

<sup>1</sup> Accessibility to Primary Care Physicians: Comparing  
<sup>2</sup> Floating Catchments with a Utility-based Approach

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<sup>5</sup> **Abstract**

Floating Catchment Area (FCA) methods are a popular choice for modelling accessibility to healthcare services because of their ability to consider both supply and demand. However, FCA methods do not fully consider aspects of travel and choicemaking behaviour as the only behavioural component is the impedance function. FCA approaches also tend to assign population demand to clinics and levels-of-service to population zones in an overlapping manner that has been shown to inflate/deflate supply and demand. While the adjustments proposed in the recent “Balanced FCA” method can rectify this, it apportions population and levels of service in a fractional manner. In response, this research proposes a utility-based measure of healthcare accessibility based on a multinomial logit (MNL) destination choice model that avoids the multiple-counting issue in FCA methods. It also considers additional behavioural aspects that define the appeal of clinics in addition to the travel time required to reach them, including their capacity and level of crowding. Comparisons of the MNL approach with the original and balanced FCA models using data for the City of Hamilton, Canada, suggests that while the accessibility patterns produced by each method are broadly similar, some key differences exist in the calculated accessibilities and their spatial patterns. The MNL model in particular estimates higher accessibilities in suburban and rural areas. After considering their strengths and weaknesses, we argue that both the FCA and MNL approaches offer merit for planning and policy.

<sup>6</sup> *Key words:* healthcare accessibility place-based accessibility utility-based  
<sup>7</sup> accessibility destination choice model accessibility analysis

<sup>8</sup> **Introduction**

<sup>9</sup> The global COVID-19 pandemic has emphasized the importance of healthcare  
<sup>10</sup> accessibility, particularly access to primary care physicians, who provide the first  
<sup>11</sup> point of contact between patients and the healthcare system. In Canada, the  
<sup>12</sup> Canada Health Act states that all residents should have “reasonable access” to  
<sup>13</sup> healthcare. However, the 2017 Canadian Community Health Survey revealed  
<sup>14</sup> that 15.3% of Canadians aged 12 or over did not have a primary care physician,  
<sup>15</sup> of whom 17.2% stated that there is no physician accessible within their area  
<sup>16</sup> (StatsCan, 2019).

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17 Accessibility to healthcare services is defined by both spatial and aspatial  
18 components (Joseph and Bantock, 1982). Aspatial factors include the cost  
19 and quality of healthcare services and the socioeconomic, demographic, and  
20 mobility profile of potential users. The second component considers geographic  
21 accessibility, which can be defined as the potential to interact with a given set  
22 of opportunities, such as healthcare facilities or primary care physicians, from a  
23 given location using the transportation network (Hansen, 1959). Accessibility to  
24 healthcare can therefore be improved through either an increase in the number of  
25 available opportunities or through improvements to the transportation network.

26 In general, four approaches for calculating accessibility exist: infrastructure-  
27 based, which focuses on the capacity of transportation infrastructure; location-  
28 based, which focuses on spatial distributions of opportunities; person-based,  
29 which focuses on accessibility on an individual level; and utility-based, which  
30 focuses on the utility derived from interacting with the opportunity or partici-  
31 pating in an activity (Geurs and van Wee, 2004). Place-based measures are the  
32 most common in the literature and, of these, the family of “floating catchment  
33 area” (FCA) methods is one of the most popular for calculating measures of  
34 place-based healthcare accessibility that takes the competition for opportunities  
35 into account. Because healthcare access is sensitive to demand and supply, Luo  
36 and Wang (Luo and Wang, 2003) (drawing on Radke and Mu (2000)) introduced  
37 the Two-step Floating Catchment Area (2SFCA) method that first estimates  
38 the demand for healthcare at service locations from population zones and then  
39 allocates the level of service back to the population zones using a binary measure  
40 of travel impedance.

41 Since then, various improvements have been made to the 2SFCA approach  
42 including adjustments to better capture the friction of distance (Apparicio et al.,  
43 2017). The original 2SFCA has also been criticized for over-estimating demand  
44 and under-estimating levels of service in the estimation of accessibilities due  
45 to the multiple-counting of zonal populations that arises from the overlapping  
46 catchments in a study area. In response, researchers have proposed solutions  
47 such as the Three-step Floating Catchment Area (3SFCA) (Wan et al., 2012),  
48 Modified 2SFCA (M2SFCA) (Delamater, 2013), and Balanced 2SFCA (B2SFCA)  
49 (Paez et al., 2019) methods. Of these, the B2SFCA is the only approach that  
50 preserves the original population and resulting levels of service in calculating  
51 floating catchment accessibilities.

52 However, despite these innovations, FCA methods remain limited in several  
53 ways. First, FCA approaches often inflate or deflate demand and supply in the  
54 calculation of healthcare access. While the B2SFCA remedies this, it does so  
55 by assigning fractions of populations to clinics and service ratios to population  
56 zones. Although the parameters of the balanced method sum to the original  
57 zonal populations and provider-to-population ratios, this fractional approach  
58 does not reflect the ways in which individuals choose to visit facilities. Second,  
59 the appeal of any given healthcare facility from the perspective of the population  
60 is based solely on its distance or travel time from the origin zone using the  
61 transportation network.

62 In response, this research utilizes a random utility-based formulation for

63 modelling accessibility to healthcare services. Compared to place-based measures  
 64 of accessibility, utility-based measures of access have a solid grounding in travel  
 65 behaviour theory (Geurs and van Wee, 2004; Miller, 2018) and allow the analyst to  
 66 include any information that corresponds to the expected value or attractiveness  
 67 of travel alternatives as well as characteristics of the individual or household  
 68 making the trip. While commonly used in alternatives appraisals for transport  
 69 infrastructure (de Jong et al., 2007), utility-based measures of accessibility have  
 70 not been as widely applied to capture other types of access. However, they  
 71 appear to be gaining some traction with recent applications considering transit  
 72 accessibility (Nassir et al., 2016), first/last mile access to transit (Hasnine et  
 73 al., 2019), regional accessibility by income class (Jang and Lee, 2020), and  
 74 accessibility to parks (Macfarlane et al., 2020). To the best of our knowledge,  
 75 utility-based methods have not yet been applied to the problem of healthcare  
 76 access.

77 In response, this research proposes a utility-based measure of healthcare  
 78 accessibility based on a multinomial logit (MNL) destination choice model. In  
 79 contrast to FCA approaches, each patient is, on average, assigned to a single  
 80 clinic, avoiding the issue of double-counting and inflation/deflation of the demand  
 81 and levels-of-service respectively in the 2SFCA methods and the assignment of  
 82 fractional individuals to clinics in the B2SFCA method. Beyond travel time, this  
 83 specification also allows the analyst to include additional characteristics of the  
 84 facilities that affect their appeal, such as capacity and competition or crowding  
 85 at the facility.

