Are real and satisfaction-adjusted distances to health services related to Quality of Life? A case study in lower-income urban neighborhoods in Quito, Ecuador

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Abstract

Health services accessibility and Quality of Life (QoL) are both multidimensional concepts but are also related to each other. In this study, subjective measures of satisfaction were analyzed together with measures of geographical access to health care facilities. In particular, this study relates real and satisfaction-adjusted distances to health services to Quality of Life based on interviews carried out in a lower-income urban neighborhood in Quito, Ecuador. Measures of self- perceived Quality of Life, self-perceived health and satisfaction regarding health care attention, and health care accessibility perceptions were extracted from questionnaires. Real distances to health care services as well as satisfaction-adjusted distances to these services were calculated. Ordinal Logistic Regression was used to relate these two kinds of distances and the self-perceived health, to the self-perceived Quality of Life. An Auto Regression Model was applied to evaluate the spatial autocorrelation of the measure of QoL. Results showed that real and satisfaction-adjusted distances do not have a real impact on QoL but also that self-perceived health could be considered as one explanatory variable for QoL. This study also found a strong spatial dependency of the interviewees' self-perceived Quality of Life. This work is a contribution to mixed-methods approaches in QoL research and Health Geography by stimulating the inclusion of citizens' perceptions in health planning.

Keywords: Health care services, Quality of Life, distance, satisfaction-adjusted distance, regression

1   Introduction

Measuring distances to health care services has been useful to identifying health inequalities [1] and satisfaction-adjusted distance (SAD) is a novel approach that considers perceived distances to health care services and the satisfaction of the patients with these services [2]. Quality of Life (QoL) is a multidimensional concept that links objective and subjective evaluations [3]. QoL can be classified into two bi-partitions: life chances and life results that include outer qualities (livability of environment and utility of life) and inner qualities (life-ability of the person and appreciation of life) [4]. Accessibility to health services is also a multidimensional concept that includes dimensions such as geographic *accessibility* in terms of the location of population in relation to health services, and dimensions such as *acceptability*, which considers patient satisfaction with the health care service received [5, 6]. Thus, the use of a specific health service depends on spatial and non-spatial factors [6, 7]. Some QoL aspects mentioned before can be related to health access analysis. A person's life-ability and the livability of his or her environment can both be related to the dimension of *accessibility* to important goods and services.

The relationship of health care and health access to QoL is an emerging field that still has a lot of research potential. Just like access to other goods and services such as fresh food markets, childcare, public transportation etc., the accessibility to health care services is also regarded to be an essential parameter which influences the overall QoL of a person, a group or a neighborhood. Obviously, location and distance-related parameters of satisfaction can be considered as geographical or geospatial factors. In this article, we focus on accessibility to health care services, both within a Euclidean space as well as by translating absolute distances into perceived distances. Here, we start by developing a satisfaction-adjusted distance (SAD) equation while modifying a method originally proposed by Hawthorne and Kwan [2]. We want to investigate the influence of perceptions of geographical access to health care locations on the overall QoL for a case study area in a lower-income urban neighborhood in Quito, Ecuador.

One of the objectives of this study is to compare real distances to health care services and satisfaction-adjusted distances to these services. A second objective is to relate these two kinds of distances to self-perceived health and self-perceived Quality of Life with the aim to better understand relationships between health care services accessibility and people's QoL measures.

2   Methods

Satisfaction-adjusted distance (SAD) is a composed measure that uses indicators of health care attention satisfaction and health care accessibility perceptions. These qualitative measures were extracted from the questionnaires conducted in the study area. The QoL measures used were also extracted from the questionnaires: one is a measure of self- perceived Quality of Life (QoL) and the second a measure of self-

perceived health (SPH). The satisfaction and QoL measures have a 1-5 Likert scale.

Ordinal Logistic Regressions (OLR) models were applied to find relationships between real and satisfaction-adjusted distances to health care services and QoL values. An Auto Regression Model (ARM) was applied to the self- perceived Quality of Life (QoL) measure to complement the OLR analysis.

