Article

Healthcare recommender system based on medical specialties, patient profiles, and geospatial information

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Abstract: The global outburst of COVID-19 introduced severe issues concerning the capacity and adoption of healthcare systems and how vulnerable citizen classes might be affected. The pandemic generated the most remarkable transformation of health services, appropriating the increase of new information and communication technologies to bring sustainability to health services. This paper proposes a novel, methodological, and collaborative approach based on patient-centered technology, which consists of a recommender system architecture to assist the health service level according to medical specialties. The system provides recommendations according to the user profile of the citizens, and a ranked list of medical facilities. Thus, we propose a health attention factor to compute semantically the similarity between medical specialties and offer medical centers with response capacity, health service type, and close user geographic location. The recommender system was tested in diverse districts of Mexico City, and the spatial visualization of the medical facilities filtering by the recommendations is displayed in a Web-GIS application.

Keywords: Recommender system; health attention factor algorithm; application ontology; semantic similarity, Web-GIS application

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1. Introduction

The global outburst of the new coronavirus (SARS-CoV-2) has introduced severe concerns regarding the capacity and adaption of healthcare systems and specifically about how vulnerable citizen classes might be affected [1]. The COVID-19 pandemic has generated the most significant transformation and disruption of many services, including healthcare and health emergency management, using digital tools, which have increased rapidly to bring sustainability to health services. Moazzami *et al.* [2] and Katz *et al.* [3] assert that a pandemic seriously alters global health systems in transmission, control, and saturation but also restricts resources and facilities, medical personnel, vaccines, access, and mobility issues.

Thus, digital technologies such as Artificial Intelligence, blockchain, machine learning, the Internet of Things, and extensive health data repositories have contributed to changing and addressing the traditional methods to provide health services to citizens and innovating in different paradigms such as mobility from a disease perspective to patients' perspective, well-being citizens and life quality. Moreover, the digital transformation focused on healthcare is continuously impacting medical approaches [4]; [5]. Nowadays, this transformation and innovation implicate new stakeholders conducted by massive patient data from various datasets in different formats, computational intelligence models and algorithms, artificial intelligence-based techniques, novel pervasive platforms for exchanging and monitoring patients, and service providers for obtaining valuable information, patterns, trends and insights in the healthcare domain.

According to [6], there are five research classifications concerning the digital transformation of healthcare: (1) patient-centered technology, (2) operational efficiency of organizations, (3) managerial implications, (4) impact on workforce practice, and (5) socio-economic aspects. By taking into consideration this categorization, sustainability in healthcare should cover all these issues to adopt new strategies, methodologies, and innovative applications to provide health value services-based technologies and responses to face a future and global health emergency in the global world.

Since the outbreak and lockdown restrictions worldwide by the COVID-19 pandemic, diverse initiatives to maintain the activity of health services have been implemented. For instance, virtual medical consultations have increased in many countries [7], and some medical departments go on using online technology to monitor non-critical patients [8]; [9]. According to [10], the pandemic has disturbed the supply chains around the world, generating issues related to supporting the medical responses, lack of essential medical supplies, deficiency in accessing and mobility to clinical and hospitals to treat medical specialties, and the resilience of citizens. Indeed, 94

According to the study presented by [11], the pandemic transformed the use of health services to attend to different emergency conditions in patients without COVID-19, showing a general reduction in the treatment of medical specialties. The study suggests that this phenomenon is due to (1) negligence by patients with severe or life-threatening disorders to pursue care, (2) release of the emergency units for non-emergency disorders, or (3) displacement of emergency unit care to other locations, such as telemedicine consultations. Moreover, the analytical study reported at least in the United States, the visits and admissions to emergency units decreased by more than 40

Therefore, we perceive the following issues concerning medical attention: less attention has been focused on geographic access to health services, hospital access, response capacity at the local level within urban areas, and lack of access to medical specialties according to the responsiveness and infrastructure. Thus, we propose a novel approach based on patient-centered technology. In this way, we have designed a recommender system that consists of a health service level, which is defined by a health attention factor. This metric is composed of two key components, the geospatial location of the health facilities and the medical specialties required by the patients.

The rest of the paper is structured as follows: the next section comprises the literature review on intelligent systems and approaches focused on health services, and their implications during the COVID-19 pandemic, Section 3 describes the methodology, Section 4 investigates the results, and the last section discusses the key findings of our research.

2. Related work

Intelligent systems based on Artificial Intelligence (AI) have permeated many areas of life. Thus, healthcare is not an exception; multiple approaches have supported health services with this type of tool; for example, in the interface between people and AI. Such interfaces could alleviate the shortage of skilled health workers, help busy medical professionals, and improve typically the quality of healthcare. There are many challenges to achieving this, such as investigating biases in clinical decision-making, and lack of trust in AI by people unaffiliated with these technologies, among others. A study is conducted in [12] in which a literature review is carried out to examine previous research, identify gaps, and propose future research directions. The authors report that there are limited studies on the interactive collaboration process in healthcare and that there is no good integration between people and AI, so work should be done on the adoption and improvement of the perception of AI in long-term organizations.

On the other hand, with the health crisis that has tied the world in recent years, telemedicine services have been essential for many users to access health services beyond this required assistance by the pandemic emergency related to COVID-19. In [13], fundamental success factors relevant to telemedicine services are identified and grouped under some contextual criteria. The causal relationships between them are explored to classify hospitals that provide telemedicine services during the pandemic. The findings revealed that technological issues provide a substantial causal impact; In other words, the more complicated the technology is, the more resistance there is to adopt it. In [14], the factors that predict the intention to use medical teleconsultation are examined by extending the unified theory of acceptance and use of technology (UTAUT2) with the three dimensions of beliefs, trust, and self-efficacy. The authors carried out their study by applying a survey of patients who had used a teleconsultation platform during the pandemic period. The results highlight the importance of trust beliefs and self-efficacy in digital health services adoption.

