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Enhancing patient care through location-allocation strategies for treatment centers utilizing wearable sensor data

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Abstract

As cities continue to grow and populations surge, ensuring easy access to essential services, including healthcare facilities, has become increasingly difficult. One of the major contributors to patient fatalities is the lack of timely access to medical care, which can severely compromise the effectiveness of treatment. To tackle this pressing issue, location-allocation models have emerged as a promising solution. In this context, this study introduces an innovative method for optimizing healthcare resource distribution by combining the P-Median model with the use of wearable sensors. The integration of these two approaches was applied in four districts within the city of Kermanshah, aiming to reduce the distance between patients and healthcare centers.

By using this method, the study achieved a significant reduction in response times, cutting the average time from 19.67 minutes to 7.5 minutes. The results underscore the potential of applying the P-Median model and wearable technology to improve access to healthcare services and ensure timely interventions for patients. This approach offers a new way to address the critical issue of delayed healthcare response, ultimately saving lives and improving patient outcomes.

The P-Median model is a well-known optimization technique commonly used in location-allocation problems, and its application in this study highlights its ability to identify optimal locations for healthcare facilities in relation to patient demand. In addition, wearable sensors provide real-time data on patient conditions, which can be integrated into the model to prioritize patient needs and facilitate faster responses.

Overall, the findings of this study demonstrate the value of combining advanced mathematical models with modern technology to improve healthcare accessibility in urban environments. This approach not only reduces response times but also offers a scalable solution for expanding urban areas where healthcare service demand is growing rapidly.

Keywords: Location-allocation model; Wearable sensors; P-median model; Healthcare facilities.

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Introduction

Today, traditional healthcare systems face numerous challenges in monitoring chronic diseases, disease prevention, and early intervention. Additionally, traditional healthcare systems often prioritize disease treatment over prevention, leading patients to delay seeking medical services until significant symptoms appear [1]. According to current statistics, approximately 55% of the global population resides in urban areas, with this population projected to increase to 68% by 2050 [2]. These statistics indicate an increase in urbanization and, consequently, an increase in the elderly and sick population, making care and assistance to this population difficult and challenging.

Remote health monitoring offers a potential solution to overcoming the challenges of continuous health monitoring for patients through wearable devices [3]. However, in today's world, with advancements in technology and widespread adoption of wearable sensors, providing healthcare services to individuals utilizing these sensors has become a major challenge. Due to their specific needs and reliance on wearable sensors, these individuals face difficulties in accessing healthcare facilities. These challenges include issues such as physical distance, mobility constraints, and the need for accurate location and healthcare facility information.

To address these challenges, creating an efficient and intelligent location-allocation model is essential. In this model, demand points can be allocated to facilities based on factors such as minimizing distance, minimizing costs, and facility capacity [4]. Location-allocation models, besides finding optimal locations for new facilities, can also serve as suitable tools for ensuring emergency services coverage for all needs efficiently [5]. Given these issues, this model, as a complex decision-making process, can significantly improve access to healthcare services for individuals with wearable sensors. Additionally, besides the mentioned factors, this model can consider factors such as geographic location, traffic, and individual needs to determine the best route and location for providing healthcare services.

Wearable sensors are key tools in this field. In the healthcare domain, wearable devices are portable electronic medical or healthcare devices that can be directly worn on the body and used for understanding, recording, analyzing, regulating, and intervening to maintain health [6]. Sensors typically convert input data into electrical signals, which are then interpreted by communication devices [7]. These sensors communicate with each other through a suitable transmission medium such as Zigbee, BLE, or Wi-Fi [8]. Due to storage limitations and computational capabilities, wearable sensors may not be able to process data locally. Therefore, they transfer collected data to a powerful remote computer or cloud space, where information is decrypted, structured, and meaningful results are produced, interpreted, and presented to the user [9]. These sensors can measure information such as heart rate, physical activity, and healthcare needs and provide accurate information to the location-allocation model to facilitate more optimal and personalized healthcare services.

Numerous studies have been conducted on location-allocation and wearable sensors. These studies have largely helped us understand the above aspects and issues in this field. However, the importance of integrating these two factors to improve access to healthcare services for individuals with wearable sensors has been overlooked.

The main objective of this research is to investigate and develop a location-allocation model based on wearable sensors to improve access to healthcare services for individuals with wearable sensors. By enhancing location accuracy and considering individual needs, this research aims to create innovative solutions to improve the quality of healthcare services for this group of individuals.

