

PRESENTED A FRAMEWORK OF COMPUTATIONAL MODELING TO IDENTIFY THE SCHEDULING PROBLEMS IN THE HEALTHCARE SECTOR

Hayder Raaid Talib (1)

University of Sumer College of Administration & Economics

h.raid@uos.edu.iq

Mohammed faris abed Ahmad (2)

Diyala Universit

College of education Department of mathematics

.fcb.prince1994@gmail.com

Ali Hamdullah Ahmed (3)

Directorate-General for Education of Qadisiyah/

Department of Educational planning²⁾

Alihamdullah8220@gmail.com

Abstract

This study summarizes the most recent research on health care scheduling issues, including patient scheduling admissions challenge scheduling of nurses challenge, operating scheduling of rooms challenge, surgical scheduling challenge, and other health care scheduling issues. I give. This study provides an overview of healthcare planning, emphasizing research on planning problems in the recent healthcare sector. The development of applied research in health care design has a vital role in cost optimization and flow of patients, in providing rapid provided treatment and optimum resource utilization and available in healthcare facilities. In recent decades, healthcare scheduling methods have improved significantly. They have been increasingly used, using meta-methods to automate determining hospitals' optimal resource management strategy. However, the reported results decompose because they solve each specific challenge independently, as many versions of the challenge definition and different datasets are available for each of these issues. Therefore, this study incorporates the existing results by conducting an overview and analyzing 190 significant challenges of the hospital sector in Iran in 2021 based on four critical elements for Defining and resolving optimization problems, formulation, data set. And methods. This study focuses on the most recent healthcare planning issues on patient admission, nursing, and surgery planning issues. Found. In addition, this





review is intended to assist researchers. Identify some of the latest developments and understand new trends in the future.

1-Introduction

In health, it is productive management in which all organizational goals can be achieved by planning, directing, controlling, and cost-effectively producing health services while maintaining the desired quality. The importance of optimal use of limited resources, productivity, and careful review of the quality of services provided to ensure, support, and promote patients' health in the hospital is the most critical mission of health service providers (Timucin, 2018).

Due to increasing demand and limited resources in the health sector, It is necessary to pay attention to productivity because of combining factors and production resources and providing the required services (Clavel et al., 2018).

Due to the limitations of medical centers and hospitals in the country, it is essential to pay attention to the factors of hospital beds. Occupying a bed and making the patient stay in the hospital for a long and unnecessary time is a waste of health resources and causes equipment depreciation. On the other hand, there will be no empty beds for other patients in need of hospitalization Varmazyar et al., 2020).

Performance in the hospital is generally discussed (Akbarzadeh et al., 2020). In his regard, Kroer (2018) defines productivity as the feeling of effectiveness, efficiency, productivity, and capability of an individual in the organization, in other words, the optimal use of labor, power, talent, and skills of human resources. A study by Khaniyev et al. (2020) entitled Productivity Indicators: A tool for evaluating the health information management system to assess productivity indicators in medical centers. Finally, the researcher states that in more than 50% of the capacity of beds, the hospital is empty and overused and out of reach of the real need.

Lin (2019), in his research, has pointed out that staffing has the highest dimension in the set of factors affecting productivity. It is done by increasing patient admission per hospital bed. Focusing on quality improvement and safety standards leads to improved hospital performance indicators.

Appropriate hospital management entails allocating and efficiently utilizing hospital resources. Making decisions and planning for a hospital bed is helpful for hospital management. In this decision, managers need objective indicators and



methods to manage resources and exploit the bed in light of limited financial resources (Akbarzadeh et al., 2020). Studies have identified occupancy-bed rates as the most essential and practical indicators for measuring hospital efficiency, which shows the functional capacity of the hospital. Due to these restrictions and unequal distribution of hospital beds and health facilities in Iran and to prevent the loss of specialized human resources and extensive coverage of health services, all efforts should be spent in planning to use (Ramli et al., 2019). This study was conducted to determine the bed occupancy rate index factors based on the multi-criteria decision approach in the selected public hospital complex in Tehran / Iran

*. Control charts for variables

Variable control charts are extensively used because they allow for more effective control and provide more information regarding process performance. These graphs are chosen because they give the user an estimate of the central tendency and distribution of the investigated situation [8]. Individual measurements control chart (\bar{x}), means control chart (\bar{x}), ranges control chart (R), and standard deviation control chart are the most widely utilised (s).

$$UCL = \bar{X} + A_2 * \bar{R}$$

$$LCL = \bar{X} - A_2 * \bar{R}$$

The capability index ppk , which is based on the selection standard deviation, describes the preliminary process capability. This can be calculated through the use of a formula.

where LSL is the lower tolerance limit

USL is the upper tolerance limit

μ is the average value of the monitored quality feature

the mean proportion defective (\bar{p})

$$\bar{p} = \frac{\text{Total Number of Defective}}{\text{Total Number Inspected}}$$

$$\delta = \sqrt{\frac{\bar{p}(1-\bar{p})}{n}}$$

Where n = sample size

Control limits are

$$UCL = \bar{P} + Z \sqrt{\frac{\bar{P}(1-\bar{P})}{N}}$$

$$LCL = \bar{P} - Z \sqrt{\frac{\bar{P}(1-\bar{P})}{N}}$$



Typically, the Z value is equal to three (as was the case with the X and R charts), because variations within three standard deviations are considered natural. However, the value of Z is determined by the environment in which the chart is used, as well as managerial judgment..

