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Advancing Urban Healthcare Equity Analysis: Integrating Public Participation GIS with Fuzzy Best–Worst Decision-Making

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Abstract: This study provides an innovative collaborative spatial decision support system (SDSS) that aims to ensure an equitable spatial distribution of healthcare services. Evaluating the equality of access to health services across different geographical areas is important, as it requires the analysis of various criteria such as the proximity of health centres and hospitals (HCHs), the quality of services offered, connectivity to primary roads, the availability of public transportation hubs, and the density and distribution patterns of HCHs. This purpose is accomplished via the use of geographic information systems (GIS) and multi-criteria decision analysis (MCDA) methods. The proposed model includes the weights of the criteria, which are determined through the ordered weighted average (OWA) and evaluated based on their ORness, which ranges from 0 to 1. Furthermore, this model is improved by the best–worst fuzzy method (F-BWM). This approach produces a spatial map that clearly shows the equity of healthcare systems in urban environments. The findings show that the maximum score observed in this study was 0.38% (with an ORness value of 1), whilst the minimum score recorded was 0.28%. In the most severe scenario (ORness = 0), over 70% of the region shows different degrees of fairness, ranging from moderate to suitable and very suitable conditions. Governments and health authorities can use this information strategically to allocate resources and address inequities in access to healthcare facilities.

Keywords: volunteered geographic information; healthcare accessibility; spatial decision support system; spatial inequalities; spatial distribution; spatial pattern

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1. Introduction

Health inequalities are an important challenge at the global level and require substantial investment in different regions. In order to identify geographic areas in terms of the health status of citizens, knowledge is needed in the decision-making and implementation of health policies in order to address the situation of inequalities, spatial measures, and coherent spatial classifications [1]. Accessibility to health centres and hospitals (HCHs), as defined by the World Health Organization (WHO), refers to the provision of health services that are easily and reasonably available to all segments of both urban and rural populations, with a particular focus on marginalised and underserved groups. The accessibility to HCHs influences the broader aspects of physical, social, and mental well-being and the prevention of preventable mortality [2–11].

Considering the fundamental importance of accessibility modeling in evaluating the equity of spatial healthcare systems, numerous studies have investigated the computation of accessibility through a variety of criteria and methodologies [12–14].

In his research, Mansour (2016) [15] focused on assessing the level of equity in access to medical centres in Saudi Arabia. The evaluation of spatial equity in healthcare is primarily based on the distance criterion. The research employed the k-nearest neighbours algorithm and the Fuzzy Inference System (FIS) as analytical methods. In China, researchers such as Lu et al. (2019) [2], Ni et al. (2019) [16], and Wang et al. (2022) [17] have used travel time criterion to assess patients' accessibility to medical centres in urban and rural areas. Neisani Samani and Alesheikh (2019) [3] investigated healthcare system inequities by considering citizens' preferences. Their suggested methodology incorporated the F-VIKOR approach to address decision-making uncertainties at multiple levels. Aside from analysing spatial accessibility, the density and distribution of HCHs were recognised as essential criteria for assessing spatial health equity. Parvin et al. (2021) [18] conducted a spatial analysis in a specific region of India, employing the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) and Weighted Linear Combination (WLC) methods to examine the status of spatial health equity. The study aimed to identify optimal locations for delivering medical services in areas with limited accessibility within the research area. GIS-based multi-criteria decision analysis (MCDA) techniques were preferred over other approaches due to their capacity to effectively incorporate various spatial metrics, spatial analysis methodologies, and evaluation analyses. Xia et al. (2022) [19] propose an assessment of hospital accessibility at various hierarchical levels and throughout time, with a specific emphasis on aspects connected to traffic. Their findings reveal substantial spatial and temporal disparities in hospital access within the study area, highlighting the impact of traffic congestion and the spatial arrangement of medical facilities. Safi et al. (2023) [20] used GIS to analyse the spatial accessibility of basic health centres in Iran. This research comprised the collection and analysis of locational information about healthcare facilities, population distribution, and urban zoning within the city of Yazd, located in Iran. The distribution maps for each of the examined applications were determined. The data were analyzed through the use of indicators and models such as hot spot analysis, Thiessen's polygonal algorithm, an access model based on two-stage floating catchment, and the average nearest neighbour distance model. The findings indicate an imbalance between the population density and the distribution of health centres. Auld et al. (2023) [21] considered criteria such as the distance from the patient's residence to a paediatric centre and HCHs. The results demonstrate the effectiveness of reinforcing primary medical services in improving patient outcomes and reducing the travel expenses associated with people living in remote areas who are seeking medical care.

By reviewing the research literature, the limitations of the studies were identified. Hence, for this particular research, two criteria, namely the density and distribution of health centres, were selected. Volunteered geographic information (VGI) was used to collect data as well. The primary aims of this research are twofold: to develop an equity map of healthcare systems, the authors first integrate spatial access criteria, the distribution of HCHs, and density indicators using the ordered weighted average (OWA) method. In the second step, volunteers were used through the VGI online platform to determine the weights of the criteria, using the best–worst fuzzy method (F-BWM) technique. VGI enables the active participation of volunteers in gathering, accessing, and distributing geographic information [22,23].

The authors used four distinct criteria for the evaluation of spatial accessibility, which included measuring the travel time to HCHs, the proximity to the nearest service level [24], the distance to primary road networks [25], and the proximity to public transportation networks [26]. The combination of these factors, alongside HCHs' density and distribution, serves as the basis for constructing the spatial healthcare systems equity map, employing the OWA method [27]. The process of assigning weights to these criteria will be facilitated through a web-based participatory platform, utilizing the F-BWM technique [28].

The innovation of this study is to examine the inherent uncertainty associated with expert opinions and VGI data in the framework of PPGIS.

The subsequent section of the work is headed "materials and methods", wherein the study area, data, and applied methods are explained. The third section provides the results, and the fourth section presents the discussion and limitations related to the present research. The conclusion constitutes the fifth part. The subsequent section consists of Supplementary Materials, which includes user interface forms specifically developed for use in this research.

2. Materials and Methods

2.1. Study Area

The focus of this research is District 6 in Tehran, which is located in Iran at the approximate coordinate system of 35.5501° N, 51.5150° E. District 6 (Figure 1) is situated in the heart of Tehran and consists of 12 hospitals and 68 medical centres. Approximately 29% of the total area is allocated for residential land use, with more than 30% of the area specifically dedicated to office and commercial use. Significantly, District 6 is renowned as one of Tehran's most polluted regions, mostly due to the high volume of vehicular traffic that contributes to air pollution from everyday commuting for work, education, and daily activities. The area of the region is 21.443335 square kilometres, and it has a population of 251,384 people.