86 To illustrate the potential of the MNL approach, we compare it against the  
 87 use of the 2SFCA and B2SFCA, both using a continuous decay function. To  
 88 facilitate open and reproducible research in the spatial sciences (Brunsdon and  
 89 Comber, 2020; Páez, 2021), all data and code for this analysis are contained  
 90 within computational notebooks available at (self-citation; .zip of files for review  
 91 available anonymously via Google Drive link).

## 92 **Methodology**

### 93 *Floating Catchment Methods*

94 The 2SFCA method, developed by Luo and Wang (2003), calculates accessi-  
 95 bility to healthcare using catchment areas based on a travel time threshold. The  
 96 first step of this method is calculating the physician- or provider-to-population  
 97 ratio (PPR),  $R_j$ , for each clinic at location  $j$ :

$$R_j = \frac{S_j}{\sum_i P_i W_{ij}} \quad (1)$$

98 where  $S_j$  is the number of physicians at clinic  $j$  and  $P_i$  is the population of zone  
 99  $i$  weighted by some function of the travel time  $W_{ij}$  between zones  $i$  and  $j$ . In  
 100 the original 2SFCA, Luo and Wang (2003) utilize a binary impedance function:

$$W_{ij} = f(t_{ij}) = \begin{cases} 1 & t_{ij} \leq t_0 \\ 0 & t_{ij} > t_0 \end{cases} \quad (2)$$

101 where the weight equals 1 for populations within the travel time threshold  $t_0$   
 102 and zero beyond. In their paper, Luo and Wang (2003) set  $t_0 = 15$  minutes. The  
 103 second step calculates accessibility  $A_i$  for the population centres as the sum of  
 104 the physician-to-population ratios  $R_j$  weighted by the impedance function:

$$A_i = \sum_j R_j W_{ij} \quad (3)$$

105 While the 2SFCA approach is a special case of a gravity-based accessibility  
 106 measure, the binary impedance function used by Luo and Wang (2003) does  
 107 not consider the effects of competition and travel impedance within a given  
 108 catchment area. All clinics within a population centre's catchment area are  
 109 considered equally accessible, regardless of distance, size, wait times, or any other  
 110 measures of attractiveness. Moreover, all clinics outside of a population centre's  
 111 catchment area are considered completely inaccessible. To remedy this, Luo and  
 112 Qi (2009) propose the Enhanced 2-step Floating Catchment Area (E2SFCA)  
 113 method that introduces categorical weights for different travel time thresholds to  
 114 account for travel impedance. Others have improved on the 2SFCA and E2SFCA  
 115 by using variable catchment sizes (McGrail and Humphreys, 2009), continuous  
 116 travel time decay functions (Dai, 2010), and adaptive approaches (Bauer and  
 117 Groneberg, 2016) to better reflect travel time costs and the greater appeal of  
 118 more proximate opportunities.

119 Researchers have also sought to improve the ways in which supply and  
 120 demand are modeled in floating catchment approaches. Previous research has  
 121 shown that both demand and supply can be inflated/deflated in FCA methods  
 122 (Delamater, 2013; Paez et al., 2019; Wan et al., 2012). This is a consequence of  
 123 the overlapping floating catchments that cause the populations in zones  $i$  to be  
 124 counted multiple times in the calculation of the provider-to-population ratio  $R_j$ .  
 125 These levels-of-service are, in turn, counted multiple times when allocated back  
 126 to the population zones in the calculation of  $A_i$ . In practice, the inflation of  
 127 demand in the first stage of the 2SFCA is generally cancelled out in the second  
 128 stage when calculating accessibility. However, researchers may be interested in  
 129 returning more meaningful measures of levels-of-service at the clinics to support  
 130 the allocation of healthcare resources. In response, Wan et al. (2012) propose  
 131 the use of additional Gaussian weights to modify the binary impedance function  
 132 used by Luo and Wang (2003). This results in a steeper impedance function  
 133 that discounts demand and supply. Corrections have also been made to discount  
 134 accessibility. Delamater's (2013) M2SFCA modifies the second step of the 2SFCA  
 135 to increase the rate of decay on the level-of-service available to population zones.  
 136 This is done to address the insensitivity of FCA approaches to the absolute  
 137 distances required to reach facilities in the calculation of accessibility. The result  
 138 reflects the increased friction population centres may experience when accessing  
 139 healthcare facilities in sub-optimally configured urban systems.

140 However, neither of these approaches fully resolves the issue of demand and  
 141 supply inflation/deflation. To that end, the B2SFCA approach from Páez et al.  
 142 (2019) replaces the impedance functions with row-standardized weights  $W_{ij}^i$  in

<sup>143</sup> the first step:

$$R_j = \frac{S_j}{\sum_i P_i W_{ij}^i} \quad (4)$$

$$W_{ij}^i = \frac{W_{ij}}{\sum_j W_{ij}} \quad (5)$$

<sup>144</sup> and with column-standardized weights  $W_{ij}^j$  in the second step:

$$A_i = \sum_j R_j W_{ij}^j \quad (6)$$

$$W_{ij}^j = \frac{W_{ij}}{\sum_i W_{ij}} \quad (7)$$

<sup>145</sup> In this formulation, the travel-time weighted populations sum to the original  
<sup>146</sup> population values and do not deflate the level-of-service at the clinics. These  
<sup>147</sup> levels-of-service reflect local PPRs at the clinic level. By extension, the levels-  
<sup>148</sup> of-service available at the population centres are not inflated through multiple  
<sup>149</sup> counting. Nevertheless, despite offering balance across both stages of the FCA  
<sup>150</sup> approach, the B2SFCA also results in fractional apportionment of the population  
<sup>151</sup> and levels-of-service between the population zones and clinics.

<sup>152</sup> For this research, both the 2SFCA and B2SFCA approaches are specified  
<sup>153</sup> with a negative exponential impedance function:

$$W_{ij} = e^{-\beta t_{ij}} \quad (8)$$

<sup>154</sup> where  $\beta$  is a parameter that determines the decay of the function and  $t_{ij}$  is the  
<sup>155</sup> travel time between clinic  $j$  and population centre  $i$ . The  $\beta$  parameter is set to  
<sup>156</sup> 0.05 as this is in the range of typical auto travel time parameters in logit mode  
<sup>157</sup> choice models calibrated in the Greater Toronto and Hamilton Area (Kasraian et  
<sup>158</sup> al., 2020). Travel times are calculated based on car travel using a street network  
<sup>159</sup> from OpenStreetMap and the `r5r` routing tool (Pereira et al., 2021).