So, in this context is necessary to understand what is required of a new type of company that provides health services using new remote work technologies. Chakraborty *et al.* [15] attempts to understand the status of these health technology companies in providing healthcare services through a study of the scientific publications on the matter. With a total of 110 journals reviewed, 76 articles were found to meet the inclusion criteria, and only five studies portrayed the status of new health technology companies in the provision of healthcare services. Acceptance of services depends on the effectiveness and affordability of the service. Similar results are presented in [16], based on three main objectives such as identifying research gaps, challenges, and open problems in the academic literature. So, the study concluded that despite the efforts to develop safer and more private systems for the health industry, none meets the necessary development attributes.

Another critical aspect to consider and arise based on the experience of using remote health services during the COVID-19 pandemic is that access to these services must be viable and available to all people regardless of their socioeconomic status. For this reason, there must be criteria for evaluating health technologies (HTA). According to [17], there are a few challenges to such an evaluation, taking into account that resources are limited to run HTAs locally. Another problem is the limited availability of local data to complete the economic models and the timely availability of relevant HTAs, among others. A further group of challenges is related to the structural characteristics of the health system. These include central or local restrictions on using HTAs or differences in how reimbursement decisions are made in different infrastructures. Many Latin American countries have parallel health systems in which mandatory health insurance or social security systems for workers, subsidized public programs, and private mechanisms coexist. Meleddu *et al.* [18] mentions that research has shown that people make health spending decisions based on their income, political attitudes, and demographics and tend to see public healthcare as a normal good that is hardly available. Users demand health services that meet their expectations. Health spending is related to the health services that a patient can access.

In general, we consider that patients can have access to public health services, which vary in quality depending on each country. Some other patients have access to private health services that are more expensive. Therefore, public services often cannot provide health services remotely, making it necessary for people to travel efficiently to the most convenient health centers. In citepmollahaliloglu2021change, data on the distributive imbalance of patients from the years 2002 to 2016 presents policies of redistribution of health services applied. The effect of these policies on the distribution of human resources in health shows a continuous decrease in inequalities in the geographical distribution of the human workforce in health. Thus, applying policies that impact the quality of health services is critical. For example, Sharma and Patil [19] presents the accessibility measure for health services by using public transport, the travel time, and the number of transit stops. In addition, Pereira *et al.* [20] shows how transport-accessibility analytics can provide actionable insights to improve healthcare coverage and responsiveness. By using network distance metrics, the vulnerable population living in areas with poor access to healthcare facilities is computed. They then use the balanced-floating catchment area (BFCA) indicator to estimate spatial, income, and racial inequalities in hospital access.

A large amount of medical information has brought many difficulties for medical professionals to make patient-oriented decisions. These difficulties lead us to the need to apply recommendation systems (RS) in the healthcare domain to help both patients and medical professionals to make more efficient and accurate health-related decisions. According to Tran *et al.* [21] three main aspects must be considered in RS: a) the context of use that describes the environment in which all elements interact with each other, b) users are the final consumers of RS, and c) the elements are the inputs that users are looking for. The authors also mention that there are four basic recommendation techniques: 1) collaborative filtering (CF) recommendations are based on the idea that if patients share similar disease profiles/health conditions, then they should have health care treatments/services Similar. 2) content-based filtering (CB) this approach suggests health services that fit the patient's health/disease situation and are similar to those assigned in the past. 3) Knowledge-Based Recommendation (KB) This approach creates recommendations based on knowledge about items, explicit user preferences, and a set of constraints that describe dependencies between user preferences and item properties. 4) hybrid recommendation (HyR) the idea of this approach is to combine the aforementioned recommendation techniques to take advantage of one approach and correct the disadvantages of another. Pincay *et al.* [22] presents the results of a comprehensive and cutting-edge study of RS used in the health field, also known as health recommender systems. The PRISMA framework has been used to provide information on the approaches and strategies used in the recommendation areas.

Recently, multiple approaches have been generated to solve this RS problem. Shaikh *et al.* [23] propose a framework for a RS for dengue patients in healthcare applications. In this framework, machine learning algorithms are used, especially content-based, collaborative and hybrid approaches. In the same vein, Vairale and Shukla [24] have discussed some recent research in the field of diet and exercise, which focused mainly on individualized recommendations based on clinical data, taking into account your food and physical activity preferences, and your nutritional needs. Fasidi and Adebayo [25] present the rule-based naive Bayesian classifier (RNBC) as a prediction and therapy guide for heart disease risk. The dataset is scanned only once, offline, while subsequent scanning of the dataset is prevented by designing the classification rule. Gohari *et al.* [26] introduced the SB-TAR (Significance-Based Confidence-Aware Recommendation) method, which employed a novel confidence metric based on the idea of item importance.

Sahoo *et al.* [27] mention that health RS are one of the new technologies used to extract additional information from a person's health care data. By measuring the similarity of choices made across patients, these systems identify preferred hospitals. Therefore, in the medical sector, they play an important role. Waqar *et al.* [28] propose an adaptive algorithm for the effective generation of medical recommendations. Specific physician-related attributes are identified through a survey. By adding treatments to patients and symptoms of a particular disease, the system could be further improved.

Mazeh and Shmueli [29] proposed an architecture for a RS based on patient data storage (PDS), which aims to improve user confidentiality without losing the reliability of the recommendation. A limitation of this work is the data sets used to evaluate the proposed model. Privacy-preserving collaborative filtering, personal data storage, and content-based model are used in the architecture. The database does not include individual data sets that would represent individual service providers in both applications.