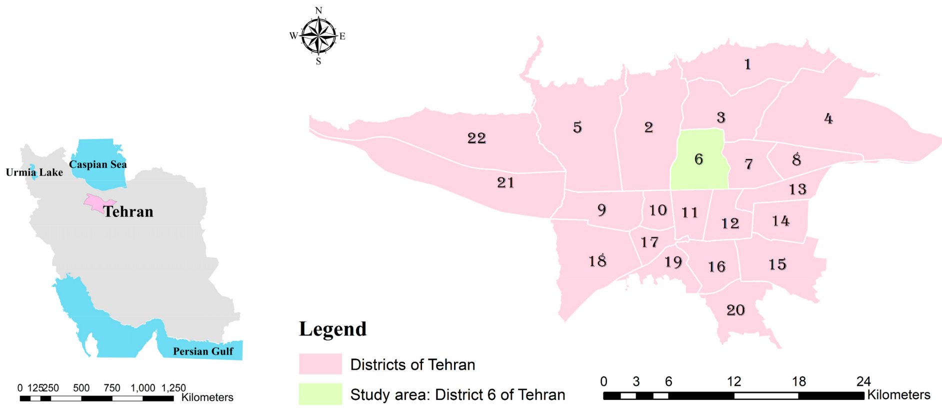


Figure 1. The study area (District 6 of Tehran).

2.2. Data

The acquisition of data from both experts and citizens for this research was carried out through a dedicated web platform (see Supplementary Figures S1 and S2). A total of 110 volunteers took part in this commitment, consisting of 24 specialists in geographic information systems (GIS) and urban planning, 18 medical practitioners, and 68 citizens.

Table 1 shows the detailed profile of these participants.

2.3. Methods

The core concept of this study is centered on using a volunteered geographic information (VGI) and multi-criteria decision analysis (MCDA) approach to assign weights to relevant criteria in order to evaluate spatial equity in urban healthcare systems. The best–worst fuzzy method (F-BWM) incorporates the assessments provided by volunteers on these criteria, whereas the OWA technique generates a healthcare systems equity map, illustrating different levels of risk factors. Figure 2 provides a clear representation of the operational steps. Initially, the criteria for accessing medical centres and the criteria for their distribution and density are established. Then, using spatial analysis, criteria maps are prepared. In order to integrate the layers of different criteria, it is necessary to ensure that all of the data are to the same scale. To achieve this, the normalisation method is implemented on the layers. The authors used the VGI online platform to apply the best–worst fuzzy method (F-BWM) technique, which allowed to determine the criteria weights most effectively. An urban spatial health equity map was developed by combining the determined criteria considering the ordered weighted average (OWA) method. Finally, the output of the urban health spatial justice map shows different levels of justice in access to medical centers.

Table 1. Characteristics of the participants.

Gender	Female	59
	Male	51
Age	15–40	58
	40–70	40
	Older than 70	12
Education	High school	4
	Undergraduate	67
	Postgraduate	39
Field of Study	Specialists in GIS and urban planning	24
	Medical practitioners	18
	Citizens	68

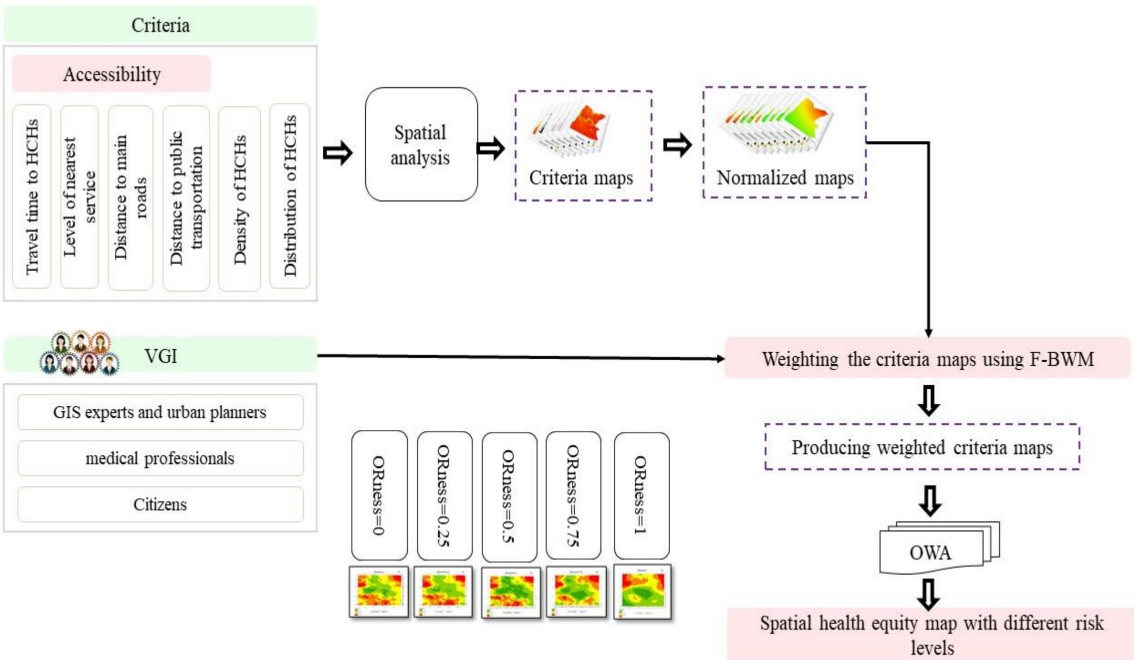


Figure 2. Flow diagram of the methodology.

2.3.1. Determining the Criteria

The responsibility of city planners and decision-makers is to identify medical centres and hospitals in a manner that ensures convenient accessibility for all patients. In addition, the distribution of these centres in urban settings should align with the population distribution or the amount of demand in different areas. Furthermore, with regards to accessibility, proximity to other amenities, and adherence to location standards, it is important that they be located in a suitable way. This becomes more and more challenging as urban environments grow more complex. The authors used six criteria, consisting of two criteria related to the density and distribution of HCHs and four distinct criteria for evaluating spatial accessibility, travel time to HCHs, proximity to the nearest service level to HCHs [21], distance to primary road networks [29], and proximity to public transportation networks [25].

