



Comment on “A Conceptual Framework for Quality Healthcare Accessibility: a Scalable Approach for Big Data Technologies”

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Abstract

Floating Catchment Area (FCA) metrics incorporate the supply of health care resources, potential population demand for those resources, and the distance separating people and supply locations to characterize the spatial accessibility of health care resources for populations. In this work, I challenge a number of assertions offered in a recently published FCA-based paper and provide a critique of the authors' proposed metric. Within my critique, I present a number of broad observations and recommendations regarding FCA metrics and their implementation in a Geographic Information System (GIS). In doing so, I aim to initiate a broader discussion of access to health care, spatial accessibility, and FCA metrics that transcends disciplinary boundaries.

Keywords Geographic information systems · Health care analytics · Health care accessibility · Gravity models

1 Introduction

Floating Catchment Area (FCA) metrics are an oft-used measure of the spatial or geographic aspects of a population's access to health care services such as primary care physicians or hospitals, as well as other amenities such as urban parks, public transportation hub, and childcare facilities. The FCA family of metrics were born out of gravity-based spatial interaction models that use (metaphorically) the Newtonian law of gravity to model the “attraction” felt between people and locations. In health care applications, FCA metrics simultaneously integrate the supply of health care services available, the potential demand for those services, and the distance separating the people and facilities in their formulation. They provide a measure of *spatial accessibility*, which characterizes the opportunities available to a population as moderated by potential competition for those opportunities (availability) and distance (accessibility) (Guagliardo, 2004). In doing so, FCA metrics overcome the known limitations of using container-based measures of regional availability (i.e., opportunities per person ratios based on administrative boundaries) and simple

distance-based measures of accessibility as separate measures of geographic access. FCA metrics also retain the output units of opportunities per person, which are easy to understand and interpret in evaluation, regulation, and planning applications.

In a recently published paper, Plachkinova et al. (2018) review a number of currently-available FCA metrics, offer an implementation of a new FCA metric that integrates hospital quality information, and discuss the use of FCA metrics in big data applications. The authors' efforts towards tackling these difficult propositions are commendable. Their idea to integrate health care quality information within the FCA framework is novel and appealing. Initiating the discussion of how FCA metrics fit into the era of high-powered computational abilities and big data is a noteworthy endeavor. Furthermore, utilizing the Design Science Research paradigm to conceptualize their research appears to be an innovative approach that has not been attempted in prior FCA-based research.

While Plachkinova et al.'s article contains the noted positive aspects, it also includes a number of general misrepresentations regarding current FCA metrics, their conceptual underpinnings, and how they are (and can be) implemented using a Geographic Information System (GIS). These appear to arise from a misinterpretation of the underlying premises of FCA metrics and their formulation, a problem that also hinders the calculation and potential utility of their proposed FCA metric. Another troublesome aspect of the work is that a major component of the proposed metric cannot be reproduced as

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presented in the manuscript, which is a crucial requirement for any new metric presented in the academic literature, as it allows other researchers to implement it and (more importantly) evaluate its merit.

In this paper, I first offer a rebuttal to a number of the statements contained in Plachkinova et al.'s paper in an attempt to ensure that FCA metrics, including their conceptual underpinnings and implementation, are properly represented in the academic literature. In addition, I provide a critique of the authors' proposed metric and comment on the component that cannot be reproduced. While this paper is critical in nature, I also aim to begin a more comprehensive discussion surrounding spatial accessibility and FCA metrics by presenting some broad observations and recommendations regarding their calculation and implementation throughout the work.