Sayeb *et al.* [30] have aimed to present a graph-based RS to manage the COVID-19 crisis considering data from patients and medical personnel. The RS has initially analysed the medical records of the patients to find and decide which profile of medical personnel could help the efficiency of this patient in a crisis situation. Then the RS, taking into account the availability of the medical staff, will try to propose other doctors with the same profile and the closest competencies. Similarly, Zhang *et al.* [31] proposed an iDoctor system to provide users with personalised medical recommendations. This system explores users' emotions and preferences about doctors through their ratings and reviews. Narducci *et al.* [32] presented a social network called HealthNet, where a recommendation component is integrated to suggest the doctors and hospitals that best fit a specific patient profile. In HealthNet, a patient enters their health data, such as conditions, treatments (drugs, surgeries, or side effects), health indicators (blood pressure, body mass index, blood levels, etc.), doctors consulted, and hospitalisations. Based on the input data, the system searches for similar patients stored in the database (Eqn. 1).

$$s(a,b) = \alpha \frac{\sum_{c_a \in C_a, c_b \in C_b} s_c(c_a, c_b)}{|C_a| + |C_b|} + (1-\alpha) \frac{\sum_{t_a \in T_a, t_b \in T_b} s_t(t_a, t_b)}{|T_a| + |T_b|} \tag{1}$$

where a y b are patients, C_x is the set of conditions that afflict the patient x, T_x is the set of treatments for the patient x, α is a parameter that allows regulating the relationship between the contributions of conditions and treatments. $s_c(c_a, c_b)$ is the similarity between two conditions: in the case that $c_a = c_b$ the similarity $s_c(c_a, c_b) = \log \frac{|C|}{|P_{c_a}|}$, being C the universe of conditions and P_{c_a} is the set of patients with condition c_a; in the case that $c_a \neq c_b$ the similarity $s_c(c_a, c_b) = \frac{1}{\delta(c_a, c_b)}$, being δ the length of the shortest path between c_a y c_b in the hierarchy of diseases. $s_t(t_a, t_b)$ is the similarity between two treatments, and is equal to 1 if $t_a = t_b$, 0 otherwise.

Now, based on this similarity of patients, a rating is calculated for doctors (Eqn. 2) and hospitals (Eqn. 3) with respect to patient p.

$$scoreDoc(d,p) = \sum_{\rho \in P} s(p,\rho) \cdot r_\rho(d) \tag{2}$$

where P is the set of registered patients and $r_\rho(d)$ is the rating given by the patient ρ to the doctor d.

$$scoreH(h,p) = \beta \left(\sum_{\rho \in P} s(p,\rho) \cdot r_\rho(h) \right) + (1-\beta) \cdot Q(h) \tag{3}$$

where $r_\rho(h)$ is the rating given by the patient ρ to the hospital h and $Q(h)$ is a quality index of the hospital h given by a rating authority.

3. The proposed approach

According to [33], the most common parameter to measure geographic access to healthcare services is the shortest distance or travel time to arrive near a medical unit. This metric is widely used and easy to compute and analyze, and therefore clear for conveying to policymakers. However, the most critical limitation of this metric is that it discharges the traffic congestion and the implicit events that originate from this condition. There are other potential approaches, such as the Floating Catchment Area (FCA) methods [34], which computes accessibility levels considering the following variables: the provider-to-population ratio of every health unit and the potential health demand regarding the infrastructure. Nevertheless, the limitation of this method concerns the overestimation of both health service demand and supply, which could induce untruthful accessibility estimation values.

Thus, we propose a novel approach based on patient-centered technology according to the classification proposed by [6]. In this way, we design a recommender system that consists of a health service level defined by a health attention factor. This metric is composed of two key components, the geospatial location of the health facilities and the medical specialties required by the patients.

The approach consists of a recommender system of health services considering the geographic location, the medical specialties defined within an application ontology, and the attention factor to offer the best health unit to treat a medical situation. So, when a medical condition is presented, the patient requires assistance at a medical facility for partial or complete medical attention. In this case, two scenarios could be presented: (1) the patient can readily identify the adequate medical unit by making a query in the recommender system, and it returns a set of medical centers to the patient according to geographic location criteria. (2) However, there is no a priori information about the most acceptable hospital for attending the emergency patient. It is possible that the nearest hospital does not have a doctor with a neurology specialty; so, according to this medical situation, a

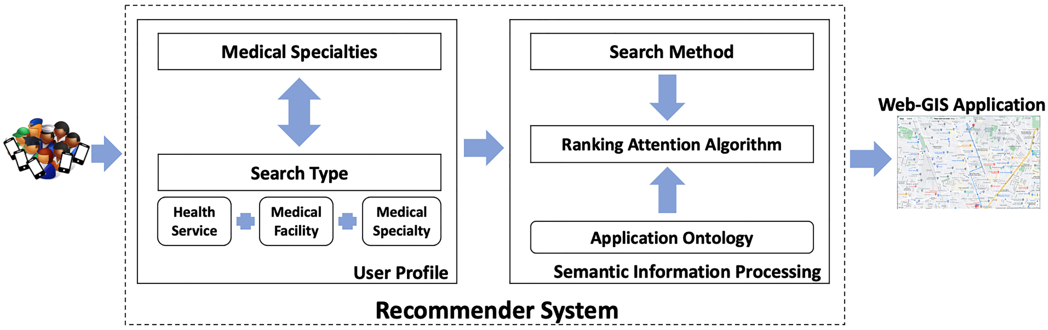

Figure 1. Architecture and components of the recommender system

recommender system semantically processes the query to provide information concerning this health service. Therefore, the recommender system performs the following duties: semantic-based recommendations, profiling of answers, and map rendering. Figure 1 presents the architecture and components of the recommender system to retrieve semantic medical information about the medical centers.

3.1. The medical application ontology

The medical application ontology was designed for semantic processing. This ontology conceptualizes the most essential medical specialties considering the Association of American Medical Colleges Standard (https://www.aamc.org/cim/). In this context, other medical ontologies were created according to their applications such as SNOMED [35], MedO [36], OBI Ontology [37], GALEN [38], Gene Ontology [39], among others.

Those ontological representations are built with diverse languages such as Resource Description Framework (RDF), Ontology Web Language (OWL), and Open Biomedical Ontology (OBO). The structures and syntaxes to describe entities and relationships are very complex, and they contain up to 900,000 concepts in their topological structure. These features are difficult and slow to be semantically processed, and the medical specialties are not explicitly defined in such ontologies. Moreover, the interoperability of these public ontologies is a big challenge because, in production systems, the performance can decrease significatively to several issues such as diverse access to different ontologies, translation among languages, different reasoning, and inference engines to provide semantic information from queries, and semantic information integration techniques.