2.3.2. Spatial Analysis with the Generation of the Criteria Maps

The criteria maps were generated through spatial analysis using the following methods: (1) Euclidean distance is used to assess the distance to main roads and public transport, (2) kernel density is used to evaluate the density of a certain region, (3) Thiessen polygon is performed to determine the distribution of a certain feature, and (4) service area analysis is used to calculate the travel time to HCHs. The level of nearest service is categorised into four levels: (a) primary care refers to the medical services provided by the primary care provider, (b) secondary care refers to the provision of specialised medical services by healthcare professionals such as oncologists or endocrinologists at HCHs, (c) tertiary care consists of specialised medical treatment provided in a hospital setting such as dialysis or heart surgery, and (d) quaternary care denotes an advanced degree of specialised medical treatment.

As previously stated, the criteria maps require volunteer-assigned weights. These criteria maps are created through spatial analysis, and the resulting normalised maps (Figure 3) are processed inside a customised web-based geographic information system (GIS).

To establish the criteria for the proposed method, it is necessary to assign weights to the criteria, based on an analysis and comparison of the data provided by the volunteers using the F-BWM method.

2.3.3. Normalisation of the Criteria

To construct suitability maps, the criteria collected from various data sets with different units had to be converted into equivalent units [27]. In order to combine different criteria layers, it is necessary for all the data to be standardised to a common scale.

2.3.4. Applying the F-BWM to Assign Weights to the Criteria

To outline the formulation of the F-BWM, it is necessary to first define the basic elements of the best–worst method:

The Fuzzy Best–Worst Method

The set of criteria, indicated as (c_1, c_2, ..., c_n), is used to construct the best–worst method (BWM). Subsequently, the basic model (c_b) is selected and compared with other criteria based on the hourly scale (1–9). The comparison involves evaluating the basic model with other models, represented as c_b = (c_{b1}, c_{b2}, ..., c_{bn}), with c_{bb} = 1, indicating that the minimum basic model (c_w) against others is represented as c_w = (c_{1w}, c_{2w}, ..., c_{nw}) and is based on the same scale of measurement. After computing the ideal weights, the consistency ratio (*CR*) was calculated utilising Equations (1) and (2) [22,28,30]. Table 2 presents the values of consistency index (*CI*).

$$\xi^2 - (1 + 2u_{BW})\xi + \left(u_{BW}^2 - \mu_{BW}\right) = 0 \tag{1}$$

$$Consistency\ Ratio = \frac{\xi^*}{\text{Consistency}\ Index} \tag{2}$$

In order to determine the best computing weights for all criteria, the greatest absolute variance between the ratios of $\left|\frac{w_b}{w_j} - c_{bj}\right|$ as well as $\left|\frac{w_j}{w_w} - c_{jw}\right|$ must be minimised for all j [27]. This may be represented mathematically as Equation (3) [30]:

$$\text{min}max_j\left\{\left|\frac{w_b}{w_j} - e_{aj}\right|, \left|\frac{w_j}{w_w} - e_{jw}\right|\right\}, \sum_j w_j = 1,\ w_j \geq 0\ for\ all\ j \tag{3}$$

which can be improved as Equation (4) [28]:

$$\text{Min } \xi, \left|\frac{w_b}{w_j} - c_{bj}\right| \leq \xi \; for \; all \; j, \left|\frac{w_j}{w_w} - e_{jw}\right| \leq \xi \; for \; all \; j, \sum_j w_j = 1, \; w_j \geq 0 \; for \; all \; j \quad (4)$$

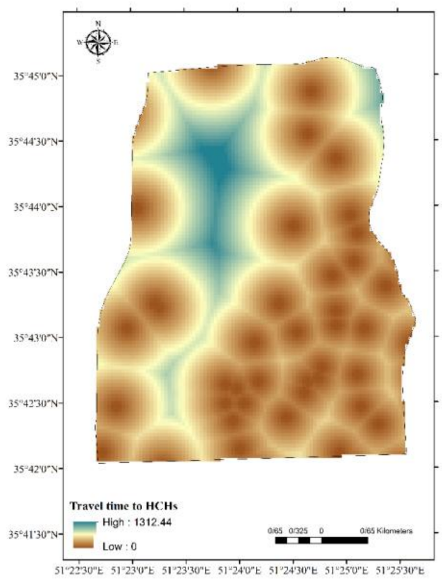
Equations (5) and (6) provide optimal weights and ξ. The weight of the best criterion is shown by the parameter w_b, while the weight of the worst criterion is represented by the parameter w_w. The comparison of the best criterion with others is indicated by the parameter c_{bj}, while the comparison of the worst criterion with others is shown by the parameter c_{wj} [23,30,31].

The concept of fuzzy theory was introduced based on the assumption that decision-making processes generally include uncertainties and ambiguities, with the aim of addressing and resolving such situations (Table 2). One of the common functions is triangular fuzzy functions. This function consists of partial, intermediate, and higher fuzzy numbers represented as $\tilde{A}$ = (l, m, n), where ($m \leq n \leq r$). Equation (5) is the membership function for the triangular fuzzy number. Table 3 explains the linguistic terms and fuzzy numbers [31,32]:

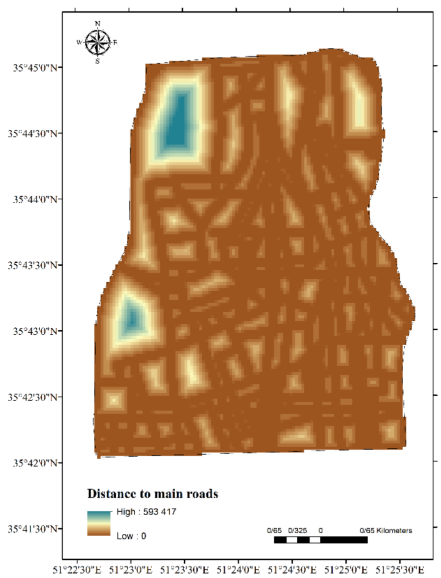
$$\mu_{\tilde{A}} = \left\{ \begin{array}{cc} 0, & x < l \\ \frac{x-l}{m-l}, & l \leq x \leq m \\ \frac{u-x}{u-m}, & m \leq x \leq u \\ 0, & x \geq u \end{array} \right\} \quad (5)$$

Table 2. Table showing the linguistic terms and fuzzy numbers [33].