2.1   Study area and participation

A survey was carried out in July 2014 in two lower-income neighborhoods of Quito, Ecuador: La Roldós and Pisulí. These areas are well known because they are peripheral and insecure places. Lower-income populations predominantly live in these zones and they face a lack of access to several services. However, some public health services are located in these neighborhoods, mainly due to some recent efforts by the Ecuadorean Government to bring more services to deprived areas such as the two neighborhoods investigated. Interviews using questionnaires were carried out in several households. Households were chosen using pseudo-random clustered sampling: two random clusters representing each neighborhood were identified and pseudo-random interviews were carried out under consideration of the population density in each neighborhoods´ census block, the availability of persons that were open to be interviewed and logistic limitations. Of the 80 persons contacted, a total of 50 persons agreed to answer the questions during an interview. From the 50 voluntary interviews carried out in the study area, 47 valid questionnaires were obtained. The confidence interval obtained was 14, at 95 % of confidence and assuming a priori expected probability of 50 %. Interviewees visited health care services located at different distances: from around 21 meters to more than 24 kilometers. Interviewees´ ages ranged between 14 and 68 years old, 68% of them were women.

2.2   Calculation of real distances (RD)

All the households in which the interviewees lived were geo-referenced. Then, using the road network of Quito, and the location of health care services in Quito provided by the Ecuadorean Ministry of Health, optimal routes from each household to its respective health care services were calculated using ArcGIS Network Analyst of ArcGIS 10.0. Optimal routes were considered as the real distances (RD) and were measured in meters.

2.3   Calculation of satisfaction-adjusted distances (SAD)

We calculated a measure of perceived distance by applying a modification of the satisfaction-adjusted distance (SAD) equation proposed by Hawthorne and Kwan [2].

The SAD equation used for this study was:

$$SAD = 100 * (m - q_i) + d_i \quad (1)$$

Where q_i represents the composite quality score of each participant (for details, see below), m is the mean of this score for all participants, and d_i is the real distance from each participant's household to the health service. 100 is the adjustment of distance, meaning that for every 1% deviation from m, the participants would have 100 meters added or subtracted from the real distance they travelled. We decided to change the original adjustment of distance proposed by Hawthorne and Kwan following their suggestions of trying different adjustments depending on the study area. In their study, they chose an adjustment measure of 0.1 (miles) after consulting the community´s health leaders. We chose the value of 100 (meters) because it represents the block distance in Quito, and participants did not suggest any specific adjustment, while many of them mentioned that sometimes they feel "like [they have] to travel more than one block of the usual distance". To calculate m and q_i, we also modified the original SAD measure that used 1-7 Likert scale questions and eight dimensions of satisfaction. In our study, we simplified this measure using four measures of health care attention satisfaction and health care accessibility perceptions: waiting time to get an appointment, the waiting time resulting from travelling to the health care service, the waiting time once they arrived at their appointment and the quality of the physician's attention. This last measure was obtained using a 1-5 Likert scale where 1 means very bad attention and 5 excellent attention. Waiting times were also converted to a 1-5 Likert scale, where 1 means higher waiting time and 5 means lower waiting time. The scores sum of the four quality of health care and access to health indicators is q_i.

2.4   Evaluation of relationships between RD and SAD to health services and QoL

A Pearson correlation analysis between RD and SAD was conducted to evaluate the strength and direction of the relationship between these two kinds of distances. Four Ordinal Logistic Regressions (OLR) were performed to evaluate the relationship between RD and SAD to health services and QoL. A measure of self-perceived health (SPH) was used in two regressions in order to evaluate if this QoL measure of health can improve the regressions that only considered RD and SAD. The models used were:

Model 1
$$OR = \exp(x_0 + b_1 RD) \quad (2)$$
Model 2
$$OR = \exp(x_0 + b_2 SAD) \quad (3)$$
Model 3
$$OR = \exp(x_0 + b_1 RD + b_3 SPH) \quad (4)$$
Model 4
$$OR = \exp(x_0 + b_2 SAD + b_3 SPH) \quad (5)$$

Where OR represents the odds ratio for each model. The dependent variable in all these four models is the self-perceived Quality of Life (QoL).

All OLR were performed in open source R environment using the software RStudio 0.98.1091.

The OLR analysis was complemented with an Auto Regression Model (ARM). A pure ARM was used to evaluate whether the values of the QoL measure were influenced by neighborhood values of QoL. The pure ARM can be expressed as:

$$QoL = \rho W QoL + \varepsilon \quad (6)$$

Where ρ is the autoregression parameter and W is the matrix of the inverse power function of geographical distances [8].