#### <sup>160</sup> Utility-based Method

<sup>161</sup> To address the limitations of existing methods, a novel methodology for de-  
<sup>162</sup> riving utility-based accessibility is developed which assigns trips from households  
<sup>163</sup> in population centres to clinics. The general form of this function is as follows:

$$T_{ij} = f(H_i, Z_j, D_j, t_{ij}, \beta) \quad (9)$$

<sup>164</sup> where:

- <sup>165</sup> •  $T_{ij}$  is the number of trips from zone  $i$  to clinic  $j$
- <sup>166</sup> •  $H_i$  is the number of households in zone  $i$
- <sup>167</sup> •  $Z_j$  is the number of doctors at clinic  $j$
- <sup>168</sup> •  $D_j$  is the demand-to-capacity ratio at clinic  $j$  (note this is inverted from  
the physician-to-population ratios used in previous FCA approaches)

- 170     •  $t_{ij}$  is the travel time between zones  $i$  and  $j$ , and  $\beta$  is a row vector of  
171     parameters to be estimated.

172     To estimate these parameters, information minimization is used as this  
173     approach allows for the least-biased parameter estimation and has been proven  
174     to be identical to utility maximization (Anas, 1983). Based on information  
175     minimization theory, the probability that a household in zone  $i$  will visit clinic  $j$   
176     can be estimated as follows:

$$MAX_{T_{ij}} E = - \sum_{j \in J} \sum_{i \in I} T_{ij} \log(T_{ij}) \quad (10)$$

177     subject to the following constraints:

$$\sum_{j \in J} T_{ij} = \alpha H_i \forall i \in I \quad (11)$$

$$\sum_{i \in I} \sum_{j \in J} T_{ij} t_{ij} = \bar{t} T \quad (12)$$

$$\sum_{i \in I} \sum_{j \in J} T_{ij} \log(C_j) = \sum_{i \in I} \sum_{j \in J} T_{ij} \log \omega Z_j = \bar{C} T \quad (13)$$

$$\sum_{i \in I} \sum_{j \in J} T_{ij} D_j = \bar{D} T \quad (14)$$

178     where:

- 179     •  $I$  is the set of all residential zones  
180     •  $J$  is the set of all clinics  
181     •  $\alpha$  is the average number of visits to the doctor per household  
182     •  $\bar{t}$  is the average observed travel time for home-based trips to clinics  
183     •  $T$  is the total number of daily trips to clinics  
184     •  $C_j$  is the nominal service capacity at clinic  $j$   
185     •  $\omega$  is the average number of patients served by a doctor per day  
186     •  $\bar{C}$  is the average observed nominal service capacity  
187     •  $\bar{D}$  is the average observed demand-to-capacity ratio  
188     •  $H$  is the total number of households  
189     •  $Z$  is the total number of primary care physicians

190     The service capacities and demand-to-capacity ratios are calculated as follows:

$$C_j = \omega Z_j \quad (15)$$

$$D_j = \frac{\sum_{i \in I} T_{ij}}{C_j} = \frac{\sum_{i \in I} T_{ij}}{\omega Z_j} \quad (16)$$

191     Solving this set of equations yields the following:

$$T_{ij} = \alpha H_i Pr_{ij} \quad (17)$$

192 This is a singly-constrained gravity model where the probability that a household  
 193 in zone  $i$  will visit clinic  $j$  is as follows:

$$Pr_{ij} = \frac{e^{\beta_1 t_{ij} + \beta_{K+2} \log \omega Z_j + \beta_{K+3} D_j}}{\sum_j' e^{\beta_1 t_{ij}' + \beta_{K+2} \log \omega Z_j' + \beta_{K+3} D_j'}} \quad (18)$$

194 Ideally, the three  $\beta$  parameters would be estimated iteratively in order to  
 195 meet the outlined constraints. However, due to a lack of observed data on trips  
 196 to doctors in the study area, these parameters are instead chosen based on the  
 197 following considerations:

- 198 • The  $\beta_1$  travel time impedance parameter is set to -0.05 to align with the  
 199 choice model rationale outlined in the 2SFCA and B2SFCA approaches  
 200 above.
- 201 • Random utility theory requires the  $\beta_{K+2}$  capacity attractiveness parameter  
 202 to lie between 0 to 1 in value. It is set equal to 1 in this case to maximize  
 203 the attractiveness of larger clinics with more physicians.
- 204 • No theory is currently available to guide the choice of the  $\beta_{K+3}$  parameter  
 205 that influences sensitivity to overcrowding when trip demand exceeds  
 206 the capacity to see patients at a clinic. In this case, -0.5 is chosen as a  
 207 “first guess” value that would produce a reasonable sensitivity to clinic  
 208 over-crowding, but not prevent over-crowding from occurring.

209 These values ensure that increased travel times and demand-to-capacity  
 210 ratios reduce the probability that a household in zone  $i$  will visit clinic  $j$ , while  
 211 increased capacity at clinic  $j$  increases the probability. Since  $D_j$  is a function of  
 212  $T_{ij}$  and vice-versa, an iterative approach is taken to estimate the  $D_j$  values. The  
 213 multinomial logit destination choice model ensures that demand at clinics is not  
 214 over-estimated, as each patient on average is assigned to a single clinic and is not  
 215 double counted, as occurs in the 2SFCA method. The end result is an approach  
 216 that involves location choice modelling by maximizing utility for patients, with  
 217 clinics with higher demand and longer travel times attracting fewer trips while  
 218 larger clinics that are uncongested and those closer to the origins attract more  
 219 trips.

#### 220 *Utility-based Accessibility*

221 While the probability of visiting a particular clinic is based on its utility  
 222 relative to the utility of others available within the choice set, following Ben-Akiva  
 223 and Lerman (1985), the expected maximum utility from all destination choices  
 224 available to a household can be understood as a random utility theory-based  
 225 measure of accessibility. For the multinomial logit (MNL) model, it can be  
 226 shown that this is the logarithm of the denominator in Equation 18 (the so-  
 227 called “logsum” or “inclusive value” term), yielding for this model the following  
 228 accessibility measure:

$$A_i = \log\left(\sum_{j'} e^{\beta_1 t_{ij'} + \beta_{K+2} \log \omega Z_{j'} + \beta_{K+3} D_{j'}}\right) \quad (19)$$

229 where accessibility is based not only on the utility of the clinic with the greatest  
 230 probability of visitation, but the utility of all clinics available to a household  
 231 considering travel impedance, clinic size and capacity, trip-based demand for  
 232 primary care physicians, and congestion or crowding.