Linguistic		Term	Triangular Fuzzy Number		
Equally	Importance	(EI)	(1,	1,	1)
Weekly	Importance	(WI)	(2.3,	1,	1.5)
Fairly	Importance	(FI)	(1.5,	2,	2.5)
Very	Importance	(VI)	(2.5,	3,	3.5)
Absolutely	Importance	(AI)	(3.5,	4,	4.5)



(**a**)



(**b**)

Figure 3. *Cont.*

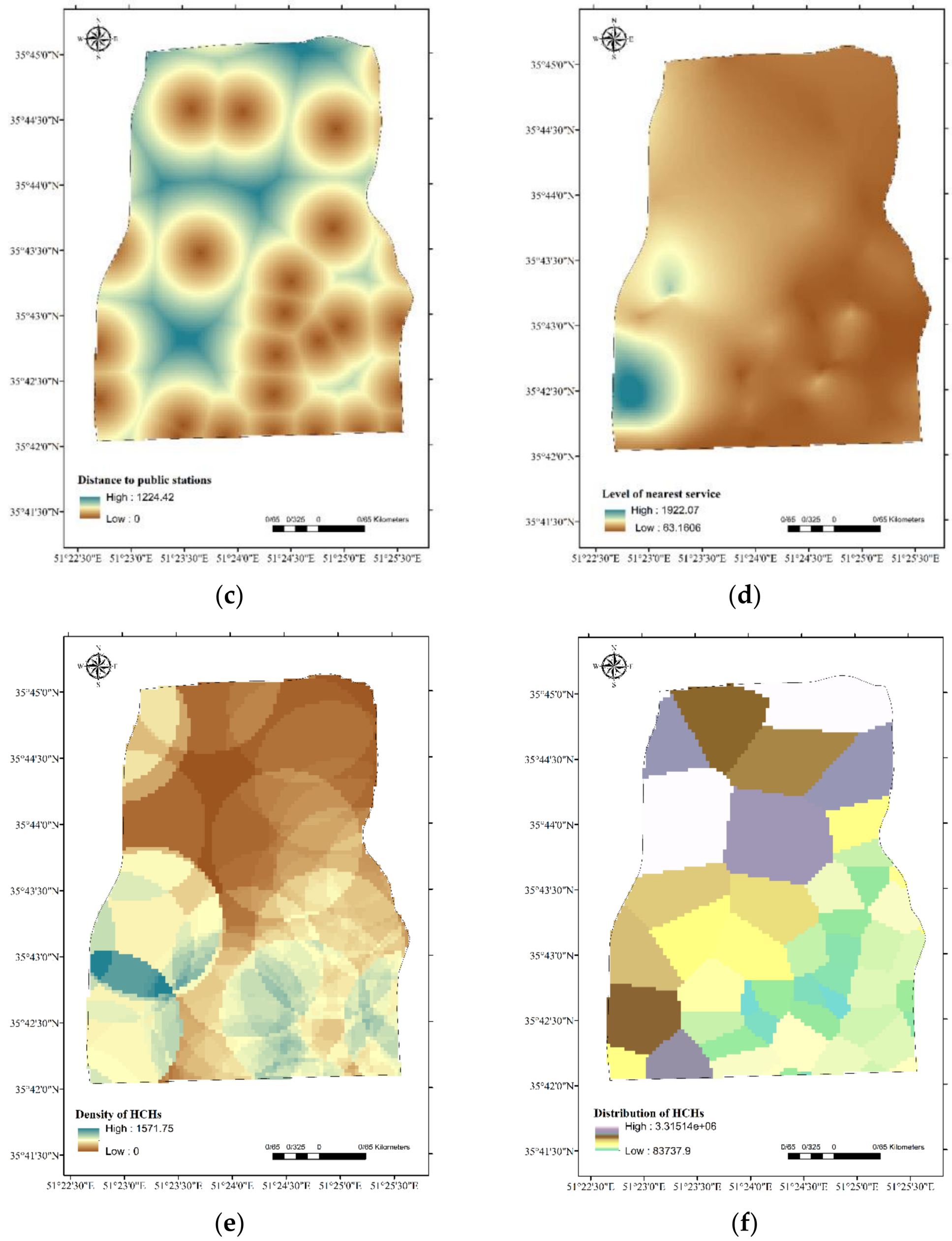


Figure 3. The criteria maps on the VGI website: (**a**) travel time to HCHs, (**b**) distance to main roads, (**c**) distance to public transportation, (**d**) level of nearest service to HCHs, (**e**) density of HCHs, and (**f**) distribution of HCHs.

Table 3. Illustrating weights assigned to various criteria concluded upon by the volunteers.

Criteria	Weights	Consistency Index
Level of nearest service	0.11	
Travel time to HCHs	0.26	
Distance to main roads	0.24	
Distance to public transportation	0.18	0.08
Density of HCHs	0.12	
Distribution of HCHs	0.09	

$\widetilde{A}_1 = (m_1, n_1, r_1)$ and $\widetilde{A}_2 = (m_2, n_2, r_2)$ are any two triangular fuzzy number, and they are calculated using Equations (6)–(10) [31]:

The plural operator:

$$\widetilde{A}_1 + \widetilde{A}_2 = (m_1 + m_2,\ n_1 + n_2,\ r_1 + r_2) \tag{6}$$

The subtraction operator:

$$\widetilde{A}_1 + \widetilde{A}_2 = (m_1 + m_2,\ n_1 + n_2,\ r_1 + r_2) \tag{7}$$

The multiplication operator:

$$\widetilde{A}_1 \times \widetilde{A}_2 = (m_1 * m_2,\ n_1 * n_2,\ r_1 * r_2) \tag{8}$$

The arithmetic operator:

$$k * \widetilde{A}_1 = (k * m_1,\ \ k * n_1,\ *r_1),\ (\mathrm{k} > 0) \tag{9}$$

$$\frac{\widetilde{A}_1}{k} = \left(\frac{m_1}{k}, \frac{n_1}{k}, \frac{r_1}{k}\right),\ (k > 0) \tag{10}$$

To rank the triangular fuzzy numbers, the average integration index sorted by the parameter $R\left(\widetilde{A}_i\right)$ and Equation (11) is used:

$$R\left(\widetilde{A}_i\right) = \frac{m_i + n_i + r_i}{6} \tag{11}$$

In the following, how to calculate the fuzzy weights of the F-BWM steps is exaplained [28]:

(a) Criteria definition. The number n of the decision criteria is indicated by c_1, c_2, ..., c_n.

(b) Determining the best and worst criteria. The worst criterion is represented by $\mathrm{c_W}$ and the best criterion is represented by the c_b. The type of criterion is determined by participation.