2-PASP formulation

First, a Schedule of Patient Admissions (1) called [Schedule Challenge (Fit of Type of Illness to Maximum Treatment Period and Occupancy Under) Main] is introduced by Zhu (2020), which assumes the date of admission and discharge from hospital after From the end of the treatment period according to the approximate schedule, the length of the treatment period for each patient is proportional to the type of disease. Furthermore, each patient must spend some time in at least one bed. The main feature of the scheduling challenge (proportionality of the disease type with the maximum treatment duration and occupancy) can be explained in the following cases:

1. Approximate: Components that show the minimum and maximum length of time for each patient in the hospital
 2. Patients need to be hospitalized Patients who need to be hospitalized and are in a bed and a room.
 3. Patient: A person who needs health care in the hospital should be assigned a room with a bed specific date requiring hospitalization as well as discharge from the hospital after the treatment period.
 - 4- Room: Each section has its room, and each room has its capacity depending on the number of beds in it, which can be a single bed/double/cabin.
- Specialty: Each hospital ward is designated employing a single or subsequent treatment... In addition, separate rooms belong to specific control and have their level of treatment, which is from 1 to 3 components depending on the patient.
- 6- Transfer: Transfer of the patient requires hospitalization during your stay, from one room to the next.

The issue that plagued the PAAP its original form is the observance of certain restrictions, which divide them into hard vs. soft limits depending on the situation effects on patients. Scheduling challenge constraints (fit of disease type with maximum treatment duration and occupancy) Patient admission scheduling schedule (main PASP) is as follows: HC1: Room availability (R_j).



HC2: Introduction The date of discharge from the hospital after completing the ADA, DDi treatment period and the minimum and maximum length of time for the selected patient should be constant and unchanged.

HC3: The minimum and maximum length of time must be continuous.

HC4: Two patients (Pi1, Pi2) is not possible placed in same bed for a minimum or maximum time.

HC5: A gender scheduling program should be done.

HC6: The patient should be placed in an acceptable ward for his age.

HC7: Room is required functions must in transit room, be available.

HC8: A particular quarantine program for patients who require isolation, depending on their medical characteristics.

In addition, the mild limitations of this scheduling challenge (proportion of disease type to maximum treatment lag and under-occupation) can be summarized as follows:

SC1: The term "room preference" refers to a patient's preference for a room-like configuration (single, double, ward, etc.).

SC2: Preferential room features, reflecting medical apparatus in the ward and personnel, such as nurses.

SC3: Degree of specialization In those instances, patients prefer to receive medical care in the wards with the a high level of specialization.

SC4: some patients should be evaluated be placed in a room equipped with specialized equipment. These restrictions apply to HC7.

SC5: Transfers, unscheduled program transfers should be minimized.

All minor restrictions should be observed as much as possible, and sometimes it is impossible to comply with all petty regulations. Otherwise, the solution may be diluted. The weight of each of these constraints is shown in Table 1.

Table 1- Weight of light constraints (Kroer et al., 2018)

Constraints	Corresponding weight
Mandatory room properties	4.4
Patient age should obey the maximum or minimum age of the department	11
Preferred room properties	2.2
Preferred room category	0.9
Department specialism	1.1
Transfer rate	9



The Patient is a Reception Scheduling Program's (PASP) objective is to minimize minor constraints while meeting patient preferences and overcome complex scheduling challenges (matching the type of disease with the maximum treatment delay and occupancy) to find feasible solutions.

Age policy: Some sections have an age limit. For example, The pediatric ward accepts from 0 to 12 patients. PASU has hard and soft restrictions and must be observed. In this specialty (DS), room properties (RF) are hard for missing parcels or need for relationship properties but are soft for partial capacity and relationship properties. Strict restrictions include

HC1: Room capacity (RC) makes it impossible to accommodate two patients in one bed at a time.

HC2 Patients should be evaluated according to their patient age (PA). be placed in an age-appropriate ward.

Mild restrictions include:

SC1: Gender Room (RG), Gender Program Room Must Be Observed.

SC2: Preference for a Room (RP), the patient prefers to be assigned a high-priority room.

