodology and data.

#### 186 *Study Framework*

187 The study focuses on shared shuttle service that includes on-demand shared mobility in shuttle,  
188 complementing existing paratransit service. The study framework is presented in Figure 1  
189 focusing on understanding rural mobility choice behavior towards the use of shared shuttle  
190 service. The choice behavior is complex and consists of observed and unobserved factors. The  
191 study framework accounts for individual taste and heterogeneity along with observed factors in  
192 consumer preferences towards the use of shared shuttle service. The preferences for different age  
193 or inconvenience for instance, are assumed to be the same across all individuals by traditional  
194 statistical models. This unrealistic assumption leads to omitted variable bias (Mannering,

195 Shankar, and Bhat 2016). Since it is impossible to collect data on all factors influencing  
196 individual preferences for use of shared shuttle service, these unobserved ‘latent’ effects could  
197 lead to erroneous estimates in the magnitudes of relation for explanatory factors and the  
198 outcomes. These issues of unobserved heterogeneity and omitted variable bias are countered  
199 using random parameters (simulated) binary logit models. The framework was designed in N-  
200 Logit package.

### 201 *Data Description*

202 Greene County is a typical rural county in Southwestern Pennsylvania bordering West Virginia,  
203 with about 39,000 in population. Waynesburg, the County seat, is home to Waynesburg  
204 University (WU). Over 13% of the population of 39,000 people in the county are food insecure,  
205 and one third of those individuals are children. In Greene County, 57% of households report at  
206 least one member with high blood pressure. Several of their non-emergency doctor appointments  
207 are delayed or missed due to insufficient and inefficient mobility services, especially among  
208 children and the elderly. There is no public transit in Greene County. Nor are there shared  
209 mobility services, such as taxi, Uber, or Lyft. The only mobility service available is through the  
210 Greene County Transportation Program (GCTP) where residents are required to book a ride in  
211 advance. This is analogous to a paratransit service where only people enrolled in Medicaid or  
212 special medical programs are eligible to ride with fully or partially reimbursed cost. The Program  
213 provided 40,323 trips in 2017, and 26% were associated with seniors. The average trip time was  
214 more than one hour at a cost of more than \$26/ride. A recent survey by the Greene County  
215 Human Services shows there are residents who have no other choice than paying more than \$50  
216 for riding the shuttle into the City of Pittsburgh, the closest major city. Mobility service in  
217 Greene County is clearly insufficient, inefficient, and unaffordable affecting access to not only  
218 healthy food, but healthcare, work, and community services.

219 Waynesburg University (WU) of Greene County (GC) enrolls approximately 2,500 students and  
220 offers shuttle services to transport students from/to bus/transit stations outside Greene County,  
221 local hospitals, and shopping retailers. Despite students finding it a challenge to get around the  
222 City of Waynesburg, the shuttle service ridership is low and dropping over the past years, due to  
223 inefficient service not fulfilling student demand.

224 In order to develop optimal shared-use mobility services open for general citizens and university  
225 affiliates, a survey was designed to collect data on behavioral preferences of travelers in rural  
226 community in Greene County, Pennsylvania. The survey captured travel behavior preferences of  
227 individuals including personal and societal factors influencing their current mode choice, attitude  
228 towards shared use shuttle, trip purposes, sociodemographic characteristics including age,  
229 income, gender, vehicle ownership, and previous experience with shared service offered by the  
230 County or Waynesburg University. The goal of this survey was to improve rural mobility by  
231 introducing a new shared shuttle service in Greene County and gauge the behavioral response of  
232 commuters.

233 The respondents were initially screened for age above 18 years and whether they resided in  
234 Greene County. The survey experiment was designed such that each respondent was presented a  
235 choice of selecting a new shared shuttle service as opposed to the existing mobility options  
236 (namely solo-driving or carpool driving). Three different types of respondents were considered  
237 for the survey including the general population or residents, students at Waynesburg University  
238 and faculty/staff at Waynesburg University since faculty and students may exhibit a different  
239 behavior compared to the public. The respondents were asked about their daily trip scenarios,  
240 trip purposes, preference for a shared shuttle use, trip mileage etc.

241 The survey was conducted online through Survey Monkey and physically distributed through  
242 field survey takers. The survey included different questions about socioeconomic characteristics,  
243 travel or trip related characteristics, individual person related factors such as vehicle ownership,  
244 licensure, or experience with shuttle. The survey is attitude based asking questions about the  
245 preference for shared use mobility, “If the new service is affordable, would you be interested in  
246 trying?” The total sample initially received was around 800 observations. The data sample was  
247 then validated using the origin-destinations (O-D) and those with invalid O-D pairs were  
248 removed, reducing the sample size to 600. Further, any incomplete records were removed to  
249 clean the dataset. The criterion of two standard deviations within the mean was used to remove  
250 potential outliers. The total sample thus, reduced to 412 observations that had all variables with  
251 complete information. This included 210 observations for residents and 112 observations for  
252 faculty and staff. Variables with potential correlation having a value above 0.8 were not used in  
253 the analysis. The variation inflation factor above 1.5 was used to screen variables for  
254 multicollinearity. The descriptive statistics for the residents and faculty/students’ data are  
255 provided Table 1- 2. These appear to be reasonable based on comparison to the average numbers  
256 across the U.S. provided in Table 3. The average age of 49 in residents’ data, compares well to  
257 the median age from (Bureau, 2019), that includes young children as well. We observe 25% of  
258 the households have an income above \$75K within the residents’ data, compared to the 29%  
259 reported by (Jeffrey, 2018). However, the data differs from the general population in the sense  
260 that it is focused on rural areas that are concentrated with white communities as opposed to US.  
261 national population that has some portion of Hispanic or Latino, for instance 17.6% (Bureau,  
262 2019)).

263 Figure 2 provides a depiction of origin and destination for the survey data, and Ecolane  
264 data represented by Greene County Transportation (GCT) Program along with the points of  
265 interest (POIs). GCTP operates under the Greene County Commissioners' Office, with the  
266 support from the state and federal grants. The OD pairs from the survey data and Ecolane data  
267 were clustered using k-means clustering algorithm. Expectation maximization was used to  
268 maximize the probability of sample coming from the distribution. The Elbow method was used  
269 to select the optimal number of clusters revealing 5 clusters to be appropriate for both O-D pairs  
270 of the survey and eco-lane data. The Elbow method is a technique used to identify the optimal  
271 number of clusters in k-mean clustering. This method determines the optimal centroid (k) by  
272 continuously iterating for k=1 to k=n, where n= represents the hyperparameter chosen per our  
273 requirement. Furthermore, within-cluster sum of squares (WSS) is determined for each value of  
274 k. The value of WSS represents the sum of square distances between centroids and each point.  
275 Finally, a graph is plotted between k and WSS to determine the optimal number of clusters. This  
276 graph appears like an elbow and the value of WSS decreases with increasing value of k. The  
277 optimal value of k also known as clusters is selected from the point where the graph starts to  
278 appear like a straight line. The clustering shown in Figure 3A-3B indicates that several trips  
279 within the survey data had O-D pairs appear within the Ecolane data. Thus, indicating that the  
280 survey data is a good representation of real data from Ecolane service data.

### 281 *Analysis Framework*

282 Given the binary choice problem of shared shuttle and non-shared shuttle, binary logit (Ben  
283 Akiva and Lerman 1985) was selected as the most appropriate model, which considers linearity  
284 of independent variables and log odds of the outcomes. The link formed by a utility function  
285 between the behavioral choice and the outcome defines a traveler's mode choice. Equation 1

286 provides a general relationship for a person  $n$  and mode  $i$  (Khattak et al. 2017) (Ben-Akiva and  
 287 Lerman 1985) (Greene 2008). The  $X_{in}$  in this formulation indicates the mode or person specific  
 288 attributes (e.g., age, familiarity). Likewise, the estimable parameters through calibration are  
 289 represented by the variable  $\beta$  (such as the coefficient for age); while the random residual or error  
 290 is given by  $\varepsilon_{in}$ .

$$U_{in} = \beta X_{in} + \varepsilon_{in} \quad (1)$$

291 Considering a set  $C_n$  of two alternatives such that  $C_n = \{i, j\}$  representing binary choice  
 292 of selection between the shared use shuttle (i.e.,  $i = 1$ ) or the alternative of no shared shuttle  
 293 (i.e.,  $j = 1$ ), given the residual term  $\varepsilon_n$  is distributed logistically (Ben-Akiva and Lerman 1985).  
 294 The residual terms indicate the difference across ( $\varepsilon_{in}$  and  $\varepsilon_{jn}$ ). The probability of person  $n$   
 295 choosing alternative  $i$  is given by:

$$296 \quad P_n(i) = \Pr(U_{in} \geq U_{jn}) \quad (2)$$

297 Considering  $\varepsilon_n = \varepsilon_{in} - \varepsilon_{jn}$  is logistically distributed.

$$298 \quad P_n(i) = \frac{1}{1 + e^{-\mu(V_{in} - V_{jn})}} \quad (3)$$

299 While Equation 3 also includes a scale parameter  $\mu$ , the scale parameter has conventionally been  
 300 assumed  $\mu = 1.0$ . Note that  $V_{in}$  and  $V_{jn}$  are linear in their parameters, giving equation 4:

$$301 \quad P_n(i) = \frac{1}{1 + e^{-\mu\beta(X_{in} - X_{jn})}} \quad (4)$$

$$302 \quad P_n(i) = \frac{e^{\mu\beta X_{in}}}{e^{\mu\beta X_{in}} + e^{\mu\beta X_{jn}}} \quad (5)$$