### 233 Study Area

234 The study area for this research is the City of Hamilton in Ontario, Canada.  
 235 Based on data from the 2016 Canadian Census of Population, the population of  
 236 Hamilton is 536,917 living in 211,596 households. The left panel of Figure 1 plots  
 237 population densities in the Dissemination Areas (DAs) in the City of Hamilton,  
 238 highlighting that the higher-density urban core is surrounded by lower-density  
 239 suburbs that extend into land that is largely rural in character. DAs are the  
 240 smallest geographic unit for which socioeconomic and demographic census data  
 241 are publicly available.

242 Information on the count and location of primary care physicians was obtained  
 243 using the College of Physicians and Surgeons of Ontario's online registration  
 244 database. Clinic locations were geocoded based on their address and records  
 245 were aggregated to count the number of physicians practicing at each unique  
 246 location. The data for this paper have been used previously by Páez et al. (2019),  
 247 although in this case we consider only clinics that are within the spatial extent of  
 248 the City of Hamilton. While this does introduce edge effects in the calculation of  
 249 accessibility, limiting the study extent to a closed system permits calculation of  
 250 the multinomial logit model's congestion effects and utility-based accessibilities.  
 251 In total, there are 631 primary care physicians available at clinics in the City of  
 252 Hamilton in our data. Note that this is not strictly the number of physicians, as  
 253 some physicians offer services at more than one clinic. Rather, it reflects the  
 254 availability of physicians at given locations. The right panel of Figure 1 plots  
 255 the location and total number of available physicians at the clinic locations.  
 256 This total produces a city-wide average physician-to-population ratio of 117.52  
 257 primary care doctors available per 100,000 people.

258 Populating the MNL model requires the specification of several parameters  
 259 related to the study area. In order to ensure that the average observed demand-  
 260 to-capacity ratio  $\bar{D}$  is approximately equal to 1, the  $\alpha$  and  $\omega$  parameters are  
 261 assumed to be 22 patients seen by a doctor per day and 0.065 visits to the doctor  
 262 per household per day respectively. The patients per day number is derived  
 263 from the Canadian Institute for Health Information who reports that the median  
 264 number of patients seen by primary care physicians during a typical work week in  
 265 Ontario was 100 in 2019 (CIHI, 2020). At an assumed 20 patients per day over a  
 266 5-day work week and 50 weeks in a typical year after holidays, this results in an  
 267 estimated patient capacity of approximately 3.2 million patients per year across  
 268 the 631 primary care physicians in the data, or 5.9 visits per person per year.

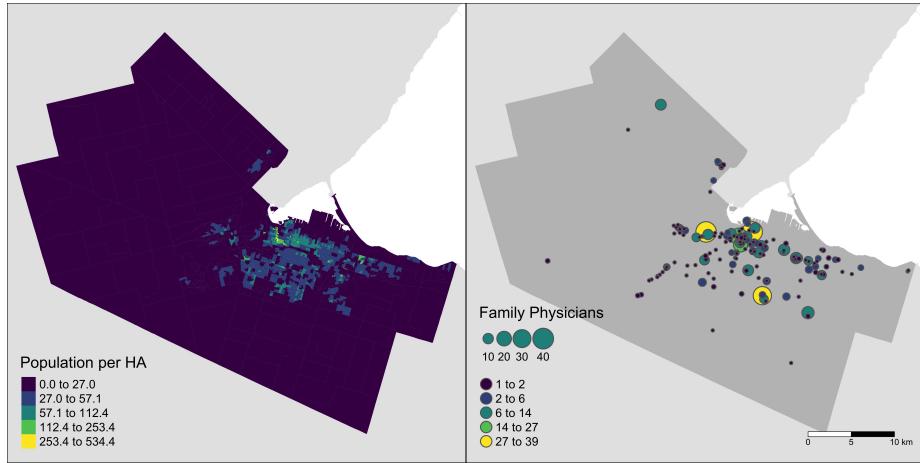


Figure 1: Population Density and Physician Locations

269 On the other hand, Vogel (2017) reports a Canada-wide average of 7.6 visits per  
 270 person per year in 2016, which would result in demand for approximately 4.1  
 271 million visits per year from the population residing in the City of Hamilton.

272 Taking into consideration that Hamilton is part of the larger Greater Golden  
 273 Horseshoe region, meaning not all trips and visits are bounded by the study area  
 274 and that there are uncertainties surrounding the estimated visits per year and  
 275 physician practices, we slightly increased the CIHI's number of patients seen per  
 276 physician per week from 100 to 110. This corresponds to 22 visits per day and a  
 277 capacity of 6.46 visits per person per year. Based on our assumption of  $\alpha = 22$ ,  
 278 this results in a total capacity of 13,882 patient visits per day in the MNL model  
 279 formulation. Dividing the total estimated number of daily trips by the number  
 280 of households yields a household trip generation rate of approximately 0.065  
 281 trips per household per day for 13,753.74 trips to the doctor entering the MNL  
 282 model.

## 283 Results

### 284 Demand and Clinic Level of Service

285 To compare the three methods, we focus first on the results associated with  
 286 how each of the methods calculates demand and levels of service at the clinic  
 287 locations. The level of service for the FCA approaches is the local provider-  
 288 to-population ratio (PPR) for each clinic while the MNL model calculates trip  
 289 demand-to-patient capacity ratios (DCR). To make this comparable, we first take  
 290 the inverse of the MNL ratios to reflect patient capacity-to-trip demand ratio  
 291 (CDR). Figure 2 displays a pair plot of the density of each level-of-service statistic  
 292 and their relationship and correlations with one another. The plot highlights  
 293 how the 2SFCA and B2SFCA methods are fundamentally similar in the ways  
 294 in which they allocate demand to the clinics with only a few clinics above or

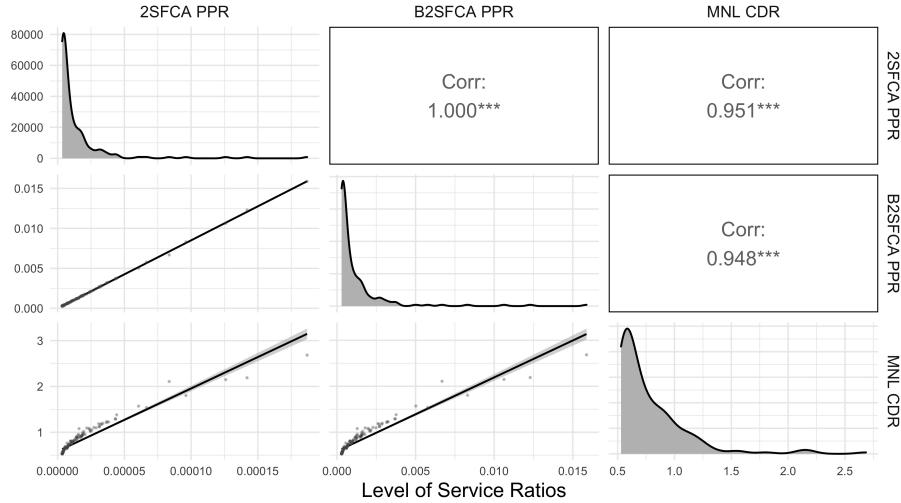


Figure 2: Comparing Level of Service Distributions (Clinics)

295 below the scatterplot trend line. Likewise, it is interesting to note the relatively  
 296 high correlations between the PPRs at the clinics in the FCA methods and the  
 297 capacity-to-demand ratios in the MNL model with the scatterplot revealing some  
 298 non-linearity in this relationship across the methods.