SC3: Transfer (Tr), the undesirable transfer of a bed from one room to another during his stay.

Delay (De): Delay inpatient admission

Risk of overcrowding (OR): The number of patients assigned to each room and the duration of frequent patient visits and room capacity was calculated.

All mild restrictions are related to weight-based on their importance to patients.

: The most significant mass is related to SC3, transferable patients (100) to the target second-highest weighted function related to SC1 related to the unique gender program for patients, its weight (50) is added to the cost of the rest of the specialty. . They are group, room features have weight (20) and room preference (20). Finally, delay (De) (2) and congestion risk (1).

PASU Phrasing in Mathematics

The PASU mathematical formula is described and formulated by (Zhu et al., 2019), and to integrate this scheduling challenge (fit the type of disease with the maximum treatment and occupancy rate) of the large hospital ward in Iran in 2021, we introduce the mathematical formula here.

A: A group of all patients.

PF: A batch of material. PM is a group of male patients. Where $PF \cup PM = P$.



PH: A group of patients needs to be hospitalized, and RP is the room where the patient has reached pH.

D: A bunch of days.

R: The category of rooms and cr is the room capacity $r \in R$.

RSG: Room suite with SG policy. In addition, we have

Dp: A group of days when a patient has $p \in P$ in the hospital.

Pd is a group of patients present on day d (i.e., a group of patients p such as $d \in Dp$).

The main components of decision making are:

If patient p is assigned to room r, $x_{p,r} = 1$, and otherwise 0. The limitations of the x component are:

$$\sum_{r \in R} x_{p,r} = 1, \forall p \in P \quad (1)$$

$$\sum_{p \in P} d_{p,r} x_{p,r} \leq cr, \forall d \in D, r \in R \quad (2)$$

$$x_{p,r} \leq a_{p,r}, \forall p \in P, r \in R \quad (3)$$

The equations illustrate how does the PASU's constraints are established.; Equation (1) details how a patient is assigned to a particular room, while Equation (2) ensures that The room's capacity is limited to RC. Finally, Equation (3) details the Impossible Tasks associated with the Patient's Room Inadequacy (PRS). The variable x denotes a search area for the challenge. Additional variables are used to denote the elements of the objective function F. The variables associated with Preference Room Management (RP) appear in the following mathematics:

$f_{r,d}$, $m_{r,d}$: 1 If there is at least one woman in room r on day d, otherwise 0.

$b_{r,d}$: 1 If there are male and female patients in room r on day d, 0 different. These new variables are related to x and each other by the following constraints:

$$f_{r,d} \geq x_{p,r}, \forall p \in P_f, r \in R, d \in D_p \quad (4)$$

$$m_{r,d} \geq x_{p,r}, \forall p \in P_m, r \in R, d \in D_p \quad (5)$$

$$b_{r,d} \geq m_{r,d} + f_{r,d} - 1, \forall r \in R, d \in D \quad (6)$$

Also, equations (4) and (5), which correlate the auxiliary variables f and m with x, state that when there is a patient (female) in the room, then all the variables f (respectively male) for the days $d \in P D_p$ must be set to 1, while constraints (d) correlate m and f with b, so if m and f = 1, b must be one. For control (OR), its over-risk components population modeling are as follows:

Year, d: 1 If room r is very crowded on day d; if not 0. As a result ;in order to define the limitations that relate the variables y to x. $p + d$: is a set of patients who can be treated on day d, the same patients on day d, plus patients presented on day d-



1 with an excessive risk of staying. $|Z|$: Cardiologically a set Z. and z^- : complement to the variable z. The constraints on y to x are:

$$\sum_{p \in P} dx_p, r \geq (|P + d| - cr). (1 - yr, d) \forall d \in D, r \in R \quad (7)$$

It is worth noting that when $yr, d = 1$, the variables XP, r can be any value. Conversely, when yr is $d = 0$, at least $(|P + d| - cr)$ included must get a value of 0. In addition, the objective function can be calculated as follows:

$$F = FPRC + FRG + FOR \quad (8)$$

The components of the PRC, RG, and OR objective function are defined as follows:

$$FPRC = \sum_{p \in P, r \in R} CP, r.XP, r. |Dp| \quad (9)$$

$$FRG = \sum_{r \in R, d \in D} WRG. br, d \quad (10)$$

$$FOR = \sum_{r \in R, d \in D} WOR. yr, d \quad (11)$$

Equation (9) calculates the cost of identifying a patient's room, while Equation (10) calculates the number of rooms occupied by male and female patients. The last Equation (11) examines the risk of overpopulation. The PASU challenge is formulated as Correct Linear Programming (ILP). In addition, it can be applied to any general-purpose IP programming solution. The challenge is generally modeled as a three-dimensional array of decision variables $z, z_p, r, d = 0$ if the patient is in room r on day d . It is worth noting that 1% is consecutive in the z matrix and equal to patients' length of stay.