303 Considering random parameters with binary logit assumes that the vector of estimable parameter  
 304 varies across observations. The utility function thus, modifies to equation 6, where unobserved  
 305 argument  $n_{in}$  indicates random term with specific distribution. Since the variation of  $n_{in}$  is  
 306 unknown,  $U_{in}$  is a random variable.

$$307 \quad U_{in} = \beta X_{in} + \varepsilon_{in} + n_{in} \quad (6)$$

308 The probability equation based on the assumption of random term distribution (Train, 2003) is  
 309 given by 7.

$$310 \quad P_n(i) = \frac{e^{\mu\beta X_{in}}}{e^{\mu\beta X_{in}} + e^{\mu\beta X_{jn}}} f(\beta|\phi) d\beta \quad (7)$$

311 Where the joint density function is given by  $f(\beta|\phi)$  while the vector parameters of density  
 312 function are given by  $\beta$  and  $\phi$  (such as mean and variance) (Greene 2008). The density function  
 313 accounts for the unobserved heterogeneity (Train, 2003). The normal distribution  
 314  $\beta_{ij} \sim Normal(\beta_j, \sigma^2)$  was selected for random parameters among different functional forms due to  
 315 better fit (Xie et al. 2018)(Ahmed et al. 2018) . The random parameters were estimated using 200  
 316 Halton draws (Halton 1960; Train 2003) from simulation based maximum likelihood (Greene  
 317 2008).

## 318 **Results And Discussion**

### 319 *Descriptive analysis*

320 This simple descriptive analysis will involve the following sub-sections.

#### 321 *Comparison of Income for use of shared shuttle*

322 Household income represents an important factor in describing population demographics and  
 323 preferences of rural communities. The income distribution and its impact for shared shuttle use  
 324 are shown for both the residents and faculty/staff and students in Figures 4a and 4b. Figure 4a

325 shows that lower income households among the general residents are more likely to adopt a  
326 shared shuttle service, specifically in the range of \$15K-\$50K while higher income households  
327 above \$75K are less likely to adopt a shared shuttle as a travel mode. This may partly be  
328 attributed to their vehicle ownership and cost of travel and partly to their perceived convenience  
329 of travel. For instance, the difference between travel cost per mile between car and transit was  
330 estimated to be only \$0.26 and \$0.48 in the United States (Polzin 2016). The cost difference  
331 could prompt lower income households to shift towards a shared shuttle. Similarly, the faculty  
332 and student population reveal similar insights. While faculty mostly have car ownership, their  
333 preference may not be affected much by their income (Figure 4b), however, students do not have  
334 their own income source unless they are coming from a privileged background.

#### 335 *Comparison of age groups for shared shuttle use*

336 Age plays an important role in mode choice and travel demand prediction because different age  
337 demographics show taste heterogeneity based on age. The age distribution of the survey  
338 participants is provided in Figure 5a and Figure 5b for the residents and faculty along with the  
339 students. It is worth mentioning that all students have been categorized into the age category of  
340 18-21. Figure 5a shows that the general residents in the younger age category are more likely to  
341 use a shared shuttle for travel as opposed to older residents. A similar trend is observed for the  
342 faculty with the younger age category more likely to adopt a shared shuttle.

#### 343 *Time of day Usage*

344 The time of day plays an important role in identifying trends of travel patterns for commuters  
345 during different peak hours of the day. The commuters' mode choice preference may vary based  
346 on their travel needs and urgency of reaching the destination. Similar trends are observed in the  
347 general residents and faculty/staff data (Figure 6a-c), with commuters less likely to adopt a  
348 shared shuttle during peak hours. This may likely be attributed to their perceived inconvenience

349 of travel with a shared shuttle having fixed schedules. Interestingly, the student population is  
350 more likely to use a shared shuttle during peak hours. This may be attributed to the lack of  
351 vehicle ownership and student travel being concentrated on peak hour schedules for travel to the  
352 University.

### 353 *Number of People in the Household*

354 Household size plays a significant role in travel choice behavior. The distribution of household  
355 size and its impact for a shared shuttle use is shown for the general residents, faculty, and  
356 students. It is worth mentioning that students report household size as living in a dorm or hostel  
357 with other people, so their travel is independent of the number of people that are living with  
358 them. Figure 7a shows that with an increase in household size, the residents are less likely to use  
359 a shared shuttle. Likewise, the faculty distribution also provides similar insights in Figure 7b.  
360 The student population (Figure 7c), however, can be considered as individual commuters  
361 traveling in each category, thus they are not affected by household size.

### 362 *Trip Purpose*

363 Trip purpose is critical to travel choice behavior. While non-essential trips such as recreation are  
364 not presented, work and non-work essential trips of healthcare, school activities, and religious  
365 activity together constitute a major portion of the total trips. Figure 8a-b shows that among the  
366 general residents and faculty, trips for healthcare and religious activity are common and these  
367 groups are more likely to use a shared shuttle for these trips. However, students (Figure 8c) take  
368 more trips for health care and school activities and are more likely to use a shared shuttle for  
369 these trips.

### 370 **Behavioral Modeling Discussion**

371 This section provides the results of behavioral choices of travelers for selecting a share use shuttle  
372 service. Both binary logit models with and without random parameters are presented. The random  
373 parameters logit model shows significant improvement in parameters significance and the  
374 variables with significant distributions for random parameters explain unobserved heterogeneity  
375 and variation across the observation. The likelihood ratio test also justifies the superiority of  
376 random parameters model over the basic binary logit model. Thus, the discussion would focus on  
377 binary logit model with random parameters.

### 378 **Behavioral choices based on resident data**

379 The results of travel choice behavior for shared shuttle use versus the existing modes are presented  
380 in Table 4. These results are based on the data of rural residents. The variables with positive  
381 coefficients indicate a higher likelihood of using shared shuttle while negative coefficients indicate  
382 higher likelihood towards using the existing modes.

383 An important personal characteristic of inconvenience shows a higher propensity toward using  
384 existing modes as opposed to a shared shuttle. This is because some residents consider  
385 inconvenience a significant factor in deciding their mode of travel. Such commuters consider  
386 personal vehicles as more convenient, have childcare responsibilities, varying schedules for work  
387 that requires them to move back and forth across locations, thus making a shared shuttle less  
388 attractive for them. Further, being male shows a higher propensity toward using a shared shuttle.

389 The variable being a random parameter explains significant heterogeneity with positive  
390 observations for 99% of the distribution. Interestingly, this finding contrasts with others (Leistner  
391 and Steiner 2017) who observed women to be more likely to adopt shared services. However, past  
392 research has not focused on mobility choices in rural communities. Gender differences elsewhere  
393 were attributed to safety perceptions and lower licensure rates (Leistner and Steiner 2017). The

394 context for such differences was that women were observed to have higher propensity to substitute  
395 shared rides (Ng and Acker 2018) for public transit at night. Such differences are minimal in the  
396 context of rural areas since rural communities are already disadvantaged in having limited mobility  
397 options.

398 Two variables related to trip characteristics, i.e., miles driven and trips for religious activity show  
399 an increase in propensity of using shared rides. The finding related to mileage may be attributed  
400 to the fact that a shared shuttle provides residents in rural areas with the opportunity of making  
401 multiple trips without worrying about the expenses of maintaining a personal car. Likewise, trips  
402 for religious activity are performed on specific days of the week, mostly on weekends and thus,  
403 rural residents would be interested in using the comfort of a shared shuttle for such trips. This is  
404 an intuitive finding and being a random parameter, the variable explains significant heterogeneity  
405 with positive observations for 86% of observations. In contrast, trips for the morning peak show  
406 lower propensity for using a shared shuttle. This may be attributed to residents' urgency of  
407 reaching their destination for such peak hour trips. The personal characteristics involving the age  
408 range of 35-50 increase the likelihood of using a shared shuttle. Interestingly, two-thirds of the  
409 middle-aged community within the National Household Travel Survey gave up driving due to  
410 some sort of medical condition. The finding related to age is intuitive since this age category  
411 includes younger to middle-aged people that are mobile and are aware of shared services. Thus,  
412 the younger population would feel comfortable in sharing their rides in a shuttle, while the middle  
413 age population could similarly have some medical conditions. This indicates the desire of the  
414 community to have the choice of freedom for mobility to their destinations.

415 Two of the household variables showed significant findings. Higher income reveals lower  
416 propensity toward using a shared shuttle as opposed to the existing mobility options, mostly

417 personal vehicles. This may be attributed to the fact that people with higher income value time  
418 positively and are more likely to have access to a personal vehicle to reach their destinations and  
419 save time that would otherwise be wasted using a shared shuttle with fixed schedules. This has  
420 also been reported elsewhere in a different context (National Academies of Sciences 2012).  
421 However, affluent travelers are observed to be more likely to adopt new mobility options  
422 (Anderson and Perrin 2017) if they are provided more flexibility in travel without disturbing their  
423 existing travel schedules. Interestingly, the licensure finding reveals that residents would prefer  
424 having another convenient mobility option irrespective of their licensure status. This random  
425 parameter explains significant heterogeneity i.e., positive for over 70% observations.