Thus, the proposed research proposes an application ontology that consists of a hierarchical structure based on an is-a relationship, with partitions associated with medical specialties. Summing up, the proposed ontology fits with the recommendations generated by the system with a conceptualization more suitable for querying medical specialties due to a single hierarchical description, specialized partitions, and granularity. We develop the proposed ontology with OWL-full language using the Protégé application with version 5.5. The root node of the ontology has three properties to perform the semantic processing: the first one establishes if the medical specialty is "diagnostic" or "therapeutic". The second property designates the age scale of patients ("pediatric", "adult", "geriatric", "all"), and the third describes if the medical specialty is "organ-based", "technique-based" or "both". Figure 2 shows the application ontology to conceptualize the medical specialties.

3.2. The profiling and semantic processing tasks

The profiling task establishes a user profile and the statement of the search type. So, the profile for each query contains the following information:

- Health Service Type. The user specifies if he requires public or private health services.;
- Medical Facilities. All units, centers, and hospitals that accomplish the type of health service are shown.

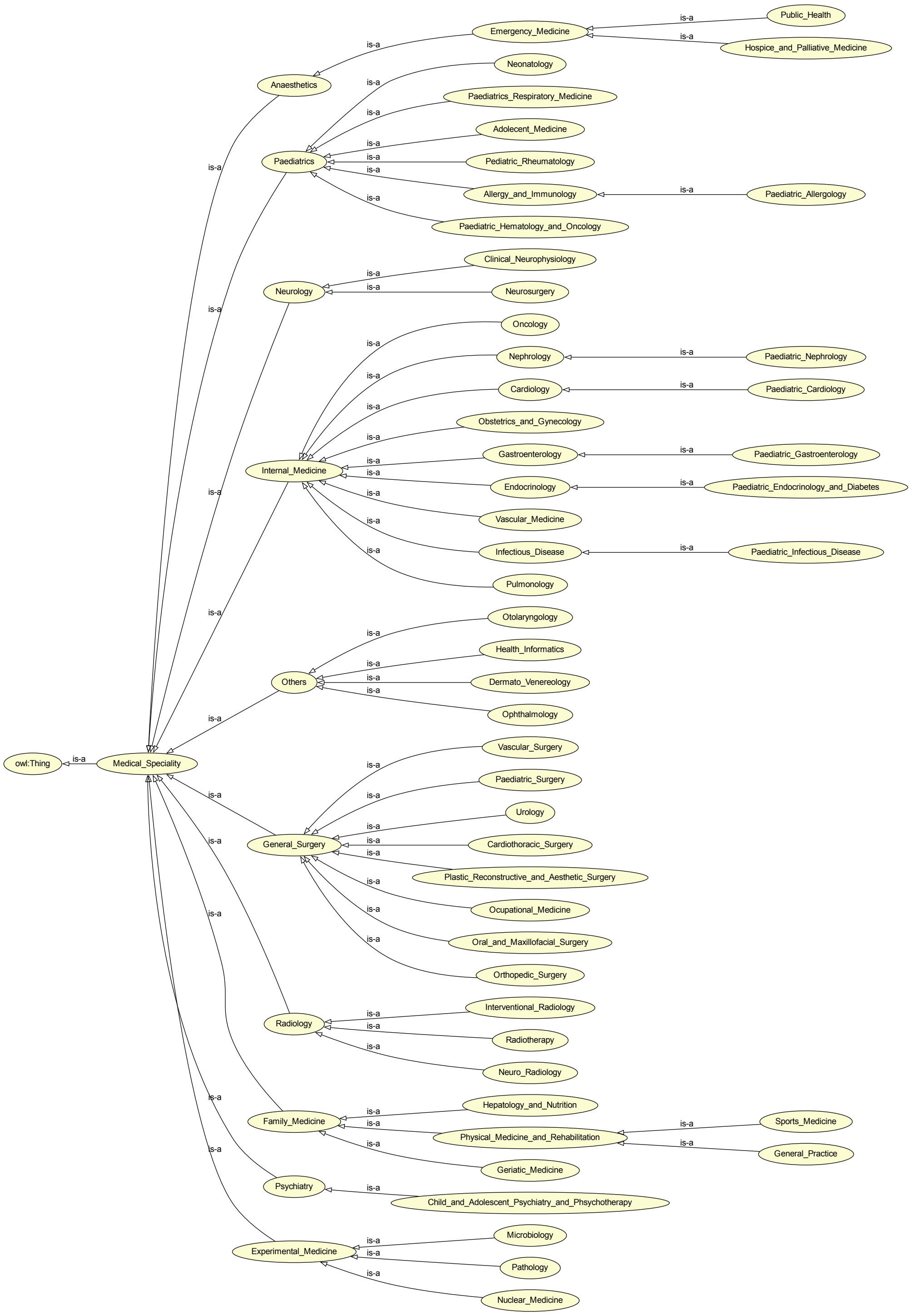

Figure 2. Application ontology representing medical specialties

- Medical Specialties. They require to select the specialties for each unit or hospital previously enrolled.

The semantic processing task is in charge of receiving the search type as an input parameter. The value of the search type defines the query to build in the application ontology using the SPARQL language. In this way, the semantic information concerning the medical centers, units, or hospitals is retrieved by taking into consideration the user's statements.

Moreover, the search type assumes one of three potential values: general, emergency, or profile-oriented. In the general search, the list of retrieved medical facilities is ranked according to the geospatial distances measured by the user's position. In consequence, the first medical facility is the nearest patient. In case of emergency, the "ER" string is allocated to the search type variable, and the previous steps are made, but the query outcome only has medical facilities that supply emergency services. Finally, in a profile-oriented query, all data stored in the user profile is employed to ask about the closest medical facilities with the medical specialties described in the profile. The final result of this task is a list of hospitals represented by the set $MF = \{mf_1, mf_2, \ldots, mf_n\}$, where MF is the set of medical facilities, centers, units or hospitals.

