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Contributions to a Theoretical Framework for Evaluating the Supply–Demand Matching of Medical Care Facilities in Mega-Cities: Incorporating Location, Scale, and Quality Factors

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Abstract: The rapid urbanization and population growth in mega-cities have led to a significant increase in the demand for medical services, highlighting the critical need for a more efficient alignment between the supply and demand of medical resources. Previous research often focuses on singular factors, such as accessibility or quantity, as the primary criteria for matching medical services, without comprehensively considering the location, scale, and quality factors of medical facilities. Addressing this gap, this study develops a theoretical framework that integrates these three critical factors to assess the supply–demand matching (SDM) of medical care facilities (MCFs) with population needs. This assessment is conducted using geospatial analysis techniques with ArcGIS and Python. The study includes an empirical analysis of 134 streets within the Chongqing municipality. The empirical results reveal significant disparities in the performance of integrated medical care facilities (MCFs), as well as variations across the dimensions of location, scale, and quality. Central districts like Yuzhong demonstrate high levels of accessibility, appropriate scale matching, and satisfactory service quality, whereas rapidly urbanizing peripheral districts such as Yubei suffer from significant mismatches in resource availability and service quality. The theoretical framework contributes to the field of medical care research, and the corresponding empirical findings provide valuable insights for urban planners and policymakers to optimize the allocation of medical resources, improve healthcare accessibility, and enhance service quality across different urban areas.

Keywords: medical care facilities (MCFs); supply–demand matching (SDM); location–scale–quality; Chongqing

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Citation: Liao, S.; Li, J.; Shen, L.; Wu, Y.; Bao, H. Contributions to a Theoretical Framework for Evaluating the Supply–Demand Matching of Medical Care Facilities in Mega-Cities: Incorporating Location, Scale, and Quality Factors. *Land* **2024**, *13*, 1606. https://doi.org/10.3390/land13101606

Academic Editor: Maria Rosa Trovato

Received: 22 August 2024
Revised: 30 September 2024
Accepted: 30 September 2024
Published: 3 October 2024

1. Introduction

Medical care facilities (MCFs) are essential physical infrastructures that serve public health and ensure the well-being of the general populace [1]. These facilities encompass comprehensive and specialist hospitals, professional public health institutions such as emergency centers, and primary health institutions like health service centers [2]. However, rapid urbanization and growing populations lead to a significant rise in demand for medical services, especially in mega-cities, which places increasing pressure on MCFs [3–5].

Despite global health reforms that have aimed to enhance medical systems—reflected in the increase of health spending from 8% to 10.3% of GDP [6]—there still remains a widespread mismatch between the supply and demand for MCFs. This mismatch is particularly pronounced in megacities, where it results in both the uneven distribution and varying quality of services, leading to overcrowded facilities in some areas and underutilized resources in others [7,8]. Such mismatches hinder the efficient use of medical resources and exacerbate inequalities in healthcare access, leading to uneven health outcomes across different regions [9,10] and contributing to higher healthcare costs [7]. Given these challenges, it is crucial to scientifically assess the supply–demand matching (SDM) of urban MCFs. Accurate SDM assessments can guide the strategic allocation and spatial distribution of healthcare facilities. By evaluating the SDM of MCFs, the stakeholders can enhance service capacity and reduce disparities in healthcare provision.

The spatial supply–demand matching (SDM) of medical services has emerged as a key focus in health geography research, and the evaluating criteria of it varied across the literature. For instance, many studies emphasize accessibility as the primary criterion for SDM, such as those by Di et al. [11], Jiang et al. [12], Song et al. [13], Regis-Hernández et al. [14], Shao et al. [15], and Chen et al. [16], in which accessibility is applied as the major indicator to evaluate the uneven distribution and insufficient supply of MCFs in urban areas. A group of researchers regard the quantity of MCFs as the key criterion of SDM performance. For instance, Lin et al. [17] and Wang et al. [18] estimated the supplied quantity of MCFs in relation to residents' demands within specific regions. Their findings revealed significant disparities across the surveyed areas. Others argue that the quality of MCFs should be the primary criterion for evaluating SDM performance. For instance, studies by Sun et al. [19], Yan and He [20], Hong et al. [21], Ta et al. [22], and Wu et al. [2] have introduced either residents' or patients' satisfaction with MCFs as key measures for assessing MCF quality in SDM research. Still, some researchers have combined both quantity and quality as the main considerations when evaluating the SDM performance of MCFs, such as the research by Guo et al. [8], who highlighted the relationship between supply capacity and service quality of MCFs in relation to the urban population when measuring the SDM level of MCFs in Tianjin, China.

In conclusion, existing research on supply–demand matching (SDM) has predominantly focused on either spatial location, quantity, or quality in isolation, without integrating these three factors comprehensively. However, drawing on the "Homo-Urbanicus" theory, Wei et al. [23] emphasized that public service facilities, such as MCFs, should be strategically located, appropriately scaled, and of sufficient quality to meet population needs. This ensures "equal accessibility, balanced carrying capacity, and equal access to high-quality services", leading to regional SDM equilibrium. In other words, the allocation of MCFs is influenced by the range and layout, scale, and quality of MCFs collaboratively. Only integrating these factors into the measurement of SDM performance can help the medical resources be fully used and can the residents benefit to the greatest extent.

To address these gaps, this study constructs a comprehensive SDM framework for evaluating the performance of MCF allocation by integrating three dimensions: location, scale, and quality. Specifically, the research endeavors to address the following objectives: (1) establish a framework for quantifying the SDM performance of MCFs, (2) conduct an empirical analysis with an example of Chongqing to verify the effectiveness of the SDM framework, and (3) spatially analyze the SDM performance for MCFs and provide effective strategies for SDM improvement.

From a planning perspective, SDM evaluation results can help authorities identify and monitor the alignment between local medical services and resident demands, providing a foundation for future improvements. This research contributes to establishing a theoretical framework for rational planning pertaining to healthcare resources in local regions. Furthermore, the findings of this study hold practical implications for cities and regions beyond the examined area. They provide valuable insights for municipal authorities aiming to improve healthcare facilities for the benefit of their residents.

This study proceeds as follows. Section 2 introduces the study area and research framework. Section 3 introduces the methodology for measuring location matching (LM), scale matching (SM), and quality matching (QM), respectively. Section 4 exhibits the study results. Section 5 describes the discussion followed by Section 6, which presents the conclusions and policy implications of the study.

2. Study Area and Research Framework

2.1. Study Area

This study selected the area within the outer ring road of Chongqing as the study area, including the streets along the ring road, as shown in Figure 1. The study area encompasses 134 streets/towns, with details provided in Appendix A Table A1. There are two primary reasons for selecting this area: (1) Chongqing is one of China's four municipalities directly administered by the central government and is the largest megacity in southwest China [24]. (2) Despite covering a vast area of 82,403 km^2, Chongqing municipality is predominantly rural, with urban areas accounting for less than 7% of the total [25]. Notably, half of Chongqing's built-up area is concentrated within the core metropolitan region enclosed by the outer ring road. Consequently, this study focuses on "urban" medical care facilities (MCFs), and the areas within the outer ring road are selected as the study area. Thirdly, Chongqing Statistical Yearbook [26] reveals a consistent decrease in the city's revenue from 2018 to 2020, with a cumulative decline of 7%. Conversely, healthcare expenditure has shown a year-on-year increase, totaling a 15% rise. This trend highlights the growing strain on medical services within the city. Given the limited medical resources and increasing demand, Chongqing municipality serves as an ideal region for evaluating the matching of MCFs between supply and demand. This evaluation could provide valuable insights for future improvements and renovations of MCFs in the region.

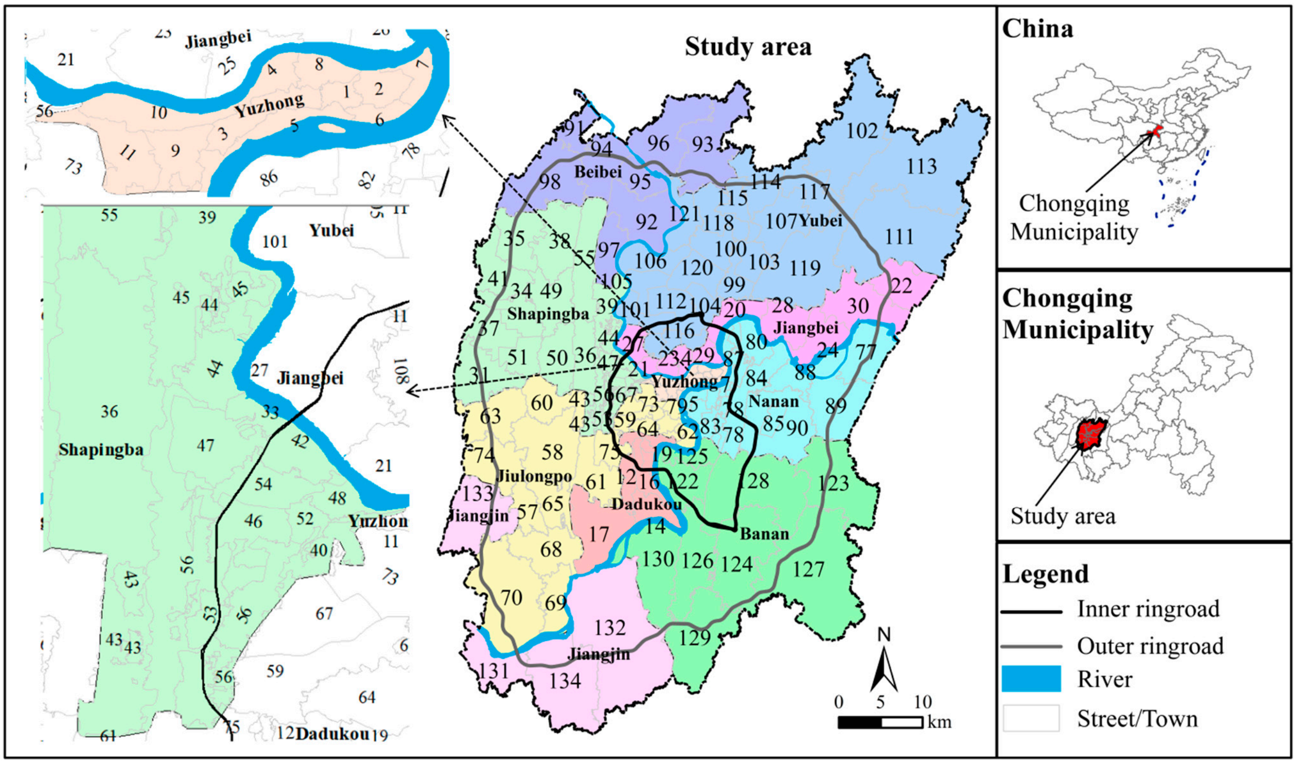


Figure 1. Location of the study area.