#### 426 **Behavioral choices based on faculty and student data**

427 Since the behavior and travel patterns of faculty and students are different compared to the rest  
428 of the community, a separate model was calibrated for this segment of the community shown in  
429 Table 5. An important personal characteristic of familiarity with shared services shows a higher  
430 propensity for using a shared shuttle. This may be attributed to the experience of faculty and  
431 students with the existing shared loop service run by Waynesburg university. Thus, any  
432 experience and familiarity with shared service is likely to increase their likelihood to adopt the  
433 proposed shared shuttle. In contrast, vehicle ownership reduces the likelihood of using a shared  
434 shuttle for travel. Students and faculty must travel to the university for classes and meetings at  
435 specific times throughout the day; thus, having a personal vehicle would make it less likely for  
436 them to utilize a shared shuttle. This finding could be attributed to faculty population, who are  
437 more likely to own a vehicle.

438 The finding with respect to gender reveals a similar insight to the residents- males more likely to  
439 adopt a shared shuttle service. While the variable is not significant, the distribution for random

440 parameters is significant and explains significant variation across observations i.e., positive for  
441 over 80% observations. Interestingly, the age category of 35-50 shows a lower propensity toward  
442 using a shared shuttle. The variable is again a normally distributed random parameter and  
443 explains significant variation across observations, i.e., positive for over 75% of observations.  
444 This age categories would mostly include faculty and staff, who would prefer the convenience of  
445 personal vehicle to make multiple trips to campus throughout the day. Faculty value their time  
446 differently than students and may have childcare and other important responsibilities that would  
447 deem a shuttle service on fixed schedules non-convenient. Further, an important trip  
448 characteristic of miles driven provides a similar insight to the previous model. Faculty and staff  
449 with higher mileage are more likely to adopt a shared shuttle. This finding may be attributed to  
450 the ability to make longer trips without the need to worry about maintaining a personal vehicle.

## 451 **CONCLUSIONS AND DISCUSSION**

453 The issues of transport disadvantage and shared use mobility in rural areas within the US. have  
454 not been well investigated. While a few studies (Pucher and Renne 2005; Rogalsky 2010) exist  
455 on this subject, they do not cover the needs of US rural communities from the perspective of  
456 behavioral choices of travelers to adopt shared use mobility shuttle in rural areas. Furthermore,  
457 transport disadvantage differs between communities and regions across the globe, thus there is a  
458 need to study the behavioral choices within U.S. context. This study fills the literature gap by  
459 studying the behavioral choices of rural communities within the U.S. through a case study site of  
460 Waynesburg, Pennsylvania for adopting a shared use shuttle service.

461 The survey data collected from students, faculty, and residents in Greene County was used to  
462 calibrate random parameters based binary logit models to study the behavioral choices of  
463 commuters for a shared shuttle service. An important personal characteristic of inconvenience

464 shows a higher propensity toward using existing modes as opposed to a shared shuttle. This may  
465 be attributed to the fact that some residents consider inconvenience as a significant factor in  
466 deciding their mode of travel. Such commuters value personal vehicles as more convenient, have  
467 childcare responsibilities, and varying schedules for work that require them to move back and  
468 forth across locations. Thus, making a shared shuttle less attractive for them. The socioeconomic  
469 factors of age and gender show a higher propensity for using shared shuttle. The findings for the  
470 faculty and students group reveal that prior experience with shared services increases the  
471 likelihood of using a shared shuttle. Furthermore, vehicle ownership and age reveal a lower  
472 propensity towards using a shared shuttle.

473 These findings indicate the importance of new mobility options for rural communities. The  
474 shared shuttle service could improve mobility across the rural community by providing a  
475 convenient service for multiple trips across different periods of the day. Rural communities are  
476 disadvantaged with fewer mobility options; thus, these research findings could serve as a  
477 guideline for other rural communities across the U.S. and would be helpful in improving rural  
478 mobility in Waynesburg and other similar regions. The results from choice models would help  
479 design better mobility services for specific segments of the communities that could reduce their  
480 inconvenience by improving their travel times.

## 481 **Appendix**

482 **Put Table A1 here**

## 483 **Acknowledgements**

484 This project is based upon work supported by the U.S. Department of Energy's Office of Energy  
485 Efficiency and Renewable Energy (EERE) under the Vehicle Technology Office's award

486 number DE-EE0008883. The contents of this paper reflect the views of the authors, who are  
487 responsible for the facts and the accuracy of the information presented herein. The views  
488 expressed herein do not necessarily represent the views of the U.S. Department of Energy or the  
489 United States Government. The authors would like to thank Melinda Walls, Cassy Dorsch,  
490 Ezekiel Olagoke and Stacey Brodak with Waynesburg University to help conduct the surveys.

#### 491 **Data Availability Statement**

492 Some or all data, models, or code that support the findings of this study are available from the  
493 corresponding author upon reasonable request.

#### 494 **References**

- 495 Ahmed, Mohamed M., Rebecca Franke, Khaled Ksaibati, and Debbie S. Shinstine. 2018.  
496 "Effects of Truck Traffic on Crash Injury Severity on Rural Highways in Wyoming Using  
497 Bayesian Binary Logit Models." *Accident Analysis and Prevention* 117:106–13. doi:  
498 10.1016/j.aap.2018.04.011.
- 499 Anderson, M., and A. Perrin. 2017. "Technology Use among Seniors." *Pew Research Center for*  
500 *Internet and Security*.
- 501 Ao, Y., Y. Zhang, Y. Wang, Y. Chen, and L. Yang. 2020. "Influences of Rural Built  
502 Environment on Travel Mode Choice of Rural Residents." *Journal of Transport Geography*  
503 85. doi: 10.1016/j.jtrangeo.2020.102708.
- 504 Ben-Akiva, Moshe, and Steven R. Lerman. 1985. *Discrete Choice Analysis*. MIT Press.
- 505 Bureau, Census. 2015. "American Community Survey." *United States Census Bureau*.
- 506 Bureau, U. S. Census. 2019. "ACS Demographic And Housing Estimates: 2013-2017 American  
507 Community Survey 5-Year Estimates." Retrieved  
508 (<https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=CF>).
- 509 Chan, N. D., and S. A. Shaheen. 2012. "Ride-Sharing in North America: Past, Present, and  
510 Future." *Transport Reviews* 32. doi: 10.1080/01441647.2011.621557.
- 511 Chen, C., H. Gong, and R. Paaswell. 2008. "Role of the Built Environment on Mode Choice  
512 Decisions: Additional Evidence on the Impact of Density." *Transportation*. doi:  
513 10.1007/s11116-007-9153-5.
- 514 Christiansen, P., Ø. Engebretsen, N. Fearnley, and J. Usterud Hanssen. 2017. "Parking Facilities  
515 and the Built Environment: Impacts on Travel Behavior." *Transportation Research Part A*  
516 95. doi: 10.1016/j.tra.2016.10.025.
- 517 Contreras, S. D., and A. Paz. 2017. "The Effects of Ride-Hailing Companies on the Taxicab  
518 Industry in Las Vegas, Nevada." *Transp. Res. Part A: Policy Practice* 115. doi:  
519 10.1016/j.tra.2017.11.008.

520 Coutinho, Felipe Mariz, Niels van Oort, Zoi Christoforou, María J. Alonso-Gonzalez, Oded Cats,  
521 and Serge Hoogendoorn. 2020. “Impacts of Replacing a Fixed Public Transport Line by a  
522 Demand Responsive Transport System: Case Study of a Rural Area in Amsterdam.”  
523 *Research in Transportation Economics*.

524 Delhomme, P., and A. Gheorghiu. 2016. “Comparing French Carpoolers and Non-Carpoolers:  
525 Which Factors Contribute the Most to Carpooling?” *Transportation Research Part D* 42.  
526 doi: 10.1016/j.trd.2015.10.014.

527 Eckhardt, J., A. Lauhkonen, and A. Aapaoja. 2020. “Impact Assessment of Rural PPP MaaS  
528 Pilots.” *European Transport Research Review* 12. doi: 10.1186/s12544-020-00443-5.

529 Ewing, Reid, Keith Bartholomew, Steve Winkelman, Jerry Walters, and Don Chen. 2008.  
530 *Growing Cooler: Evidence on Urban Development and Climate Change*. Urban Land  
531 Institute.

532 Greene, W. H. 2008. “Econometric Analysis.” *Pearson Prentice Hall, Upper Saddle River, New*  
533 *Jersey*.

534 Grue, B., K. Veisten, and Ø. Engebretsen. 2020. “Exploring the Relationship between the Built  
535 Environment, Trip Chain Complexity, and Auto Mode Choice, Applying a Large National  
536 Data Set.” *Transp Res Interdiscip Perspect* 5. doi: 10.1016/j.trip.2020.100134.

537 Halton, J. 1960. “On the Efficiency of Evaluating Certain Quasi-Random Sequences of Points in  
538 Evaluating Multi-Dimensional Integrals.” *Numerische Mathematik* 2 84–90. doi:  
539 10.1007/BF01386213.

540 Hult, Asa, Liisa Perjo, and Goran Smith. 2021. “Shared Mobility in Rural Contexts:  
541 Organizational Insights from Five Mobility-as-a-Service Pilots in Sweden.” *Sustainability*.