Admission program with operating room boundaries, flexible horizons, and patient delays

This version of the challenge of planning patient care with surgery planning (Sigurpalsson, 2019) is presented in two stages, the stage of patient admission restrictions and the stage of restrictions on surgery.

Patient Admission Schedule with Operating Room Limits, Flexible Horizons, and Patient Delay Formula (Version 3) in Mathematics

The mathematical formula for this challenge is version number 2 (PASU). However, the cost function of this challenge can be calculated according

Cost component	Accounting	Value
Missing room equipment (PRC1)	per day, per patient	20
Unsatisfied room preference (PRC2)	per day, per patient	10
Partial specialty level (PRC3)	per day, per patient	20
Unsatisfied gender policy (PRC4)	per day, per patient	10



Cost component	Accounting	Value
Transfer (Tr)	per patient	100
Delay (De)	per day, per patient, per priority	5
Overcrowd Risk (Ri)	per patient	1
Idle Operating Room Slots (IOS)	per minute	10
Idle Room Capacity (IR)	per day, per bed	20
Overtime (ORO and ORTO)	per minute	3

3-PASP data set version

The original dataset, which belongs to the first version of problemFootnote1, was first reported (Hammouri et al., 2020). The data set contains 13 relationships that are as illustrated in Table 3. Items 1 to 6 have a 14-day duration. While cases 7 to 12 last between 14 and 91 days. All patients in these cases require only one type of treatment, but 13 patients require multiple types of treatment during their stay. This demonstrates that Example 13 is more difficult to understand than the others. Additionally, this data set, cited in (Zhu et al., 2019), describes the characteristics of the original set of data, which included all patients present, including those with arrival and departure dates of the same day.

More information about this source text For more translation information, the source text is required

Table 2-Data set 1

Instances	Bed	Room	Patients	Planning horizons
1	286	98	693	14
2	465	151	778	14
3	395	131	757	14
4	471	155	782	14
5	325	102	631	14
6	313	104	726	14
7	472	162	770	14



Instances	Bed	Room	Patients	Planning horizons
8	441	148	895	21
9	310	105	1400	28
10	308	104	1575	56
11	318	107	2514	91
12	310	105	2750	84
13 multi specialism	368	125	907	28

The second is type set of data was created by (Bastos et al., 2019); the author developed and designed a data generator capable of generating actual data for many different-sized data sets. The generator accepts parameters such as the number of patients, the number of wards, the number of days, the number of rooms, and the number of features. Random data due to predefined versions related to various features such as length of stay, the room's capacity, the number of specialties, and more. Meanwhile, the gener for one-day eater isnt built to last vents to provide the opportunity to solve a set. The data set includes nine families in every 50 samples. Data collection units are three divisions different in terms of dimensions patient number and programming horizon. Maintaining this is a data set, doubling the number of days, doubles the patient popultion evenly to keep the average stay balanced. Tables 5 and 6 list data set characteristics.

Table 3- Database 2 (Diamant et al, 2015)

Family	Depts	Rooms	Features	Patients	Specialism	Days
Small Short	4	8	4	50	3	14
Small Mid	4	8	4	100	3	28
Small Long	4	8	4	200	3	56
Med Short	6	40	5	250	10	14
Med Mid	6	40	5	500	10	28
Med Long	6	40	5	1000	10	56
Large Short	8	160	6	1000	15	14
Large Mid	8	160	6	2000	15	28
Large Long	8	160	6	4000	15	56

Table 4- Data set 3

Family	Rooms	Depts	OR	Specs	Treats	Patients	Days
Short1	25	2	2	9	15	391-439	14
Short2	50	4	4	18	25	574-644	14
Short3	75	6	5	23	35	821-925	14
Long1	25	2	2	9	15	693-762	28
Long2	50	4	4	18	25	1089-1169	28
Long3	75	6	5	23	35	1488-602	28

6-Nurses' Planning Challenge

The challenge of nursing planning has its roots in the healthcare mechanism, which is considered resource planning in healthcare and requires the planning of staff (Bolaji, 2018) or hospital staff, balancing workload and preferences. The challenge of nursing planning requires the rigorous challenge of NP optimization, which is determined by assigning a team of different experienced nurses in various shifts, such as Table 8, on a predetermined schedule (Doush, 2018). To achieve the possible timetable, strict restrictions must be taken, while mild limits are allowed, but will be punished. Nurses' planning priorities should be maximized, and overall costs should be minimized.

Table 5- Nursing Planning Type Programming(Doush, 2018).

