Health Recommender System for Smart Cities

Houda El Bouhissi[1,2], Dyhia Tagzirt[1] , Faycal Bouredjioua[1] and Olga Pavlova[3]

[1] *LIMED Laboratory, Faculty of Exact Sciences, University of Bejaia, Bejaia, 06000, Algeria*
[2] *Laboratoire LITAN, Ecole Supérieure en Sciences et Technologies de l'Informatique et du Numérique, Bejaia, Algeria*
[3] *Khmelnytskyi National University, Instytuts'ka str., 11, Khmelnytskyi, 29016, Ukraine*

Abstract

Recommender systems are a key element in transforming cities into smart cities, improving the quality of life of citizens, reducing costs, solving complex problems and provide quality services through personalized solutions. Nowadays, tourism is valuable for smart cities through its contributions to improve business, employment and economy. Smart city tourism can be enhanced by various services to improve citizen's life quality of. In this paper, we survey the existing literature on health recommender systems for smart cities and propose a novel approach to help tourists finding the appropriate doctor. The experiments showed that the built recommendation system has great effective promise to improve the efficiency of smart city tourism services.

Keywords 1

Recommender Systems, Healthcare, Smart cities, machine learning, tourism

1. Introduction

Smart cities have become a priority for governments and citizens around the world, as they enable the use of information and communication technologies to improve the citizen's life quality, make cities more sustainable and efficient, and solve complex urban problems. The emergence of innovative solutions for smart cities will provide a stimulating environment for urban recommendations

Recommendation systems (RS)s are a key component in transforming cities to smart cities, improving the life quality of citizens by finding the services they need quickly and efficiently.

For instance, if a visitor disease occurs in a smart city, without any support, it becomes difficult to find a nearby doctor. Moreover, he/she can use a RS to find the nearest and most appropriate doctor based on his/her health status and geographical location. Recommendations are therefore very important for smart cities to solve complex problems regarding healthcare, mobility, energy, and environment through using data and technologies to provide personalized responses/services to citizens.

The purpose of this paper is to review the existing literature on health RSs for smart cities and propose a novel approach for assisting tourists in selecting appropriate doctor.

This paper is organized as following. In the next section, we provide a background of RSs and smart cities, and then we present the state of the art summarizing some of the existing works. In section 4, we describe our proposal in detailed. The next section concerns the implementation where we present the implementation environment and we describe the data source. In section 5, we analyze and discuss the generated results. We conclude this paper with the conclusion and some perspectives.

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EMAIL: Houda.elbouhissi@gmail.com (H. El Bouhissi); dyhia.tagzirt@se.univ-bejaia.dz (D. Tagzirt); faycal.bouredjioua@se.univ-bejaia.dz (F. Bouredjioua); pavlovao@khmnu.km.ua(O.Pavlova)
ORCID: 0000-0003-3239-8255 (H. El Bouhissi); 0000-0003-2905-0215 (O.Pavlova)

2. Background

In this section, we discuss the many ideas and basic principles associated with RSs and smart cities, as well as their types, features and principles.

2.1. Recommender systems

RSs have been defined in several ways. "RS can be defined as programs that attempt to recommend the most appropriate items (products or services) to specific users (individuals or companies) by measuring user interest [1] [2]".

By pulling the most pertinent data and services from a dataset, RSs are being developed with the goal of reducing information overload and providing individualized services. RS aims to create individualized suggestions by inferring the preferences and interests of the user from that person's activity and/or those of other users is its most crucial component.

A RS model involves mainly two key components: "users" and "items" (figure 1). The system provides recommendations to the users, who provide feedback by either vote or notes. These ratings are registered as a triplet of (user, item, note), and used to create the "score matrix," which represents the interactions between users and items. The ratings can take different forms, such as numerical scores on a scale of 1 to 5 or binary "like/dislike" options.