542 Jeffrey, T. B. 2018. “29.2% of U.S. Households Had Incomes of \$100,000+ in 2017.”  
543 *CNSNews.Com, Media Research Center*.

544 Khattak, Zulqarnain H., Mark J. Magalotti, John S. Miller, and Michael D. Fontaine. 2017.  
545 “Using New Mode Choice Model Nesting Structures to Address Emerging Policy  
546 Questions: A Case Study of the Pittsburgh Central Business District.” *Sustainability*. doi:  
547 10.3390/su9112120.

548 Knierim, L., and J. C. Schlüter. 2021. “The Attitude of Potentially Less Mobile People towards  
549 Demand Responsive Transport in a Rural Area in Central Germany.” *Journal of Transport*  
550 *Geography* 96. doi: 10.1016/j.jtrangeo.2021.103202.

551 Lee, B. H. Y., M. Coogan, L. Aultman-Hall, and T. Adler. 2016. “Rideshare Mode Potential in  
552 Non-Metropolitan Areas of the Northeastern United States.” *Journal of Transport and Land*  
553 *Use* 9. doi: 10.5198/jtlu.2015.669.

554 Leistner, D. K., and R. L. Steiner. 2017. “Uber for Seniors? Exploring Transportation Options  
555 for the Future.” *Transportation Research Record: Journal of the Transportation Research*  
556 *Board* (2660).

557 Madani, N., L. Creemers, M. Moeinaddini, I. Saadi, and M. Cools. 2022. “Low-Cost Shared  
558 Mobility Alternatives in Rural Areas: A Case Study of Ride-Sharing Benches in the  
559 German-Speaking Community of Belgium.” *Case Studies on Transport Policy* 10. doi:  
560 10.1016/j.cstp.2022.11.002.

561 Maeder, Stefanie, Michael Stauffacher, and Florian Knaus. 2023. “Zooming in and out on  
562 Everyday Mobility Practices in a Rural, Mountainous Area of Switzerland.” *Journal of*  
563 *Transport Geography*.

564 Mannering, Fred L., Venkatarman Shankar, and Chandra R. Bhat. 2016. "Unobserved  
565 Heterogeneity and the Statistical Analysis of Highway Accident Data." *Analytical Methods*  
566 *in Accident Research*. doi: 10.1016/j.amar.2016.04.001.

567 Mattson, J. 2017. *Rural Transit Fact Book*.

568 Mattson, J., D. Peterson, D. Ripplinger, W. Thoms, and J. Houg. 2010. "An Assessment of  
569 Demand for Rural Intercity Transportation Services in a Changing Environment."  
570 *Transportation Research Record*. doi: 10.3141/2145-13.

571 Mulley, Corinne, John Nelson, Chinh Ho, and David Hensher. 2006. "MaaS in a Regional and  
572 Rural Setting: Recent Experience." *Transport Policy*.

573 National Academies of Sciences, Engineering and Medicine. 2012. "Travel Demand Forecasting:  
574 Parameters and Techniques." *Washington, DC: The National Academies Press*.

575 Neoh, J. G., M. Chipulu, and A. Marshall. 2017. "What Encourages People to Carpool? An  
576 Evaluation of Factors with Meta-Analysis." *Transportation* 44. doi: 10.1007/s11116-015-  
577 9661-7.

578 Ng, W. S., and A. Acker. 2018. "Understanding Urban Travel Behaviour by Gender for Efficient  
579 and Equitable Transport Policies." *International Transport Forum*.

580 Pike, Susan, Caroline Rodier, and Jose Martinez. 2018. "The Potential for Shared Use Mobility  
581 in Affordable Housing Complexes in Rural California." *University of California*  
582 *Transportation Institute*. doi: 10.7922/G2K935PV.

583 Polzin, S. E. 2016. "Implications to Public Transportation of Automated or Connected Vehicles."  
584 *National Center for Transit Research*.

585 Pucher, J., and J. Renne. 2005. "Rural Mobility and Mode Choice: Evidence from the 2001  
586 National Household Travel Survey." *Transportation* 32.

587 Rietveld, P., B. Zwart, B. van Wee, and T. van den Hoorn. 1999. "On the Relationship between  
588 Travel Time and Travel Distance of Commuters Reported versus Network Travel Data in  
589 the Netherlands." *The Annals of Regional Science* 33. doi: 10.1007/s001680050105.

590 Rodier, C., B. Harold, and Y. Zhang. 2021. "Early Results from an Electric Vehicle Carsharing  
591 Service in Rural Disadvantaged Communities in the San Joaquin Valley." *University of*  
592 *California Institute of Transportation Studies*. doi: 10.7922/G2765CNH.

593 Rogalsky, J. 2010. "The Working Poor and What GIS Reveals about the Possibilities of Public  
594 Transit." *Journal of Transport Geography* 18.

595 Rosenbloom, S. 2003. "Facing Societal Challenges: The Need for New Paradigms in Rural  
596 Transit Service." *Journal of Public Transportation* 6:1–18.

597 Sandow, E., and K. Westin. 2010. "People's Preferences for Commuting in Sparsely Populated  
598 Areas: The Case of Sweden." *Journal of Transport and Land Use*. doi:  
599 <https://www.jtlu.org/index.php/jtlu/article/view/21/79>.

600 Schwanen, T., F. M. Dieleman, and M. Dijst. 2004. "The Impact of Metropolitan Structure on  
601 Commute Behavior in the Netherlands: A Multilevel Approach." *Growth Change* 35. doi:  
602 10.1111/j.1468-2257.2004.00251.x.

603 Shaheen, Susan, Nelson Chan, Apar Bansal, and Adam Cohen. 2015. "Shared Mobility: A  
604 Sustainability and Technologies Workshop." *University of California Berkeley*  
605 *Transportation Sustainability Research Center*. doi: [http://innovativemobility.org/wp-](http://innovativemobility.org/wp-content/uploads/2015/11/SharedMobility_WhitePaper_FINAL.pdf)  
606 [content/uploads/2015/11/SharedMobility\\_WhitePaper\\_FINAL.pdf](http://innovativemobility.org/wp-content/uploads/2015/11/SharedMobility_WhitePaper_FINAL.pdf).

607 Tirachini, A., and Marianadel Rio. 2019. "Ride-Hailing in Santiago de Chile: Users'  
608 Characterisation and Effects on Travel Behaviour." *Transport Policy* 82. doi:  
609 10.1016/j.tranpol.2019.07.008.

610 Train, Kenneth. 2003. *Discrete Choice Methods with Simulation*. first. Cambridge, United  
611 Kingdom: Cambridge University Press.

612 Wang, C., M. Quddus, M. Enoch, T. Ryley, and L. Davison. 2015. "Exploring the Propensity to  
613 Travel by Demand Responsive Transport in the Rural Area of Lincolnshire in England."  
614 *Case Studies in Transport Policy* 3. doi: 10.1016/j.cstp.2014.12.006.

615 Xie, Meiquan, Wen Cheng, Gurdiljot Singh Gill, Jiao Zhou, Xudong Jia, and Simon Choi. 2018.  
616 "Investigation of Hit-and-Run Crash Occurrence and Severity Using Real-Time Loop  
617 Detector Data and Hierarchical Bayesian Binary Logit Model with Random Effects."  
618 *Traffic Injury Prevention* 19(2). doi: 10.1080/15389588.2017.1371302.

619 Zhou, X., Hu Du, Yue Liu, Huang Huang, and B. Ran. 2017. "Investigating the Intention of  
620 Rural Residents to Use Transit in Cixi, China." *Journal of Urban Planning and*  
621 *Development* 143. doi: 10.1061/(ASCE)UP.1943-5444.0000367.

622  
623  
624  
625  
626  
627  
628  
629  
630  
631  
632  
633  
634  
635  
636  
637  
638  
639  
640  
641  
642  
643  
644  
645  
646  
647  
648  
649  
650  
651  
652  
653  
654  
655