The public software SAM 4.0 [9] was used to perform the pure ARM.

3   Results

In our study area, 68 % of interviewees use only public health care services. A further 23% use mainly public health care services and sometimes private health care services. However, in some cases they did not visit the closest health care service. The RD to health care services varies from 21.45 meters to 24593.19 meters. The mean of RD is 5331.32 meters. The SAD to health services varies from -408.86 meters to 25203.19 meters. This means that the adjustment process, as a function of patients' perceptions, can result in adjusted distances lower than real distances and adjusted distances higher than the real ones. A negative distance means that the real distance from the patient household to the health service is less than a block of distance. The SAD mean is very similar to the RD mean: 5330.68. As expected, the Pearson coefficient of the correlation between RD and SAD was very high: 0.99.

OLR are showed in Table 1:

Table 1: Results of the OLR

Model	Odds ratio	Lower CI (2.5%)	Upper CI (97.5%)	AIC
Model 1	0.99	0.99	1	110.01
Model 2	0.99	0.99	1	109.95
Model 3	RD: 0.99 SPH: 1.01	0.99	1	112.01
Model 4	SAD: 0.99 SPH: 1.01	0.99	1	111.95

Table 1 shows that Model 1 and Model 2 perform better because the Akaike Information Criterion (AIC) is lower in these models. AIC offers a relative estimate of the information lost when a given model is used to represent the process that generates the data. However, odds ratios show that RD and SAD do not explain the variation in self- perceived Quality of Life (QoL).

Model 3 and model 4 reveal that the variation of the self-perceived health variable explains some variation of the QoL measure: for one unit of increase in self-perceived health, the odds ratio increases by 1.01. This result can be interpreted as that for each additional unit of increase in self-perceived health the self- perceived Quality of Life increases by 1%.

Nevertheless, the confidence intervals (CI) showed that this independent variable is not significant.

The pure ARM results showed a spatial autoregressive coefficient of 0.99 (standard error 2.78), which indicates a strong spatial dependency of the interviewees´ self- perceived Quality of Life. This result could also mean that the phenomenon of QoL in the study area can be characterized for endogenous variables that influence the QoL of the people.

4   Conclusion

Through the inclusion of perceptions and emotions into distance measures of accessibility, this study contributes to the mixed-methods literature of QoL and Health Geography studies. We also modified and enhanced the satisfaction-adjusted distance (SAD) measure originally proposed by Hawthorne and Kwan [2], as well as relating the real and satisfaction-adjusted distances to QoL values. Results showed that perceptions and satisfaction have an impact on objective measures at the level of an individual. For the study area, we found that SAD and real distances do not have an impact on the self-perceived Quality of Life. Contrarily, such a measure of self-perceived health can be considered as a suitable indicator to partially explain QoL. The values of self-perceived Quality of Life also showed a strong spatial autocorrelation. This suggests that for the interviewees, the life conditions of one individual may influence the life conditions of his or her neighbors. Here, one needs to be careful in order to avoid speculation. The investigated area in a lower-income urban neighborhood in Quito, Ecuador, may exhibit much stronger social interactions than other areas in richer neighborhoods and other geographical regions. Therefore, mixed-methods approaches including social science methods are needed to explore causal relationships in addition to the Geoinformatics methods, such as the spatial analysis used here, which may be falling short in classic social science studies. Indeed, including individual perceptions in distance measures can support a better understanding of health inequalities in a specific area. Our study shows that evaluating RD and SAD with QoL cannot fully explain QoL variations. However, we aim to show that individual evaluations of SAD could be considered as useful information for health staff and health planners in order to improve health care integral strategies. Future studies in this field can incorporate individual SAD evaluations and empirical tests as well as the fine-tuning of the adjustment of distance parameter. Future work related to this study could also include more explanatory indicators considering social, economic and cultural dimensions when relating SAD and QoL. A comparison of the methodology applied in different socio-economic neighborhoods can also offer better perspectives of the advantage of using SAD measures. This study could be considered as an experience that can lead to a major inclusion of society´s experience and behavior to health service planning.

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