2.2. Research Framework and Data Sources

2.2.1. Research Framework

As discussed in the previous section, this study aims to construct models to measure the levels of location matching (LM), scale matching (SM), and quality matching (QM) within the SDM framework. The research framework is illustrated in Figure 2.

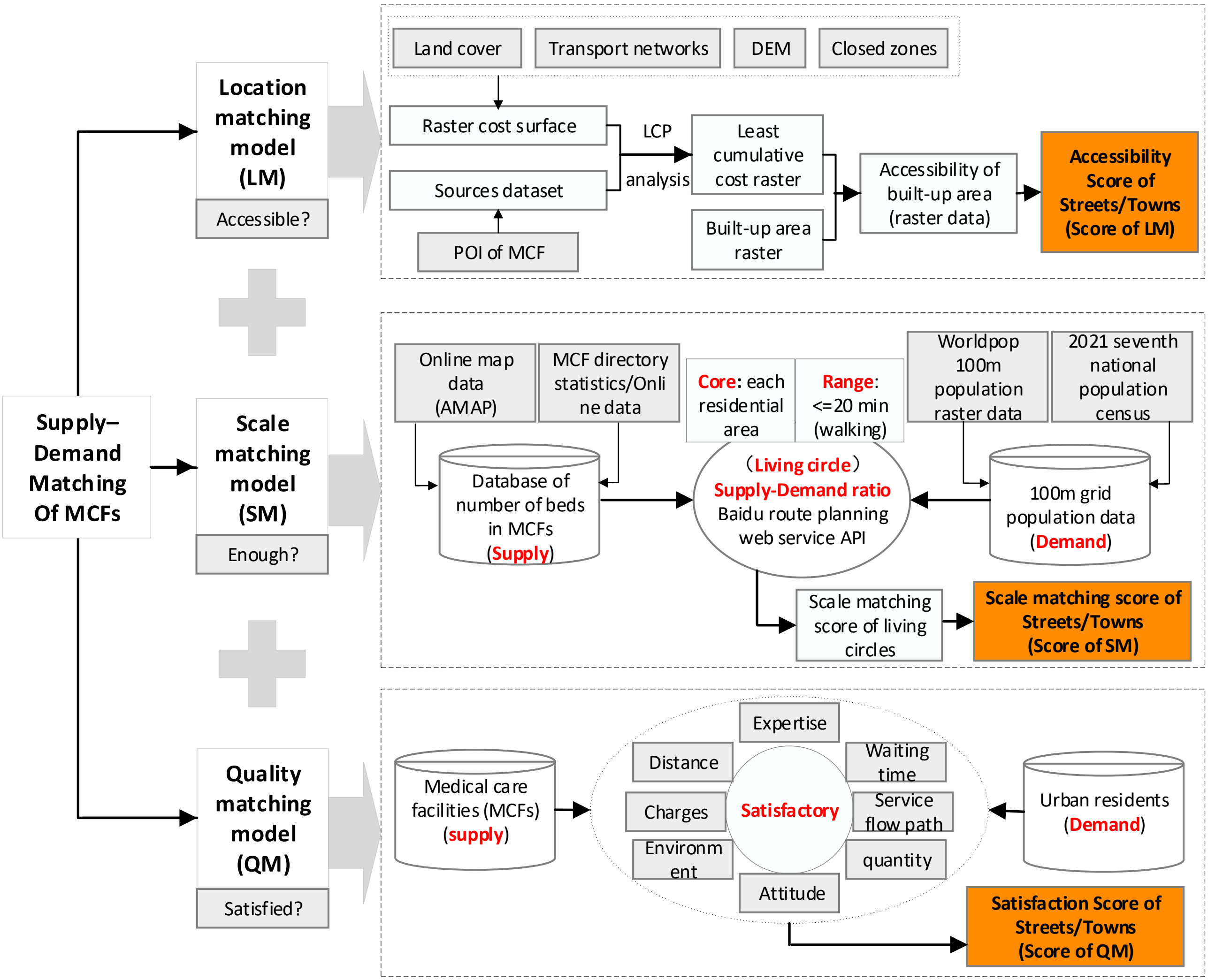


Figure 2. Research framework for measuring the SDM of MCFs.

Location matching (LM) is the process of aligning medical resource distribution with local demands, and it varies across regions [27]. Proper layout of medical resources is crucial for medical service planning. Inappropriate layouts can lead to either over-concentration or fragmentation, hindering access to essential services for residents, especially in outlying areas. This undermines SDG 11.7, which emphasizes universal access to public services [28]. In a word, LM evaluates whether the spatial distribution of medical care facilities (MCFs) is accessible to residents within a certain time range, addressing the basic question of "accessible or not accessible". The least-cost model in ArcGIS is employed to assess the accessibility of MCFs to residents, and the LM score is calculated based on these accessibility results.

Scale matching (SM) involves aligning the quantity of medical resources with local demands [29]. When medical services are configured to meet precise demand levels, more citizens can obtain the required healthcare. Insufficient medical resources may exclude disadvantaged groups from essential services or force them to relocate to areas with poorer living conditions. Conversely, an oversupply of medical resources can lead to underutilization and waste [7]. As such, effectively achieving the quantitative matching between the supply of and demand for medical services becomes a crucial concern, particularly during medical emergencies like the COVID-19 pandemic [30,31]. In a word, SM assesses whether the number of facilities within a certain accessible range matches the population, addressing the question of "enough or not enough". The SM score is calculated based on the indicator of "number of MCFs per 1000 people".

Quality matching (QM) refers to the matching of medical resources with local demands [32]. A mismatch in this aspect often leads residents to seek appropriate medical services outside their region. Such disparities can result in the underutilization of low-quality medical services and overcrowding of high-quality public services. This situation will lead to further pressure on the surrounding high-quality medical service and affect the overall balance between supply and demand in turn. In a word, QM examines whether the quality of services provided by MCFs meets the needs of residents, focusing on "satisfaction or not satisfied". Residents' satisfaction with MCFs around their streets is used as the QM indicator.

In this study, the analyses of the three dimensions (LM, SM, and QM) are conducted at different research scales (grid scale, living circle scale, and street scale, respectively). However, for comparative analysis, the final results are unified to the street scale.

2.2.2. Data Source

In this study, medical services include general hospitals, specialized hospitals, emergency hospitals, and primary medical institutions. The information of point-of-interest (POI) of MCFs is obtained from AMAP, which is a major mapping platform serving Hong Kong, Macau, and Mainland China. Secondly, the transportation network and river data are also collected from AMAP. Land cover data are obtained from GlobeLand 30-2020. GlobeLand30 is a global high-resolution land cover product with a 30 m spatial resolution, which is provided by China to the United Nations for global change research [33]. Topography data include relief (m) and slope (°). Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) data are the radar digital elevation data with a total area of more than 1.19×108 km^2, which were obtained by the SRTM system carried by the US Space shuttle Endeavour, and covers more than 80% of the world's land surface. The spatial resolution of the original DEM data is 30 m $\times$ 30 m (https://lta.cr.usgs.gov/GTOPO30 (accessed on 25 August 2022)). The population by streets is obtained from the 2020 Population Census. The population density is obtained from the WorldPop dataset with a 100 m spatial resolution. The WorldPop dataset was developed collaboratively by multiple organizations and institutions including the University of Southampton to provide geospatial data on population distributions, demographics, and dynamics to meet wide-ranged users [34]. The data of the administrative division are obtained from the third territorial survey of Chongqing. All data were collected for the year 2022 or the most recent year available, ensuring the study's relevance to current conditions.

3. Methodology

3.1. Methods for Measuring Location Matching (LM)

Location matching (LM) evaluates whether the spatial distribution of MCFs is accessible to residents within a reasonable time frame, and the Least-Cost Path (LCP) method was employed. The primary objective is to determine how effectively these facilities serve the local population, particularly in terms of accessibility. Given Chongqing's complex urban environment, characterized by varied topography and dense development, the LCP method provides a robust framework for assessing the actual travel time required for residents to reach MCFs. This method is especially suited to this study. It enables the calculation of the most efficient routes between residential areas and MCFs by considering various spatial factors, including road networks, elevation, and land use types. This comprehensive approach ensures that the analysis reflects actual conditions compared to Euclidean distances, which may underestimate travel times in complex urban landscapes [35–37]. Moreover, previous research has validated the efficacy of the LCP method in urban planning and public health studies, where accurate accessibility modeling is crucial [38–40]. By integrating diverse spatial data into the cost surface model, the LCP method allows for a detailed evaluation of how well the spatial distribution of MCFs aligns with residents' needs.

(1) Construction of the cost surface

The raster cost surface was first constructed at a grid scale of 10 m. The datasets used to construct the cost surfaces include spatial data on roads, rivers, water bodies, topographical features (slope and relief), and land cover, as shown in Table 1. The "value" in Table 1 represents the time (seconds) required to traverse a 10 m cell, assuming a walking speed of 1.3 m/s (7.6923 s/10 m) without obstacles [41]. On this basis, other cost values are determined by reference to the research by Yin and Kong [42]. The Cost Distance and Cost Path tools within ArcGIS are central to this process and are adopted to generate the cost surface by assigning resistance values to different landscape features.

Table 1. Assignment of resistance value for different variables in the construction of cost raster surface.

Categories	Factors	Classification	Value
Land cover	Roadless land area	-	10
Transport networks	National and provincial road Urban arterial road County and township roads Country road	-	7.6923
DEM	Slope (°)	<8	10
		8–15	15
		15–25	30
		25–35	50
		35–45	70
		>45	100
	Relief (m)	<15	10
		15–30	15
		30–60	20
		60–90	30
		90–120	50
		120–150	70
		>150	100
Closed zones	Water (m)	>50	200
		<50	100
	Railway and expressway	-	200

(2) Calculation of score of location matching (LM)

After the construction of the cost surface, the POIs of MCFs were imported into the source dataset. Subsequently, the Cost Distance tool within the ArcGIS Spatial Analyst extension was used to calculate the shortest accumulated time (cost) to the nearest MCF for each raster cell. This was based on the least-cost path analysis. The accessibility score for each raster cell was calculated using Formula (1). To avoid miscalculations of street-level accessibility scores, only the results for built-up areas were retained for further calculations. This filtering step is critical to ensure that the accessibility of streets with significant non-construction land cover, such as mountains, hills, and water bodies, is not inaccurately represented in the analysis.

$$A_{ij} = \begin{cases} 1, & if\ t_{ij} \le 1200 \\ 1 - \frac{t_{ij}-1200}{1200}, & if\ 1200 < t_{ij} < 2400 \\ 0, & if\ t_{ij} \ge 2400 \end{cases} \quad (1)$$

where A_{ij} denotes the accessibility score of jth raster cell in the ith street; t_{ij} represents the least cumulative cost (time in seconds) from cell j in ith street to the nearest POI of MSF; 1200 s (20 min) is the threshold established based on the "Chongqing Territorial Spatial Master Plan (2021–2035) (exposure draft)" for accessible MCFs. If the travel time t_{ij} is less than or equal to 1200 s, the accessibility score A_{ij} is assigned a maximum value of 1, indicating optimal accessibility; 2400 s (40 min) is considered the upper limit for accessibility.