2 Distance, Travel Time, and Travel Costs

The first and most important misrepresentation contained in Plachkinova et al.'s work is the claim that previous FCA metrics have not incorporated “travel time behavior” (p. 2), “travel behavior” (p. 2), or “travel costs” (p. 10). Human travel behavior, whether characterized as travel distance, time, or cost, has been an essential component of all spatial accessibility metrics since the inception of gravity models (e.g., Joseph and Bantock 1982; Radke and Mu 2000) and their eventual evolution into FCA metrics. In Luo and Wang's (2003) original Two Step FCA (2SFCA), travel costs are incorporated in a very rudimentary form by creating catchment areas centered on facilities and population locations using travel distance or travel time. A binary weight variable (w) is then utilized to distinguish locations by whether they fall inside or outside of the catchment areas. Specifically, in this conceptualization, travel behavior is incorporated such that populations located within the catchment area of a facility can freely access or travel to that facility ($w = 1$, no cost to travel), while those outside the catchment area cannot ($w = 0$, fully restricted travel). The dichotomous representation of travel costs based on the boundary of a catchment area was improved upon in the Enhanced Two Step FCA (E2SFCA) and the introduction of the concept of *distance decay* within the metric's calculation (Luo and Qi 2009). Distance decay is a well-understood concept in the health care accessibility and geographic literature, positing that distance, whether it be measured as physical or perceived distance, travel time, or travel cost, has the potential to affect relationships or interactions among people and facilities. For example, a person that must overcome a greater distance to visit a facility (than another person) will incur a greater cost in order to make that journey. The concept of distance decay asserts that the higher cost acts as a deterrent and results in lower potential access or a reduced ability to interact with that facility. The E2SFCA

metric implements this concept by first creating a set of concentric catchment areas or rings around each facility. A distance decay weight (w) falling between 0 and 1 is then assigned to each population location based on which catchment ring it is located within. Because the weights are estimated as an inverse function of travel distance or travel time (see Kwan (1998) for examples of distance decay functions), populations located near a facility receive weights near 1 (low travel costs), while those located farther from a facility receive weights near 0 (high travel cost). McGrail and Humphreys (2014) state that the integration of distance decay is considered an essential component of FCA metrics. Following suit, nearly all of the FCA metrics that have been offered since the E2SFCA was introduced have incorporated this fundamental concept by including some form of distance decay weights in their calculation and thereby offering a rational approach to model the effects of distance or separation on human travel behavior and geographic access to health care. Delamater (2013, p. 32) provides a short conceptual summary of how distance decay has been implemented in FCA metrics and illustrates the increasing sophistication in how it has been applied in FCA metrics using distance decay weights and travel costs.

3 Catchment Areas vs. Pairwise Distance Measurements

Another mischaracterization of previous FCA-related research found in Plachkinova et al. is the statement that previous FCA metrics have not explored the use of pairwise distance measurements between population and provider locations (p. 2). In fact, this exact approach to calculating continuous distance measurements for use in FCA metrics was offered by Dai and Wang (2011, p. 663), Langford et al. (2012a, p. 14), and Luo (2014, p. 440–441). Furthermore, Delamater (2013) also discussed the use of pairwise distance measurements in FCA metrics from both a conceptual standpoint (p. 32) and in applied form (p. 38). To summarize, an Origin-Destination (OD) matrix of travel distances or travel times can be created using a GIS if all population and provider locations are referenced to a travel network (e.g., a road network). The resulting OD matrix contains the pairwise distance measurements between all population and provider locations and therefore renders the creation of the catchment areas or rings as polygon features unnecessary, as previously suggested by Delamater (2013) and Fransen et al. (2015). Because all of the necessary information to calculate any FCA metric can be extracted from an OD matrix via simple queries, the manual creation of catchment areas followed by a spatial join or overlay operation to link populations to their catchment areas in a GIS is a redundant step (if the OD matrix has already been created). Furthermore, for big data applications, the creation of

catchment areas and subsequent spatial overlay operation would likely be prohibitively time- and computing-intensive.