Shift type	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Morning	3	3	3	3	3	3	3
Afternoon	3	3	3	3	3	3	3
Night	2	2	2	2	2	2	2

6- Research method

Block diagram of the proposed method

In this research, the researcher intends to explain the participatory improvement algorithm in the field of health programming identification, taking into account the data examined in this research, a basic framework for assessing the level of involvement of caregivers, providing a database of health websites in the field of identifying programming problems in the field of healthcare.



In the present study, using the pre-filtration technique, the situations related to the areas of design problems in health are grouped. Next, using a cosine similarity criterion and the participatory approach to improving the hospital ward in Iran, similar to the hospital ward in Iran, the goal will be determined. The interests of the selected hospital ward in Iran are likely to be introduced in the control of the hospital in the target Iran. In other words, to reduce the complexity in the current study, we use the grouping approach, and within the clusters, using a similarity criterion, we will increase the accuracy. The proposed similarity criterion is asymmetric and uses a combination of participatory and demographic filtering approaches. It is done. Leveraging the demographic approach leads to resolving the cold start.

In this research, the researcher, taking into account the database of this database in the field of programming problems in the field of healthcare, intends to evaluate the different groups of people listed on this site taking into account the elements of participatory improvement. They have used his services.

6-1-Research stages

- 1- Data and data are collected from the website of the Ministry of Health of Iran.
- 2- Grouping 150 hospital wards in Iran using K-algorithm and applying cosine similarity criteria and work implementation using MATLAB software.
3. Grouping using the K-means algorithm should be based on equipment and systems challenges, human resources challenges, and activity-related challenges. We come first and divide all the challenges related to equipment and systems into the biggest challenges related to equipment and systems among the agents of the healthcare department, which is the number of challenges related to the equipment and systems of each hospital ward. Received in Iran.

6-2-Indicators used in research

Network characteristics in participatory refinement

3-10 Participatory Cluster	Number of large clusters
6-10 Participatory Cluster	Number of small clusters
2000	Number of resources and repetitions (factors in the health care sector)
0-800	Number of repetitions

Traffic management of people with improved health care providers based on gender characteristics, challenges related to equipment and systems, network

training, and fitness profile characteristics. And the age challenges of patients appropriate for the hospital environment, rooms, and wards are the precursors to the ability to create participatory network improvement structures in the participatory refining network.

In this network, the number of features studied includes six categories of specific feature structures. Identify healthcare planning problems with equipment and systems challenges, human resources challenges, and age-appropriate challenges. The rooms and wards were networked with the hospital area.

Insert clusters at cosine levels for final input to the analysis

Insert groups at cosine levels for last information to the analysis

Diakheírisi kykloforías atómon pou diathétoun veltioménous foreís ygeionomikís períthalpsis me vási ta charaktiristiká tou fýlou, tis proklíseis pou schetízontai me ton exoplismó kai ta systímata ka tin taikíi ka tin kapaíi. kai oi proklíseis tis ilikías ton asthenón pou éinai katálliles gia to nosokomeiakó perivállon, ta domátia kai tous thalámous éinai oi pródromoi tis dynatótitas dimiourgías domón symmetochikoú diktýv ve dll symt

Se aftó to díktyo, o arithmós ton charaktiristik pn pou meletíthikan se aftí ti meléti perilamvánei 6 katigoríes synkekriménon charaktiristikón domón fysikís katástasis. Prosdiorismis provlimáton programmatismo ston toméa tis ygeionomikís perithalpsis me proklíseis pou schetízontai me exoplismó ka systímata, proklíseis pou schetízontai me to anthrópino dynamikó kai proklíseis catáll tin. Ta domátia kai oi thálamoi ítan diktyoména me ton chóro tou nosokomeíou.

Eisagogí systádon se epípeda synimitónou gia telikí éisodo stin análysi

Eisagogí systádon se epípeda synimitónou gia telikí éisodo stin análysi

Show more

Percentage of cluster fit in participatory filtering	Cosine Coefficients	Clusters
%78	4.55	Nursing planning challenges
%65	7.11	Challenges related to operating room planning
%67	5.25	Challenge the quality of activities for patients
%63	3.23	The patient age challenge is tailored to the hospital space, rooms and wards
%55	6.75	The challenge of proportional distribution of patients in communities and rooms
%79	7.23	Patient transfer challenge



Investigation of Relative Distribution and Selected Features to Determine the Relative Distribution of Gring Recommendation System Features Recommending system based on means and dbscan clustering methods:

The significance level	Cluster statistics in DBSCAN	Cluster statistics in KMEANS	F statistic	Recall criteria	Precision criteria	A portion of groups serving together	Percentage of cluster fit in participatory filtering	Clusters
0.000	37.64	80.75	51.64	1.15	0.029	%100	%78	Nursing planning challenges
0.001	33.96	6.74	66.56	1.5	0.065	%99	%65	Challenges related to operating room planning
0.000	39.4	58.0	27.50	1.13	0.045	%99	%67	Challenge the quality of activities for patients
0.000	24.7	07.69	57.52	0.296	0.036	%95	%63	The patient age challenge is tailored to the hospital space, rooms and wards
0.000	19.6	68.23	88.38	0.81	0.078	%95	%55	The challenge of proportional distribution of patients in wards and rooms
0.003	39.44	53.9	93.34	1.41	0.63	%99	%79	Patient transfer challenge

Based on the above table, we examined six features of participatory refinement network structures among clusters in the participatory refinement network, including the type of features of the recommender system.