If the travel time t_{ij} exceeds 2400 s, the accessibility score A_{ij} is set to 0, indicating that the location of MCFs is effectively inaccessible within a reasonable time frame.

Based on the accessibility scores of individual built-up areas, the location matching score for each street was calculated using Formula (2):

$$LMS_i = \sum_{j=1}^{n} w_{ij} A_{ij} = \sum_{j=1}^{n} \frac{POP_{ij}}{POP_i} A_{ij} \quad (2)$$

where LMS_i denotes the location matching score of ith street/town; n denotes the number of raster cells within an ith street unit; A_{ij} denotes the accessibility score of the jth raster cell in the ith street; w_{ij} denotes the population weight of the jth raster cell within the ith street area; POP_{ij} and POP_i represent the population in the jth raster cell within the ith street area and the population of the ith street, respectively.

3.2. Methods for Measuring Scale Matching (SM)

Scale matching (SM) assesses whether the number of MCFs within a certain accessible range matches the local population's needs. This dimension emphasizes the relationship between the supply and demand elements of MCFs. It focuses on achieving a quantitative balance between these two factors. The goal is to examine the existing medical services and the pressures imposed by the urban population to ensure an appropriate balance. Therefore, scale matching is represented by the quantitative ratio between the supply and demand elements.

While prior research has investigated the spatial alignment between MCFs and population distribution, most studies have been conducted at city, county, or street/township levels. These scales frequently do not correspond with residents' behavior and habits, as individuals often travel to urban areas in search of higher-quality MCFs [2,23]. The living circle theory offers a more nuanced approach, examining supply and demand imbalances from the perspective of residents' living quarters. This approach assists in the proper allocation of facilities while reflecting principles of equality and social justice [43]. It captures the interactive relationship between urban public service facilities and residents' needs. The "Urban Residential Area Planning and Design Standards" was approved and published by the Ministry of Housing and Urban–Rural Development of the People's Republic of China. It embraces the planning concept of allocating public service facilities based on varying levels of residential circles. Therefore, the study of scale matching of MCFs in this research is conducted from the perspective of the living circle. This section is divided into several steps, including the construction of living circles, identification of supply and demand, and calculation of scale matching scores.

(1) Construction of living circle

To construct living circles, three key elements need to be confirmed: cores, range, and delineation method.

Cores: Residences, as the origin and destination points for residents' daily activities, are central to these living circles. The approach of centering public service facilities around residential areas is consistent with the living circle model, which aims to meet most residents' daily needs within a short distance. Consequently, points of interest (POIs) within residential communities are designated as the central hubs of these living circles. However, using each residential community as a core directly would lead to significant data redundancy and make observation difficult. Additionally, interface usage limitations (5000 requests per day) present further challenges. To address these issues, this study merges residential community POIs that are within a distance less than the median radius of the minimum bounding circles derived from the AOI (area of interest) of these communities. The "Sub points" plug-in tool developed by Esri China was used to facilitate this integration process.

Range: As previously mentioned in the method for measuring location matching (LM), Chongqing's Territorial Spatial Planning requires that MCFs should be located within a

20 min walking distance from residences. In alignment with the requirements, this study adopts a 20 min walking range for constructing living circles. This approach ensures consistency with local planning standards while evaluating the scale matching of MCFs.

Delineation Method: Existing research has demonstrated that the living circle range derived from the navigation distance method is the most precise [44]. This method takes into account factors such as the road network smoothness, intersection waiting time, and others, providing a more accurate description of distance. Therefore, the 20 min living circles were established with each residential area as the origin. This was accomplished by utilizing the route planning (walking) web service API of Baidu Maps (https://lbsyun.baidu.com/faq/api?title=webapi/guide/webservice-lwrouteplanapi/walk, accessed 3 June 2023) through Python 3.9.

(2) Identification of supply and demand of MCFs in living circles

Supply: The supply of service capacity of MCFs is often expressed by the number of beds in medical institutions [45]. The total number of beds of MCFs within each living circle was used to represent the supply aspect. Because the majority of community health stations and many non-public hospitals have no data on formal beds, these missing data are supplemented according to the Hospital Classification Management Standards.

Demand: In this study, the population within each living circle is used to represent the demand for medical care facilities. Population data were sourced from the 2020 WorldPop raster population data with a 100 m resolution (https://www.worldpop.org/geodata/summary?id=24926, accessed on 3 June 2022) and the Seventh National Population Census in Chongqing. The WorldPop raster data were aggregated by street boundaries by applying ArcMap, and the Zonal Statistics tool was used to calculate population estimates for each street. A correction coefficient was then computed by dividing the census population of each street by the WorldPop-derived population. The specific steps are as follows: (1) calculate the ratio of the Seventh National Population Census population to the WorldPop population for each street or town, denoted as R; (2) connect the R-value to the shapefile of the respective street or town district; (3) designate the R-value as the "value field" and perform a " Polygon to Raster" operation on the shapefile at the street or town level, ensuring that the "processing range" and "pixel size" in the environmental settings are consistent with the WP population grid; (4) use the " Raster Calculator" command to multiply the grid data obtained from the previous step by the WP grid data to derive the adjusted grid population data; (5) finally, the Zonal Statistics tool was used again to sum the adjusted population densities within each living circle, providing the total population as the load.

(3) Calculation of score of scale matching (SM)

The level of scale matching (SML) is calculated using the following Formulas (3)–(5):

$$R_i = \frac{S_i}{D_i} \tag{3}$$

$$SML_i = \begin{cases} R_i > G_i, & High\ Matching\ (HM) \\ R_i \in G_i, & Appropriate\ Matching\ (AM) \\ R_i < G_i, & Low\ Matching\ (LM\prime) \\ R_i = 0, & Missing\ matching\ (MM) \end{cases} \tag{4}$$

$$G = [G_1,\ G_2] \tag{5}$$

R_i represents the number of total beds of medical institutions per 1000 people in living circle i; S_i and D_i correspond to the supply and demand of medical services, respectively. SML_i refers to the scale matching level in living circle i. G_i denotes the standard requirements of moderate matching; G_1 and G_2 represent the lower and upper limits of G_i, respectively. The upper limit is set at 7.5 beds according to the construction target of the "Guiding Principles for the Establishment of Medical Institutions (2021–2025)" issued by the National Health Commission of PRC. The lower limit is established at 1.0 based on the "Basic Standards of Community Hospitals" from the same commission.

Based on the results of SML_i, the scale matching score (SMS) is calculated. As discussed in the introduction section, insufficient medical resources may exclude certain disadvantaged groups from accessing essential medical services, while an oversupply may lead to under-utilization of MCFs. Therefore, the value of R_i should be balanced, not too high nor too low. A higher R_i may indicate resource waste, while a lower R_i suggests that resident needs are not being met. Therefore, the scale matching score is determined using the following formula:

$$SMS_i = \begin{cases} R_i/G_1,\ R_i \in [0,\ G_1) \\ 1,\ R_i \in [G_1,\ G_2] \\ 0.75,\ R_i \in (G_2,\ \mu+\sigma] \\ 0.5,\ R_i \in (\mu+\sigma,\ \mu+2\sigma] \\ 0.25,\ R_i > \mu+2\sigma \end{cases} \tag{6}$$

SMS_i refers to the scale matching score of i living circle. μ and σ represent the mean value and standard deviation of R_i, respectively. The results were further aggregated from the living circle scale to the street scale using a two-step process in ArcMap: (1) Polygon to Raster Conversion: The SM results for living circles were firstly converted into raster data. For each raster cell, the SM score was calculated as the average of all living circles that cover that cell. (2) Raster to Polygon Conversion: These raster cells were then converted back into polygons at the street scale. The final SM score for each street was calculated as the average of the SM scores of all raster cells within that street.

3.3. Methods for Measuring Quality Matching (QM)

Quality matching (QM) assesses whether the quality of services provided by MCFs meets the expectations and needs of residents. The quality of medical services is the result of collaboration between the patient and the healthcare provider within a supportive environment [46]. Previous studies have extensively discussed various indicators for measuring the quality of MCFs [47–49] and have found that patient satisfaction is the most commonly used metric for evaluating the performance of medical services. Consequently, this study uses residents' satisfaction with the MCFs around their streets as the primary indicator to measure the quality matching in the SDM framework. This section is organized into four steps: questionnaire design, survey administration, data processing, and the calculation of quality matching scores.

(1) Questionnaire design

Through an extensive literature review, this study identified various dimensions of patient satisfaction related to healthcare services. These dimensions encompass the entire process from admission to discharge, waiting times for care, the attitudes of physicians, nurses, and support staff, the environment of MCFs, and the associated charges [50–54].

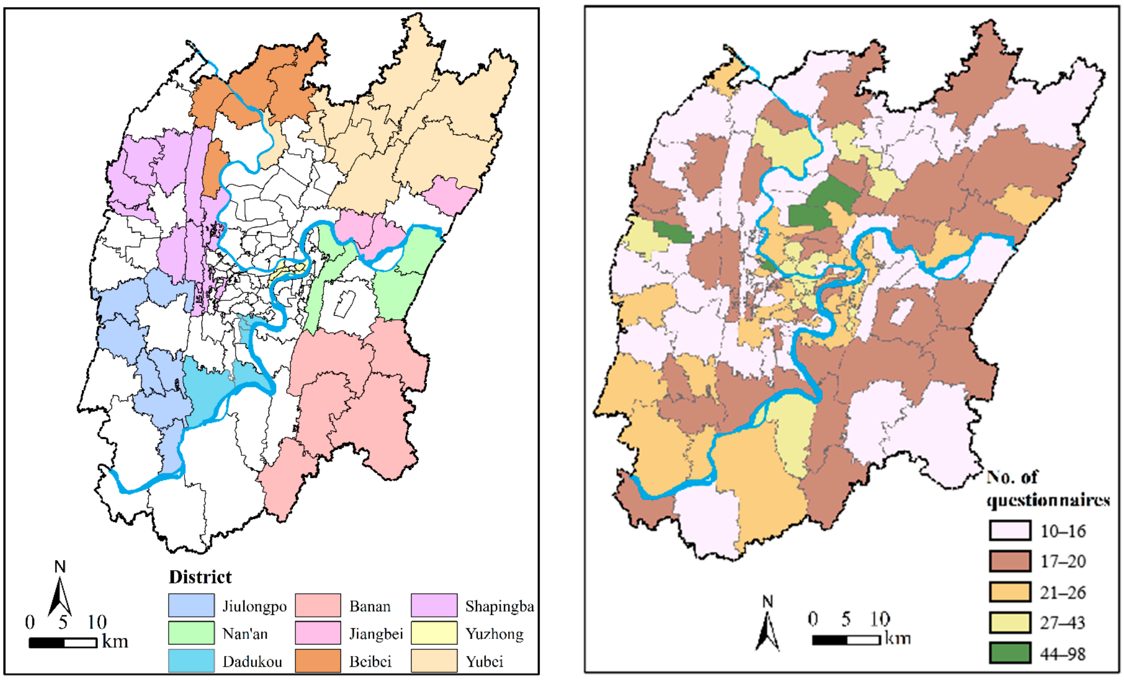
Building on existing research, this study introduced additional question items. These included aspects such as satisfaction with the distance to and the scale of MCFs. This enhancement was made to better align with the research objective of measuring residents' satisfaction with MCFs located in and around the streets where they live. Ultimately, the questionnaire was designed to separately assess residents' satisfaction with primary medical institutions (including clinics, community hospitals, health service centers, and health service stations) as well as hospitals (such as tertiary hospitals, secondary hospitals, and specialized hospitals) in and around their living areas, as listed in Table 2.