4 Distance Decay Functions, Parameters, and Weights

Table 1 in Plachkinova et al. provides highlights from a number of FCA metrics. For the E2SFCA, they focus on the distance decay weights, stating (p. 4), “The weights create other assumptions, which have not been elucidated by researchers.” This statement is vague and somewhat inaccurate. The use of distance decay functions as representations of human travel behavior, as well as how functions can be represented via distance decay weights, has continuously been at the forefront of FCA-based research. Notably, the researchers most adept at using FCA metrics acknowledge that the choice of both the distance decay function and its specific parameter value(s) will influence the resulting FCA metric values, and they often include a sensitivity analysis as part of their research design. When Luo and Qi (2009) introduced the E2SFCA and incorporated the distance decay concept into the FCA framework, they implemented their new metric with two different sets of distance decay weights to illustrate how they affected the output values, acknowledging the importance of choosing an appropriate distance decay function and parameter value(s) (see p. 1105). Other researchers have followed suit by examining the effects of different distance decay functions and parameter settings on the results of FCA calculations (e.g., McGrail 2012; Langford et al. 2012b; Luo 2014). In this context, Wan et al. (2011) introduced the Spatial Accessibility Ratio (SPAR), which normalizes the output of an FCA metric by dividing the resulting value for each population unit by the mean value of all population units. The SPAR output showed to be useful for comparing the results of FCA metrics calculated using different distance decay parameter settings. In general, while the choice of a distance decay function and its particular parameter settings can be arbitrary when using an FCA metric, it is generally guided by previous research or can be estimated from observed data (e.g., Delamater et al. 2013, p. 5–6). In this matter, Plachkinova et al.’s statement invokes an important, if not well-known, challenge in any spatial application that employs the concept of distance decay. Specifically, the ability to establish a rational link between the *process* under examination (e.g., the potential ability of a person to travel) and its quantitative *representation* (e.g., a distance decay function and corresponding weights) is an area that deserves further research. However, suggesting that this challenge has been overlooked or unexplored by previous researchers in FCA-based research is unwarranted.

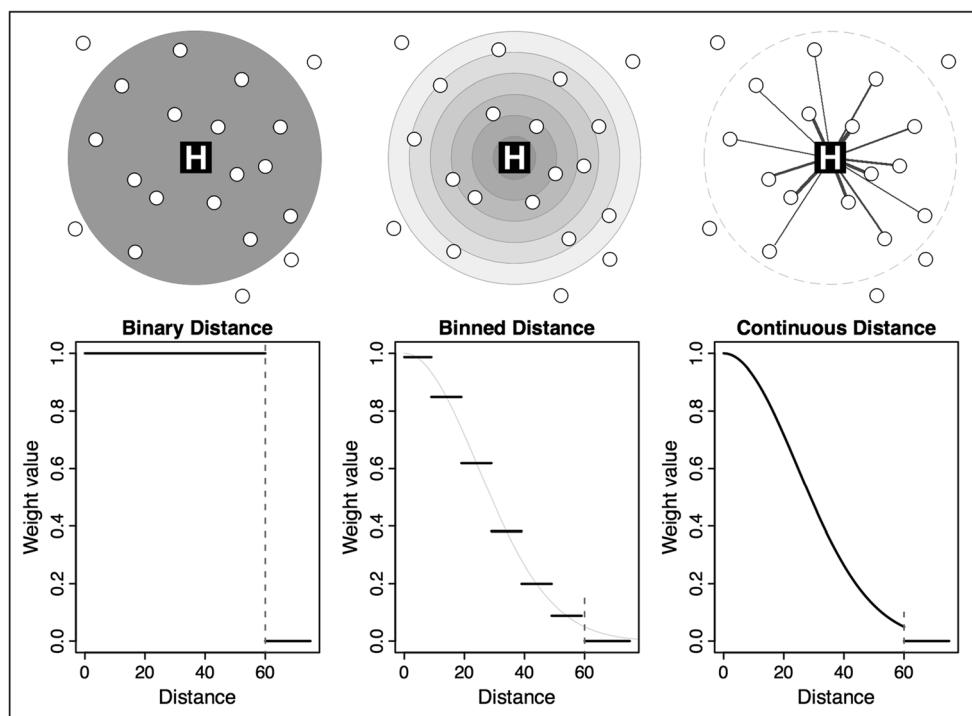
5 Catchment Sizes and Threshold Distances in FCA Metrics