Literature review

Previous research in the fields of location-allocation and wearable sensors have closely examined the relationship between location-based technologies and wearable tools to enhance access to healthcare services. Many previous studies in these areas have focused on the complexities and challenges associated with wearable sensors in location positioning. Some recent studies have shown that integrating wearable sensors with location systems can lead to improved accuracy and efficiency in allocating healthcare services to individuals with wearable sensors. Initial studies have shown that location-allocation models based on these sensors are capable of determining the best routes and medical locations for these individuals.

Furthermore, recent research in the field of wearable sensors has demonstrated that these tools can serve as personal physiological atlases for each individual. By using low-cost and lightweight body-worn sensors placed near the patient's body, lifestyle data can be collected, and in turn, information can be shared remotely with healthcare providers and caregivers [10].

By measuring the mentioned parameters and other health indicators, these sensors provide healthcare organizations with accurate information about the individual's condition. Despite significant advancements made in past research, we still face challenges and issues that require investigation and resolution. In the following, we will examine the main issues and challenges raised in previous research in this field.

Optimizing disease diagnosis accuracy in smart healthcare was done in a study by utilizing evolutionary algorithms and neural networks. Furthermore, in this research, it is mentioned that intelligent disease diagnosis in this system includes cloud services, normalization, noise removal, and classification. In the designed model of this research, it is assumed that information is collected using the Internet of Things (IoT) within the patient's body. Then preprocessing operations are performed to remove noise and normalize the data. Finally, evolutionary algorithms and machine learning are used for classification and disease diagnosis. The proposed model in this research utilizes two evolutionary algorithms, PSO, and a Multilayer Perceptron neural network (MLP). After data normalization, the most important feature for disease diagnosis is determined using the PSO algorithm. As a result, disease classification is performed using PSO and MLP neural network algorithms, achieving an accuracy of 93.3% in the proposed model [11].

A recent paper delves into the integration of Internet of Things (IoT) devices in medical practices. It highlights how these sensors monitor patients and transmit crucial data to healthcare providers and patients alike, revolutionizing medical care. Furthermore, medical data is recorded by sensors and transferred to cloud servers, with this transfer being done using various radio spectra, which increases based on medical applications of these spectra [12].

Utilizing GIS-based optimization algorithms, a study focuses on enhancing the deployment of IoT networks for environmental and healthcare purposes. The research emphasizes minimizing energy usage in Wireless Sensor Networks (WSNs) while maximizing their reach. The researchers, while mentioning minimizing energy consumption in these sensors and maximizing their coverage, have employed the Minimum Spanning Tree (MST) algorithm, which is a routing protocol. Finally, they have utilized two algorithms, Bee Algorithm (BA) and Particle Swarm Optimization (PSO), to evaluate the deployment of GIS-based WSNs. The criteria for evaluating these algorithms include convergence rate, repeatability, and modeling complexity. The research results indicate that PSO has less complexity compared to BA, resulting in better performance in this study [13].

Addressing the optimization of COVID-19 vaccine distribution, researchers employ location-allocation models to strategically place vaccine centers, aiming to reduce travel time and distance for recipients. The general approach in the model used in the mentioned research is to minimize transportation time and travel distance. Researchers have employed the Maximal Covering Location Problem (MCLP) model in analyzing COVID-19 centers. This model has been used in two ways in this study, including: 1- Maximum coverage without restrictions on the number of facilities and their capacity, 2- Maximum coverage while maintaining restrictions [14].

Investigating the dynamic allocation of Emergency Medical Services (EMS), a study aims to balance cost efficiency and coverage effectiveness within a set timeframe. Real-time IoT data aids in optimizing EMS location decisions. The objective of this research is to minimize costs and maximize the coverage of individuals under EMS within a predefined timeframe. To address this problem, they have utilized a Variable Neighborhood Search Adaptive Strategy for Multiobjective Variable Neighborhood Sterategy Adaptive Search (M-VaNSAS). Additionally, researchers have mentioned that the travel time of EMS depends on two factors, including the distance from the EMS location to the patient's location and the traffic condition, for which real-time traffic status tracking from the Internet of Things (IoT) has been used. Finally, these data have been employed with M-VaNSAS to compute the optimal EMS location [15].