656  
657  
658

**Table A1. Summary of literature studies**

**Tables**

Study Origin	Study reference	Type of study	Method used	Important Finding
USA	(Bureau 2015)	Studies related to influence of socio-economic factors	Cluster analysis	The study analyzed access to public transit in rural and urban regions. They observed only 4% of the rural population does not have access to an automobile while the proportion for urban residents is 10%.
Netherland	(Schwanen et al. 2004)		Mixed logit	The study analyzed potential socioeconomic factors affecting travelers' intention to try transportation modes other than personal vehicles. They observed that women in most polycentric regions are less likely to commute as an auto driver. Income level was the most determinant of all socioeconomic factors in rural travel mode choice.
Sweden	(Sandow and Westin 2010)		Interaction modeling	The study assessed mobility in urban and rural areas. They observed that in sparsely populated areas, low-income households without car accessibility are more inclined toward walking and cycling than urban areas.
North Dakota and Minnesota, USA	(Mattson et al. 2010)		Survey and descriptive analysis	The study assessed factors influencing choice of personal vehicles and observed that travelers, especially those of lower income respond to higher gasoline prices by choosing alternative modes to personal vehicles in greater numbers.
China	(Zhou et al. 2017)		Revealed preference data and structure equation model	The study analyzed transit use in rural areas. They observed that the intention of rural residents to use transit shows that income and car ownership have negative relationship with transit mode choice
USA	(Ewing et al. 2008)	Studies related built environment effects	Survey and market research	The study researched the influence of built environment on shared use mobility. They recognized that built environment is composed of density, diversity, design, dimensions of destination accessibility, and distance to transit, known as the 5D theory
Norway	(Grue et al. 2020)		Travel survey data	The study analyzed the influence of density on mode choice selection. They found that higher minimum density at destinations is associated with lower auto mode choice, while increasing distance from the residence to the nearest center increases the odds of auto mode choice.
Norway	(Christiansen et al. 2017)		Travel survey data	They studied parking availability influence on use of personal mobility options and observed parking lot availability at work facilitates the use of car.
China	(Ao et al. 2020)		Travel survey data and multinomial logit	The study analyzed different factors that influence selection of personal mobility. They proposed that aside from density, accessibility, and parking lot availability, people who consider the residential area as safe would likely not choose to drive a car. An increase in road density was observed to increases the travel frequency of electric bicycles and motorcycles in rural Sichuan
Switzerland	(Maeder et al. 2023)		Social practice approach	The study analyzes the key characteristics and dynamics of everyday transport in Switzerland by zooming on practices of configuration and zooming out

				on connection between mobility purposes and characteristics. The study also conducted semi-structured interviews and observed geographical conditions and infrastructure availability to be more important compared for mobility services in rural areas. The observed mobility purpose to influence how travelers valued their time spent on mobility, leading to different mode choices.
France	(Delhomme and Gheorghiu 2016)	Shared mobility	Survey and logistic regression	The study analyzed factors influencing ride share usage. They showed that older people are less likely to ride share, which is possibly due to lack of digital knowledge. Other than age, gender, income, and car ownership are also influential factors.
Netherland	(Rietveld et al. 1999)		Revealed data and travel diary data	The study analyzed the influence of trip related factors and safety concerns on ride sharing. They found travel time for ride sharers to be 17% longer, which greatly affects people's tendency to rideshare. People may also avoid ride sharing if they feel it is unsafe. To summarize, in general, demographic characteristics, trip related factors and safety influence whether individuals participate in ridesharing.
USA	(Lee et al. 2016)		Survey data and multinomial logit model	The study analyzed some pilot ridesharing projects in rural areas and suggested that certain ride sharer characteristics can be identified. Lee and Coogan's research on rideshare mode potential in non-metropolitan areas indicates that younger individuals and females are more likely to rideshare, but they would not participate in the programs that would match them to strangers. People living in denser areas or having a rural workplace showcased higher willingness to participate but are less likely to indicate ridesharing to replace driving alone.
Belgium	(Madani et al. 2022)		Survey data	The research on the ridesharing bench case study in rural Germany showed that the strongest association with bench usage is related to population density and car ownership, while gender plays a weaker role. They also summarized some reasons for why rural residents choose not to ride share, which are car ownership, safety concerns, and no guarantee of a return. Overall, the survey demonstrated the high potential of the use of ridesharing benches in rural areas.
Germany	(Knierim and Schlüter 2021)	Studies related to demand responsive transit	Survey data and linear regression	The study analyzed demand responsive transportation (DRT) that offers flexible (non-fixed route) mobility services in low density areas and is an important segment of the Mobility as a Service (MaaS) concept. The study researched the intention of less mobile people to use DRT, and several determinant factors were found. They argued that car ownership harms the intended use of DRT while physical impairment increases the likelihood of using DRT in a rural area in Germany. Intention to use DRT was observed to only increase with age for people living in small settlements.

England	(Wang et al. 2015)		Survey data and ordered logit	Besides car ownership and disability, Wang indicated a negative correlation between population density and the frequency of DRT use in rural areas. In summary, they agree that car ownership and physical impairment affect the intention to use DRT in rural areas.
Porvoo, France	(Eckhardt et al. 2020)		Survey and interviews	The study analyzed the demand responsive nature of DRT and MaaS, as innovative modes of transportation. They observed that an impact assessment of rural MaaS pilot projects showcased a clear modal shift from private cars to DRT minibuses and better accessibility of transport services. The survey on DRT use in rural Germany indicated that a quarter of all trips people would like to take via DRT are for medical purposes, demonstrating an urgent need for improving rural mobility
San Joaquin Valley, California	(Rodier et al. 2021)		Surveys	The study analyzed the potential of car sharing for lower income population in rural areas. For the Miocar carsharing pilot program, 59% respondents indicated that they would not have been able to travel to the primary destination without Miocar. The demographics revealed that most user households have four or more family members, and the median household income was approximately \$37,500, which is lower than the average median income (\$46,721) reported for the census block groups.
California, USA	(Pike et al. 2018)		Survey and descriptive analysis	The study surveyed residents in rural California for their choices of using ride sourcing services. They observed a strong willingness to use ride sourcing and carsharing services for people living in rural California.
Sweden	(Hult et al. 2021)		Survey and descriptive analysis	The study analyzes the role of shared mobility in complementing public transit in rural areas and mitigating transport poverty. The study utilized interviews with municipalities, involved in five pilots in rural Sweden. They observed new tools empowered by digital technologies to contribute to renewal and/or complement demand responsive public transit.
Sweden and Finland	(Mulley et al. 2006)		Review of existing mobility services	The study conducted a review of existing mobility services utilizing technology to assess factors contributing to transport disadvantages in rural areas. They observed digital literacy to be an important contributor to the success of any mobility service since the whole population cannot be assumed to be digitally literate. Furthermore, they observed population density to be less relevant to rural mobility while the degree of rurality was more relevant.
Netherland	(Coutinho et al. 2020)		Before-after analytical approach	The study conducted a before-after assessment of with a pilot DRT service that replace a fixed route public transit. They observed the overall system's efficiency improve with the DRT system despite the drop in ridership of 28%, which was rationalized by an 11% reduction in mileage. The DRT system was well perceived by users.

660

661 **Table 1. Summary of Independent Variables for resident data**

Category	Variable	Mean	Standard Deviation	Minimum	Maximum
Travel Characteristics	Trip distance (miles)	23.14	24.54	4.00	175
	Work trip	0.54	0.49	0.00	1.00
	Purpose of the trip is religious activity	0.11	0.31	0.00	1.00
	Purpose of trip is for healthcare	0.12	0.33	0.00	1.00
	Purpose of trip is for school related activity	0.01	0.09	0.00	1.00
	Frequency of trips	1.76	1.42	0.00	10.00
Personal Characteristics	Male	0.32	0.47	0.00	1.00
	White	0.96	0.19	0.00	1.00
	Age range of 35-45	0.196	0.36	0.00	1.00
	Age range of 45-72	0.47	0.50	0.00	1.00
	Driving license	0.87	0.33	0.00	1.00
	Consider inconvenience as a significant factor	0.24	0.43	0.00	1.00
	Traveler has previous experience with using shared rides	0.49	0.50	0.00	1.00
Household Characteristics	Income higher than \$50,000 per year	0.17	0.38	0.00	1.00
	Income higher than \$75,000 per year	0.25	0.43	0.00	1.00
	More than 1 vehicles in household	0.77	0.42	0.00	1.00
	Number of People in household	2.44	1.54	0.00	8.00
Time of day	Morning peak	0.46	0.49	0.00	1.00
	Midday peak	0.23	0.42	0.00	1.00

662

663

**Table 2. Summary of Independent Variables for faculty and student's data**

Category	Variable	Mean	Standard Deviation	Minimum	Maximum
Travel Characteristics	Trip distance (miles)	21.55	31.04	2.00	150
	Purpose of the trip is religious activity	0.058	0.23	0.00	1.00
	Purpose of trip is for healthcare	0.026	0.161	0.00	1.00
	Purpose of trip is for school related activity	0.058	0.23	0.00	1.00
	Frequency of trips	1.78	1.42	0.00	10.00
Personal Characteristics	Male	0.38	0.48	0.00	1.00
	White	0.91	0.27	0.00	1.00
	*Age range of 35-45	0.19	0.39	0.00	1.00
	**Age range of 75 and higher	0.39	0.48	0.00	1.00
	Driving license	0.97	0.16	0.00	1.00
	Consider inconvenience as a significant factor	0.82	0.38	0.00	1.00
	Traveler has previous experience with using shared rides	0.28	0.45	0.00	1.00
Household Characteristics	Income higher than \$50,000 per year	0.96	0.17	0.00	1.00
	Income higher than \$75,000 per year	0.42	0.49	0.00	1.00
	Vehicle ownership	0.88	0.32	0.00	1.00
	Number of People in household	2.79	1.54	0.00	6.00
Time of day	Morning peak	0.30	0.47	0.00	1.00
	Midday peak	0.27	0.45	0.00	1.00

664 \*,\*\* indicates age for faculty/staff data

665

666

667

668

669

670

671

672

673

674

675

676

677

678 **Table 3. Survey Comparison with Census Data from Greene County (US. Census Bureau)**

<b>Variable</b>	<b>Survey Data</b>	<b>Census Data (Greene County)</b>
Age (Person 65 and over)	17.6%	20.2%
Median HH Income	50K-75K	57,497
White (Race)	93%	94.2%
Average People in the HH	2.5	2.34

679  
680  
681  
682  
683  
684  
685  
686  
687  
688  
689  
690  
691  
692  
693  
694  
695  
696  
697  
698