For example, we showed that in the cluster of manpower challenges, the proportion of groups in participatory refinement was high at 78%. This indicates that in the group of challenges related to staffing, the participatory elegance of health care sector factors compared to the type of exploitation of the field of identifying planning problems in the health care sector has been high in the database of the Ministry of Health. We also showed that the percentage of clusters



fit with each other, and precisely 100% of the health care sector agents have been introduced with staffing challenges and entered the relevant cluster or cluster. In other words, the classification of health care sector factors in the group of challenges related to accurate human resources has been done.

Examination of the prestige purification criterion shows that at the level of 0.029, there was a relationship between the interests of health care agents about the nurses' shift schedule and the type of challenges related to their human resources. In other words, a high percentage of female or male health care sector agents correlate to the kind of attitude resulting from the challenges related to their manpower and identifying planning problems in the health care sector of this database.

Examination of the recalculation criterion shows that at level 1.15, there was a relationship between the interests of health care agents in the field of nurses' shift schedule and the type of challenges related to their human resources.

Cluster statistics in the K-means clustering criterion show that at the level of 80.75, there is a correlation between the interests of health care agents and their level of participatory refinement in nurses' shift scheduling.

Cluster statistics in the DBSCAN clustering criterion show that at level 37.64, there is a correlation between the interests of health care agents and their level of participatory refinement in nurses' shift scheduling.

Finally, at an acceptable level of significance, it can be shown that between the challenges related to nursing planning and their level of interest in exploiting the field of identifying planning problems in the health care sector in the database of the Ministry of Health of Iran. Consider the ability of correlated communication. The study showed that the appropriateness of identifying planning problems in the health care sector with the challenges related to human resources by the DBSCAN model in different parts of the participatory refining network had been done with high accuracy.

The data accuracy of the K-means clustering model is higher than the DBSCAN clustering model, and therefore KMEANS clustering model has higher power for participatory refining network.

In this part of the review and appropriateness of identifying planning problems in the health care sector with challenges related to automatic manpower, the suitability of identifying planning problems in the healthcare sector with challenges related to equipment and systems, challenges pertaining to manpower Humanity and patient age challenge tailored to the hospital space, rooms and

wards or adopt participatory refinement network structures By analyzing the recommendation system data using MATLAB participatory refinement, we provide some general information about the impact of each From six fitness classes, we identified the characteristics of planning problems in the health care sector with the challenges related to equipment and systems, the challenges related to manpower and the challenge of patient age-appropriate to the hospital space, rooms and wards discussed in this study. . Based on the table presented in the following section, demographic information and the appropriateness of identifying planning problems in the health care sector with challenges related to equipment and systems, challenges pertaining to manpower and age challenges appropriate to the hospital space, rooms and Sections or adopt statistical samples are provided.

Table - Data set without applying feature selection methods

Data accuracy	number of samples	The initial number of features	Database name
88.09	2000	6	Process (A) Exact fit between clusters (clusters) with the interest of health care sector agents in identifying planning problems in the data health care department of the Ministry of Health of Iran
92.13	2000	6	Process (B) Exact fit between Precision and Ritual criteria with the interest of health care sector agents in identifying planning problems in the data health care department of the Ministry of Health of Iran ...