Proposing an integrated model for post-disaster shelter distribution, researchers combine various algorithms to efficiently allocate resources. The model accounts for route reliability and vehicle breakdown probabilities, ensuring effective relief efforts. The proposed model clusters affected areas using Adaptive Neuro-Fuzzy Inference System (ANFIS) and then prioritizes cluster points based on the impact of factors on route reliability using a permanent priority matrix. The objectives considered for this model include minimizing maximum service time, maximizing route reliability, and minimizing fulfilled demand. Additionally, the probability of vehicle breakdown during ground rescue operations is also taken into account. To find an efficient solution, the Non-dominated Sorting Genetic Algorithm (NSGA-II) and the Multi-Objective Firefly Algorithm (MOFA) are employed, with MOFA yielding higher accuracy and lower computational time [16].

In a comprehensive analysis of Primary Health Care Centers (PHCCs) in Syria's Idlib Governorate, researchers employ a multi-stage methodology incorporating GIS and decision-making techniques to optimize healthcare access. The methodology in this research consists of four stages. Firstly, needs assessment, questionnaire design, etc., are conducted to evaluate the requirements. The second stage involves identifying the objectives and constraints of the model, with each objective weighted using the Analytic Hierarchy Process (AHP) multi-criteria decision-making technique. The third stage involves building a road network dataset using Geographic Information System (GIS). The fourth and final stage aims to construct a mixed-integer mathematical model and solve it to identify PHCCs and allocate individuals to these centers [17].

Exploring the application of wearable sensors in cardiovascular health, a study reviews the materials, mechanisms, and recent advancements in sensor technology for monitoring vital signs. Specifically, the study highlights the practical materials, configurations, mechanisms, and recent advancements of these sensors for monitoring heart rate, blood pressure, blood oxygen saturation, and blood glucose levels [18].

Investigating sleep and movement patterns for health assessment, researchers deploy Smart Wearable Sensors (SWS) capable of detecting various activities and potentially enabling fall detection or sleep quality assessment. For this purpose, they utilized Smart Wearable Sensors (SWS) based on a dual-channel triboelectric nanogenerator. These sensors can be worn on the wrist, ankle, shoe, or other parts of the body. Furthermore, the study suggests that these sensors can continuously detect motion states such as walking, running, jogging, and jumping. This capability enables the development of a fall alert system or the assessment of sleep quality for family members or healthcare providers [19].

Investigating pain and stress detection through wearable sensors, researchers analyze physiological and behavioral signals to categorize and detect pain and stress levels, highlighting the potential of such technology in healthcare. In this study, various physiological signals such as heart activity, brain activity, respiration, pulse, skin temperature, and behavioral signals were used to analyze different individuals. Initially, the study introduces and categorizes pain and stress. Then, it discusses common devices and wearable sensors for pain and stress detection [20].

Data and methods

Wearable sensors

Wearable sensors are recognized as advanced tools, with their most significant feature being the ability to directly interact with the patient's body. Consequently, due to their direct placement on the body, they can provide more accurate information about physiological status over the long term to healthcare professionals, which can lead to better analysis of the individual's health status.

With advancements in technology, wearable sensors have become smaller, more accurate, and more capable. These sensors exhibit a wide variety across different sectors. This diversity and ongoing development have led to the use of these sensors in healthcare services and personal care. This diversity allows individuals to select the type of sensors based on their specific needs and ensures that the required information is accurately collected. Furthermore, these sensors enable healthcare professionals to provide better prevention and treatment approaches based on the gathered information.

The data related to patients in this study has been obtained from 4 regions in the city of Kermanshah. These patients have been examined in groups of 10 in each region. This data includes the physiological status of the patients, such as heart rate, oxygen levels, and blood pressure. Information about the patients has been obtained through Apple watches, which are a type of wearable sensors. In addition to recording physiological data of the patients, they also provide us with their geographical locations.

The information is transferred from the Apple Watches by being installed on the patients' wrists and measuring and transmitting physiological data such as heart rate, oxygen levels, and blood pressure. These data are then transmitted via Bluetooth to a smartphone. After the data is transferred via Bluetooth, it is transmitted to healthcare centers via Wi-Fi, allowing physicians to remotely monitor patients at all times.

Figure 1: Types of wearable sensors that can be attached to different parts of the body [8].