(c) Fuzzy comparisons for the best criterion to the others. This pairwise comparison is carried out with the parameter $\widetilde{a}_{ij}$ and Equation (12). The transformation of fuzzy judgments into triangular fuzzy numbers is carried out in the previous steps (Table 3).

$$\widetilde{A}_B = \left\{\widetilde{a}_{b1},\ \widetilde{a}_{b2},\ \ldots,\ \widetilde{a}_{bn}\right\} \tag{12}$$

$\widetilde{A}_B$ is for the fuzzy best-to-others; $\widetilde{a}_{bj}$ is for fuzzy comparison of the best criterion c_b due to the j^{th} criterion, $j = 1, 2, \ldots, n$ and $\widetilde{a}_{bb}$ = (>1, 1, 1).

(d) Fuzzy comparisons for the worst criterion to the others. Based on the principles of step (c), in this stage, the fuzzy others-to-worst vector $\widetilde{A}_W$, is computed using Equation (13):

$$\begin{gathered}\widetilde{A}_W = \left\{\widetilde{a}_{w1},\ \widetilde{a}_{w2},\ \ldots,\ \widetilde{a}_{wn}\right\},\\ \left\{\widetilde{a}_{ww} =\ (1,\ 1,\ 1),\ \mathrm{i}\ =\ 1,\ 2,\ \ldots,\ \mathrm{n}\right\}\end{gathered} \tag{13}$$

$\widetilde{a}_{iw}$ is for the fuzzy comparison of c_w (the worst criterion).

(e) The optimal fuzzy weights for each criterion. It is computed for each fuzzy pair $\widetilde{w}_b/\widetilde{w}_j$ and $\widetilde{w}_j/\widetilde{w}_w$, where $\frac{\widetilde{w}_b}{\widetilde{w}_j} = \widetilde{a}_{bj}$ and $\frac{\widetilde{w}_j}{\widetilde{w}_w} = \widetilde{a}_{jw}$. The result is the maximum absolute gaps across $\left|\frac{\widetilde{w}_B}{\widetilde{w}_j} - \widetilde{a}_{Bj}\right|$ and $\left|\frac{\widetilde{w}_j}{\widetilde{w}_W} - \widetilde{a}_{jW}\right|$ minimised for all j. $\widetilde{w}_b$,$\widetilde{w}_j$ and $\widetilde{w}_w$ in the F-BWM are triangular fuzzy numbers. Triangular fuzzy numbers in the F-BWM are $\widetilde{w}_b$, $\widetilde{w}_j$ and $\widetilde{w}_w$.

In certain cases, for the set of optimal criteria $\widetilde{w}_j = \left(I_j^w, m_j^w, u_j^w\right)$ is used. Equation (14) converted the triangular fuzzy weight of the criterion $\widetilde{w}_j = \left(m_j^w, n_j^w, r_j^w\right)$ to a crisp value:

$$\begin{gathered} \min \max_j \left\{ \left| \frac{\widetilde{w}_b}{\widetilde{w}_j} - \widetilde{a}_{bj} \right| - \left| \frac{\widetilde{w}_j}{\widetilde{w}_w} - \widetilde{a}_{jw} \right| \right\}, \\ \textstyle\sum_{j=1}^{n} R\widetilde{w}_j = 1, \\ m_j^w \leq n_j^w \leq r_j^w \\ m_j^w \geq 0 \\ ,\ j = 1, 2, \ldots, n. \end{gathered} \tag{14}$$

where

$$\begin{gathered} \widetilde{w}_B = (m_b^w, n_b^w, r_b^w), \\ \widetilde{w}_j = \left(m_j^w, n_j^w, r_j^w\right), \\ \widetilde{w}_W = (m_w^w, n_w^w, r_w^w), \\ \widetilde{a}_{Bj} = \left(m_{bj'}^w, n_{bj'}^w, r_{bj'}^w\right) \\ \widetilde{a}_{bjw} = \left(m_{bj'}^w, n_{bj'}^w, r_{bj'}^w\right) \end{gathered}$$

Equation (15) is converted to the non-lineary constrained optimisation problem:

$$\begin{gathered} \min \xi \\ \left| \frac{\widetilde{w}_b}{\widetilde{w}_j} - \widetilde{a}_{bj} \right| \leq \xi \\ \left| \frac{\widetilde{w}_j}{\widetilde{w}_w} - \widetilde{a}_{jw} \right| \leq \xi \\ \sum_{j=1}^{n} R\widetilde{w}_j = 1 \\ m_j^w \leq n_j^w \leq r_j^w \\ m_j^w \geq 0 \\ ,\ j = 1, 2, \ldots, n. \end{gathered} \tag{15}$$

in which $\xi = (m^\xi, n^\xi, r^\xi)$.

Where $m^\xi \leq n^\xi \leq r^\xi$, it is assumed that $\xi^* = (k^*,\ k^*, k^*)$, $k^* \leq m^\xi$, Equation (16) can be changed to:

$$\begin{gathered} \min \xi^* \\ \left| \frac{(m_b^w, n_b^w, r_b^w)}{(m_j^w, n_j^w, r_j^w)} - (m_{bj}, n_{bj}, r_{bj}) \right| \leq (k^*,\ k^*, k^*), \\ \left| \frac{\left(m_j^w, n_j^w, r_j^w\right)}{(m_w^w, n_w^w, r_w^w)} - (m_{jw}, n_{jw}, r_{jw}) \right| \leq (k^*,\ k^*, k^*), \\ \sum_{j=1}^{n} R(\widetilde{w}_j) = 1, \\ m_j^w \geq 0,\ m_j^w \leq n_j^w \leq r_j^w \\ j = 1, 2, \ldots, n. \end{gathered} \tag{16}$$

(f) CR calculation. The *CR* calculations are the same as in the BWM method.

Aggregating the Criteria Weights and Normalised Criteria Maps with OWA

As mentioned earlier, the participatory evaluation of spatial urban facilities by citizens and experts requires setting priorities and weights to determine their importance. The system should be capable of mixing the groups of different criteria weights into a single set of collection weights [34].

Finally, the separate weights could be combined through the geometric or arithmetic average. This paper adopts a geometric mean because it is more appropriate for combining weights with the pairwise judgments (Equation (17)) [31]:

$$W_{jg} = \sqrt[u]{w_{j1}w_{j2}\ldots w_{ju}} \tag{17}$$

In which w_{jk} is the j^{th} criterion weight due to the opinion of k^{th} citizen, u is the participants quantity, and w_{jg} relates to the j^{th} criterion group weight.