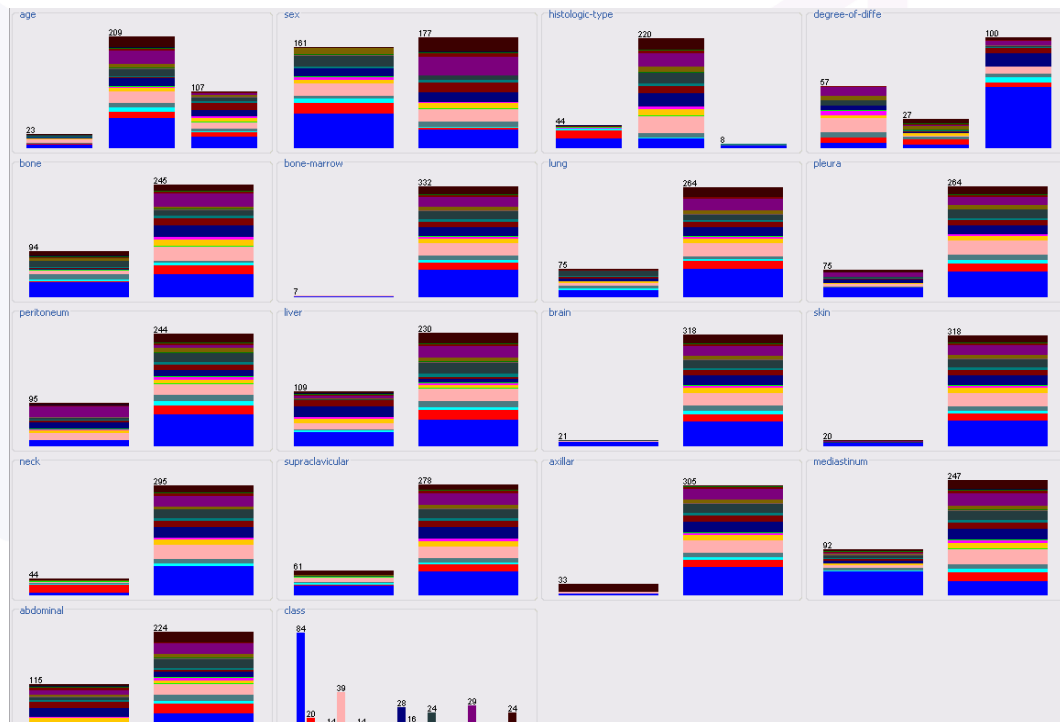
In this section, information is related to the customization features of healthcare scheduling problems with equipment and systems challenges, human resources challenges, and patient age-appropriate space challenges. Of the hospital, the rooms and the related modules listed in this research are listed. Review and categorize data based on participatory filtering filters

The general level of Recall criteria for all clusters	The general level of Precision criteria for all clusters
1.006	0.037



Collaborative filtering filters	Total data
29.4	Nursing planning challenges
29.22	Challenges related to operating room planning
29.33	Challenge the quality of activities for patients
29.16	The patient age challenge is tailored to the hospital space, rooms and wards
28.42	The challenge of proportional distribution of patients in communities and rooms
29.11	Patient transfer challenge
32.44	Nursing planning challenges

Relative graph distribution:



Assess the level of accuracy and significance obtained from each fitness class to identify planning problems in the health care sector with challenges related to equipment and systems, challenges about human resources and age of the patient under the hospital space, rooms, And sections or adopt Software output



Detailed Accuracy By Class:

F statistic DBSCAN F-Measure Precision recall Area

Items	Classify adopt	F statistic	Precision	recall
Genus	4.717	0.000	0.075	0.197
Age	4.566	0.000	0.063	0.16
Education Level	4.732	0.000	0.042	0.023
Jobs	4.019	0.000	0.056	0.199
Film Interest	4.23	0.000	0.078	0.656
Location	4.04	0.000	0.039	0.202

In reviewing and categorizing the six demographic criteria in the fit of each class of people with (different characteristics in terms of challenges related to equipment and systems, challenges about human resources and patient age challenges appropriate to the hospital space, rooms, and wards And its adaptation by refining the identification of planning problems in the health care sector, it can be shown that at the level of statistical F, a correlation can be made between classifying adopt or adaptation of classes to class interests characteristics for nurses' shift scheduling. They were observed on Webdastast. Because at criterion level 5, Classify adopt most classes have been at an acceptable level. F statistic Level: All criteria are complete and can match interests with classification with .low margin confidence

Check the level of accuracy in Classify adopt

Items	Accuracy	Classify adopt
genus	0.075	4.717
Age	0.063	4.566
Education Level	0.042	4.732
Jobs	0.056	4.019
Film Interest	0.078	4.23
Location	0.039	4.04

Based on the estimation of participatory refinement in this study, it has been found that the level of density in creating unfavorable conditions among the statistical sample is clearly defined among the six classes studied, including the



highest vulnerability group of refining health care agents based on characteristics. Gender, equipment and systems challenges, group network education with 42 to 78% accuracy.

About the fit efficiency group, identifying planning problems in the health care sector with the challenges related to Haiti equipment and systems, it has been determined that the incidence of participatory refinement network structures for the fit efficiency group identifies planning problems in the health care sector. With more challenges related to equipment and systems, medium and low is more. The study showed that in the Film Interest class and then the genus of different degrees of incidence, the relative type of participatory refining network structures had the highest probability of accuracy level.