Location-allocation model

Location-allocation models are a type of optimization model designed to allocate facilities to target communities. The main components of these models include facilities, locations, and customers. One of the most common models is the P-Median model, which aims to find a set of service locations that minimize the total distance or time traveled to visit those service points.

Therefore, this study aimed to minimize the travel distance for patients equipped with wearable sensors using the P-Median model. This approach identifies P locations that minimize the average distance between a demand node and a facility location.

Table 1: Information related to hospitals.

Hospitals	Districts
Imam Ali	1
Taleghani	1
520 Artesh	4
Imam Sajjad	4
Imam Reza	7
Imam Hossein	7

The names and regions of the facilities in Kermanshah city they are located in are provided in (Table 1). Python programming language was used for implementing the model, coded in Jupyter notebook environment. Finally, the Folium library was utilized for visualizing the results.

The specifications of healthcare facilities indicated in (Table 1).

The objective model for this study is formulated as follows:

$$\text{Min} \sum_{i}^{I} \sum_{j}^{J} h_i D_{ij} X_{ij} \quad (1)$$

Subject to

$$\sum X_{ij} = 1 \quad (2)$$

$$\sum Y_j = p \quad (3)$$

$$X_{ij} \text{£} Y_J \quad (4)$$

$$X_{ij} \hat{\text{I}} \{0.1\} \quad (5)$$

$$Y_j \hat{\text{I}} \{0.1\} \quad (6)$$

Indices

I: Demand i (i = 1, 2, 3, …, i)

J: Facility j (j = 1, 2, 3, …, j)

Parameters

h_i: The demand volume at point i

D_{ij}: The distance between demand point i and candidate facility j

P: The number of facilities that need to be constructed

Decision Variables

X_{ij}: If the demand point is covered by constructed facilities, it is 1; otherwise, it is 0

Y_j: If a facility is constructed at demand node, it is 1; otherwise, it is 0

In the above relationships, the objective is to minimize the distance between the patient and the desired facilities. Constraint (2) states that each patient must be served by exactly one hospital. Constraint (3) indicates that there is a problem and thus proves the establishment of a center. Constraint (4) means that open centers can serve demand points. Constraints (5) and (6) are binary variables.

Results

After equipping the patients with wearable sensors for monitoring their physiological status and defining the P-Median model, the results of the location-allocation model in this section are presented. As previously mentioned, the objective of this model is to minimize the distance to healthcare centers for patients, which, by adhering to this objective, can provide better services to patients with more critical conditions. Additionally, the Euclidean distance between demand nodes and healthcare centers has been utilized.

The objective model implementation has been conducted in 4 zones in Kermanshah city. Access for 10 patients has been evaluated in each zone. Additionally, along with the implementation results, the physiological data of patients obtained through wearable sensors has been provided in (Table 2) to

Table 2: Physiological information pertaining to patients in Zone 1.

Patient	Heart rate	Oxygen level	Blood pressure
1	124	99	130/85
2	136	96	140/90
3	143	90	160/100
4	145	95	170/110
5	149	93	180/120
6	140	88	80/50
7	137	89	85/55
8	133	90	90/60
9	133	91	120/80
10	120	92	130/85

Figure 2: The result of model implementation in Zone 1 for Taleghani and Imam Ali hospitals.

Table 3: Physiological information pertaining to patients in Zone 4.

Patient	Heart rate	Oxygen level	Blood pressure
1	133	88	170/110
2	145	92	90/60
3	143	91	140/90
4	120	93	130/85
5	137	99	180/120
6	149	95	80/50
7	133	90	130/85
8	136	96	130/85
9	124	89	120/80
10	140	90	85/55

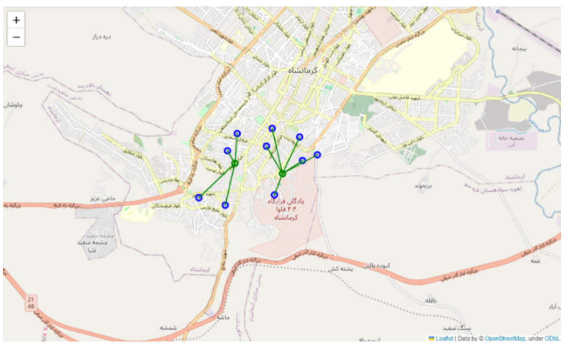

Figure 3: The result of model implementation in Zone 4 for 520 Artesh and Imam Sajjad hospitals.