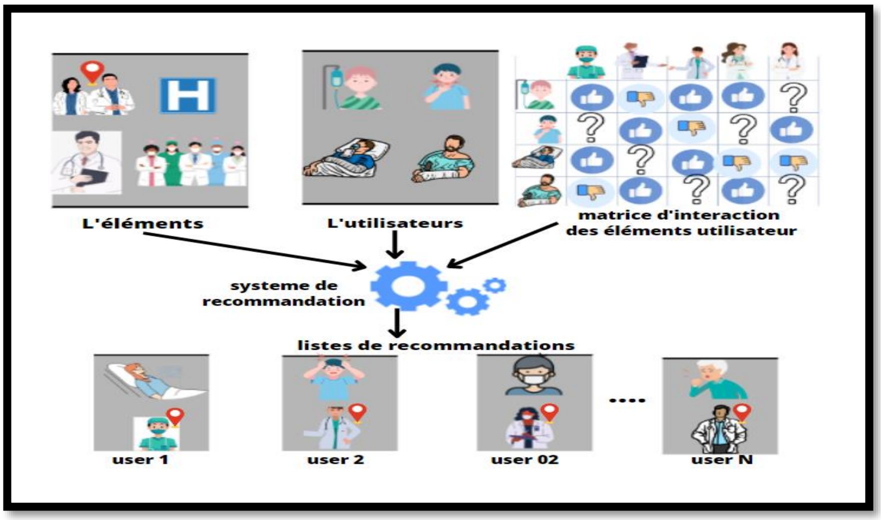

Figure 1: RS general architecture

Today, we live in a digital world where RSs are the most powerful and practical used tools. RSs can be classified into three types: content-based filtering, collaborative filtering, and hybrid filtering [3]. These strategies need to be studied in order to provide the final consumer with the best recommendations according to his/her interests [4].

Different types of models are used in content-based filtering to identify similarities between elements and produce actionable recommendations. To illustrate the relationship between the various components of a corpus, probabilistic models like the classifier Naive Bayes, decision trees, or neural networks may be used. These models are trained using artificial intelligence and indexing approaches.

Collaborative filtering includes a database (user-item matrix) which considers user ratings on specific items to recommend the same items to other users without considering the content of such items.

Generally, the collaborative filtering employs clustering and probabilistic approaches and involves two major sub methods:

- User-based method, which is a heuristic method, where the user's preferences that are similar to other users to provide predictions and inferences.

- Item-bade method: Collaborative filtering based on items suggests items that are similar to other items the active user liked.

Due to their capacity to boost performance, hybrid systems are becoming more and more common. They use a number of recommendation techniques to produce predictions and recommendations.

In addition to these recommendations, knowledge-based is another type [5], which use specific information to identify items that match the user's preferences. When data is limited, knowledge-based systems are generally more reliable than other types of recommendations that depend on the user's history.

However, if the knowledge system is not able to learn from the user's notes or actions, it may not provide personalized recommendations. It is important to note that knowledge-based RSs are often used in conjunction with other methods to ensure an optimal user experience.

Numerous online platforms, including e-commerce websites and social media sharing platforms, are heavily reliant on RSs today. These systems use algorithms to provide users with recommendations for articles or products based on their past behavior and preferences.

However, the RSs continue to face a number of challenges [1] that might hinder their effectiveness despite their widespread use:

- Cold start: refers to à situation where the recommender system does not have enough information about a new user or item to make accurate recommendations. These problems can also be resolved by hybrid filtering.
- Scalability: refers to the ability of the system to handle increasing amounts of data and users while maintaining its performance.
- Privacy: refers to the protection of sensitive user information, such as their preferences and behaviors that are used by the RS to generate recommendations.
- Sparsity: In online shops, we find that the number of candidate items for recommendation is often high and that users evaluate only a small subset of them. This makes it difficult to determine a user's interests and may be associated with a bad neighborhood. As a result, the evaluation matrix (user-item interaction) is a hollow matrix with a high rate of missing values.

These constraints provide significant obstacles to the development and implementation of effective recommendation systems, necessitating careful consideration and methodical resolution throughout these processes.

2.2. Smart cities

The term "smart city" originated in the early 1990s, highlighting the significance of information and communication technologies in building a modern city's infrastructure [6]. The meaning of "intelligent" varies depending on its usage.

Different papers and works have used various terms, such as "smart city", "knowledge city", or "digital city" to describe this concept. There is a significant difference between a smart city and a digital city, which are often confused or used as synonyms, but they are not exactly the same [7].

Generally, a smart city is an interconnected city including sensors and other devices, employs digital tools to enhance the life quality for populations.

The relationship between SRs and smart cities is essential. As a smart city comprises a whole range of services, users may it difficult to choose the best service among a multitude of services offered by smart cities. Users can benefit from RSs by receiving personalized recommendations for products and services that fit their requirements and interests and simplifying their daily life.