Plachkinova et al.’s discussion of catchment sizes (p. 5) appears to again present a mischaracterization of how most modern FCA metrics integrate the concept of distance decay. The authors state, “This process offers research improvement potentials: to figure out the appropriate catchment sizes and the number of catchments. It is imperative to choose catchment sizes correctly since they create a dichotomous boundary for access.” The specific meaning of this statement is somewhat unclear and thus deserves further discussion. If the authors refer to the dichotomous boundary for access as being a part of the calculation of the FCA, their statement is only true for the original 2SFCA and those few FCA metrics that do not incorporate distance decay. However, this statement is more troubling for those that integrate distance decay, which is the common approach in recent FCA metrics. The authors are correct in that the researcher or analyst much choose the size and number of catchments, as well as the *threshold distance*. The threshold distance represents the distance, time, or cost that is considered to represent no ability to access a facility and any population located outside of the threshold is assigned a weight of 0. An example approach is to create catchment areas based on the following distance bins: 0–10, 10–20, 20–30, 30–40, 40–50, and 50–60 miles. In this case, the threshold distance would be 60 miles. The next step requires assigning a distance decay weight to each of the distance bins, which itself does create some potential issues because a bin represents a range of distance values (e.g., should the bin weight be based on the minimum, middle, or maximum distance of that particular bin?). As it pertains to the authors’ statement, the use of the concentric catchment ring approach clearly creates *discontinuities* in the representation of access via distance decay, but is not a dichotomous characterization. Moreover, when pairwise distance measurements are used in lieu of catchment areas, which is a more computationally efficient approach, this issue is resolved as the binned representations of distance are replaced with continuous measurements. Figure 1 demonstrates how distance decay weights used in FCA metrics have evolved from dichotomous, to binned, to continuous.

A broader discussion of the use of a threshold distance is warranted. This parameter in FCA metrics appears to be a remnant of their early incarnations, when the concentric catchment ring approach was used (prior to the regular integration of continuous distance). When creating the catchment areas in a GIS, the prohibitive processing requirements necessitated the implementation of a cutoff value. Yet, if all the pairwise distances have been measured, there really is no reason to implement a threshold distance, as this does create a discontinuity as illustrated at 60 miles in the continuous distance decay curve in Fig. 1. Because the decay weights become

Fig. 1 Examples of distance decay characterization in FCA metrics. In each example, the threshold distance is equal to 60 miles. The binned distance values are based on 10 mile travel rings and a Gaussian decay function, using the middle distance of the bin for the calculation. In the continuous distance example, the weights are based on the Gaussian function. For both the binned and continuous distance examples, the Gaussian function takes the form,

$$w = e^{-\frac{d^2}{1200}}$$



smaller as distance increases (in all decay functions), the drop off at the chosen threshold can be quite small. For example, using the distance decay function and parameter settings in Fig. 1, the weight value for a travel distance of 0 miles is $w = 1$, which decreases per the particular function to $w = 0.055$ at 59 miles. At the chosen threshold distance of 60 miles, the function is no longer implemented and the weight is set to 0. While the discontinuity created may be minor, the actual use of the threshold distance is not required portion of the mathematical formulation of the FCA metrics. As such, this term could be removed altogether under the assertion that even people located far from a facility (e.g., further than the threshold distance) do feel some attraction to or have the potential to use that facility.