299 Figure 3 displays the levels of service for the clinic locations. In general, more  
 300 urban clinics tend to exhibit higher levels of demand and lower levels of service  
 301 across all three models. However, the PPR values for the individual clinics in  
 302 the 2SFCA are extremely small compared to results from the B2SFCA model,  
 303 highlighting how the original method's multiple counting tends to inflate the  
 304 (travel time weighted) population numbers in each clinic's catchment and deflate  
 305 the level of service available at the clinics. In contrast, the PPRs in the B2SFCA  
 306 method are readily interpretable as the local ratio of doctors per person for a  
 307 given clinic considering the (travel-time weighted and apportioned) populations  
 308 within its catchment. Similarly, the MNL CDRs reflect the relationship between  
 309 trip demand and patient capacity based on the assumed rates. In terms of spatial  
 310 trends, results from the 2SFCA and MNL models suggest both calculate higher  
 311 levels of service at larger clinics in the urban core as well as at a larger clinic in  
 312 the city's rural north-west. In contrast, the B2SFCA method generally produces  
 313 higher levels of service in an east-to-west direction. This could reflect boundary  
 314 effects in the study area that omit the large populations present in the rest of  
 315 the Greater Toronto Area on the northern side of Lake Ontario that may also  
 316 have access to these clinics by driving.

317 *Healthcare Accessibility*

318 With the levels of service calculated above, the three models then calculate  
 319 accessibility to healthcare services in Hamilton. Distributions, relationships, and

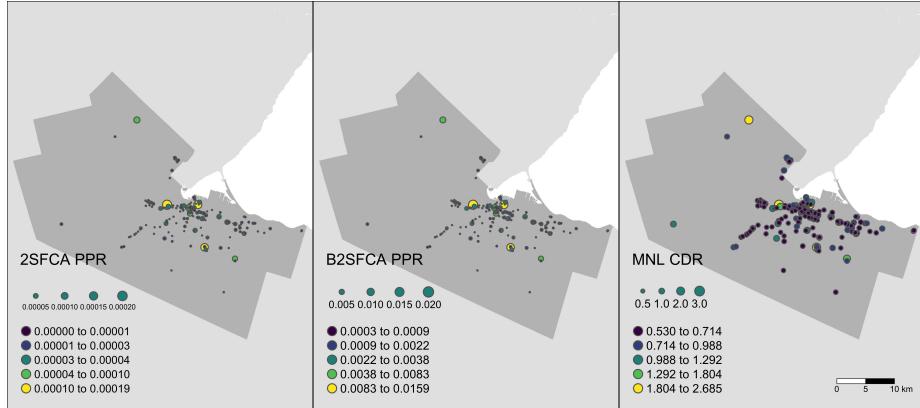


Figure 3: Mapping Levels of Service (Clinics)

correlations for the accessibility results are shown in Figure 4. In this case, all three models are highly correlated. The 2SFCA and B2SFCA produce nearly identical distributions of results. As above, their main difference is in the scaling of parameters. In the 2SFCA, accessibilities can be interpreted relative to the city-wide average provider-to-population ratio of 0.0012 doctors per person. In the case of the balanced method, the accessibilities correspond to the sum of travel time weighted and apportioned provider-to-population ratios available in the population zones free of the inflation and deflation that occurs in the 2SFCA. In contrast, the scatterplots of the MNL results again highlight some non-linearity in the way the utility-based accessibilities are calculated compared to the FCA methods. The thinner tail of the MNL distribution suggests the method also results in fewer population zones with lower accessibility compared to the FCA methods.

The general spatial trends are similar across all three models (Figure 5). The absolute accessibility values differ in accordance with the ways each method calculates its accessibility results. The FCA methods define accessibility based on the physician-to-population ratios of clinics, resulting in smaller values. In contrast, the MNL method defines accessibilities as the logsum of the denominator of the multinomial logit model, resulting in larger values that have no direct physical interpretation. In general, the highest accessibilities to primary care physicians correspond to the downtown area of Hamilton, where a large number of clinics are concentrated. Accessibility to physicians generally decreases with increased distance from the downtown area.

To better highlight significant differences in the spatial patterns of accessibility produced by each method, Figure 6 displays the absolute differences in normalized accessibilities across models. To make the values comparable, we first normalize each accessibility vector between 0-1 and take the differences of the normalized values across each approach. In general, the MNL method tends to produce higher accessibilities for most zones compared to the FCA methods. In line

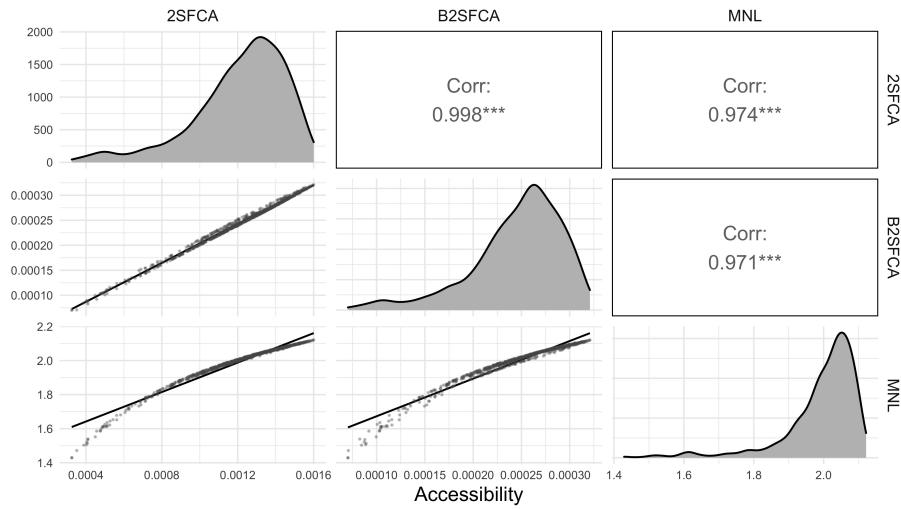


Figure 4: Comparing Accessibility Distributions (DAs)