Table 4: Physiological information pertaining to patients in Zone 4.

Patient	Heart rate	Oxygen level	Blood pressure
1	124	90	170/110
2	133	91	90/60
3	145	92	130/85
4	136	99	85/55
5	137	95	160/100
6	149	93	120/80
7	120	89	180/120
8	133	90	80/50
9	143	96	140/90
10	140	88	130/85

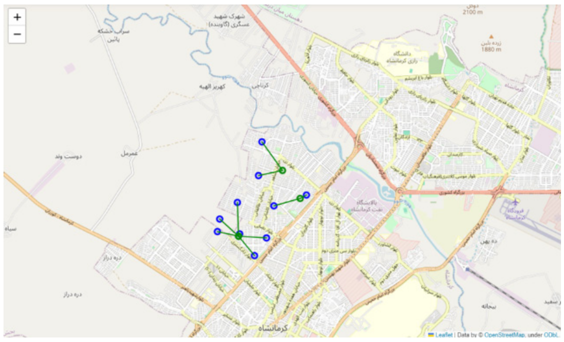

Figure 4: The result of model implementation in Zone 6.

Table 5: Physiological information pertaining to patients in Zone 7.

Patient	Heart rate	Oxygen level	Blood pressure
1	137	95	180/120
2	136	89	85/55
3	133	96	90/60
4	145	92	170/110
5	124	91	160/100
6	143	90	140/90
7	120	90	120/80
8	140	99	130/85
9	149	93	130/85
10	133	88	80/50

Figure 5: The result of model implementation in Zone 7 for Imam Hossein and Imam Reza hospitals.

make these symptoms understandable for the readers to comprehend the issue.

(Figures 2 to 5) illustrate the implementation of the target model in various regions. In each region, the model has been applied to two hospitals that were accessible to the patients. Alongside the implementations, the physiological information of the patients is also provided. The blue points indicate the locations of the patients, while the green points indicate the locations of the hospitals.

For allocating these centers to patients, several factors have been considered, such as the proximity of patients to healthcare centers, the limited capacity of the hospitals, and differences in medical specialties. In Zone 6, there were no hospitals available. Therefore, the locations of general and specialized clinics were identified, and allocation was carried out based on the same criteria used for patients in other zones.

In general, the allocation analysis is conducted based on two crucial criteria: minimizing the distance between patients and hospitals, and considering the medical needs of each patient. The model is designed in a way that minimizes the distance between patients' residence and healthcare centers. Additionally, medical needs are also considered as a vital criterion in patient allocation. By analyzing the patient's condition in real-time using wearable sensors, patients are allocated to centers capable of meeting their medical needs. This criterion helps us enhance patient care and improve the quality of healthcare services.

Table 6: Comparison of patient access time before and after model implementation and equipping patients with wearable sensors.

Patients' ID	Going to the hospital	Returning to the hospital	The time taken to go to and return from the desired hospital in minutes.	The improved time in minutes.
1	Hazrat abolfazl	Imam Ali	12	7
2	Bisetoon	Taleghani	19	5
3	Hakim	Taleghani	22	5
4	Imam Sajjad	520 Army	22	12
5	520 Army	Imam Sajjad	23	4
6	Imam Hossein	Imam Reza	20	12

To assess the model and its impact on the conditions, the results have been numerically presented in (Table 6).

Conclusion

Given the available statistics, it is predicted that the population of cities, and consequently, aging and sick communities will increase. Therefore, developing innovative solutions to respond to these communities in emergency situations is considered important. Many studies indicate that the allocation of healthcare facilities to patients has not been well-planned. Additionally, obstacles such as geographical distance, limited resources, and patient preferences further challenge this issue. In this study, the P-Median model was used to allocate healthcare facilities to patients. This model aimed to minimize the patients' access time to these facilities. To find an optimal solution, wearable sensors were also used in patients. These sensors have capabilities such as transmitting patients' physiological information and geographical location. The obtained results show that the average access time of patients to healthcare facilities before implementing the model was 19.67 minutes, which reduced to 7.5 minutes after implementing the model and equipping patients with wearable sensors. Therefore, this method provides a new solution to find an optimal answer to meet patients' needs. By using this approach, the government will be able to plan appropriately to save patients' lives.

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