Table 2. Question items of citizens' satisfaction with MCFs in and around their living streets.

Question Item	Assessment Items	Code
Distance	Convenience and proximity to the patient's home	Q_1
Scale of MCFs	Adequate quantity and reasonable scale	Q_2
Convenience of registration	Ease of completing the registration forms	Q_3
Waiting time for outpatient visits	Length of time spent waiting for the appointment	Q_4
Ease of admission	Simplicity of the admission process	Q_5
Charges	Reasonableness of the charge at one's own expense	Q_6
Expertise	Professional competence of medical staff	Q_7
Attitude	Friendliness and professionalism of physicians, nurses, and support staff	Q_8
Environment	Cleanliness, neatness, and convenience of the environment (including internal space design, arrangement, and hygiene)	Q_9
Comprehensive evaluation	Overall evaluation of primary medical institutions/hospitals	Q_{10}

(2) Survey administration

This study primarily employed an online questionnaire survey to assess residents' satisfaction with the MCFs available in and around the streets within the study area. However, relying solely on online questionnaires posed a risk of insufficient data collection for certain streets, as some areas might not generate adequate responses. To address this limitation and ensure comprehensive data coverage, a mixed approach incorporating both online and offline questionnaires was implemented. The first round of the online survey was conducted from 15 December 2021 to 10 February 2022. After analyzing the initial responses, we identified 56 streets where the effective sample size was less than 10, as shown in Figure 3a. To ensure adequate representation, an offline questionnaire survey was carried out for these streets from 15 February to 12 April 2022, while the online survey continued simultaneously. During the offline survey, we also conducted interviews, site visits, and other field investigation activities to gather additional insights and validate the collected data. In total, 2771 feedback questionnaires were collected, comprising 2074 online responses and 697 offline responses. The distribution of the feedback questionnaires is shown in Figure 3b.



(**a**) Offline surveyed streets (with color-coded) (**b**) Distribution of 2771 questionnaires

Figure 3. The offline surveyed streets and the distribution of 2771 questionnaires.

(3) Data processing

The data collected from respondents were based on a five-point Likert scale, ranging from "not satisfied" (scored as 1) to "very satisfied" (scored as 5), as shown in Table 3. To provide respondents with more flexibility, an option of "not familiar" was also included. Responses marked with "not familiar" were excluded from the analysis for this specific question.

Table 3. Five-point Likert scale on survey feedback.

Satisfaction Level	Very Satisfied	Satisfied	General	Not Very Satisfied	Not Satisfied
Value	5	4	3	2	1

To ensure the validity of the responses, the research team implemented a rigorous filtering process for the questionnaires. The filtering criteria included checking the time taken to complete the questionnaire, the response rate to individual questions, and identifying any abnormal patterns, such as identical answers across all questions or multiple submissions from the same respondent. Following this filtering process, a total of 2514 valid questionnaires were retained, with 1823 collected online and 691 collected offline. This resulted in effective recovery rates of 87.90% for online responses and 99.14% for offline responses, respectively.

Further reliability and validity tests were conducted to assess the quality of the data. The reliability of the questionnaires was evaluated using Cronbach's alpha coefficient. The results indicated that the lowest Cronbach's alpha value across the 134 sample streets was 0.961, while the overall alpha value for all valid questionnaires was 0.988, both well above the recommended threshold of 0.70, as suggested by Nunnally, J.C., Bernstein, I.H. [55].

For validity testing, the Kaiser–Meyer–Olkin (KMO) test and Bartlett's sphericity test were conducted. Among the 134 sampled streets, the lowest KMO value was 0.907, while the overall KMO value for all valid questionnaires was 0.978. The results of Bartlett's sphericity test were statistically significant ($p \leq 0.05$). These results confirm that the collected data are suitable and valid for further analysis.

(4) Calculation of score of quality matching (QM)

The effective data collected through the questionnaire survey were further analyzed statistically. To ensure consistency with the other two dimensions, the satisfaction scores were first standardized to a range of 0 to 1. This standardization was directly applied to the raw scores of each survey item, as shown in Formula (7):

$$R'_{ijk} = \frac{R_{ijk} - 1}{5 - 1} \tag{7}$$

where R_{ijk} represents the original score of the k-th resident's satisfaction on the j-th item in street i. R'_{ijk} represents the standardized value of the satisfaction score of the k-th resident on the j-th question item in street i; 5 and 1 denote the levels on the Likert scale.

After standardizing the scores, principal component analysis (PCA) was employed to determine the weights assigned to each survey item, and the procedures were completed via SPSS 26. The procedures are shown in Figure 4, and the results of PCA are demonstrated in Table 4.

These weights were then used to calculate the quality matching score (QMS) for each street. The final QMS for each street was calculated following Formula (8):

$$QMS_i = \frac{1}{n}\sum\nolimits_{k=1}^{n}\sum\nolimits_{j=1}^{m} w_j \times R'_{ijk} \tag{8}$$

where QMS_i refers to the quality matching score of street i; w_j represents the weight of the j-th question item, determined through PCA; R'_{ijk} represents the standardized value of the satisfaction score of the k-th resident on the j-th question item in street i obtained in Equation (7); m represents the number of question items; n represents the number of valid survey responses in street i.

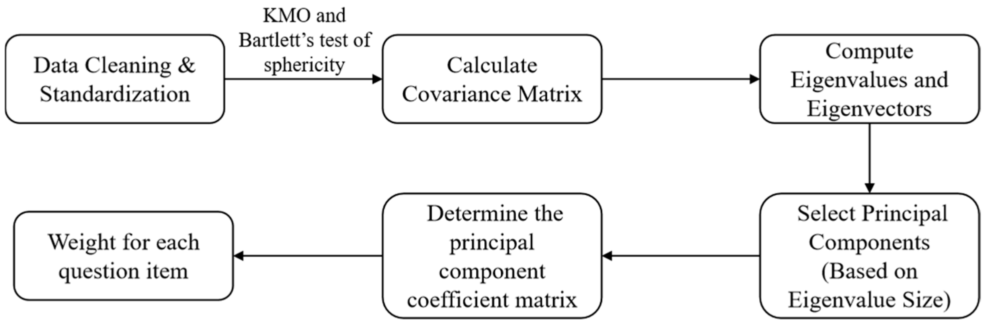


Figure 4. PCA procedures.

Table 4. The weights of the question items based on PCA method.

Code	Weight	Code	Weight
Q_1	0.0945	Q_6	0.1
Q_2	0.0995	Q_7	0.0995
Q_3	0.1005	Q_8	0.1015
Q_4	0.1005	Q_9	0.099
Q_5	0.102	Q_{10}	0.1045

3.4. Calculation of the Integrated Performance of MCFs

Considering that the performance of MCFs is collaboratively determined by the metrics of LM, SM, and QM, it is essential to integrate these three dimensions. Previous research has utilized summation, geometric mean, or arithmetic mean to quantify the overall performance of multidimensional results. However, these methods inherently require the determination of weights prior to achieving integrated results. Since the significance of LM, SM, and QM varies across regions, identifying appropriate weights for them poses a challenge. Therefore, this study adopts the "tripartite framework" based on the research of Malakar and Lu [56], as illustrated in Figure 5. In Figure 5, the origin O (0,0,0) and the point B (1,1,1) represent the zero levels and ideal levels of LM, SM, and QM after normalization, respectively. Therefore, the final results will be constrained between these two points (0,0,0 and 1,1,1) and will be cubic in shape. The point (1,1,1) represents the maximum development of the three dimensions. This approach can eliminate the challenges mentioned above well. The formula is expressed as follows:

$$MCF_i = \sqrt{(1 - LMS_i)^2 + (1 - SMS_i)^2 + (1 - QMS_i)^2} \tag{9}$$

where LMS_i, SMS_i, and QMS_i denote the normalized scores of LM, SM, and QM dimensions. MCF_i represent the integrated value. Greater MCF_i represents poorer $MCFs'$ performance.

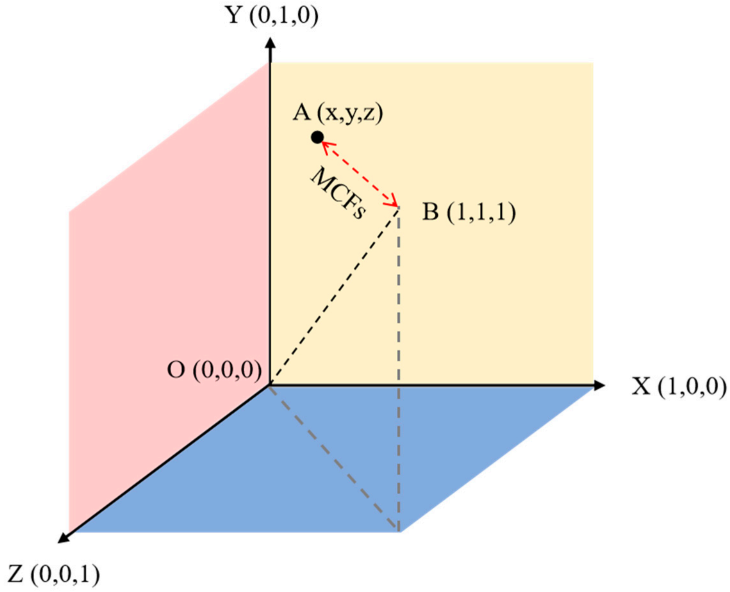


Figure 5. Tripartite framework.

4. Results of Empirical Study

4.1. Overview of the Score of LM, SM, and QM and the Integrated MCFs Performance of 134 Streets

By applying the method and data described in the previous section, the results of LMS, SMS, and QMS and the integrated MCFs performance of 134 streets/towns in Chongqing city can be obtained, as shown in Table 5. The data presented in Table 5 provides a comprehensive overview of the LM, SM, and QM scores and overall MCF performance across the 134 streets, reflecting the disparities in the spatial distribution, resource allocation, and service quality of medical facilities across different regions. Table 5 also exhibited the descriptive statistics of the three dimensions, including mean, minimum, maximum, and coefficient of variation (CV). The high CV value of LMS, SMS, and QMS means that there is a large significant difference in SDM performance across 134 streets in Chongqing.

Table 5. The results of LMS, SMS, and QMS and overall MCF performance of 134 streets/towns.