3.3. The ranking attention factor

We propose a novel ranking algorithm for determining the health attention factor and sorting the medical facilities that accomplish a medical specialty. So, the algorithm computes the attention feature for a collection of medical units, centers, or hospitals numerically. For example, in an emergency such as a heart attack, it is desirable a doctor with a cardiology specialty to care about the patient. However, in the case that this medical specialist is unavailable, it is critical to compute the semantic similarity and identify all potential physicians with some corresponding knowledge for treating the patient.

Consequently, we design the following equation to determine the number of doctors who can respond to an emergency involving a particular medical discipline. This value specifies the medical specialties semantically associated with the desired specialization, as indicated in the user profile. Let f be a function, where MF_B is the number of hospitals within a ratio obtained by using the buffer geographic operator from the current user geographic location, $\mathbf{S}$ is the set of all medical specialties described by the application ontology, $\mathbf{S}_{mf_i}$ is a subset and represents the number of medical disciplines offered by some medical facility. Finally, the value of medical doctors for a specific hospital is retrieved by applying Equation 4.

$$related\_doctors(mf_i) = \sum_{\forall s \in \mathbf{S}} medical\_doctors(s, mf_i) * sim(s, s_u), mf_i \in MF_B. \quad (4)$$

Where $medical\_doctors(s, mf_i)$ denotes the number of medical doctors with a specialty s in the mf_i hospital, and $similarity(s, s_u)$ determines the semantic similarity between s and s_u according to the user profile described by u. Thus, to compute this similitude value, the semantic similarity proposed by Resnik [40] between two terms t_1, t_2 is applied. In this case, we use Equation 5.

$$Sim(t_1, t_2) = \max_{t \in S(t_1, t_2)} [-log\, p(t)] \quad (5)$$

Where $S(t_1, t_2)$ is the set of common ancestors of two terms t_1 and t_2. The Resnik similarity has a minimum of zero.

3.4. The map rendering task

This task interprets the obtained results from the ranking algorithm to display the medical facilities on a map using Google Maps API version 2. Therefore, we employ this map server because the downloading, visualization, and responding times for requests in mobile devices are optimal, in constrast with other map servers such as Yahoo Maps, and Microsoft Bing Maps, among others. Moreover, it is possible to use a temporal layer to add different visual analysis options (markers, polygons, route lines, and change of map type). This task processes the data input that contains a geographically ordered (general and oriented-profile queries) or ranked (emergency search) list of hospitals to add markers for all medical facilities enlisted in the input list. A geographic marker represents each medical facility, and a label that contains the name and related information of every medical center, the address, and the distance are measured in kilometers. So, to obtain an estimation of the time required to arrive at the desired location, we operate with Google Directions API. The developed query has the following pattern:

https://maps.googleapis.com/maps/api/directions/json?
origin=*latitude_origin*, *longitude_origin*&
destination=*latitude_destination*, *longitude_destination*&
key=*YOUR_API_KEY*

On the order hand, it is possible to compute the geographic distance between the two locations (origin and destination), applying the Haversine function [41]. See Equations 6 - 8.

$$distance(o(lat_1, lon_1), d(lat_2, lon_2)) = R \times c \tag{6}$$

$$a = sin^2\left(\frac{rad(\Delta_{lat})}{2}\right) + cos(rad(x_1)) \times cos(rad(x_2)) \times sin^2\left(\frac{rad(\Delta_{lon})}{2}\right) \tag{7}$$

$$c = deg\big(2 \times arcsin\big(min(1, \sqrt{a})\big)\big) \tag{8}$$

Where:
$\Delta_{lon} = lon_2 - lon_1$ is the longitude coordinates difference.
$\Delta_{lat} = lat_2 - lat_1$ is the latitude coordinates difference.
$rad(value)$ is a function to convert $value$ from degrees to radians.
$deg(value)$ is a function to convert $value$ from radians to degrees.
R equal to 6378.137 kilometers, is the Earth radius.

Finally, the complete pseudocode of this proposal is described in Algorithm 1.

4. Tests and results

This section describes a comparative result of the attention factor algorithm, with a set of 4 medical facilities computed after applying the buffer operator, at a radius of 1,000 meters, from the user's geographic current position to the clinical units. Table 1 describes the medical specialties and the algorithm parameters, such as the number of patients and the maximum capacity of each medical center.

Input:
$MF_B = \{mf_1, mf_2, ..., mf_n\}$, set of medical facilities inside buffer R.
s_u, required speciality by the user.
R, search ratio to apply buffer operator.
$pat(mf_i)\ \forall\ mf_i \in MF$, current patients of mf_i.
$cap(mf_i)\ \forall\ mf_i \in MF$, maximum patients capacity of mf_i.
$P_u(lon_u, lat_u) \leftarrow$ user current latitude and longitude.
$max(at(P_u, P_{mf_k})) \leftarrow$ maximum arrival time.
Output:
$AF_B = \{mf_1, mf_2, ..., mf_n\}, af(mf_i) > af(mf_k), i < j \leq n.$
for $i = 1 \rightarrow n$ **do**
  $P_{mf_i}(lon_{mf_i}, lat_{mf_i}) \leftarrow i-$medical facility latitude and longitude.
  $|at(P_u, P_{mf_i})|$
  $related\_doctors(mf_i) = 0$
  for $j = 1 \rightarrow m\ \forall\ s_j \in \mathbf{S}_{mf_i}$ **do**
    $related\_doctors(mf_i) += medical\_doctors(s_j, mf_i) * sim(s_j, s_u)$
  end
  $af(mf_i) = related\_doctors(mf_i) * [1 - pat(mf_i)/cap(mf_i)]$
  $af(mf_i) = af(mf_i) * [1 - at(P_u, mf_i)/max(at(P_u, P_{mf_k})]$
end
$AF_B = \{mf_1, mf_2, ..., mf_n\}, af(mf_i) > af(mf_k), i < j \leq n.$

Algorithm 1: Algorithm to compute the attention factor

Table 1. Information on specialties and patient capacity of a group of hospitals.