The OWA technique involves the normalised criteria maps of other location i ($a_{ij} \in [[0,1]]$), the weights of criteria ($w_j \in [[0,1]]$) gained from the F-BWM, and the order weights ($v_j \in [0,1]$) for $j = 1,2, \ldots,n$ specify the suitability level of alternative location a_{ij}. The OWA aggregator is determined using Equation (18) [35]:

$$OWA(a_i) = \sum_{j=1}^{n}\left(\frac{u_j v_j}{\sum_{j=1}^{n} u_j v_j}\right) z_{ij} \tag{18}$$

where v_j is attained through an arrangement of the normalised values of criteria including $a_{i1}, \ldots, a_{in}$ in a descendant instruction, and uj stands for the matching weights of criteria w_j that are restructured based on z_{ij} location. Indeed, there are two different weights type that consist of criteria weights and order weights (Equation (19)) [35]:

$$v_j = \left(\frac{\sum_{k=1}^{j} u_k}{\sum_{k=1}^{n} u_k}\right)^{\alpha} - \left(\frac{\sum_{k=1}^{j-1} u_k}{\sum_{k=1}^{n} u_k}\right)^{\alpha} \tag{19}$$

where α is associated with ORness (risk degree), Equation (20). The ORness values change between 0 and 1.

$$ORness = 1/(\alpha + 1),\ \alpha \geq 0 \tag{20}$$

ORness values display the operation of OWA from AND (minimum) to OR (maximum). Indeed, this demonstrates the risk-taking or risk-aversion tendency of a decision-maker. ORness is computed with Equation (21).

$$ORness = \frac{1}{n-1}\sum_{i=1}^{n}(n-i)v_i, 0 \leq ORness \leq 1 \tag{21}$$

Higher values of ORness leads to more risk-taking decision-making whereas the lower values signify that the risk-aversion tendency is foremost. Five ORness value as ‘1′, ‘0.75′, ‘0.5′, ‘0.25′, and ‘0′ are considered in this study.

Procedures

To develop a WebGIS platform (see Supplementary Figures S1 and S2) for the capturing of VGI data, a client–server architecture is implemented. The server component includes a geospatial database constructed using PostgresSQL (PostGIS) and a geographic information system (GIS) server, GeoServer.

3. Results

The process of assigning weights to the criteria using the F-BWM is facilitated through the designated interface on the VGI website. The F-BWM equations were used to compute the weight for each criterion, ensuring that an acceptable level of inconsistency was maintained, as specified in Table 3.

Using the normalised criteria maps, criteria weights, and ORness values, the OWA operator generated maps that illustrate distinct levels of spatial health equity. Potential maps were generated using uniform criteria weights for all ORness values, within the range of 0 to 1 (specifically 0, 0.25, 0.5, 0.75, and 1).

This research used the OWA model, in conjunction with a set of spatial criteria, to identify optimal areas for healthcare service provision across five different levels: extremely pessimistic, pessimistic, neutral, optimistic, and extremely optimistic. Higher values of ORness signify a more risk-accepting decision-making approach, while lower values reflect a predominant risk-averse tendency.

The resulting spatial health equity maps vary based on the ORness parameter. When ORness equals 0, the method adopts a fully risk-averse approach, assigning higher importance to smaller criteria values. This conservative and pessimistic strategy results in a minimised suitable area compared to higher ORness values. Conversely, when ORness reaches a value of 1, the strategy embraces a more risk-accepting characteristic. The ORness mode is equal to 1, which means that the level of urban health equity is high.

The ORness values are employed to categorise the level of spatial health equity in the study area into five distinct levels: very unsuitable (0–0.2), unsuitable (0.2–0.4), moderate (0.4–0.6), suitable (0.6–0.8), and very suitable (0.8–1). Figure 4 illustrates five spatial health equity maps corresponding to these five ORness values. The terms "suitable" and "very suitable" denote areas characterised by high spatial equality.

Along with Figure 4, for all values of ORness, the central part of District 6 was put into suitable and very suitable levels. This is due to the high number of HCHs and the quality of public transportation services in this region. But some northern parts of the study area are classified as very unsuitable and unsuitable according to the spatial health equity levels. This shortcoming is related to the quality of HCH services in this region and also the unbalanced distribution of HCHs in this portion.

To assess the portion of each level, the assigned area in each ORness value was computed and is depicted in Figure 5 diagrammatically. The minimum extent in all ORness values is assigned to very unsuitable areas. In contrast, the maximum value of it is 0.14% in ORness = 0 (extremely pessimistic condition), and the minimum value is 0.07% in ORness = 1 (extremely optimistic). About the maximum extent in all ORness values, the results showed that it belongs to a suitable level, while the maximum value of it is 0.38% in ORness = 1 (extremely optimistic), and the minimum value is 0.28% in ORness = 0 (extremely pessimistic condition); also, it should be noted that in the full risk condition (ORness = 0), about 70% of the region has moderate, suitable, and very suitable conditions, which indicates almost fair spatial health equity. Spatial equity increased in 81% of the study area in the full risk-aversion condition (ORness = 1); also, the assigned values for ORness = 0.5 (Neutral) are equal to 78%. All of these values show reasonable spatial health equity in the study area.

Sensitivity Analysis

This paper employed a feature screening technique, specifically the one-at-a-time approach, to evaluate the impact of each individual factor on changes in value [34]. In this regard, the sensitivity analysis was carried out by fluctuating the criterion weights, recomputing the results, and assessing the corresponding difference of the fallouts [32].

The sensitivity of changes in the weights of the criteria in the output model was checked by changing the values of the weights from 0 to 1 in a fixed time. The total value of the substitute location i, $v(A_i, W_t)$, is a function of w_t as stated in Equations (22) and (23) [35].

$$v(A_i, W_t) = w_t v(a_{it}) + \sum_{k=t} w_{k^*} v(a_{ik}) \quad (22)$$

$$w_{k^*} = \frac{(1 - w_t) w_k}{\sum_{k=t} w_k} \quad (23)$$

where $v(a_{ik})$ and $v(a_{it})$ show the function's value for the criteria i, and the kth weight is k, w_k. The adjusted kth weight is w_{k^*} , and w_t *is* the related weight. To assess the impact of each criterion on the quantity of area nominated to the suitable level to spatial health equity, for a specified ORness = 0.5, a sensitivity analysis was performed. Then, the area of the suitable level was measured. The suitable class was selected since the assigned portion is the greatest one compared to the others. The sensitivity analysis results for each of the criteria are displayed in Figure 6.