699

**Table 4. Random Parameter Model for residents' behavior**

Variable	Binary logit (Shared shuttle)	Binary logit with random parameters (Shared Shuttle)
	Coeff Value (p-value)	Coeff Value (p-value)
Alternative Specific Constant	-0.507 (0.006)	-3.114 (0.05)
<b>Personal Factors</b>		
<i>Considering Inconvenience as a significant factor</i>	-3.484 (0.006)	-3.158 (0.000)
<i>License</i>	0.638 (0.572)	0.884 (0.068)
<b>Socio-economic Factors</b>		
<i>Variable for Gender (1 if Male)</i>	1.095 (2.40)	0.333 (2.09)
<i>Income of 75K or higher</i>	-1.257 (0.056)	-1.023 (.086)
<i>Age (35-50)</i>	0.178 (0.655)	1.527 (0.000)
<b>Trip Characteristics</b>		
<i>Miles driven</i>	0.028 (0.0004)	0.025 (0.000)
<i>Morning Peak</i>	-0.951 (0.221)	-0.498 (0.115)
<i>Religious activity</i>	0.847 (0.556)	0.544 (.720)
<b>Scale Parameters for Random distribution</b>		
<i>Gender</i>	NA	1.067 (.0028)
<i>Religious activity</i>	NA	1.844 (.0364)
<i>License</i>	NA	1.228 (.000)
<b>Goodness of Fit measures</b>		
<i>Log likelihood at convergence LL(<math>\beta</math>)</i>	-116.4	-81.50
<i>Likelihood ratio chi-square</i>	69.8	
<i>Chi square critical (degree of freedom)</i>	11.35	
<i>Number of Observations</i>	210	210

700

701

702

703

704

705

706

707

708

709

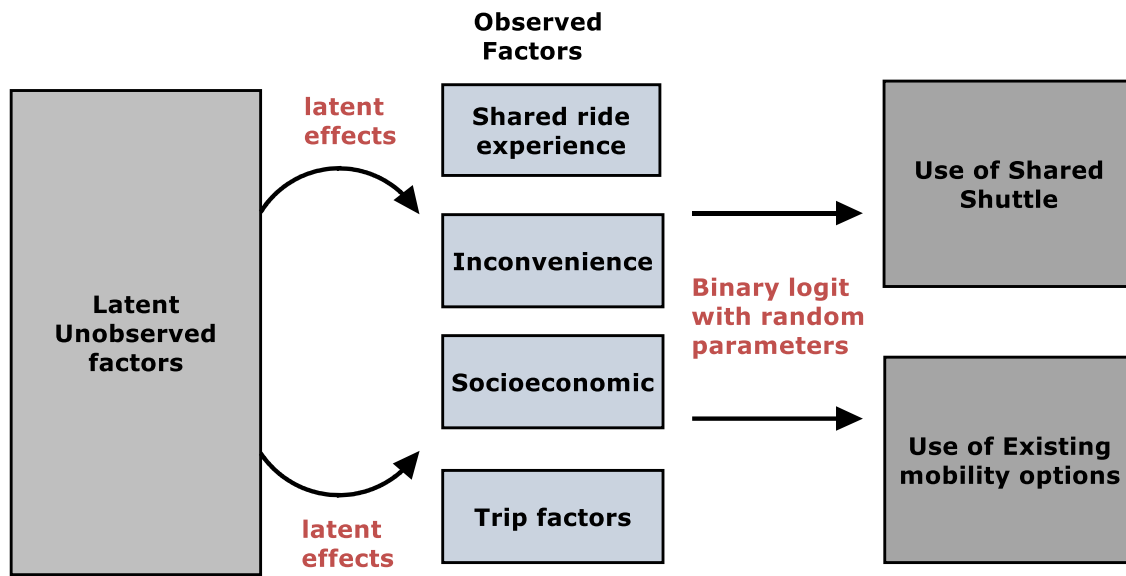
710

**Table 5. Random Parameter Model for faculty and students' behavior**

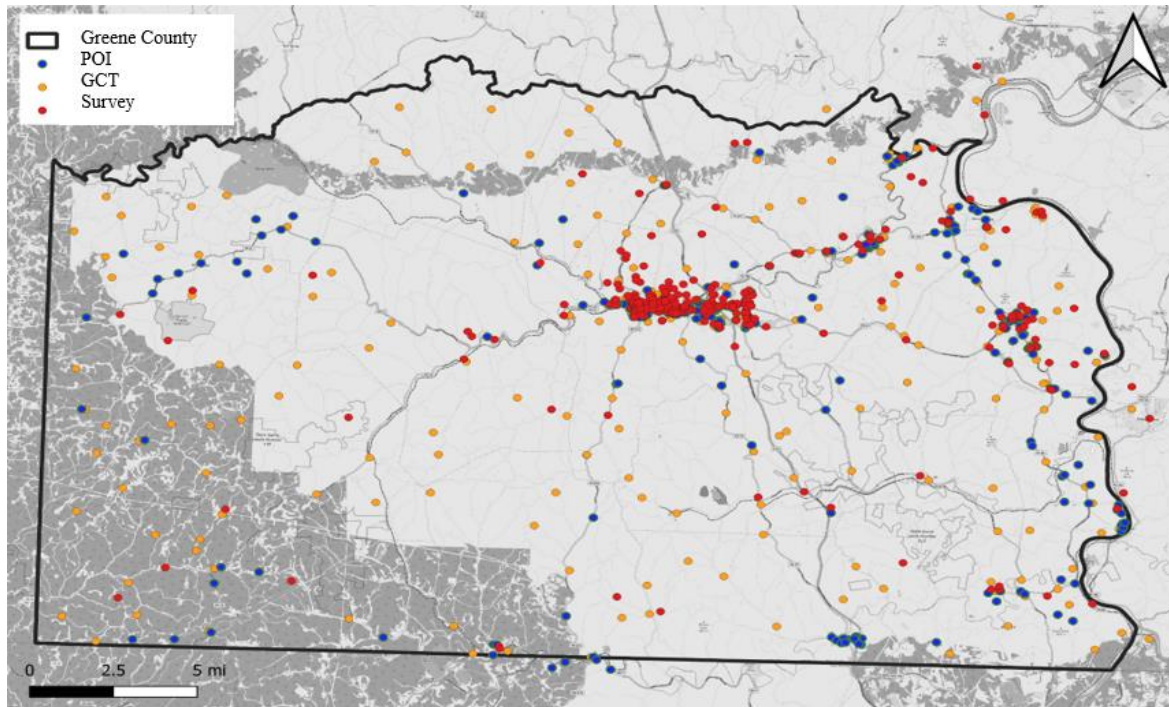
Variable	Binary logit (Shared shuttle)	Binary logit with random parameters Shared Shuttle
	Coeff value (p-value)	Coeff value (p-value)
Alternative Specific Constant	-0.633 (0.678)	0.909 (0.057)
<b>Personal Factors</b>		
<i>Familiarity with shared services</i>	2.379 (0.014)	4.157 (0.007)
<i>Vehicle ownership</i>	-4.116 (0.019)	-6.915 (0.008)
<b>Socio-economic Factors</b>		
<i>Variable for Gender (1 if Male)</i>	-0.027(0.967)	0.251 (0.751)
<i>Age (35-50)</i>	-1.550(0.054)	-5.250 (0.097)
<b>Trip Factors</b>		
<i>Miles driven</i>	0.024(0.053)	0.037 (0.044)
<b>Scale Parameters for Random distribution</b>		
<i>Gender</i>	NA	0.935 (0.024)
<i>Age</i>	NA	3.887 (0.003)
<b>Goodness of Fit measures</b>		
<i>Log likelihood at convergence LL(<math>\theta</math>)</i>	-86.40	-72.20
<i>Likelihood ratio chi-square</i>	28.4	
<i>Chi square critical (degree of freedom)</i>	9.2	
<i>Number of Observations</i>	192	192