Hospital	Patients	Capacity	Oncology	Cardiology	Obstetrics and Genycol-ogy	Emergency Medicine	Nephrology
mf_1	15	50	5	1	3	2	3
mf_2	10	30	2	2	0	3	4
mf_3	60	80	6	2	5	3	2
mf_4	50	120	6	3	4	5	4

On the other hand, Table 2 shows the values obtained by applying the Resnik similarity measure, as well as the attention factor, arrival time, and normalized values described in the previous section.

Table 2. The obtained values by applying the attention factor algorithm.

Hospital	Arrival time (minutes)	Related Doctors	Attention Factor	Final Attention Factor
mf_1	12	8.1859241	5.7301469	1.1460293
mf_2	10	6.6240311	4.4160207	1.4720069
mf_3	15	12.373001	3.0932502	0.0000000
mf_4	13	14.466539	8.4388146	1.1251752

According to previous results in Table 2, the medical facility mf_2 contains the best care factor, considering the cardiology specialty required by the user created in this scenario.

Figure 3 shows an extract of the relevant information from the response file in JSON format, which is obtained using the Google Directions API, taking as parameters for the query: the origin with coordinates (19.503147,-99.147667), being a medical facility with coordinates (19.4663758,-99.147163). This response extracts descriptive information with indications of the path to follow reaching the point of interest.

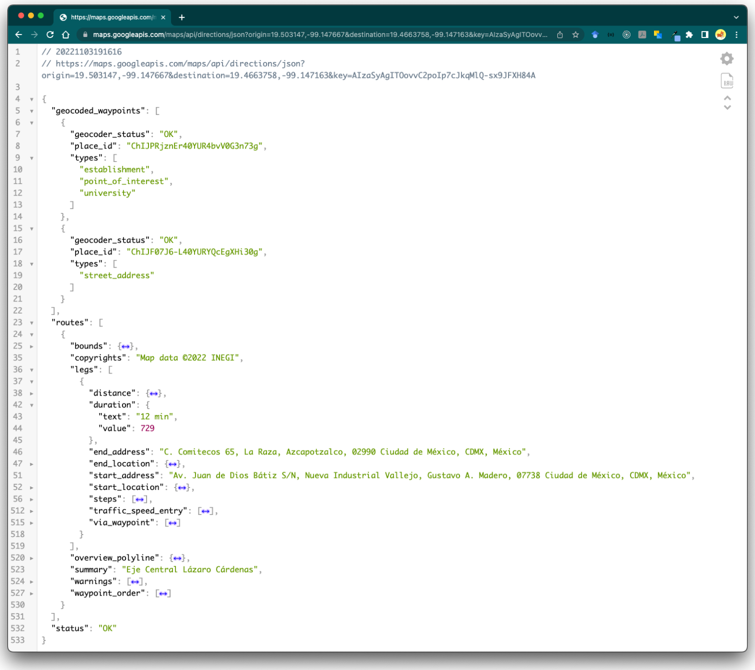

Figure 3. Query result in JSON format obtained using Google Directions API.

To calculate the estimated time for arrival, the user can select one of the following options: 'driving', 'walking', and 'bicycle'. The next two figures depict the result of computing the optimal route. 364 365 366

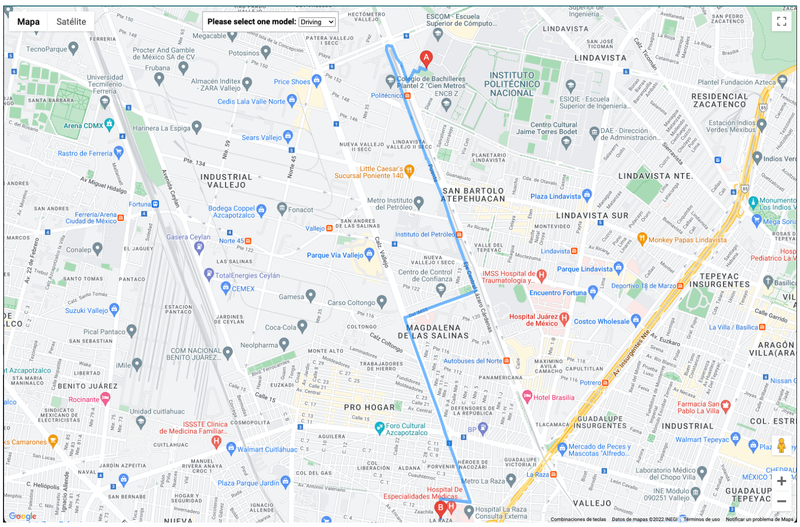

Figure 4. Visualization of route. Case 1.

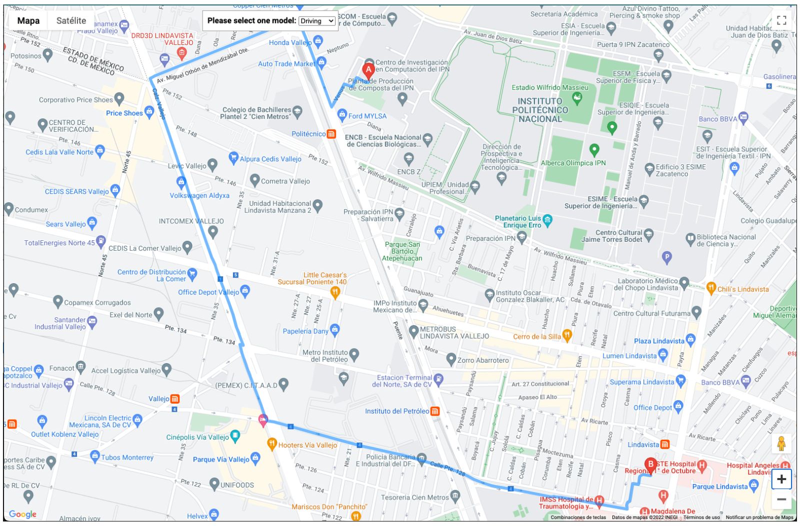

Figure 5. Visualization of route. Case 2.