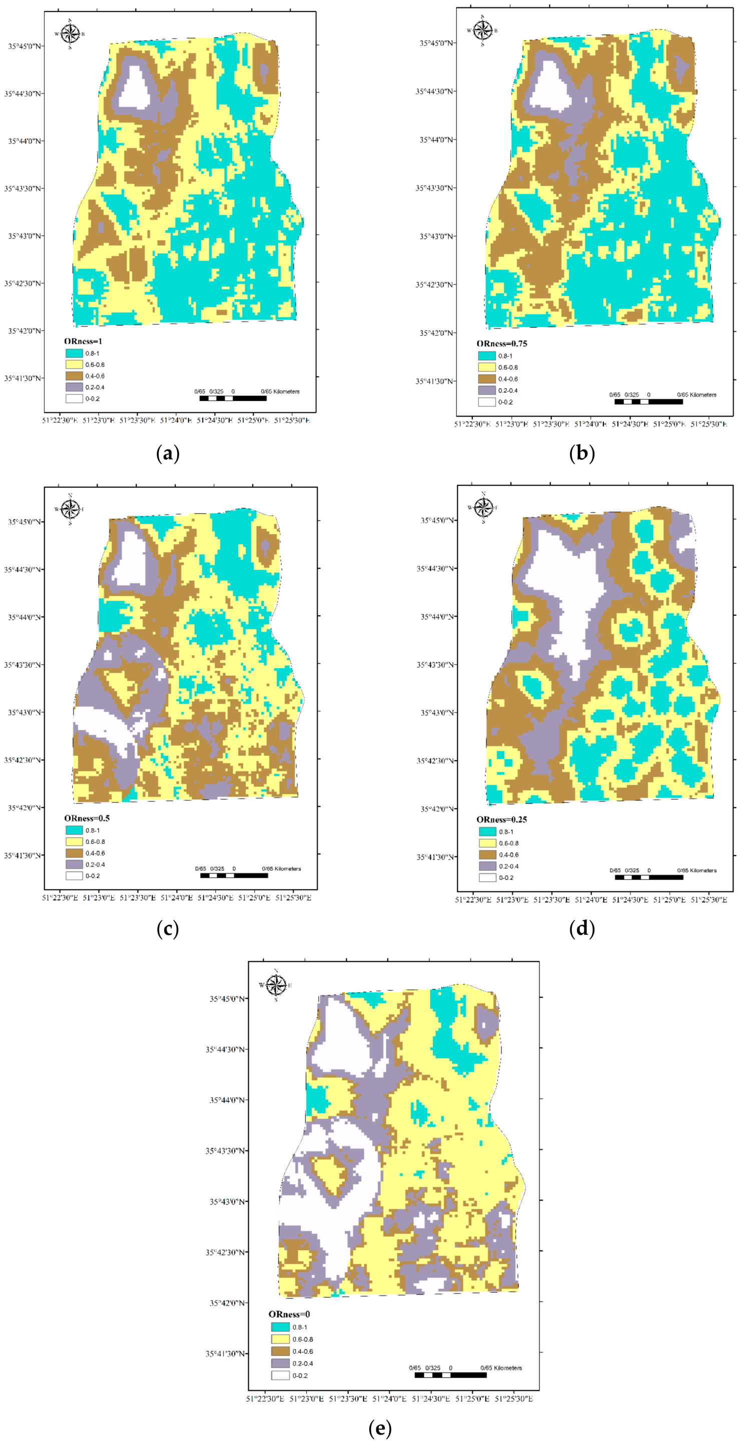


Figure 4. HCH map of the study area using the proposed method: (**a**) ORness = 0, (**b**) ORness = 0.25, (**c**) ORness = 0.5, (**d**) ORness = 0.75, and (**e**) ORness = 1.

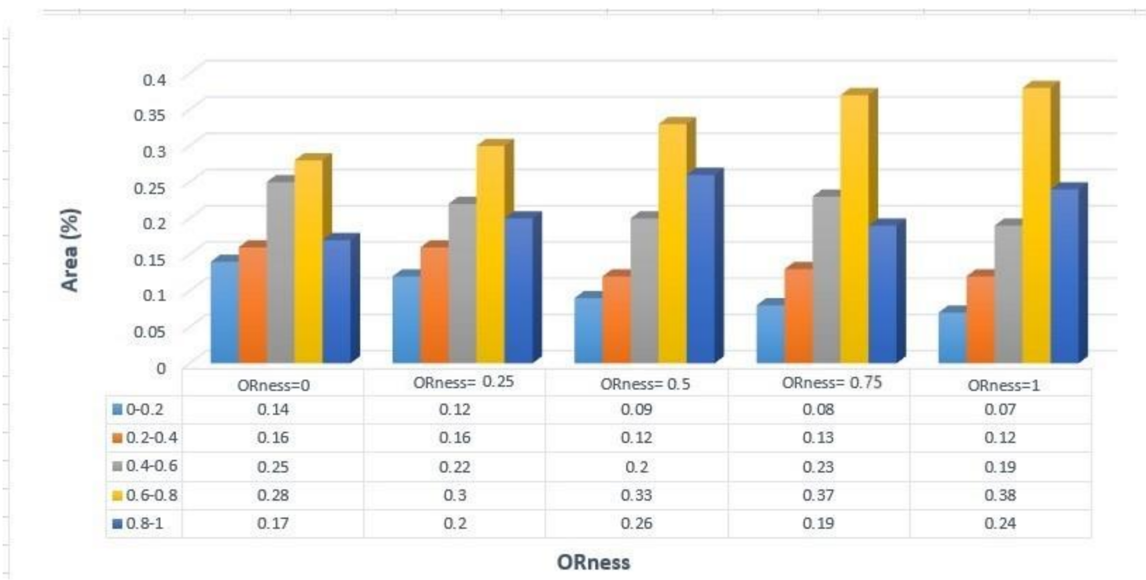


Figure 5. The portion of each suitability level from the study area.