ID	LMS	SMS	QMS	Overall	ID	LMS	SMS	QMS	Overall	ID	LMS	SMS	QMS	Overall
1	1.000	0.907	0.547	0.463	47	1.000	0.974	0.673	0.328	93	0.818	0.487	0.618	0.665
2	1.000	0.994	0.669	0.331	48	1.000	0.987	0.521	0.479	94	0.922	0.832	0.486	0.546
3	1.000	0.674	0.548	0.557	49	0.687	0.366	0.484	0.875	95	0.567	0.462	0.454	0.881
4	1.000	0.866	0.778	0.259	50	0.942	0.548	0.542	0.646	96	0.913	0.504	0.41	0.776
5	0.994	0.620	0.505	0.624	51	0.941	0.860	0.467	0.554	97	0.841	0.538	0.529	0.679
6	0.999	0.995	0.513	0.487	52	1.000	0.792	0.615	0.438	98	0.988	0.678	0.479	0.613
7	1.000	0.932	0.604	0.402	53	0.981	0.795	0.565	0.481	99	0.893	0.562	0.547	0.639
8	1.000	0.893	0.548	0.465	54	1.000	0.750	0.497	0.562	100	0.938	0.478	0.421	0.782
9	1.000	0.782	0.683	0.385	55	0.713	0.432	0.632	0.735	101	0.991	0.714	0.535	0.546
10	0.996	0.599	0.528	0.619	56	0.988	0.765	0.628	0.440	102	0.679	0.582	0.62	0.649
11	0.995	0.617	0.573	0.573	57	0.810	0.502	0.376	0.821	103	0.886	0.457	0.516	0.736
12	0.999	0.626	0.563	0.575	58	0.978	0.562	0.525	0.646	104	0.987	0.490	0.525	0.697
13	1.000	0.900	0.616	0.397	59	0.999	0.791	0.549	0.497	105	0.870	0.362	0.413	0.877
14	0.794	0.690	0.697	0.480	60	0.971	0.414	0.432	0.817	106	0.601	0.156	0.544	1.039
15	0.983	0.500	0.657	0.607	61	0.926	0.826	0.529	0.508	107	0.733	0.591	0.502	0.698
16	0.980	0.620	0.451	0.668	62	0.995	0.610	0.496	0.637	108	1.000	0.892	0.568	0.445
17	0.804	0.324	0.589	0.815	63	0.898	0.299	0.551	0.839	109	1.000	0.879	0.492	0.522
18	0.995	0.690	0.533	0.561	64	0.998	0.878	0.601	0.417	110	1.000	0.830	0.554	0.477
19	0.939	0.708	0.469	0.609	65	0.689	0.638	0.377	0.784	111	0.415	0.202	0.485	1.115
20	0.913	0.717	0.59	0.506	66	1.000	0.794	0.57	0.477	112	0.876	0.571	0.551	0.633
21	0.978	0.894	0.52	0.492	67	1.000	0.842	0.473	0.550	113	0.623	0.484	0.551	0.781

Table 5. *Cont.*

ID	LMS	SMS	QMS	Overall	ID	LMS	SMS	QMS	Overall	ID	LMS	SMS	QMS	Overall
22	0.674	0.361	0.508	0.870	68	0.768	0.363	0.406	0.901	114	0.977	0.460	0.449	0.772
23	0.994	0.875	0.547	0.470	69	0.981	0.579	0.585	0.591	115	0.985	0.423	0.607	0.698
24	0.499	0.134	0.421	1.156	70	0.853	0.528	0.507	0.698	116	0.998	0.679	0.447	0.639
25	1.000	0.842	0.59	0.440	71	1.000	0.811	0.578	0.462	117	0.657	0.365	0.576	0.838
26	0.976	0.905	0.606	0.406	72	1.000	0.869	0.629	0.393	118	0.951	0.289	0.536	0.850
27	0.825	0.548	0.577	0.643	73	0.999	0.843	0.53	0.495	119	0.473	0.230	0.535	1.043
28	0.811	0.316	0.507	0.864	74	0.963	0.505	0.495	0.708	120	0.807	0.317	0.487	0.876
29	1.000	0.875	0.529	0.487	75	0.985	0.699	0.504	0.580	121	0.322	0.056	0.594	1.231
30	0.397	0.220	0.506	1.102	76	0.937	0.177	0.588	0.923	122	0.950	0.465	0.507	0.729
31	0.833	0.334	0.575	0.807	77	0.493	0.639	0.637	0.721	123	0.780	0.421	0.561	0.759
32	0.971	0.415	0.508	0.765	78	0.999	0.842	0.497	0.527	124	0.914	0.594	0.477	0.667
33	0.980	0.838	0.492	0.534	79	0.990	0.794	0.574	0.473	125	0.992	0.695	0.494	0.591
34	0.974	0.497	0.608	0.638	80	0.925	0.486	0.601	0.655	126	0.971	0.508	0.526	0.684
35	0.862	0.277	0.441	0.924	81	1.000	0.578	0.670	0.536	127	0.577	0.806	0.519	0.669
36	0.973	0.696	0.538	0.554	82	1.000	0.921	0.53	0.477	128	0.657	0.428	0.508	0.829
37	0.986	0.562	0.519	0.651	83	0.980	0.791	0.478	0.563	129	0.815	0.654	0.71	0.488
38	0.785	0.496	0.451	0.776	84	0.967	0.495	0.424	0.767	130	0.987	0.584	0.438	0.700
39	0.950	0.850	0.526	0.500	85	0.683	0.468	0.514	0.787	131	0.966	0.720	0.588	0.499
40	0.997	0.750	0.494	0.564	86	0.971	0.593	0.479	0.662	132	0.793	0.521	0.5	0.723
41	0.955	0.620	0.689	0.493	87	0.984	0.405	0.542	0.751	133	0.862	0.422	0.547	0.748
42	1.000	0.842	0.599	0.431	88	0.758	0.535	0.675	0.617	134	0.942	0.515	0.663	0.594
43	0.996	0.500	0.538	0.681	89	0.764	0.667	0.514	0.635	Mean	0.891	0.610	0.540	
44	0.994	0.787	0.632	0.425	90	0.350	0.285	0.589	1.050	Max	1.000	0.995	0.778	
45	0.992	0.917	0.588	0.420	91	0.965	0.372	0.54	0.779	Min	0.322	0.056	0.266	
46	1.000	0.892	0.608	0.407	92	0.863	0.304	0.266	1.021	CV	0.174	0.352	0.139	

As shown in Table 5, the LM dimension recorded the highest score, ranging from 0.322 to 1, with an average of 0.891. This suggests that the distribution of medical care facilities across the 134 streets within the study area is generally suitable, allowing the vast majority of residents to access the nearest facility within 20 min. The SM dimension has a lower score, with a range of 0.056 to 0.995 and an average of 0.610. This indicates a relatively poor match between the supply and demand in the SM dimension. The reasons for this may include high matching leading to low resource utilization or low matching/missing matching resulting in unmet MCFs' demands among residents. The QM dimension, which measures residents' satisfaction with the quality of medical services, showed scores ranging from 0.266 to 0.778, with an average of 0.540. This suggests a moderate level of satisfaction with the quality of services provided by MCFs.

The coefficients of variation (CV) for LM, SM, and QM are 0.174 0.352, and 0.139, respectively. These values indicate that SM exhibits the greatest variability across the study area, highlighting significant disparities in the allocation of MCFs. Conversely, quality matching (QM) shows the least variability, suggesting more consistent perceptions of service quality among residents across different regions.

When ranking the districts by their average LM scores, Yuzhong (0.999) is at the top, followed by Shapingba (0.942), Jiulongpo (0.938), Dadukou (0.937), Jiangjin (0.891), Beibei (0.860), Nan'an (0.854), Banan (0.849), Jiangbei (0.824), and Yubei (0.811). This ranking list reflects the generally high accessibility of medical services in central districts, with a gradual decline as one moves toward the more peripheral areas.

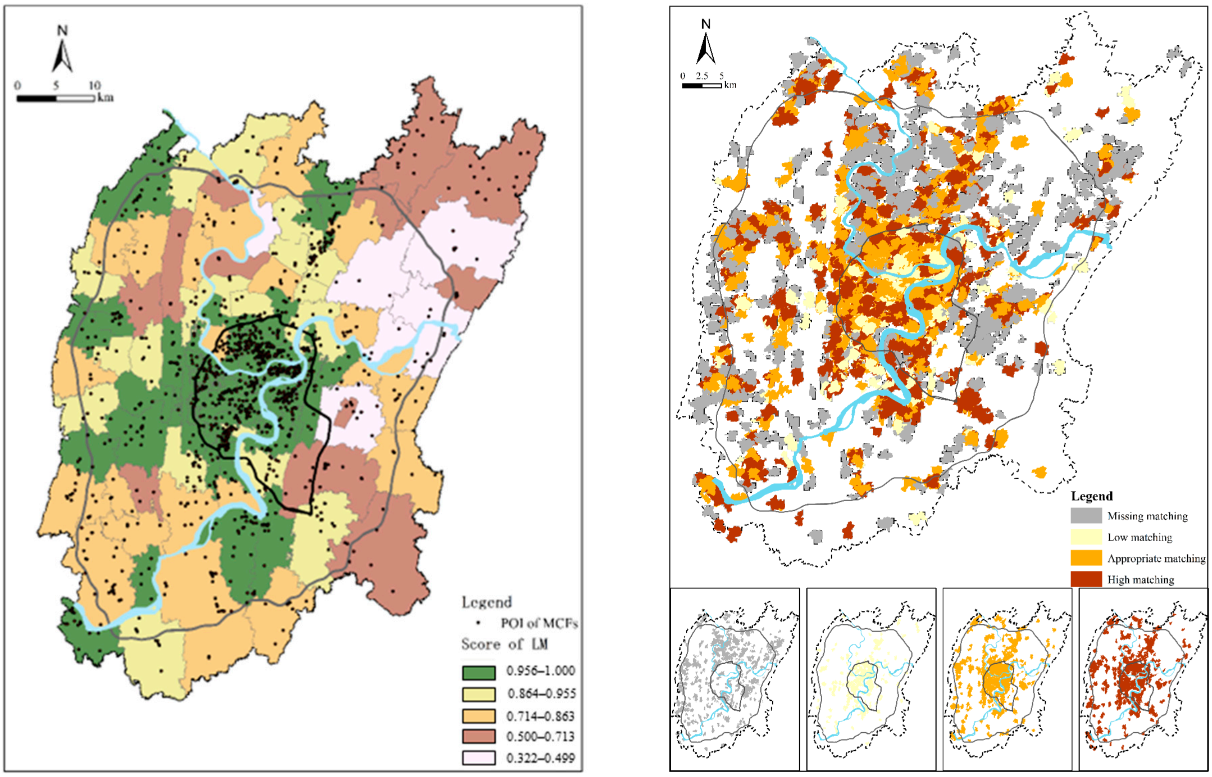
For SM scores, Yuzhong still takes the lead with an average of 0.807, followed by Shapingba (0.675), Jiulongpo (0.650), Dadukou (0.632), Jiangbei (0.608), Nan'an (0.578), Banan (0.573), Jiangjin (0.544), Beibei (0.522), and Yubei (0.481). The lower scores in more peripheral districts, especially Yubei, highlight the challenges in balancing the supply and demand for medical services across these regions.