5. Conclusion and discussion

In this paper, we propose a methodological and collaborative architecture to promote the assistance of citizens to medical facilities. The approach consists of a recommender system in which the metric health attention factor assesses which medical facility, center, unit, or hospital with the better infrastructure and diverse health specialties is available to bring attention to patients. Thus, the proposed attention factor quantitatively computes the lower number of patients at an emergency and semantically the number of medical specialties, as well as the economic costs for the medical service. In addition, the geographic location ranks the medical facilities according to the user profile of the citizens, and the visualization is carried out in a Web-GIS application.

As collateral findings, we conclude that the efficient control of traffic congestion addressed the access to hospitals and facilities to provide health services according to geographic location and medical specialties. So, it is a critical challenge that highly urbanized spaces such as Mexico City are facing. While such unexpected events are tough to avoid, novel computation and quick broadcast information about alternative routes could be the only way to decrease the loss of lives in health emergencies and services.

Thus, medical emergency responses require quick and reliable access and optimal routing. We know that road networks in a megalopolis are becoming increasingly complex, and the density of traffic congestion are rising continuously at least in Mexico City. Indeed, recommender systems should be oriented towards improving health services by incorporating filtering approaches to multicriteria evaluation for health emergency routing services. Moreover, the new medical necessities require intelligent and automatic decision support considering the dynamic situation around the world.

In this sense, we assume that the responsibility of clinicians and public health officials is to emphasize to patients the significance of ongoing attending the medical centers, units, or hospitals to receive appropriate treatments, not only in emergencies but also for continuous and progressive actions to follow diseases. Nevertheless, patient-centered technology has demonstrated an innovative performance in managing and monitoring clinical settings, providing sustainable actions for the well-being of citizens.

Our future efforts will be focused on developing m-Health applications, considering the complete infrastructure of medical facilities, establishing mechanisms based on crowdsensing and crowdfunding to evaluate massive and collaborative information concerning medical services, and clinical records of patients to generate prediction models based on machine learning methods, and according to the healthcare services required by the citizens.

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1. Lancet, T. COVID-19: learning from experience. *Lancet (London, England)* **2020**, *395*, 1011.
2. Moazzami, B.; Razavi-Khorasani, N.; Moghadam, A.D.; Farokhi, E.; Rezaei, N. COVID-19 and telemedicine: Immediate action required for maintaining healthcare providers well-being. *Journal of Clinical Virology* **2020**, *126*, 104345.
3. Katz, J.N.; Sinha, S.S.; Alviar, C.L.; Dudzinski, D.M.; Gage, A.; Brusca, S.B.; Flanagan, M.C.; Welch, T.; Geller, B.J.; Miller, P.E.; et al. COVID-19 and disruptive modifications to cardiac critical care delivery: JACC review topic of the week. *Journal of the American College of Cardiology* **2020**, *76*, 72–84.
4. Sousa, M.J.; Pesqueira, A.M.; Lemos, C.; Sousa, M.; Rocha, Á. Decision-making based on big data analytics for people management in healthcare organizations. *Journal of medical systems* **2019**, *43*, 1–10.
5. Massaro, M. Digital transformation in the healthcare sector through blockchain technology. Insights from academic research and business developments. *Technovation* **2021**, p. 102386.
6. Kraus, S.; Schiavone, F.; Pluzhnikova, A.; Invernizzi, A.C. Digital transformation in healthcare: Analyzing the current state-of-research. *Journal of Business Research* **2021**, *123*, 557–567.
7. Banerjee, M.; Chakraborty, S.; Pal, R. Teleconsultation and diabetes care amid COVID-19 pandemic in India: scopes and challenges. *Journal of Diabetes Science and Technology* **2020**, *14*, 714–715.
8. Pinar, U.; Anract, J.; Perrot, O.; Tabourin, T.; Chartier-Kastler, E.; Parra, J.; Vaessen, C.; de La Taille, A.; Roupret, M. Preliminary assessment of patient and physician satisfaction with the use of teleconsultation in urology during the COVID-19 pandemic. *World journal of urology* **2021**, *39*, 1991–1996.
9. Tamayo, A.L.; Espinós, E.L.; González, E.R.; Guzmán, C.T.; Álvarez-Maestro, M.; de Castro Guerín, C.; Fernández-Pascual, E.; de Francisco, M.G.; de Vicente, J.G.; Rivas, J.G.; et al. Evaluation of teleconsultation system in the urological patient during the COVID-19 pandemic. *Actas Urológicas Españolas (English Edition)* **2020**, *44*, 617–622.
10. Shahed, K.S.; Azeem, A.; Ali, S.M.; Moktadir, M.; et al. A supply chain disruption risk mitigation model to manage COVID-19 pandemic risk. *Environmental Science and Pollution Research* **2021**, pp. 1–16.
11. Rosenbaum, L. The untold toll—the pandemic's effects on patients without Covid-19, 2020.
12. Lai, Y.; Kankanhalli, A.; Ong, D. Human-AI collaboration in healthcare: A review and research agenda **2021**.
13. Chauhan, A.; Jakhar, S.K.; Jabbour, C.J.C. Implications for sustainable healthcare operations in embracing telemedicine services during a pandemic. *Technological Forecasting and Social Change* **2022**, *176*, 121462.
14. Baudier, P.; Kondrateva, G.; Ammi, C.; Chang, V.; Schiavone, F. Digital transformation of healthcare during the COVID-19 pandemic: Patients' teleconsultation acceptance and trusting beliefs. *Technovation* **2022**, p. 102547.
15. Chakraborty, I.; Ilavarasan, P.V.; Edirippulige, S. Health-tech startups in healthcare service delivery: A scoping review. *Social Science & Medicine* **2021**, *278*, 113949.
16. Qahtan, S.; Yatim, K.; Zulzalil, H.; Osman, M.H.; Zaidan, A.; Alsattar, H. Review of healthcare industry 4.0 application-based blockchain in terms of security and privacy development attributes: Comprehensive taxonomy, open issues and challenges and recommended solution. *Journal of Network and Computer Applications* **2022**, p. 103529.
17. Drummond, M.F.; Augustovski, F.; Bhattacharyya, D.; Campbell, J.; Chaiyakanapruk, N.; Chen, Y.; Galindo-Suarez, R.M.; Guerino, J.; Mejía, A.; Mujoomdar, M.; et al. Challenges of Health Technology Assessment in Pluralistic Healthcare Systems: An ISPOR Council Report. *Value in Health* **2022**, *25*, 1257–1267.
18. Meleddu, M.; Pulina, M.; Scuderi, R. Public and private healthcare services: What drives the choice? *Socio-Economic Planning Sciences* **2020**, *70*, 100739.
19. Sharma, G.; Patil, G.R. Public transit accessibility approach to understanding the equity for public healthcare services: A case study of Greater Mumbai. *Journal of Transport Geography* **2021**, *94*, 103123.
20. Pereira, R.H.; Braga, C.K.V.; Servo, L.M.; Serra, B.; Amaral, P.; Gouveia, N.; Paez, A. Geographic access to COVID-19 healthcare in Brazil using a balanced float catchment area approach. *Social Science Medicine* **2021**, *273*, 113773. https://doi.org/https://doi.org/10.1016/j.socscimed.2021.113773.