Since smart cities handle many sensors data, this data takes many forms and can either add value or be of insignificant value. In this context, RSs are a way of filtering an excess of data, adding personalized features and providing a selection of value adapted to the user's preferences and context. RSs are strong tools that filter relevant information, upgrading the relations between stakeholders in the polity and civil society, and assisting in decision making tasks through technological platforms

We assume that there is a critical need to build more RSs for the overall Smart City offering services in different domains like healthcare, tourism, and education.

3. Related works

The investigation of RSs in the context of a comprehensive, interconnected smart city is still in its initial phases. It is important that we were unable to locate only few documents that discuss the RS for smart cities. Therefore, a number of works in literature is associated to the recommendation in healthcare. According to the recommendation approach, we divide these works into three categories: collaborative filtering, content filtering and hybrid filtering.

We present here the most important works, which fit our proposal.

3.1. Collaborative filtering

In the healthcare domain, collaborative filtering can be used to recommend treatments by examining a patient's medical history, current health status, and responding to various treatments.

By providing information about treatment choices that have been effective for patients with similar conditions, collaborative filtering systems can help doctors in their decision-making about patient care. We review the works that have been proposed in this area and discover what strategies are often used to achieve efficient results.

Leanza and Carbonaro [8], propose deploying real-time RSs combined with the sensor infrastructure of smart cities to provide residents with route suggestions that take into account their health status and preferences. The authors have described all the components, architecture, and operation of the proposed system.

In addition, experiments were conducted and a smartphone application called "SmartRoute" was developed using real data provided by the smart city IoT infrastructure as well as participatory contributions from users who tested the system in real-life circumstances. The experimental results show that the approach is efficient and can provide citizens with helpful recommendations, despite the large amount of unknown data. The author's project is part of a larger discussion about environmentally friendly investments in smart cities.

The project of Erdeniz [9], is part of a broader research context on the use of RSs to improve the health status of individuals. In this research area, many works have examined the benefits and applications of recommender technologies in IoT-based mobile health systems (m-health).

In this context, the paper refers to a previous study that proposes two new recommenders for an IoT project to provide new health applications, devices, and physical activity plans for patients. The authors used collaborative and content-based filtering techniques to recommend personalized mobile health apps and devices to patients based on their health profile.

Forouzandeh et al. [10], studied the use of RSs in IoT (Internet of Things) devices and collected data from companies such as Telus, Libelium and BlueRover. Based on a survey of 1,875 users, the RS provides possibilities to users based on popular IoT devices (IOTPO), popular IoT services (IOTPS) and profile similarity (IOTSRS). The results show that the highest accuracy is achieved by recommending services based on users' profiles, indicating the importance of users' profiles in determining their interests and preferences for IoT devices. The accuracy of the RS increases with the number of users, making it an effective tool for analyzing user preferences for IoT devices.

3.2. Content filtering

Content filtering is a RS approach used in healthcare that provides recommendations based on information in health data. It can be used for diagnostic purposes, to allow patients to find information about their health status, or for healthcare companies to improve patient care.

In this work by Sun et al. [11], a RS has been proposed to provide people with personalized exercise route recommendations based on their health status, using real-time data to improve their lifestyle and enhance their daily health activities. The system uses collaborative filtering algorithms based on deep learning to recommend appropriate exercise routes based on the user's health data. The system has been successfully evaluated on a test dataset, showing high accuracy of recommendations and significant improvement in the user's health and well-being.

3.3. Hybrid filtering

Hybrid filtering systems are a combination of collaborative and content-based filtering that use both user and product data to recommend products or services. In healthcare, they can recommend treatments based on medical history, preferences and guidelines. Hybrid systems offer more accurate and personalized recommendations, but these systems are data intensive and complex to implement.

Jabeen et al. [12], presented a hybrid Internet of Things (IoT) based RS to diagnose heart disease symptoms and provide personalized physical and dietary recommendations. The system was designed to collect patient data using IoT sensors, which gather important information such as blood pressure, heart rate, and physical activity level. Then, a heart disease prediction model was used to diagnose cardiovascular diseases and classify them according to patients' gender and age.

The hybrid RS proposed by the authors combines two recommendation approaches: collaborative filtering and content-based filtering. The first approach recommends articles similar to those the patient liked, using data from patients with similar characteristics. The second approach recommends articles based on their content and patient information, such as age, gender, medical history, etc.