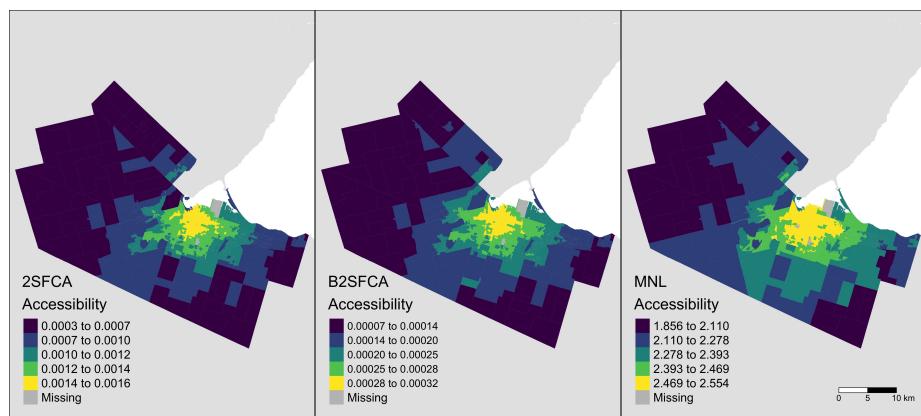


Figure 5: Mapping Accessibility Results (DAs)

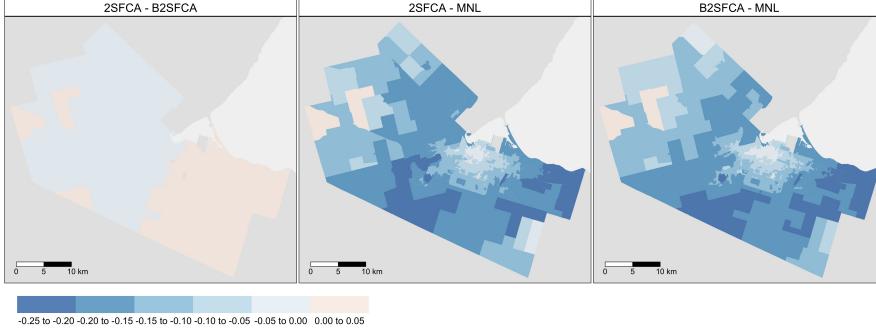


Figure 6: Normalized Accessibility Differences

349 with the distributions above, the 2SFCA and B2SFCA models appear to be  
 350 most similar, with only slight absolute differences in the calculated accessibility  
 351 values. Nevertheless, paired Wilcoxon Rank Sum tests across all three types  
 352 of normalized accessibilities are statistically significant at  $p = 0.05$ , suggesting  
 353 that while the accessibility results are highly correlated, their distributions are  
 354 significantly different.

355 To examine whether there are any spatial patterns in these differences, Figure  
 356 7 plots the results of Local Moran's I tests. The Local Moran's I is calculated  
 357 on the differences using queen-style contiguity weights, a critical significance  
 358 level of  $p = 0.05$ , and without correcting for multiple testing. The resulting  
 359 maps reveal some interesting patterns of spatial clustering in the calculated  
 360 normalized differences, particularly across the two FCA models compared to  
 361 the MNL model. Here, differences in accessibility are greatest between the FCA  
 362 and MNL methods in the low-low (LL) cluster in the ring of outer suburbs that  
 363 surround the city where the MNL model tends to estimate higher accessibilities.  
 364 In contrast, the calculated accessibilities are more consistent across the methods  
 365 in the high-high (HH) cluster in the central part of the city. Differences in  
 366 the remaining zones are generally not significant (NS) aside from a very small  
 367 number of high-low (HL) and low-high (LH) outliers.

368 This overall pattern is likely due to the way the MNL approach handles  
 369 clinic choices and accessibilities. Higher accessibilities in the urban core are  
 370 generally due to populations having access to a larger number of clinics that are  
 371 closer, have higher capacities, and are less congested. The iterative trip-based  
 372 calculations in the MNL model should also result in fewer individuals from  
 373 more urban locations competing for healthcare resources at more suburban and  
 374 rural clinics, leading to higher accessibilities in these areas relative to the other  
 375 methods. In contrast, the FCA methods allocate populations to all clinics within  
 376 their catchment area using weights derived from the impedance function. While  
 377 this produces a smoothing of the accessibilities, it can result in lower levels of

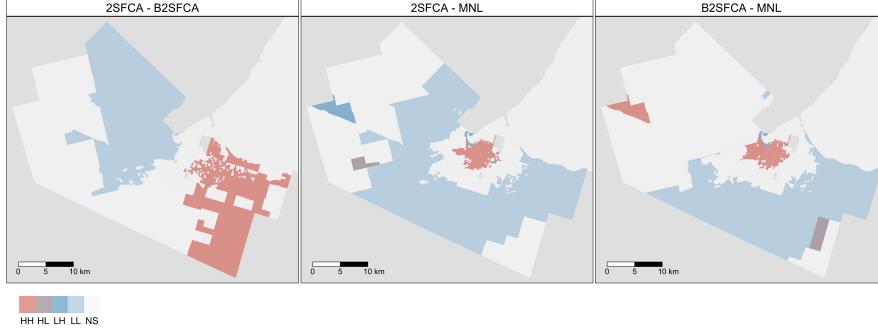


Figure 7: Accessibility Difference Hot Spots

378 service and accessibility for clinics that populations may not actually use. This  
 379 effect seems to be minimized in more urban locations featuring higher population  
 380 densities and a greater number of clinics with available physicians. Comparing  
 381 the normalized results from the 2SFCA and the B2SFCA models, the patterns of  
 382 spatial clustering in the differences appears to be less associated with the city's  
 383 urban-suburban-rural urban structure. While the B2SFCA method generally  
 384 calculates slightly higher accessibilities across the western half of the city, the  
 385 2SFCA produces slightly higher accessibilities in the east.

#### 386 *MNL Model Sensitivity Analysis*

387 In order to assess the impact of the asserted  $\beta_{K+2}$  and  $\beta_{K+3}$  parameters on  
 388 the results generated by the MNL method, a sensitivity analysis was undertaken.  
 389 The  $\beta_{K+2}$  parameter that influences the attractiveness of higher-capacity clinics  
 390 was gradually increased from 0.1 to 1 and the  $\beta_{K+3}$  parameter that influences  
 391 sensitivity to congestion or crowding at the clinics was gradually increased  
 392 from -1 to -0.1. Increments of 0.1 are used for each variable. Results are  
 393 summarized by calculating average CDRs and accessibilities across the clinics  
 394 and DAs respectively in each of the 100 scenarios (Figure 8). Two example  
 395 scenarios are also created for illustration. In Scenario 1, the  $\beta_{K+2}$  parameter  
 396 was decreased from 1 to 0.5 relative to the original calculations while the  $\beta_{K+3}$   
 397 parameter was decreased from -0.5 to -1 in Scenario 2 (increasing the sensitivity  
 398 to overcrowding).