21. Tran, T.N.T.; Felfernig, A.; Trattner, C.; Holzinger, A. Recommender systems in the healthcare domain: state-of-the-art and research issues. *Journal of Intelligent Information Systems* **2021**, *57*, 171–201.
22. Pincay, J.; Terán, L.; Portmann, E. Health recommender systems: a state-of-the-art review. In Proceedings of the 2019 Sixth International Conference on eDemocracy & eGovernment (ICEDEG). IEEE, 2019, pp. 47–55.
23. Shaikh, S.G.; Suresh Kumar, B.; Narang, G. Recommender system for health care analysis using machine learning technique: a review. *Theoretical Issues in Ergonomics Science* **2022**, pp. 1–30.
24. Vairale, V.S.; Shukla, S. Recommendation framework for diet and exercise based on clinical data: A systematic review. *Data Science and Big Data Analytics* **2019**, pp. 333–346.
25. Fasidi, F.; Adebayo, O. Rule-based naïve Bayes classifier for heart disease risk prediction and therapy recommendation. *International Journal of Clinical & Medical Informatics* **2019**, *2*, 51–59.
26. Gohari, F.S.; Aliee, F.S.; Haghighi, H. A significance-based trust-aware recommendation approach. *Information Systems* **2020**, *87*, 101421.
27. Sahoo, A.K.; Mallik, S.; Pradhan, C.; Mishra, B.S.P.; Barik, R.K.; Das, H. Intelligence-based health recommendation system using big data analytics. In *Big data analytics for intelligent healthcare management*; Elsevier, 2019; pp. 227–246.
28. Waqar, M.; Majeed, N.; Dawood, H.; Daud, A.; Aljohani, N.R. An adaptive doctor-recommender system. *Behaviour & Information Technology* **2019**, *38*, 959–973.
29. Mazeh, I.; Shmueli, E. A personal data store approach for recommender systems: enhancing privacy without sacrificing accuracy. *Expert Systems with Applications* **2020**, *139*, 112858.
30. Sayeb, Y.; Jebri, M.; Ghezala, H.B. A graph based recommender system for managing Covid-19 Crisis. *Procedia computer science* **2022**, *196*, 348–355.
31. Zhang, Y.; Chen, M.; Huang, D.; Wu, D.; Li, Y. iDoctor: Personalized and professionalized medical recommendations based on hybrid matrix factorization. *Future Generation Computer Systems* **2017**, *66*, 30–35.
32. Narducci, F.; Musto, C.; Polignano, M.; de Gemmis, M.; Lops, P.; Semeraro, G. A recommender system for connecting patients to the right doctors in the healthnet social network. In Proceedings of the Proceedings of the 24th international conference on World Wide Web, 2015, pp. 81–82.
33. Neutens, T. Accessibility, equity and health care: review and research directions for transport geographers. *Journal of Transport Geography* **2015**, *43*, 14–27.
34. Matthews, K.A.; Gaglioti, A.H.; Holt, J.B.; Wheaton, A.G.; Croft, J.B. Using spatially adaptive floating catchments to measure the geographic availability of a health care service: pulmonary rehabilitation in the southeastern United States. *Health & place* **2019**, *56*, 165–173.
35. Cornet, R.; de Keizer, N. Forty years of SNOMED: a literature review. *BMC medical informatics and decision making* **2008**, *8*, 1–6.
36. Fujita, H.; Hakura, J.; Kurematsu, M. Multiviews ontologies alignment for medical based reasoning ontology based reasoning for VDS. In Proceedings of the 2010 11th International Symposium on Computational Intelligence and Informatics (CINTI). IEEE, 2010, pp. 15–22.
37. Bandrowski, A.; Brinkman, R.; Brochhausen, M.; Brush, M.H.; Bug, B.; Chibucos, M.C.; Clancy, K.; Courtot, M.; Derom, D.; Dumontier, M.; et al. The ontology for biomedical investigations. *PloS one* **2016**, *11*, e0154556.
38. Rector, A.; Rogers, J. Ontological and practical issues in using a description logic to represent medical concept systems: Experience from GALEN. In Proceedings of the Reasoning Web International Summer School. Springer, 2006, pp. 197–231.
39. Consortium, G.O. The gene ontology resource: 20 years and still GOing strong. *Nucleic acids research* **2019**, *47*, D330–D338.
40. Resnik, P. Semantic similarity in a taxonomy: An information-based measure and its application to problems of ambiguity in natural language. *arXiv preprint arXiv:1105.5444* **2011**.
41. Sinnott, R.W. Virtues of the Haversine. *Sky and telescope* **1984**, *68*, 158.