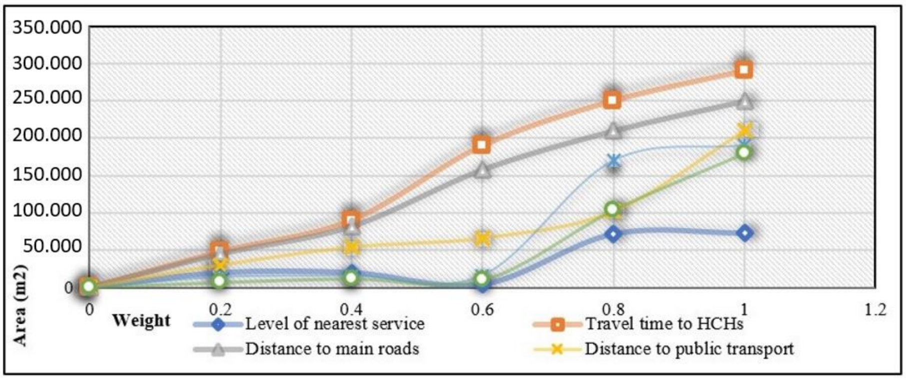


Figure 6. Diagram of the sensitivity analysis results of the area classified as suitable (0.6–0.8).

According to Figure 6, in the case study area, it is evident that the nearest service criterion exerts the least influence on the expansion of or reduction in criterion weight in the proposed method. Changes in the quantity of area were found to be relatively negligible. Conversely, travel time to HCHs and distance to main roads are of paramount significance across all scenarios, as modifying the weights significantly impacts the area associated with the suitable level.

4. Discussion

In this study, the authors applied a combination of MCDA (multi-criteria decision analysis), VGI (volunteered geographic information), OWA (ordered weighted averaging), and F-BWM (fuzzy best–worst method) techniques to evaluate the spatial health equity in the distribution of medical centres within urban areas. MCDA focuses on the organisation and resolution of decision and planning issues that include multiple criteria. Because there is usually no one best answer for these problems, it is important to include the preferences of decision makers in order to differentiate between potential solutions.

The F-BWM was utilised to assess six criteria: (1) the level of nearest service, (2) travel time to HCHs, (3) distance to primary roadways, (4) public transportation availability, and (5) density of healthcare facilities, and (6) distribution of healthcare facilities gathered through VGI. Utilising the OWA method, the authors generated an equity map illustrating varying levels of health centre distribution across urban areas.

The volunteers assigned weights to specific criteria, with travel time being deemed most critical and the distribution of medical centres considered the least significant. Our analysis, based on these criteria, reveals notable disparities in the allocation of medical service centres across the study area. The central region of District 6 displays an exceptionally favorable distribution of medical centres, attributed to both the substantial number of facilities and the quality of public transportation services. Conversely, the northern part of District 6 is characterised by distributions labeled as very unsuitable and unsuitable, primarily due to the uneven distribution of medical service centres in that area.

In line with the findings, a review of pertinent studies on spatial equity in healthcare centre assessments provides valuable insights. Whitehead et al. (2019) [4] conducted an analysis of access distribution in rural regions of China, employing methods such as geographic weighted regression and multi-criteria decision analysis. They highlighted that the accessibility of all medical services, encompassing hospitals and pharmacies, stands out as the pivotal factor in assessing spatial equity, a perspective consistent with this research approach. Neisani Samani and Alesheikh (2019) [3] conducted a study focusing on the inequity in the distribution of medical centres, integrating volunteered geographic information (VGI) and F-VIKOR to address decision uncertainties. They emphasised that an increase in the number of volunteers enhances the reliability of the results. Similarly, Parvin et al. (2021) [18] employed spatial analysis techniques such as Weighted Linear Combination (WLC) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Their research involved a three-layer analysis approach, aiming to assess accessibility and identify suitable locations for healthcare facilities, incorporating shortest path network analysis. This study supported the significance of proximity, as indicated by traffic network analysis, aligning with the time–distance concept in this proposed method. Auld et al. (2023) [21] integrated criteria such as the proximity of the patient's residence to healthcare hubs (HCHs) and a pediatric centre. The findings underscore the effectiveness of strengthening primary medical services in enhancing patient outcomes and reducing travel expenses for individuals in remote areas seeking medical care. This study also affirmed the significant role of time distance to HCHs. Poleto et al. (2023) [36] developed an SDSS for maternal mortality analysis. Lopes et al. (2021) [37] measured accessibility to healthcare services to formulate health policies and improve the population's health status and mitigate inequities in health. Mansour (2016) [15] concentrated on the spatial analysis of public health facilities to evaluate spatial variations in service delivery and access in Saudi Arabia, utilizing the k-nearest neighbours (KNN) method. The study considered the criterion of the distance from patients to medical centres and examined the equilibrium in providing public health facilities to the target population. Their work highlighted the importance of accessibility criteria, as defined in this research.

After an extensive review of the existing research literature relevant to this current study, the consensus is that augmenting the accessibility criterion with additional effective factors, such as the level of service to HCHs and the distribution of HCHs, proves advantageous. Moreover, it is imperative to consider and address uncertainty in participatory surveys.

Limitations

This study has a few limitations. Firstly, limitations emerged in gathering information from survey participants. Various VGI platforms are available, and data collected through such means necessitate rigorous accuracy and precision checks, incurring substantial time and cost. In this study, the investigation was confined to a single area, leading to the development of a dedicated VGI data collection platform. To enhance the algorithm and streamline VGI collection, it is advisable to consider the utilisation of open-source public participation platforms like OpenStreetMap (OSM).

The second limitation pertains to the unavailability of traffic and population data specific to the study area. District 6, situated in the heart of Tehran city, encompasses a multitude of primary functions such as commercial centres, educational institutions, offices, and medical facilities, making it one of the most densely populated and high-traffic regions.

5. Conclusions

This study employs a WebGIS approach with VGI, MCDA, F-BWM, and OWA methods to evaluate the spatial equity of urban health services. Urban health spatial equity is categorised into five levels, ranging from "very suitable" to "very unsuitable". The results reveal that the eastern and central parts of District 6 exhibit higher spatial equity in health services compared to the northern part. Specifically, the spatial equity in health services is healthier in the eastern and central regions of District 6, while the northwest region shows lower equity than other areas. Sensitivity analysis indicates that the "Level of nearest service" has the least impact, with "travel time to HCH" and "distance to main roads" having the most significant influence. Managing the uncertainty of these weighted parameters is crucial for accurate spatial equity evaluation. Future research is recommended to include additional parameters such as traffic data, population density, and demographic characteristics for a more comprehensive analysis of spatial health service equity in urban settings. To improve the algorithm and restructure VGI collection, it is sensible to reflect on the use of OSM.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16051745/s1, Figure S1: The criteria maps on the VGI website. Figure S2: illustrates weighting the criteria using comparison table: (a) comparison to best criterion, (b) comparison to worst criterion.

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