6 Modifications of Previous FCA Metrics

Table 1 in Plachkinova et al.'s paper also contains two minor misrepresentations that deserve to be corrected. First, the Modified 2SFCA (M2SFCA) metric is not a modification of the 3SFCA. While Delamater (2013) does provide a critique of the 3SFCA, the M2SFCA metric is a direct modification of the E2SFCA. Further, the M2SFCA addresses the potential for overestimation of spatial accessibility that is present in *all* FCA metrics (Delamater 2013, p. 31). Second, the table incorrectly identifies the metric offered by Luo (2014) as the Huff Model-based 2SFCA. Luo (2014, p. 440–441) integrates the Huff Model as a modification of the 3SFCA by using the Huff-derived probabilities based on facility size and distance

to assign selection weights in the first step of the metric in lieu of the distance-based measures used in the original 3SFCA.

7 Representing Supply and Demand in FCA Metrics

Plachkinova et al.'s statement (p. 5), “Past research has not focused on these two preceding processes; rather, researchers use default values for supply and demand of healthcare. Supply of healthcare involves either hospitals or physicians while demand of healthcare is determined by population.” could also be considered as misleading. There are numerous examples of FCA-based research that pays great attention to the characterization of supply and demand. Lin et al. (2016) use the location of publically available automated external defibrillator locations and emergency medical stations as supply locations for potential out-of-hospital cardiac arrests, as well as incorporating a regression-based method to determine the potential demand in the population. Fransen et al. (2015) consider the number of people commuting among zones as the potential demand in using an FCA metric to examine spatial accessibility of daycare centers. Li et al. (2015) use FCA metrics to examine spatial accessibility of specialty care locations for Cystic Fibrosis patients. In another example, Bell et al. (2013) integrate additional information for both supply and demand (languages spoken) within their FCA-based calculations. The preceding examples are just some of many that illustrate that the researchers using the FCA metrics have

moved past the default considerations of supply and demand to tailor an input dataset that is appropriate for their analysis.

8 Integrating Travel Costs in FCA Metrics

The integration of a travel cost variable (TC) in the calculation of Plachkinova et al.'s FCA metric appears to result from their belief that previous FCA metrics have not integrated this important information. While this idea was shown to be misguided earlier in this critique, their approach to integrating this information also deserves examination. Interestingly, the authors disregarded the well-established practice of including travel costs via the use of distance decay weights *within* the equations used in the two basic steps of FCA metrics. Instead, they apply a single TC value to each supply location and population location, which is moderated by a user-supplied weight parameter. Importantly, the TC value appears to be calculated as the average value of the individual costs for each population location (in the first step) and for each supply location (in the second step). Specifically, the 2SFCA approach of defining a single catchment is implemented, and then an *average* value of the travel costs for the entire set of locations falling within the catchment is calculated. The reasons for why they chose to eschew the common approach of including this information within the equations via the inclusion of distance decay weights is left unexplained. It appears that a highly similar objective (accounting for variations in the ability to access supply locations based on distance) can be accomplished with much greater precision by simply implementing the previously discussed binned or continuous distance decay approaches. This methodological choice seems especially peculiar considering that the authors had calculated the pairwise distance measurements (p. 5) that would have allowed them to implement the continuous decay approach. Surprisingly, the effect of this approach to assigning travel costs on the validity or accuracy of the resulting FCA values is not evaluated, nor is it discussed in the article.

9 FCA Metric Output Values

Plachkinova et al. rescale the output of their FCA metric from 0 to 100, stating that this provides for an easier interpretation (p. 2, 10–11) and makes the output comparable to other score-based indices (p. 8). This rescaling of the FCA output values suggests a misinterpretation of the output units of FCA metrics and the advantages they provide. Specifically, as mentioned by other researchers (e.g., Luo and Wang 2003, p. 874; Luo and Qi 2009, p. 1103; Delamater 2013, p. 32), the output of the FCA metrics retain an important theoretical and applied link to the input data. Specifically, the units of the inputs for the metrics are supply