Finally, the ranking by QM scores places Yuzhong at the top with an average of 0.591, followed by Jiangjin (0.575), Dadukou (0.572), Shapingba (0.555), Nan'an (0.554), Jiangbei (0.536), Banan (0.527), Yubei (0.524), Jiulongpo (0.511), and Beibei (0.473). These results suggest that Yuzhong consistently performs well across all dimensions; however, other districts, particularly Beibei, face challenges in achieving comparable levels of resident satisfaction with medical service quality.

In summary, Yuzhong District consistently ranks highest across all three dimensions (LM, SM, and QM), underscoring its strong overall performance in terms of accessibility, resource matching, and service quality. In contrast, districts like Yubei and Beibei, despite being significant urban areas, exhibit lower scores across these dimensions, indicating the need for targeted improvements to better satisfy the healthcare needs of their residents.

4.2. Spatial Distribution Characteristics of LM, SM, and QM of MCFs

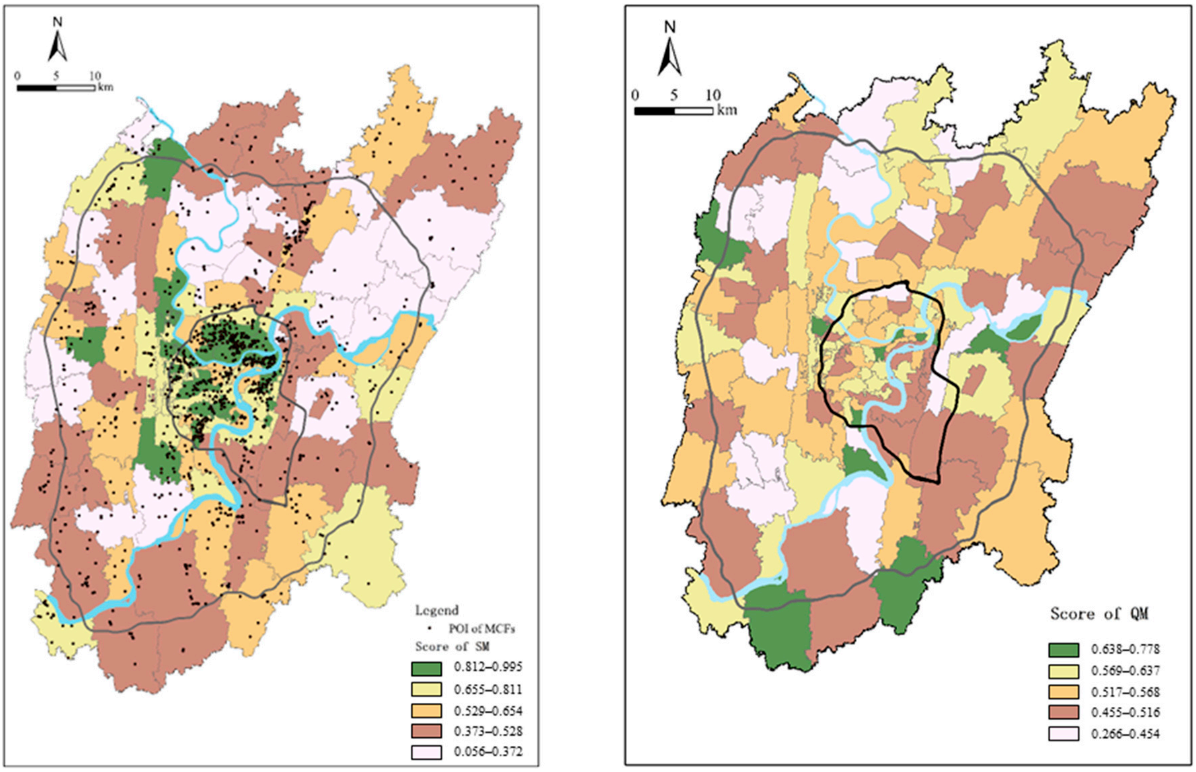
To gain a deeper understanding of the spatial patterns and the geographical context of the disparities of three dimensions, it is essential to visualize the distribution of these scores across the study area. The data in Table 5 were classified into five grades using the Natural Breaking Method to illustrate the spatial distribution of LM, SM, and QM scores [57]. This classification was performed with ArcMap 10.6 software. The classification results are presented in Table 6 and the spatial distribution is mapped in Figure 6. This figure provides a detailed view of how these dimensions vary across different districts. It highlights specific areas where MCFs are either well-matched or inadequately aligned with the needs of the population. The results of the scale matching level (SML) of the 3365 living circles are also presented in Figure 6.



(**a**) Score of LM

(**b**) Results of the level of SM

Figure 6. *Cont.*



(**c**) Score of SM

(**d**) Score of QM

Figure 6. Spatial distribution of results of LM, SM, and QM.

Table 6. The classification results of LMS, SMS, QMS, and overall performance of 134 streets/towns. (No. indicates the number of streets with score values in different intervals).

Grades	LMS			SMS			QMS			Overall		
	Interval	**No.**	**Ratio**	**Interval**	**No.**	**Ratio**	**Interval**	**No.**	**Ratio**	**Interval**	**No.**	**Ratio**
Grade I	(0.956, 1.000)	73	54.48%	(0.812, 0.995)	31	23.13%	(0.638, 0.778)	11	8.21%	(0.259, 0.445)	17	12.69%
Grade II	(0.864, 0.955)	21	15.67%	(0.655, 0.811)	26	19.40%	(0.569, 0.637)	33	24.63%	(0.446, 0.580)	39	29.10%
Grade III	(0.714, 0.863)	21	15.67%	(0.529, 0.654)	25	18.66%	(0.517, 0.568)	39	29.10%	(0.581, 0.736)	40	29.85%
Grade IV	(0.500, 0.713)	12	8.96%	(0.373, 0.528)	30	22.39%	(0.455, 0.516)	34	25.37%	(0.737, 0.924)	30	22.39%
Grade V	(0.322, 0.499)	7	5.22%	(0.056, 0.372)	22	16.42%	(0.266, 0.454)	17	12.69%	(0.925, 1.231)	8	5.97%

4.2.1. Location Matching (LM) Spatial Distribution

As shown in Table 6 and Figure 6a, the LM scores for 73 streets range from 0.956 to 1, representing 54.48% of the total. This indicates that nearly all built-up areas within these streets can access MCFs within a 20 min walk. These streets are predominantly concentrated in the central districts, particularly within the inner ring road segments of Yuzhong, Shapingba, Jiulongpo, Jiangbei, and Nan'an districts. In contrast, 54 streets exhibit LM scores ranging from 0.500 to 0.955, accounting for an additional 40.30% of the total. This suggests that most residents in these areas can reach MCFs within a slightly extended time of 20 to 30 min. These streets are generally situated between the inner and outer ring roads, functioning as transitional zones between the central districts and more peripheral areas. In these regions, urban development is less dense, and accessibility to medical services gradually declines.

Lastly, seven streets, making up 5.22% of the total, have LM scores below 0.499. These streets are predominantly located in the outer areas of Yubei District, where accessibility is significantly lower, resulting in average walking times exceeding 30 min for residents to reach the nearest MCF. In particular, the LM score in Yuelai Street was exceptionally low, at just 0.322, indicating that residents in this region may require nearly 35 min of walking time to access. The distribution of POI for MCFs in Figure 6a further supports this low score, as it shows that this area has relatively few facility configurations. These findings underscore the urgent need for targeted improvements to enhance the accessibility of medical services in these regions.

4.2.2. Scale Matching (SM) Spatial Distribution

As outlined in Table 6 and illustrated in Figure 6b,c, the SM dimension provides key insights into the quantitative balance between the supply of MCFs and the population demands across the 134 streets in the study area.

According to the method described in Section 3.2, a total of 3365 living circles were constructed to analyze the SDM status of each living circle. These living circles were classified into four distinct states based on Formulas (3)–(5): High Matching (HM), Appropriate Matching (AM), Low Matching (LM), and Missing Matching (MM). Among the 3365 living circles analyzed, the proportions of HM, AM, LM, and MM categories are 28.94%, 33.43%, 9.36%, and 28.26%, respectively. As shown in Figure 6b, the spatial distribution of HM and AM living circles shows similar characteristics, mainly distributed in areas along the two rivers and four banks within the inner ring road, Longxing–Yuanyang belt of Yubei District, and Xiyong Cluster in Shapingba District. The LM living circles are concentrated within the inner ring road, indicating that the available medical services are insufficient relative to the population's needs in part of living circles in central districts. In contrast, in the areas between the inner and outer ring roads, there is a large distribution of MM living circles, resulting from the low density and dispersed configuration of MCFs in these areas. Table 6 and Figure 6c reveal that only 31 streets, representing 23.13% of the total, achieved SM scores in the highest range of 0.812 to 0.995. High SM scores are notably distributed in the city center. These areas have a long history of development, featuring numerous facilities and a large population, resulting in a more balanced relationship between facilities and residents. In contrast, 30 streets have SM scores between 0.373 and 0.528, accounting for 22.39% of the total, signaling a significant mismatch between population size and available medical resources. Additionally, 22 streets have SM scores in the lowest range of 0.056 to 0.372, representing 16.42% of the total. These streets are mainly distributed in the Yubei District.

4.2.3. Quality Matching (QM) Spatial Distribution

As shown in Table 6 and Figure 6d, the QM scores reflect a complex pattern of resident satisfaction with the quality of MCFs across different areas. Eleven streets achieved the highest QM scores, ranging from 0.638 to 0.778, representing 8.21% of the total. These high scores are primarily concentrated in central districts such as Yuzhong and Jiangjin.

On the other hand, 34 streets, accounting for 25.37% of the total, exhibit QM scores between 0.455 and 0.516. These areas, which include portions of Banan and Beibei Districts, show moderate satisfaction levels. This suggests that while access to medical services is relatively convenient, the quality may not meet residents' expectations.

Interestingly, 17 streets recorded the lowest QM scores, ranging from 0.266 to 0.454, representing 12.69% of the total. These lower scores are found in both central and peripheral areas, indicating that accessibility and quantity do not always correlate with resident satisfaction. For instance, some peripheral areas with lower LM and SM scores, such as Banan and Beibei Districts, also show lower QM scores, indicating that the quality of services in these regions may not adequately meet residents' needs. Conversely, some areas with moderate to high LM scores, such as parts of the Shapingba and Nan'an Districts, demonstrate lower QM scores, indicating that even though residents can easily access medical facilities, the perceived quality of care may not be satisfactory.