711

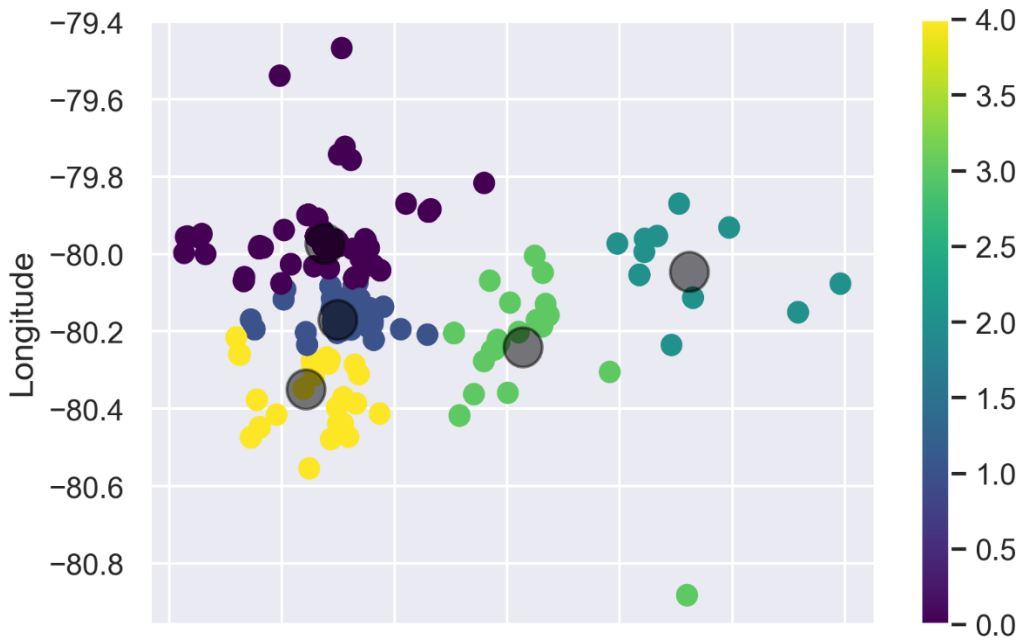
712



**Figure 1. Study Framework**

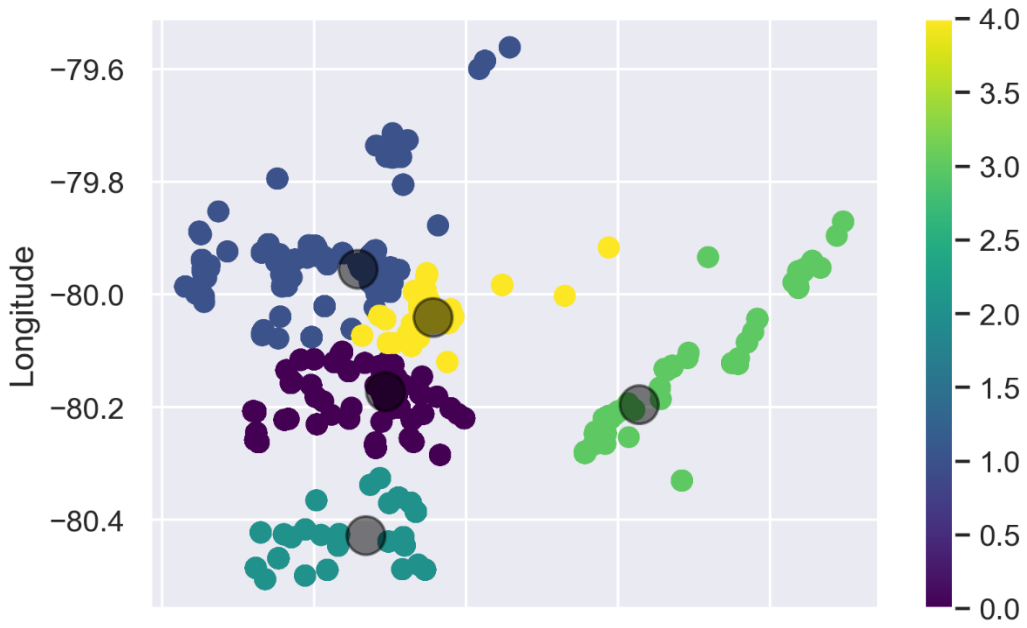


**Figure 2.** Origin/destination locations: POIs and pickup and drop-off locations from GCT



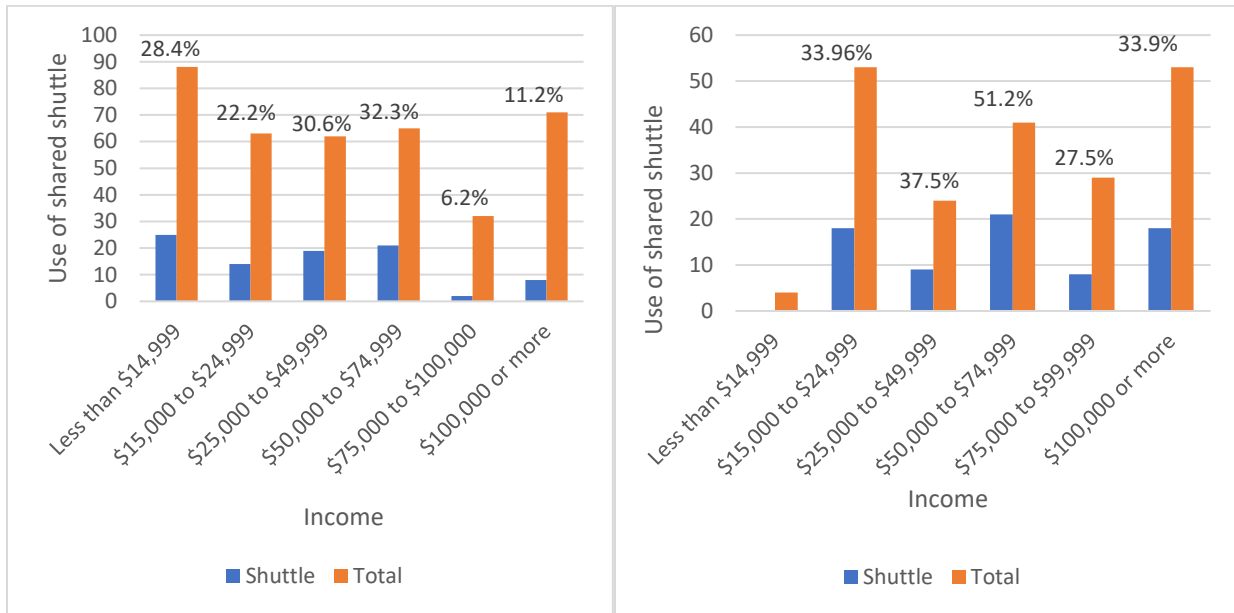
a) Survey data

**Figure 3.** Clusters representing trips from the data



b) Ecolane data

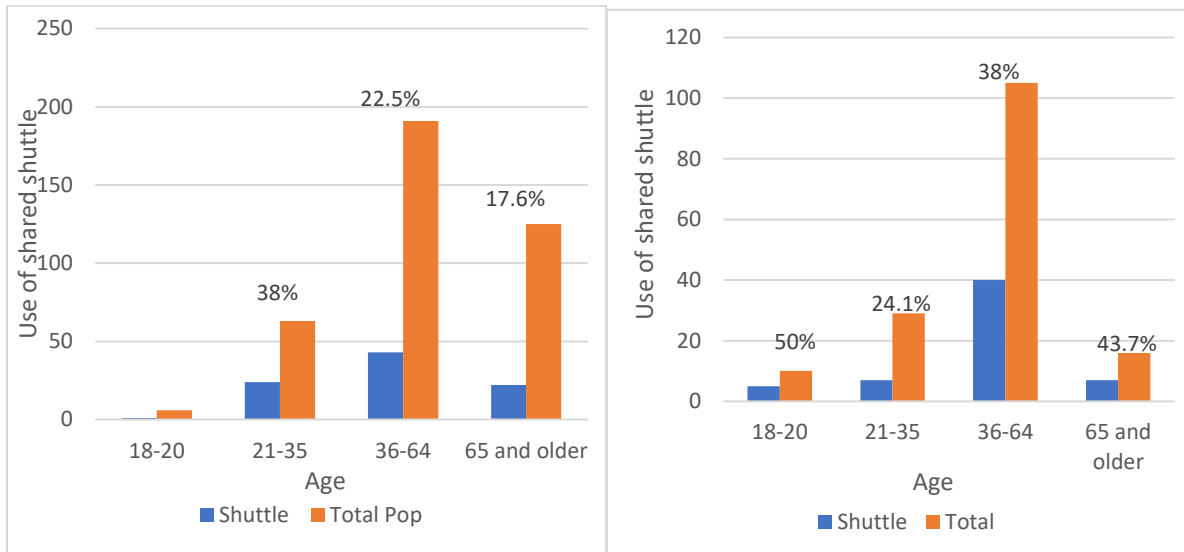
**Figure 3.** Clusters representing trips from the data



(a) Residents

(b) Faculty/staff

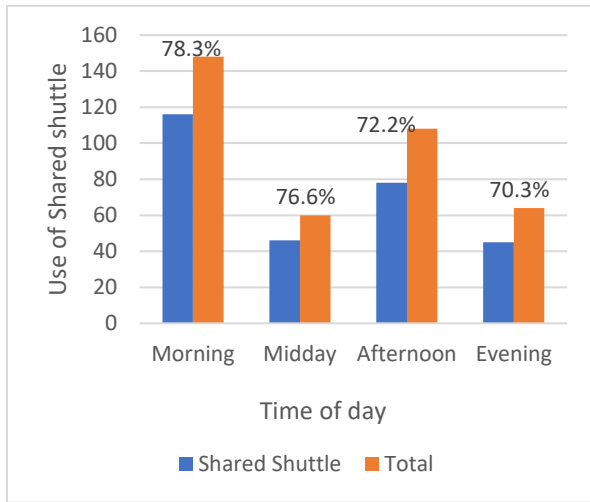
**Figure 4. Income comparison for shared shuttle use, (% shows the share of shuttle)**