opportunities (e.g., hospital beds) and potential demand (e.g., counts of people) and the output values of FCA metrics are expressed as supply opportunities per person (e.g., hospital beds per person or physicians per person). This property of FCA metrics should not be overlooked, as it allows their output values to be *directly interpreted* as they relate to spatial accessibility and allows for the output values to be *directly compared* to the output of other FCA metrics. This oft-noted and well-understood benefit of using an FCA metric is nullified if the output values are rescaled to an arbitrary range and thereby decoupled from the input data units. Using the approach suggested by Plachkinova et al., the resulting values are not directly interpretable (e.g., does a region with a score of 50 have twice as many opportunities available as a region with a score of 25?). What may be a more pressing concern is that the output of Plachkinova et al.'s metric cannot be directly compared against the output of other FCA metrics due to the rescaling step. This property is extremely important as it allows other researchers to evaluate how changes in the underlying calculations affect the output of the new FCA metric in comparison to the previously established FCA metrics. While the rescaling process does make the FCA output more similar to a “Walkability” or “Sun Number” score, it also makes it *less similar* to an FCA metric output, which seems to be a counterintuitive decision. Finally, the implementation of the rescaling step in the case study is also questionable, as the mapped FCA output in Plachkinova et al.'s Figure 5 does not appear to conform to the 0–100 range as described by the authors (minimum = 0.000907 and maximum = 98.032472).

10 Integrating Health Care Quality Information in FCA Metrics

Plachkinova et al.'s idea to integrate quality of health care services within the FCA framework is innovative and interesting from a conceptual standpoint. While the genesis for the development of the FCA metrics was to improve upon “container-based” measures of regional availability by using a gravity-based model to simultaneously consider availability (supply/demand) and accessibility (distance or separation), there are other, non-spatial components of access to health care (Penchansky and Thomas 1981; Khan 1992) that have yet to be considered in the FCA framework. Plachkinova et al. are correct in that this offers a potential area of improvement for future metrics. However, the potential problems identified in the integration of travel costs (TC) are again present in their approach to integrating quality information in their metric. Namely, this step is performed outside of the supply to demand calculation. Unfortunately, they overlook a straightforward opportunity to integrate the star rating quality information *within* the previously established FCA conceptual approach. Specifically, the star rating (range of 1–5) at each facility could be normalized (divided by 5) such that the

values represent the *proportion of quality beds* at a facility. For example, a one star hospital would receive a quality bed proportion of 0.2 (1 / 5). This proportion could easily be integrated into the first step of an FCA calculation by multiplying the number of total opportunities by the quality information. Using the previous example, a hospital with 100 beds and a star rating of 1 out of 5 would only have a supply of 20 quality beds in the provider to population ratio calculation. Although this suggestion is an extremely simple integration of health service quality information, it could easily be incorporated within the calculations of the existing FCA metrics. Furthermore, with this approach, the output of the “quality-based” FCA would also be directly comparable to the FCA output without the quality information. Returning to the hospital beds example, it could be used to compare the spatial accessibility of hospital beds and the spatial accessibility of “quality” hospital beds for each region’s population.

11 Reproducibility

The ability of other researchers to implement any new or modified FCA metric is paramount to understanding both their benefits and drawbacks, as well as their applicability to measuring spatial accessibility for specific types of health care services or other amenities. Unfortunately, the methods used to estimate the travel costs (*TC*) in Plachkinova et al.’s FCA metric (p. 7–8) are not reproducible as presented. As such, the metric itself is not reproducible. As a note, the following examination of the steps required to calculate *TC* only considers the method for the first step (the *Supply Step*), as the steps required for the second step (the *Demand Step*) appear to be similar (replacing facility locations with population locations). The Supply Index formula is given as (p. 6):

$$SI_j = \beta_1 * R_j + \beta_2 * St_j + \beta_3 * TC_j$$

In this formula, TC_j is defined as the travel cost function (see Plachkinova et al. text for full description of the remaining terms). Given that TC_j is not otherwise noted, it is assumed to be a single numeric value for each site j . TC_j is defined as (p. 7):