The spatial distribution of QM scores underscores the necessity to enhance not only access to medical services but also the quality of care provided. The variation in QM scores further highlights that satisfaction levels are influenced by residents' expectations, the type of services available, and the overall healthcare experience. Meanwhile, the differing performance of QM compared to LM and SM indicates a need for targeted improvements in service quality, particularly in areas where accessibility is adequate but resident satisfaction remains low.

4.3. The Overall MCFs Performance 134 Streets

In terms of the integrated performance of MCFs, higher values indicate poorer overall performance, the integrated results of 134 streets, and classified statistical results as shown in Tables 5 and 6, respectively. The data are further illustrated in Figure 7. Shangqingsi in the Yuzhong District stands out with a commendable final score of 0.259, reflecting exceptional performance. Conversely, Yuelai Street in the Yubei district ranks the lowest with a score of 1.231. Notably, the top five performers are primarily concentrated in Yuzhong District, while underperformers are mostly found in Yubei and Jiangbei Districts. Districts like Yuzhong and Shapingba frequently demonstrate both high individual metric scores and favorable integrated scores, indicating a balanced level of development. In contrast, the Yubei District exhibits subpar performance across both individual and integrated metrics, suggesting a need for comprehensive improvement in medical services rather than a narrow focus on a single dimension. At the street level, over 55% of the total streets exceed the average integrated performance. Interestingly, among the 55% of streets above the average, 90% achieved above-average scores in any two dimensions. This implies that if one desires to enhance the overall performance of MCFs, it is necessary to improve MCFs in at least two dimensions concurrently. Spatially, streets with better integrated MCFs performance are mainly concentrated in the northwest and central within the inner ring road; conversely, the poorer counterparts are scattered along the outer ring road. The outer ring road's scattered underperformers may reflect a lack of cohesive urban planning, resulting in a fragmented development that fails to address the needs of residents toward MCFs.

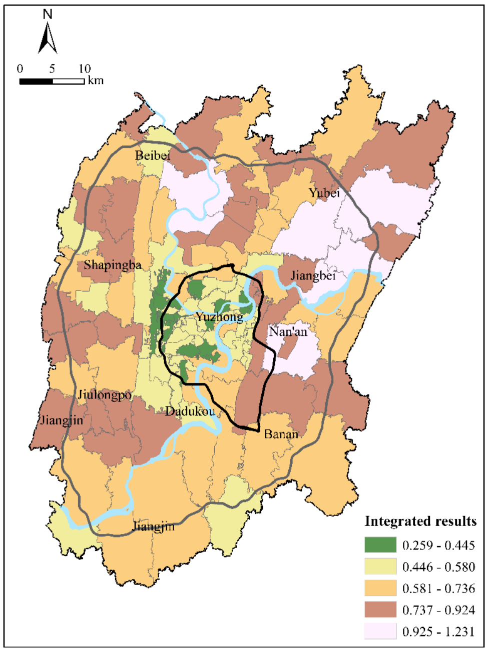


Figure 7. The results of the integrated MCFs performance.

5. Discussion

5.1. Analysis on the Empirical Results

5.1.1. Location Matching (LM)

It can be seen from Table 5 that the location matching of MCFs within the study area is relatively good, with an average LM score of 0.891. The districts that scored the highest in the analysis are Yuzhong, Shapingba, and Jiulongpo. Conversely, the districts with the lowest scores are Banan, Jiangbei, and Yubei (the lowest). The results are consistent with the studies by Liu et al. [58] and Wei et al. [59].

Figure 6a shows that streets with high LM scores are mainly concentrated in areas along the two rivers and four banks within the inner ring road. These areas represent the old city of Chongqing's main urban zone, characterized by mature development, a dense road network, and abundant MCFs [60,61]. In contrast, the streets with the lowest LM scores are primarily located in the Yubei District, which is undergoing the fastest pace of urbanization. The research by Zhao et al. [61] supported the analysis result and highlighted that Yubei District experienced the most significant expansion in urban construction land during rapid urbanization, increasing from 29.22 km^2 to 273.75 km^2 between 2000 and 2020. Yubei District hosts major transportation hubs, such as Chongqing North Railway Station and Jiangbei Airport, which further accelerate its urban development. However, it is evident from the distribution of POI for MCFs in Figure 6 that the configuration of these facilities has not kept pace with the rapid urban expansion, resulting in low accessibility to MCFs. In addition to the lag in MCFs' configuration, another significant factor contributing to the lower LM scores in these areas is the uneven development of transportation infrastructure [58]. The insufficient pedestrian road network extends the travel time for residents seeking essential services, including healthcare.

In regions where residents cannot access MCFs within a 20 min walk, it is crucial to optimize the spatial layout of these facilities to ensure comprehensive coverage. This necessitates a scientifically informed approach to planning locations and establishing a reasonable service radius that effectively meets the needs of the population [62]. Additionally, instead of solely increasing the number of medical facilities, enhancing the density of the road network is equally critical. As the smallest administrative units responsible for managing MCFs, streets should conduct thorough assessments of transportation networks within their jurisdiction, particularly in areas surrounding residential communities. This analysis will provide valuable insights into access barriers and facilitate the optimization of medical facility locations to better serve the local residents. Moreover, by identifying gaps in transportation infrastructure, street-level authorities can collaborate with urban planners to implement targeted improvements, such as connecting dead-end streets and T-intersections, thereby enhancing road network continuity. These enhancements will promote smoother travel for residents, effectively increasing the accessibility of medical care facilities and improving the LM within the region.

5.1.2. Scale Matching (SM)

The scale matching of MCFs within the study area is not so good, with an average SM score of only 0.610. The districts that scored the highest in the analysis are Yuzhong, Shapingba, and Jiulongpo. Conversely, the districts with the lowest scores are Banan, Yubei, and Beibei (the lowest). The results are consistent with the studies by Liu et al. [58].

It can be seen from Figure 6c that the streets with the lowest SM score are primarily concentrated along the borders of Yubei and Jiangbei, as well as Yubei and Beibei, with the majority located within the Yubei District. These streets are included in the scope of urban land under the northward development framework of Chongqing, but it is obvious that they are not the main development direction, and many of them have the administrative status of incorporated towns [63]. Medical institutions in these streets are few and low in grade, mainly dominated by town public health centers, resulting in the low SM score of these streets.

In addition, it is observed that several new development areas in this city also scored poorly, such as the New North Zone (the Longxing–Yuanyang belt) of Yubei District, Xiyong Cluster in Shapingba District, and the Yudong–Longzhouwan cluster in Banan District. The main functions of the Xiyong Cluster are education and scientific research, high technology, and the modern logistics industry. The regional functions and orientation of the New North Zone are the modern manufacturing industry, airport logistics, and the high-tech industry. The development orientation of the Yudong–Longzhouwan cluster is to build a riverside ecological new city integrating residence, business, culture, and leisure. These areas are recognized as new development zones, with their evolving patterns largely influenced by policy guidance [64–66]. After Chongqing was designated as a municipality in 1997, its political significance increased markedly, leading to robust support for its socio-economic growth and rapid urban construction, particularly around the two rivers [67]. The relocation of Chongqing Railway Station to the north in 2003, along with the approval of Chongqing University Town, prompted the city's main urban area to expand northward and westward. Moreover, the establishment of the "Liangjiang New Area", a national-level new area, in 2010 further spurred urban development in the northern regions [63]. Despite rapid development and significant population growth driven by these policies, the provision of medical service facilities has not kept pace, resulting in the lowest SM scores in these new districts.

To improve the scale matching dimension status, this study provides three improvement suggestions: (1) Enhancing the allocation of medical resources in vulnerable areas is essential to meet basic healthcare service needs effectively. (2) The construction of medical service facilities should be accelerated in rapidly urbanizing areas like Yubei and Shapingba districts. This can be achieved through targeted investments and strategic planning that take into account population growth rates and the corresponding increase in healthcare demands. (3) Enhance resource allocation strategies. Policymakers should reevaluate current resource allocation strategies to ensure a more equitable distribution of medical facilities, particularly in regions undergoing significant population growth. This reassessment should involve regular monitoring of demographic shifts and healthcare demand through predictive analytics, enabling timely adjustments to facility placement. Additionally, implementing flexible facility designs that permit easy expansion or reconfiguration can address future needs without necessitating major overhauls. By incorporating adaptability into the planning and design process, policymakers can ensure that medical care facilities remain responsive to evolving community requirements, thereby maintaining service quality and accessibility over time.

5.1.3. Quality Matching (QM)

The results of the satisfaction survey reveal that residents' satisfaction with MCFs generally falls within the range of "General" to "Satisfied", with a notable gap in achieving "Very satisfied" ratings. Across various districts, the overall variation in QM scores is minimal, with the average scores ranging from 0.473 to 0.591. Yuzhong District consistently ranks highest in satisfaction, while Beibei ranks the lowest.

Interestingly, the QM results do not exhibit significant spatial regularity and show a considerable degree of randomness. Further analysis of the correlations between QM, LM, and SM produced the results shown in Figure 8. The scatter plot in Figure 6 illustrates the relationships between QM scores and both LM and SM scores. The correlation coefficients between QM and LM (0.215) and between QM and SM (0.234) indicate that satisfaction is not strongly correlated with performance in the location and scale dimensions. This is reflected in the scattered distribution of points across the graph. These results diverge from the common expectation that higher accessibility to MCFs, along with a greater quantity and scale of surrounding facilities, would naturally lead to higher resident satisfaction.

Additionally, field research conducted alongside the offline survey revealed that the medical service facilities in the peripheral streets of the study area are significantly inferior to those in the core areas in terms of facility environment, the professionalism of medical staff, and treatment processes. However, as observed in Figure 6d, satisfaction levels in these peripheral areas do not significantly lag behind those in core areas. This phenomenon primarily arises from the discrepancy between expected and perceived levels of MCFs, which fundamentally influences satisfaction [68–70]. Service recipients often have specific expectations about the services they anticipate, and the actual services received may either meet, exceed, or fall short of these expectations. When expectations exceed the perceived service level, satisfaction tends to be lower. Conversely, when expectations are lower than the perceived service level, satisfaction levels are generally higher. Different streets, shaped by their unique geographical locations and stages of development, have developed varying expectations for the service standards of their medical facilities. These expectations are a reflection of the streets' historical development and evolution. Residents' perceptions of MCFs are often shaped by the unique geographical locations and stages of development of their streets, leading to distinct expectations regarding the service standards of their medical facilities. For instance, the field survey results suggest that many residents from peripheral areas remarked that MCFs have notably improved compared to the past. This expectation generally conforms to a pattern: Residents' expectations regarding the quality of medical care facilities tend to be lower as the developmental stage of a street decreases. Consequently, despite the lower allocation levels of peripheral areas compared to core and newly developed areas, residents in peripheral areas have not exhibited a pattern of lower satisfaction regarding the quality of medical care facilities.