399 For the CDRs in the left panel of Figure 8, the sensitivity analysis reveals that  
 400 decreasing sensitivity to the attractiveness of capacity (as  $\beta_{K+2}$  approaches 0.1)  
 401 and decreasing sensitivity to overcrowding (as  $\beta_{K+3}$  approaches -0.1) combine  
 402 to produce more balance between the supply of physician capacities and patient  
 403 demand, on average. Examining the clinic data in greater detail, this weighting  
 404 results in more trips being made to smaller and more congested clinics relative to  
 405 larger ones where there is more supply relative to demand. Greater weight placed

406 on facility capacity (as  $\beta_{K+2}$  approaches 1) and high sensitivity to overcrowding  
407 (as  $\beta_{K+3}$  approaches -1) also results in more balanced CDRs, but in this case,  
408 more trips are made to larger clinics that become more congested versus smaller  
409 ones that are less congested. Scenarios along the diagonal exhibit relatively less  
410 balance, on average, across the clinics.

411 In terms of accessibilities, average accessibilities are, in general, more sensitive  
412 to changes in the  $\beta_{K+2}$  parameter than  $\beta_{K+3}$ . Comparing the original results  
413 against Scenario 1, average accessibilities increase by around 22% when  $\beta_{K+2}$   
414 increases from 0.5 to 1. In contrast, accessibilities in the original scenario  
415 are about 11% greater than those calculated from Scenario 2 where the  $\beta_{K+3}$   
416 sensitivity to overcrowding parameter increases in weight from -0.5 to -1. The  
417 greatest average accessibilities in Figure 8 result from high attractiveness to  
418 clinic capacity and low weight on overcrowding ( $\beta_{K+2} = 1$  and  $\beta_{K+3} = -0.1$ ).  
419 This produces high levels of average access as households benefit from the overall  
420 availability of large clinics accessible by car despite the greater levels of congestion  
421 that occur at smaller clinics.

422 To examine whether the sensitivity analysis impacts the spatial distributions  
423 of calculated accessibilities, Figure 9 plots normalized accessibility results from  
424 the original and two sensitivity scenarios. Although both adjustments to the  
425 parameters result in decreased absolute accessibilities in Figure 8, comparisons  
426 of normalized values suggest there are no distinct spatial trends associated with  
427 changes in  $\beta_{K+2}$  and  $\beta_{K+3}$  across the sensitivity scenarios. Overall, both Figures  
428 8 and 9 indicate that the MNL results are relatively robust with respect to the  
429 parameter value assumptions. CDR average values are relatively constant across  
430 wide combinations of parameter values (except at the extremes of values), and  
431 the relative spatial distributions of average accessibilities are quite consistent as  
432 parameter values change. In addition, both the average CDRs and accessibility  
433 values change in expected ways as the parameters are varied, providing some  
434 indication of behavioral soundness of the MNL specification.

#### 435 Discussion and Conclusions

436 Since the 2SFCA was proposed by Luo and Wang (2003), the floating catchment  
437 area approach has been a popular one for calculating place-based accessibility  
438 to healthcare services that considers both the supply and demand components  
439 and several key innovations have been made to FCA methods since. However,  
440 FCA methods are still limited in two important ways. First, FCA methods do  
441 not fully consider aspects of travel and choicemaking behaviour. Like many of  
442 the other place-based accessibility measures, the only behavioural component  
443 of FCA methods is the impedance function that is used to weight the value of  
444 opportunities by the distance or travel time required to reach them. Second,  
445 FCA approaches also tend to assign population demand and levels-of-service to  
446 facilities or population zones in an overlapping manner, using the impedance  
447 function (and other adjustments) to weight each value within a catchment area.  
448 Crucially, this use of overlapping catchment areas in previous FCA approaches  
449 has been shown to inflate/deflate supply and demand. Although the B2SFCA

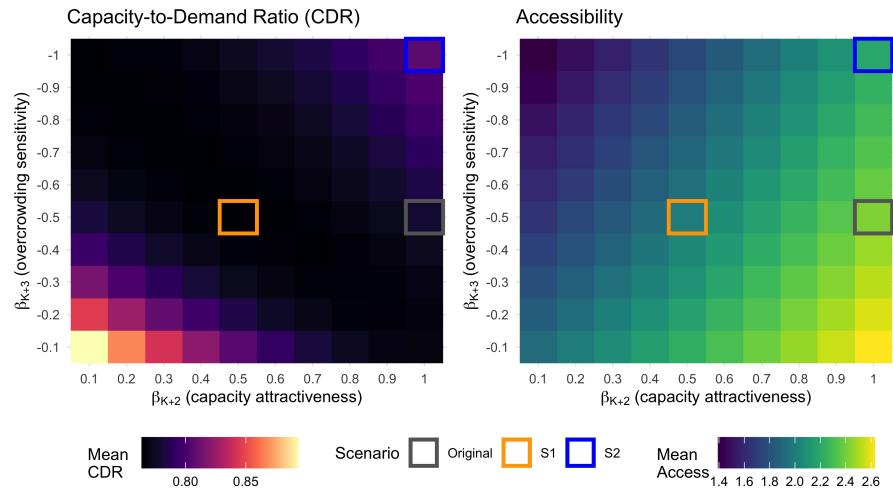


Figure 8: MNL Sensitivity Analysis Results

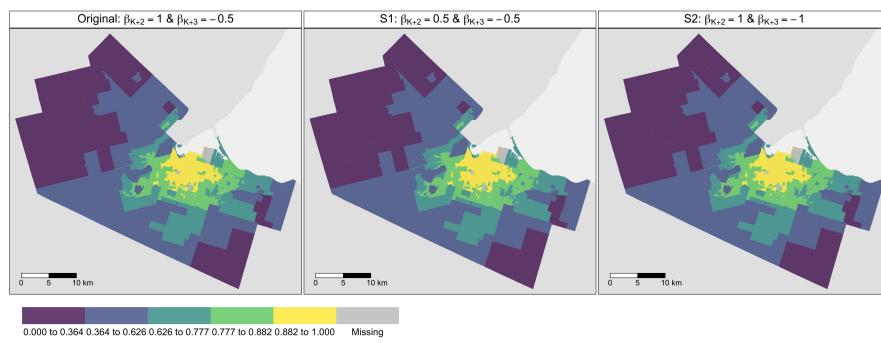


Figure 9: Sensitivity Scenario Maps

450 proposed by Páez et al. (2019) rectifies this, it does so by apportioning fractions  
451 of populations and levels-of-service through adjustments to the impedance  
452 function.