$$TC_j = \left(\frac{1}{k} \sum_1^k E(C_{j,k}|c_{j,k}) \right)^{-1}$$

and

$$E(C_{j,k}|c_{j,k}) = A_j * c_j^2 + B_j * c + \varepsilon_j$$

In this set of equations, $E(C_{j,k}|c_{j,k})$ is defined as the expected value of the cost function. However, the notation is not well

explained in the text. Given the subscripts and notation of $E(C_{j,k}|c_{j,k})$, this appears to be a set of estimated cost values $E(C_{j,k})$ that correspond to the set of population locations (1 to k) that fall within the threshold distance (d_0) of site j , which are conditional upon a set of corresponding values $c_{j,k}$. The TC_j equation requires a set of k values for the mean calculation (prior to taking the inverse), thus defining $E(C_{j,k}|c_{j,k})$ as a set of k values makes sense. However, the data and steps required to estimate the $E(C_{j,k}|c_{j,k})$ values are much more difficult to decipher. The text states (p. 7) that “ A and B are the coefficients of the cost c at site j ” and “ ε is the residual of the function”, and that the coefficients are estimated using “quadratic curve fitting”. The first issue that arises is whether c_j and c are different sets of values, as both are listed in the equation, but only one is defined. Assuming that c_j and c are equivalent sets of values, the next issue that arises is that the method used to calculate these values or what they actually represent is not defined. The article text defines c as “costs”, but the reader is left to determine how this is measured or what the units of measurement are (e.g., are they measured travel distances or travel times from the GIS?). Further, the $E(C_{j,k}|c_{j,k})$ values used to estimate the curve are not defined anywhere in the article text either. Because quadratic curve fitting requires a set of Y and X pairs (to estimate the coefficient values A and B for X^2 and X , respectively), there must be a defined set of Y values to fit the function to. In this case, a set of $E(C_{j,k}|c_{j,k})$ values are required. The authors state they create a series of one-minute catchments from 1 to 30 min, and the results of this step inform the curve fitting. However, they never explain what these results actually are and how they are related to the $E(C_{j,k}|c_{j,k})$ values. Unfortunately, these important omissions leave others ultimately unable to recreate the c_j or $E(C_{j,k}|c_{j,k})$ values, which are required to estimate TC and reproduce Plachkinova et al.’s FCA metric.

12 Conclusion

Plachkinova et al. state (p. 4), “The myriad methods in the FCA family that have proliferated in recent years have not paved the way for a better assessment or more accurate measures of quality healthcare accessibility. Rather, they have actually hampered the robustness of the newly developed FCA methods.” This statement is undoubtedly true as more and more researchers have offered new or modified FCA metrics without a full consideration of the conceptual underpinnings of potential spatial accessibility, a comprehensive understanding of how gravity-based FCA metrics are implemented, or a well-reasoned argument for modifying previous metrics. While Plachkinova et al.’s contribution does contain the noted positive aspects, it unfortunately appears to fall victim to the very statement they warn about in their text.

It is encouraging to come across FCA-based research in a multidisciplinary journal such as *Information Systems*

Frontiers. This can be viewed as a sign that potential spatial accessibility, as a research area and topic, continues to expand outside the realm of its subdiscipline home and may be reaching a broader audience. However, it appears that as the FCA-based research has moved further from the relatively few researchers that have been involved in the development of the metrics themselves, the number of opportunities for misinterpretation and misrepresentation appears to have expanded as well. Throughout this critique, I have attempted to correct a number of misinterpretations and misrepresentations regarding FCA metrics and their calculation in Plachkinova et al.'s text, as well as to offer a general clarification regarding some of the conceptual and applied aspects of FCA metrics. I have also pointed out some methodological shortcomings in the authors' metric and identified a reproducibility issue. While this paper is critical in nature, I do hope that it promotes a broader discussion and deeper understanding of FCA metrics and their use.

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