The results showed that the hybrid recommendation system had an accuracy of 87.20% for diet recommendation and 91.50% for exercise recommendation. The authors also compared their RS with other traditional RSs, such as collaborative filtering and content filtering, and showed that their hybrid approach was more effective

Subramaniyaswamy et al. [13] present a personalized RS called ProTrip that helps travelers by generating suggestions based on their interests, preferences, travel sequence, activities, motivations, opinions, and demographic information. ProTrip is a health-focused system that suggests foods based on climate characteristics, personal choice and nutritional value. It can also help travelers with chronic diseases or strict diets. ProTrip is based on ontological knowledge and customized filtering mechanisms, and has improved accuracy and efficiency over existing models.

Zhang et al. [14] present a state of the art of medical RSs and propose a new system called iDoctor which is based on hybrid matrix factorization methods. iDoctor differs from existing RSs by using sentiment analysis to understand the influence of emotions on users' opinions, and by incorporating users' preferences and physicians' characteristics into the RS. Experimental results show that iDoctor provides more accurate predictions and greater precision in healthcare recommendations. The authors show that iDoctor could have practical applications in the healthcare industry, including providing personalized healthcare recommendations to patients. The paper highlights the importance of analyzing user sentiments and preferences in the design of healthcare RSs.

Farman [15] presents an IoT-based approach for patients to receive dietary recommendations using ontology-based systems. The author's paper discusses the use of sensors to collect patient health information and the use of smart refrigerators and medicine boxes to provide diet and medication recommendations. The aim is to reduce the burden of chronic patients on hospitals and enable patients to receive care remotely.

Han et al. [16], investigate how RSs can be used to facilitate patient-physician matching in primary care. The paper proposes a hybrid RS that uses both content-based and collaborative approaches. The authors collected patient and physician data in a primary care setting, such as demographic information, medical history, patient assessments, physician notes, etc. They then used this data to create patient and physician profiles.

Ben Abdessalem Karaa et al. [17] developed a system called RecSPSC that uses tweets to provide recommendations for startup projects in the smart city and smart health domains. The system uses machine learning and the Word2Vec algorithm to analyze tweets, as well as an ontology-based recommendation method to improve the accuracy of recommendations. The results show that RecSPSC outperforms traditional recommendation approaches in terms of accuracy. The goal of this work is to improve the quality of life by providing recommendations for startup projects in smart cities, which can have a positive impact on the economic and social development of a country.

The present study enables evaluating the effectiveness of various SR approaches and methods by examining the results in terms of accuracy, recall, and precision. Based on the studies reviewed above, we conclude that the majority of the most cited projects in the health services domain use the collaborative approach.

However, using the collaborative filtering method is an issue for newly enrolled users. This is because to generate personalized recommendations, these systems typically rely on user ratings. Therefore, because they have not provided enough information for the system to understand them, new users who have not yet provided feedback or ratings cannot receive personalized recommendations.

4. Proposed approach

Nowadays, tourism is valuable for smart cities in different ways. Tourism contributes to improve business, employment and economy. Smart city tourism can be enhanced by various services to improve citizens' life quality.

Tourists select the wellbeing sites in this context; the tourism state health is a major skill in a smart city. If a tourist becomes sick, we have to provide him the most appropriate treatment.

Our proposed RS use the patient's symptoms as well as his geographical location to suggest the suitable doctor. In this section, we present our approach in detailed. Using collaborative filtering techniques, our system suggest doctors that other patients with similar symptoms have checked and been satisfied. This would enable to provide personalized, effective recommendations to patients who travel to an unfamiliar city and require emergency medical care.

Figure 2 represent the proposed architecture of the proposed RS and it mainly consists of the following four functional steps. The first step involves the creation of user profile. The second step comprises the research of similar profiles according to the profile built in the previous step. The third step concerns the recommendation proposal at the whole and finally, the fourth step involves choosing the best doctor.