453 To respond to these issues, this research developed a multinomial logit  
454 destination choice model for calculating utility-based transportation accessibility  
455 to primary care physicians. While FCA approaches consider accessibility in  
456 terms of provider-to-population ratios weighted by distance or travel time, the  
457 MNL approach re-frames the measurement of health accessibility into individual  
458 trips to visit primary care physicians and the utility-bearing aspects of clinics.  
459 With its comparatively strong basis in random utility theory, the MNL model  
460 considers several additional aspects that define the appeal of clinics in addition  
461 to the travel time required to reach them, including the number of physicians  
462 available at the clinic and the level of crowding. The destination choice model  
463 also avoids multiple-counting as the iterative fitting procedure results in the  
464 assignment of each patient trip to a single clinic on average.

465 Comparisons of the MNL approach with 2SFCA and B2SFCA models using  
466 data for the City of Hamilton suggests that the accessibility patterns produced  
467 by each method are broadly similar, with the highest accessibilities in the central  
468 core of the city where many clinics and physicians are located. However, further  
469 analysis of the distributions, correlations, and spatial clustering of accessibility  
470 differences reveals that the MNL method produces generally higher accessibilities  
471 throughout much of Hamilton with the greatest differences seen in the ring of  
472 suburban and rural zones that surround the city. These results are generally  
473 a product of the MNL model assigning higher trip probabilities to the most  
474 proximate clinic for suburban and rural residents while more urban residents  
475 are being drawn to more urban clinics. From this, the expected maximum  
476 utility (logsum) measure being used to define accessibility recognizes that in  
477 addition to the benefits derived from having access to the closest or largest  
478 clinics, people will tend to find the “best” clinic for their needs. In contrast, the  
479 FCA approaches assign population values to all clinics within their catchment  
480 area and all population zones share the levels-of-service of accessible clinics,  
481 likely leading to higher demand and lower available supply at these rural and  
482 suburban clinics.

483 Our analysis suggests that both the FCA and MNL approaches offer merit.  
484 The 2SFCA is generally straightforward to calculate with limited data requirements  
485 and returns accessibilities that can be interpreted relative to city-wide  
486 provider-to-population ratios. However, as a consequence of multiple counting,  
487 the 2SFCA method has been shown to significantly inflate population levels in the  
488 accessibility analysis that deflate clinic levels of service. The B2SFCA requires  
489 the same data as the 2SFCA method but preserves the population being serviced  
490 and returns interpretable levels of service for clinics. Accessibilities calculated  
491 using the B2SFCA method are interpretable as each population centre’s share  
492 of the levels-of-service available at clinics within their catchment. Results from  
493 both the 2SFCA and B2SFCA approaches are very highly correlated, indicating  
494 that while they return different values, they fundamentally capture much of the  
495 same information. However, the only travel behaviour component in both the

496 2SFCA and B2SFCA approaches is the impedance function. While it does tend  
497 to result in the greatest weight placed on the nearest locations in practice, it  
498 still results in a spreading or smoothing of demand and supply as populations  
499 are allocated across multiple clinics.

500 In contrast, the MNL model's utility-based approach has a stronger behavioral  
501 foundation in terms of tripmaking and competition and considers more aspects  
502 that define the appeal of particular clinics, such as capacity. It also appears to  
503 produce what are arguably more realistic results in suburban and rural areas,  
504 suggesting that compared to the fixed travel time catchments used in the FCA  
505 approaches in the present work, the MNL method can more dynamically account  
506 for changes in supply and demand associated with variations in a city's urban  
507 structure. The MNL approach, however, requires additional parameters to be  
508 estimated relative to the other models. Calibrating the model's parameters to  
509 match observed trip distributions would be ideal. Such data are not available  
510 in the present case. There is no reason, however, why the needed data could  
511 not be gathered, either as part of typical large-scale travel surveys that are  
512 routinely collected in most urban regions, or through custom surveys of clinic  
513 patients conducted by public health agencies. The data could also be gleaned  
514 from government health billing records, which are already often used in a wide  
515 variety of epidemiological studies.

516 While the MNL expected maximum utilities associated with accessible clinic  
517 destinations do not have the same direct healthcare interpretation of the PPRs  
518 generated by the FCA approaches, they do have an important economic inter-  
519 pretation. They represent the consumer surplus associated with clinic visits, and  
520 hence are a direct economic measure of social welfare (Ben-Akiva and Lerman,  
521 1985). Further, while not undertaken in this paper, the logsum values can be  
522 converted into equivalent units of either travel time or money, thereby providing  
523 a more interpretable measurement, and opening the possibility of including the  
524 measure in broader assessments of the benefits of investing in greater health care  
525 accessibility (Miller, 2018).

526 In terms of extensions to planning and policy, it has been argued that com-  
527 pared to place-based measures, utility-based measures of accessibility are more  
528 difficult to explain and understand in general (Geurs and van Wee, 2004). Never-  
529 theless, while FCA-based approaches can account for some degree of competition  
530 when calculating accessibility and may be easier to interpret, the results gener-  
531 ated from such place-based measures more disconnected from microeconomic  
532 theories associated with choicemaking behaviour and consumer surplus that  
533 ground utility-based models of access. Thus, while this paper focuses on compar-  
534 ing and contrasting the two approaches, there is no reason why there needs to  
535 be an "either/or" choice between the two methods. They might most properly  
536 be viewed as complementary, providing different insights into the same problem.

537 Finally, it is important to note that this paper only focuses on the spatial  
538 component of accessibility and does not consider the aspatial components that  
539 also play a significant role in defining an individual's potential to reach and  
540 utilize healthcare services (Joseph and Bantock, 1982). In this regard, future  
541 research should utilize the FCA and MNL approaches for welfare analysis to

measure place- and utility-based accessibility to primary healthcare services for different socioeconomic, demographic, and mobility profiles. To this end, place-based accessibility analysis can indirectly consider aspects of welfare and equity by incorporating factors such as income and mode share (e.g. Higgins et al. (2021)). Nevertheless, areal average accessibilities calculated for different places may not reflect the subjective preferences, tastes, or needs of heterogeneous individuals or households. In this regard, the flexibility of random utility-based approaches can also allow for individual- or household-level characteristics to be modelled directly as part of tripmaking behavior and social welfare analyses.

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