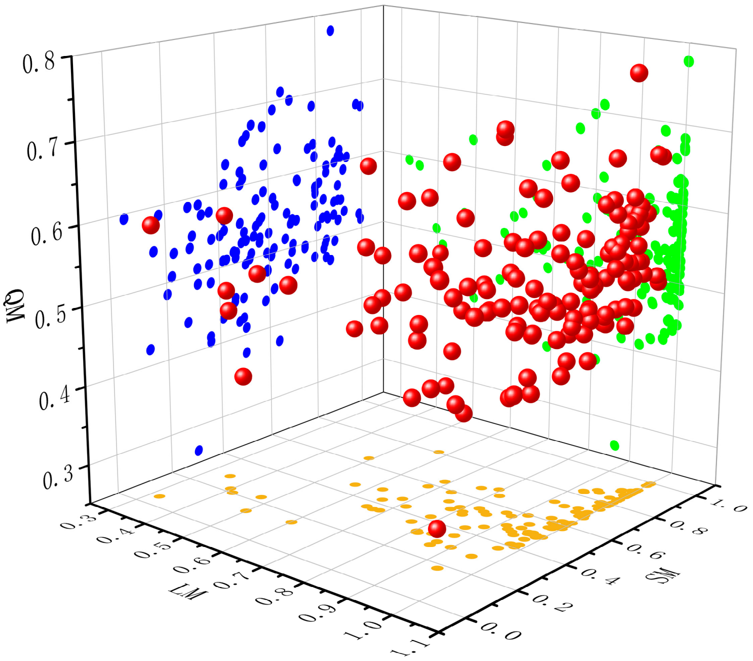


Figure 8. The correlation between LM, SM, and QM scores.

Based on the above discussion, it is essential to focus on service quality enhancement and effective "expectation management", to improve the quality matching dimension. Service quality improvement should adopt a "people-oriented" approach. Specifically, regarding the demand aspect, the people-oriented approach should prioritize addressing the actual needs of residents and tailor services to accommodate the diverse and personalized requirements of different population groups. For instance, in areas with substantial aging populations, healthcare facilities should adapt to the trends of demographic aging by offering more medical services that cater to the needs of elderly residents. Expectation management involves the government implementing effective measures to help residents maintain stable and rational expectations regarding medical service facilities [71]. Notably, expectations should be carefully managed. Setting them too high can lead to decreased satisfaction if actual service levels fall short. Conversely, setting expectations too low may suggest a lack of trust in the government's provision of medical services, which could also negatively impact satisfaction levels.

5.2. Effectiveness of the SDM Model

The supply–demand matching (SDM) model employed in this study has demonstrated significant advantages in evaluating the performance of urban medical services allocation. Unlike previous research that often focuses on a single dimension, this study integrates three key dimensions: "location matching", "scale matching", and "quality matching", offering a more comprehensive framework for assessment. This approach is particularly effective in complex urban environments, where it is essential to consider not only the spatial distribution and quantity of medical facilities but also how well service quality aligns with residents' needs. Without factoring in quality, even well-placed and adequately scaled facilities may still lead to dissatisfaction if they fail to meet quality expectations, potentially causing residents to seek services elsewhere. This behavior can result in the underutilization of lower-quality facilities and overcrowding at higher-quality ones, ultimately disrupting the balance of service provision. The model provides a more accurate reflection of the match between medical resource allocation and the demands of different regions, thereby offering valuable decision-making support for urban planners and policymakers.

The data used in this study are both extensive and reliable, sourced from official statistical platforms and commonly used academic resource-sharing platforms. The integration of multiple data sources and the use of advanced data processing methods, such as ArcMap and Python, enable precise quantitative assessments, thereby enhancing the credibility and applicability of the study's conclusions. Moreover, for the calculation of quality matching (QM), this study employs a mixed-method approach by utilizing both online and offline surveys. While it is acknowledged that the quality of responses may vary significantly between these two formats, which can introduce potential biases and complicate data comparability, the integration of both survey types enhances the breadth of the research. Online surveys effectively engage tech-savvy individuals who are comfortable with digital platforms, whereas offline surveys facilitate connections with populations lacking internet access, thereby ensuring a more comprehensive and representative data collection process. This dual approach not only enriches the dataset but also contributes to a more nuanced understanding of community needs regarding medical care facilities, ultimately supporting more informed decision-making in urban healthcare planning.

Finally, the previous discussion reveals that the empirical results for the 134 streets in the study area align with the actual urban development context. This indicates that the application of the model effectively evaluates the suitability of urban medical services across the dimensions of location, scale, and quality, thereby validating the model's effectiveness. In practice, this method can assist decision-makers in understanding the status of location, scale, and quality matching across different urban areas, enabling them to implement targeted measures to enhance the overall matching level.

6. Conclusions

This study contributes to the development of a theoretical framework for evaluating the supply–demand matching (SDM) of medical care facilities (MCFs) in mega-cities by integrating three critical factors: location, scale, and quality. The empirical analysis, conducted in Chongqing, China, revealed significant disparities in the distribution and quality of medical services across different regions. Central districts, such as Yuzhong, demonstrated superior performance in the integration of medical care facilities, along with exemplary outcomes in terms of location, scale, and quality dimensions. This demonstrates a stronger alignment between supply and demand in Yuzhong and also reflects a well-balanced medical care facilities characterized by high accessibility, appropriate facility scaling, and satisfactory service quality. In contrast, peripheral districts such as Yubei exhibited poorer performance in the integration of medical care facilities and faced significant mismatches in terms of location, scale, and quality dimensions. This situation reflects inadequate resource allocation and lower service quality in these areas, highlighting the challenges encountered by rapidly urbanizing regions.

These findings highlight the importance of adopting a more holistic approach to urban healthcare planning. By considering location, scale, and quality together, urban planners and policymakers can better understand and address the complex dynamics of healthcare provision in rapidly evolving urban environments. Without a balanced approach that integrates these three dimensions, efforts to improve healthcare accessibility and service quality may fall short, leading to persistent disparities in healthcare access and outcomes across different urban areas.

Furthermore, the study's methodological approach, utilizing advanced geospatial analysis with ArcGIS and data processing in Python, provides a replicable model for other mega-cities facing similar challenges. This model can be adapted and applied to different urban contexts, offering valuable insights for optimizing the allocation and layout of medical resources, improving healthcare service capacity, and reducing disparities in health service provision.

The results of this study have important implications for urban healthcare policy. Policymakers should prioritize investments in peripheral areas to enhance the scale and quality of medical services, thereby improving overall healthcare equity. Additionally, continuous monitoring and reassessment of MCFs are necessary to adapt to the evolving demographics and needs of urban populations. By fostering a more equitable distribution of healthcare resources, cities can ensure that all residents have access to high-quality medical care, thereby improving public health outcomes and contributing to the overall well-being of the urban population.

Some limitations of this study need to be acknowledged. Firstly, the differentiated demands of various resident groups (such as age, income, and social class) were not considered. Future studies are recommended to apply big data, which holds great potential for quantifying these varied needs, to enhance the accuracy of demand-side characterization. Secondly, the analysis did not consider the categorization of facilities across different levels, which is important due to the significant differences in service scope among various facility tiers. This oversight may impact the accuracy of the scale matching (SM) results. It is recommended that future studies incorporate a classification of facilities to improve the accuracy and credibility of supply-side characterization. Additionally, the questionnaire results might be constrained by a small, non-representative sample size and limited survey distribution, which could be improved through the integration of big data, such as social media data in future studies. Despite these limitations, this study provides a new perspective and framework for assessing the supply–demand matching of MCFs, contributing to a better understanding of the multidimensional relationships involved in medical service allocation.

Author Contributions: Conceptualization, S.L., L.S. and Y.W.; methodology, S.L.; supervision, L.S., Y.W. and H.B.; validation, S.L., L.S., Y.W. and H.B.; visualization, S.L.; writing—original draft, S.L. and J.L.; writing—review and editing, S.L. and J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Open Fund 2023 (214000-581827/008) of the Research Institute for Urban Planning and Development, Hangzhou City University.

Data Availability Statement: Dataset available on request from the authors. The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Appendix A

Table A1. The details of street/town in the study area.

ID	District	Street/Town	ID	District	Street/Town	ID	District	Street/Town
1	Yuzhong	Qixinggang	46	Shapingba	Tianxingqiao	91	Beibei	Beiwenquan
2		Jiefangbei	47		Tongjiaqiao	92		Caijiagang
3		Lianglukou	48		Tuwan	93		Fuxing
4		Shangqingsi	49		Tuzhu	94		Longfengqiao
5		Caiyuanba	50		Xiyong	95		Shijialiang
6		Nanjimen	51		Xianglushan	96		Shuitu
7		Chaotianmen	52		Xiaolongkan	97		Tongjiaxi
8		Daxigou	53		Xinqiao	98		Xiema
9		Daping	54		Yubeilu	99	Yubei	Baoshenghu
10		Hualongqiao	55		Zhongliang	100		Cuiyun
11		Shiyoulu	56		Qinjiagang	101		Dazhulin
12	Dadukou	Baqiao	57	Jiulongpo	Bafu	102		Gulu
13		Chunhuilu	58		Baishiyi	103		Huixing
14		Jiansheng	59		Erlang	104		Jinshan
15		Jiugongmiao	60		Hangu	105		Kangmei
16		Qiezixi	61		Huayan	106		Lijia
17		Tiaodeng	62		Huangjiaoping	107		Lianglu
18		Xinshancun	63		Jinfeng	108		Longshan
19		Yuejincun	64		Jiulong	109		Longta
20	Jiangbei	Cuntan	65		Shiban	110		Longxi
21		Dashiba	66		Shipingqiao	111		Longxing
22		Fusheng	67		Shiqiaopu	112		Renhe
23		Guanyinqiao	68		Taojia	113		Shichuan
24		Guojiatuo	69		Tongguanyi	114		Shuangfengqiao
25		Huaxinjie	70		Xipeng	115		Shuanglonghu
26		Jiangbeicheng	71		Xiejiawan	116		Tiangongdian
27		Shimahe	72		Yangjiaping	117		Wangjia
28		Tieshanping	73		Yuzhoulu	118		Xiantao
29		Wulidian	74		Zouma	119		Yufengshan
30		Yuzui	75		Zhongliangshan	120		Yuanyang
31	Shapingba	Zengjia	76	Nan'an	Danzishi	121		Yuelai
32		Chenjiaqiao	77		Guangyang	122	Banan	Huaxi
33		Ciqikou	78		Haitangxi	123		Huimin
34		Fengwen	79		Huayuanlu	124		Jieshi
35		Fenghuang	80		Jiguanshi	125		Lijiatuo
36		Geleshan	81		Longmenhao	126		Longzhouwan
37		Huxi	82		Nanping Street	127		Nanpeng
38		Huilongba	83		Nanping Town	128		Nanquan
39		Jingkou	84		Nanshan	129		Yipin
40		Lianfang	85		Tianwen	130		Yudong
41		Qingmuguan	86		Tongyuanju	131	Jiangjin	Dingshan
42		Shapingba	87		Tushan	132		Luohuang
43		Shandong	88		Xiakou	133		Shuangfu
44		Shijingpo	89		Yinglong	134		Zhiping
45		Shuangbei	90		Changshengqiao			

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