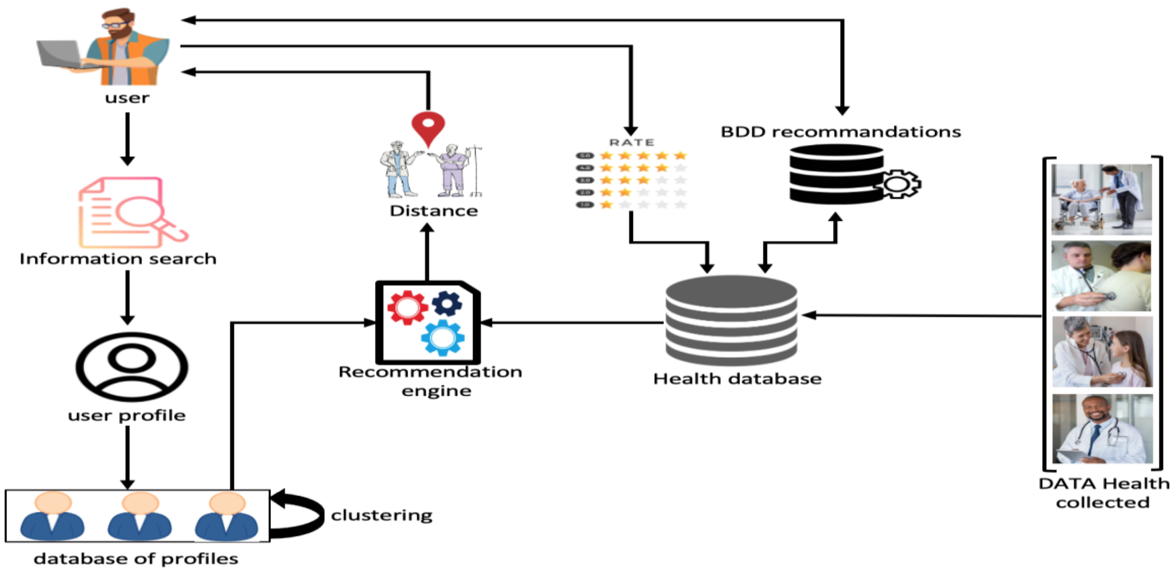

Figure 2: Proposed approach

In the following, we will summarize and present the steps of our approach in detail:

4.1. Step 1: Creating the user profile

The first step in creating a personalized patient RS is to create a user profile that includes information such as the patient's medical history, symptoms, personal preferences and contact information. This profile modeled a system user with significant information.

This step is very important for our methodology, hence, for our ML algorithm, User data is obtained from information introduced manually by the user using his smartphone or sensor devices.

4.2. Step 2: Searching similar profiles

The recommendation algorithm will then use the user profile information to identify other users with similar characteristics. The user database includes different clustered profiles formed previously. The characteristics used to identify similar profiles include age, gender, diagnosis, medical history, etc. Searching similar profiles involves the use of similarity measure algorithm, in our case, we use Jaccard similarity [18] because of its low complexity and simplicity since it is the suitable one for our methodology.

Jaccard similarity returns a value between 0 and 1 and is defined (formula 1) as the number of common elements between the two sets divided by the total number of unique elements in the two sets.

The formula for Jaccard similarity is:

$$Sim\ (A, B) = |A \cap B| \,/\, |A \cup B| \qquad (1)$$

Where : A and B are two sets.
|A| and |B| represent the number of elements in each set.
$|A \cap B|$ represents the number of elements common to A and B.

In other words, we build a set of symptoms associated with the patient's disease, and then compare this set with the sets of symptoms corresponding to the areas of expertise of different doctors. Jaccard's similarity is used to rank doctors according to their similarity to the patient and recommend the most similar doctors first.

This step is important for the recommendation at the whole. If the built profile is similar to an existing profile, the recommendation is submitted directly to the user based on the recommendation history. Moreover, if no similar profile is found among the existing clusters, then a new cluster will be created automatically to accommodate the new user's profile and the process continue to the third step.

4.3. Step 3: Recommending the suitable doctors

There are several unsupervised learning techniques, such as clustering, dimensionality reduction, anomaly detection and data generation.... Unsupervised learning is used in a variety of fields, including pattern recognition, data analysis, bioinformatics, and the medical field. Our approach is based on K-means [19] clustering algorithm since it is the most suitable algorithm for the recommendation.

K-means is used to group users sharing common interests into clusters, to avoid searching for a match for each new user joining the site with all existing users and to quickly produce lists of similar users.

In the K-Means clustering algorithm, we first select K initial centroids, where K represents the number of desired clusters. Then, each data point is assigned to the cluster with the closest mean, i.e., the centroid of the cluster.