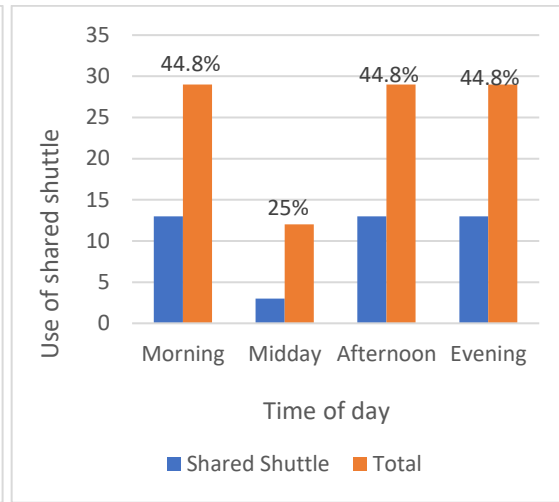
a) Residents

b) Faculty/staff

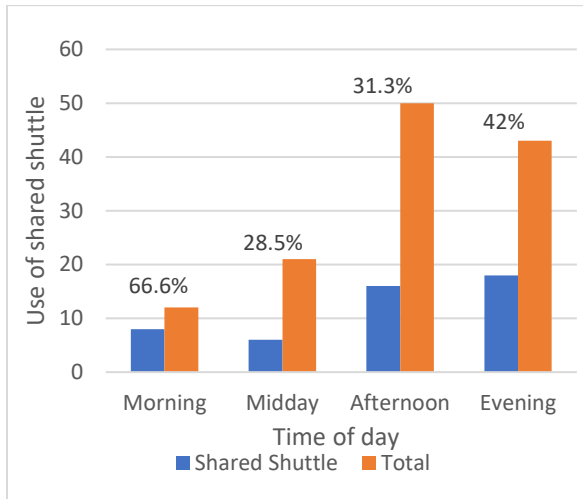
**Figure 5. Age comparison for shared shuttle use, (% shows the share of shuttle)**



(a) Residents

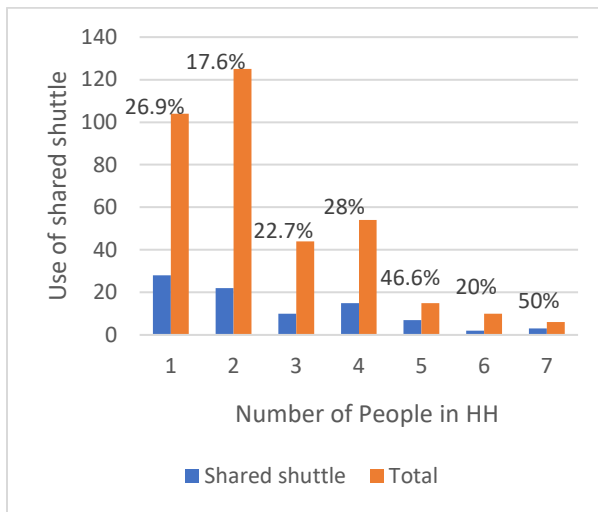


(b) Faculty/staff

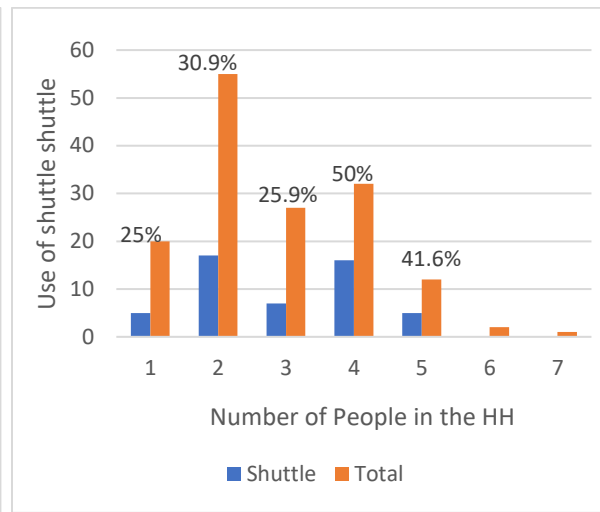


(c) Students

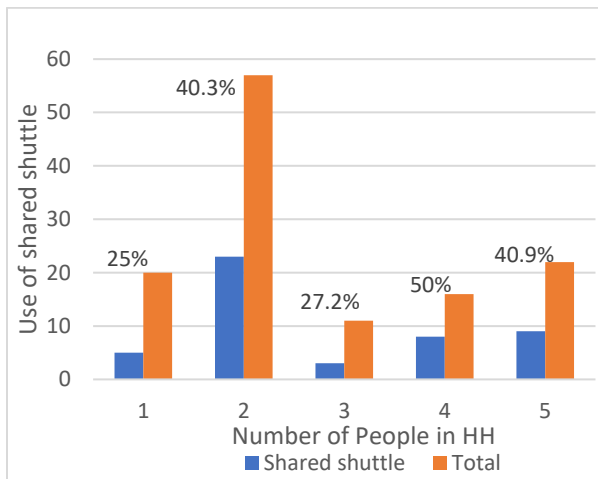
**Figure 6. Time of day comparison for shared shuttle use, (% shows the share of shuttle)**



a) Residents

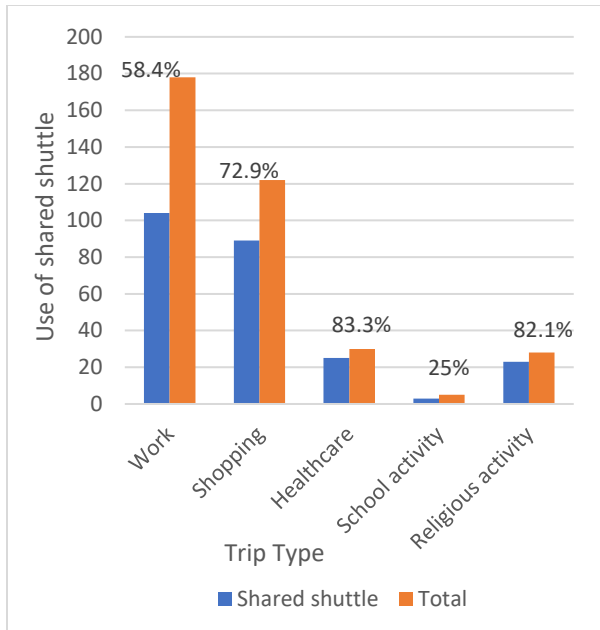


b) Faculty

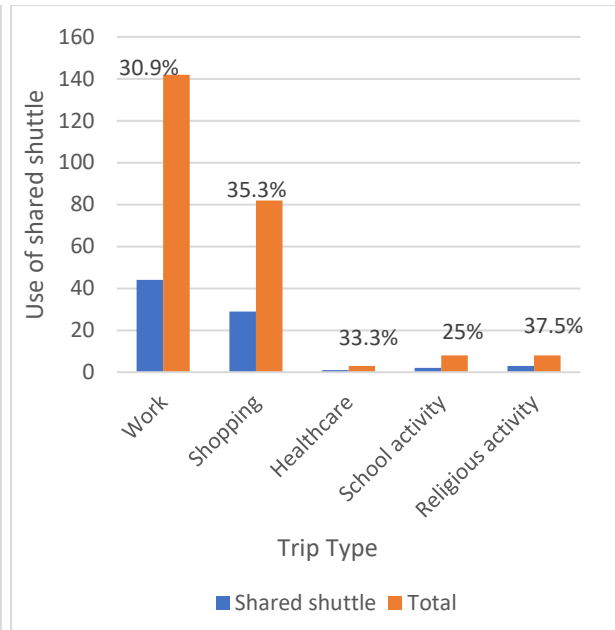


c) Students

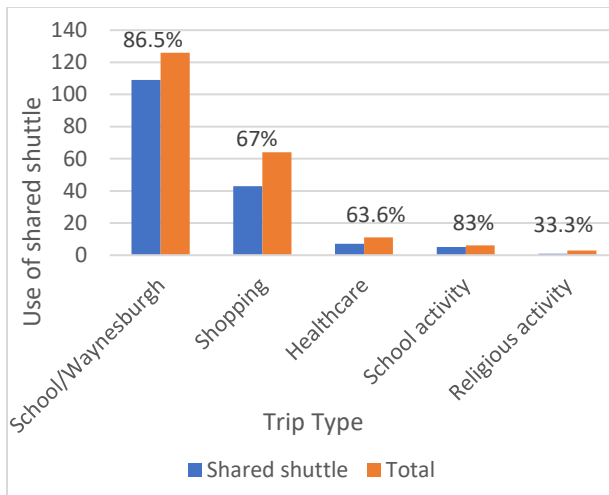
**Figure 7. Number of people for shared shuttle use, (% shows the share of shuttle)**



a) Residents



b) Faculty/staff



c) Students

**Figure 8. Trip Purpose for shared shuttle use, (% shows the share of shuttle)**

## List of Figures

**Figure 1.** Study Framework

**Figure 2.** Origin/destination locations: POIs and pickup and drop-off locations from GCT

**Figure 3.** Clusters representing data; (a) Survey data, (b) Ecolane Data

**Figure 4.** Income comparison for shared shuttle use, (% shows the share of shuttle), a) Residents, b) Faculty/staff

**Figure 5.** Age comparison for shared shuttle use, (% shows the share of shuttle), a) Residents, b) Faculty/staff

**Figure 6.** Time of day comparison for shared shuttle use, (% shows the share of shuttle), a) Residents, b) Faculty/staff, c) Students

**Figure 7.** Number of people for shared shuttle use, (% shows the share of shuttle), a) Residents, b) Faculty/staff, c) Students

**Figure 8.** Trip Purpose for shared shuttle use, (% shows the share of shuttle), a) Residents, b) Faculty/staff, c) Students