Then, the centroids of each cluster are updated according to the points assigned to it, and the process is repeated until the cluster center (centroid) does not change.

To optimize the process, it is recommended to divide the data into smaller groups, so that the similarity calculation is performed within groups with fewer users.

We choose the K-means clustering method to help patients finding a doctor based on their disease. We use patients' medical data to create clusters of patients with similar symptoms. Then, we assign each cluster to a doctor who specializes in treating the diseases associated with these symptoms. Finally, we assign each cluster to a specialized doctor in treating the diseases associated with the patients' symptoms in the considered cluster.

4.4. Step 4 : Choosing the best doctors

In the area of RSs, the user needs to collect the best recommended items. In this way, to further refine the recommendation and choosing the best doctors, i.e., the nearest doctors according to the patient geographical location, we calculate the Manhattan distance [20] between the patient's geographical location and the doctors.

This would take into account the user's geographic proximity to similar doctors and optimize the patient's care by minimizing the distance to travel, which can be an important feature in choosing a doctor.

5. Experiment and Evaluation

In the field of health, evaluating and experimenting a RS are crucial steps to measure its reliability. This may involve various methods such as collecting test data, analyzing errors, evaluating user satisfaction, and analyzing performance metrics such as accuracy, speed, and scalability.

The results of the evaluation and experimentation help to improve the system for more satisfactory outcomes for users. We conduct our experiments and simulations in Bejaia, a Mediterranean town in northern Algeria to investigate the problem and evaluate our methodology using Python 3.4.

Python is a popular choice for machine learning due to its wide range of libraries and high level of abstraction. The experiments employ libraries such as numpy for numerical computation, pandas for data manipulation, and matplotlib for plotting results.

A user-friendly application was developed with reduced menus and convivial interface, where the user introduces personal data and click on the recommendation button. Sensorized IoT devices were used to gather data, which was connected to a PC for data input.

Our main issue is the dataset, since the proposed methodology is the newest in our city; we create our dataset involving useful information about city doctors and diseases. A cleaning and filtering process was performed to obtain a significant dataset that could be used by the machine-learning algorithm.

The Precision, Recall, and F-measure metrics are used to benchmark the proposed model's outcome [21].

Precision (formula 2) is a metric that measures the quality of a classification model's results by calculating the proportion of true positives (TPs) over the sum of true positives and false positives (FPs). It indicates how often a positive prediction by the model is correct, and is defined by the Equation A:

$$Precision = TP / (TP + FP) \tag{2}$$

Recall (formula 3) is a metric that measures how well a classification model can identify all relevant items by calculating the proportion of true positives (TPs) over the sum of true positives and false negatives (FNs). It indicates how many of the actual positive cases the model can identify, and is defined by the Equation B:

$$Recall = TP / (TP + FN) \tag{3}$$

F-measure (also known as F1 score) is one of the most popular metrics used for measuring the overall accuracy of a classification model, rather than cluster accuracy. It is based on both precision and recall values, and can be computed by the following formula Equation C:

$$F1\ score = 2 * (Precision * Recall) / (Precision + Recall) \tag{4}$$

The F1 score combines precision and recall into a single metric that balances both measures, and provides a way to compare the performance of different models. It ranges from 0 to 1, with higher values indicating better overall performance.

For the experiment, we consider three scenarios:

- First scenario: 60% of data for training and 40% remaining for testing.
- Second scenario: 70% of data for training and 30% remaining for testing.
- Third scenario: 80% of data for training and 20% remaining for testing.

For a beginning, the obtained results are encouraging, about 86% in term of precision.

6. Conclusion

RS for smart cities can have a significant impact on the health and wellbeing of citizens. However, ensuring that SRs are reliable, accurate, and used by citizens and healthcare providers is critical to their effectiveness. Smart cities offer innovative solutions to improve the citizens' quality life, including health.

In this paper, we conduct a literature review of the related works and propose a collaborative filtering method for doctor recommendation for smart cities.

The main insights of our approach are to provide an efficient recommendation in a short time since the issue concerns the citizen's health. It also eliminates the limitation of the cold-start problem by providing recommendations to a new user even if we do not have much information about the user's transactions.

This project is just the beginning of a big project regarding smart cities. In future work, we focus further on data collection from sensor devices and the use of deep learning for a better recommendation.

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