KMEANS clustering model:

===Run information===

Scheme:weka.clusterers.Cobweb -A 1.0 -C 0.0028209479177387815 -S 42

Relation: Film Interest

Instances: 2000

Attributes: 63211

]list of attributes omitted]

Test mode:evaluate on training data

PART decision list

NM_65514 <= 0.233 AND

AL190551 > -1.661 AND

NM_56651 <= 7.323 AND

AF10266 <= 11.102 AND

NM_26541 > -5.32: non-relapse (12.0/32.10)

Relapse (102.0/6.0)

Number of Rules: 6

Time taken to build model: 2.32 seconds

===Stratified cross-validation===

===Summary===

Correctly Classified Instances 6 88.112%

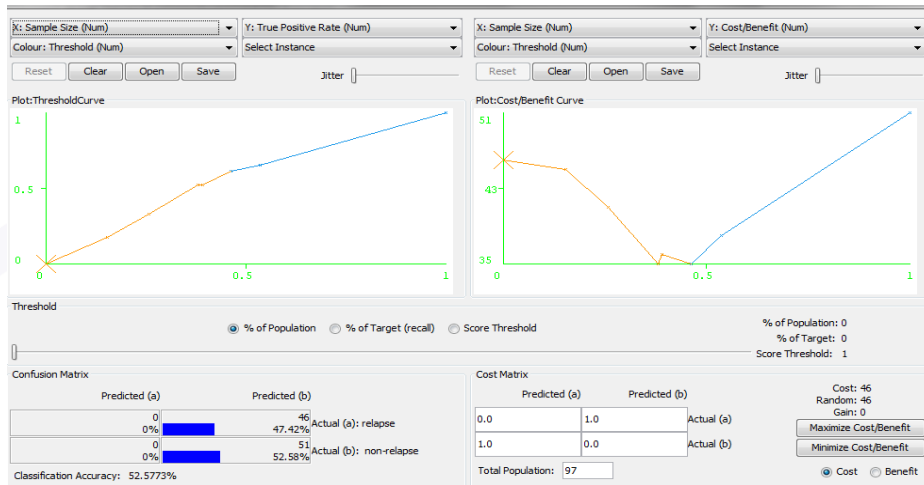
Incorrectly Classified Instances 0 42.665%

Kappa statistic 0.623

Mean absolute error 0.545



Root mean squared error	0.722
Relative absolute error	11.16%
Root relative squared error	199.1%
Total Number of Instances	16



7- Research Discussion

The challenge of nursing list optimization (NRP) has become an important issue for the researcher among personnel planning issues. This has become an intriguing challenge for many optimization researchers. Lack of nursing is an important and multifaceted challenge in health care mechanisms and is very important in optimization. Several researchers have solved problems with various techniques like precision methods, exploratory methods and extraterrestrial methods. The list of nurses challenge is a research challenge that is open to utilizing the operational level different metaheuristic approaches. The combination of meta-metrology with local search demonstrates the ability to deal with NRP (Kroer et al, 2018), because of to strike a balance between exploration and exploitaion.

The challenge of enrolling nurses with different types of limitations, characteristics has been related to research and in different countries (Xiang et al, 2017) using real hospital data sets has been examined. Most research focuses on INRC-I and INRC2010 data sets. Creating authentic hospital data sets in distinct countries is limited, this is a matter of hospital privacy. The dynamic version of INRC-II has limited research due to the scenario's multi-stage and complexity nature. Most research INRC-II has focused on the details cases (4-8) weeks for this challenge. The challenge of nursing planning can be developed by considering the circumstances of each country. Combining nursing planning with



other health care issues such as patient planning and physician planning can increase the performance of the medical institution.

Our main goal in this study is a hybrid system to explain the position of the recommender system in the fit of the identification of planning problems in the health care sector with the challenges related to manpower. The fit of identifying planning problems in the health care sector with related challenges Equipment and systems, manpower and education challenges have been participatory refinement network structure using F STATISTIC and DbSCAN clustering methods. To this end, we have designed an automated system that can use machine learning techniques to make it appropriate for us to identify the nature of planning problems in the healthcare sector with the challenges of manpower. To do this, we first identify and delete data and features unrelated to the participatory refining network structures by a proposed technique to reduce computational and classification costs. We have called this stage the feature selection stage. Using the combined categorization technique, we have identified the specifics of identifying planning problems in the health care sector with the challenges related to the manpower of the structures of the participatory refining network.

In this study, the effective characteristics for profiles for health care agents are investigated. It was suggested that in this study, the researcher examines the information of 150 hospital wards in Iran, the data of the Ministry of Health of Iran. In this study, the researcher examined six clusters that include Challenges related to nurses' planning, challenges related to operating room planning, challenges to the quality of activities for patients, challenges to the patient's age-appropriate to the hospital space, rooms and wards, challenges to the appropriate distribution of patients in wards and rooms and challenges There has been patient transfer.

The number of large clusters in this study was equal to 10-3 participatory clusters and the number of small clusters was equal to 6-10 participatory clusters.

The study showed that the appropriateness of the specificity of identifying planning problems in the health care sector with the challenges related to human resources by the KMEANS model in different parts of the participatory refining network except for programming configuration has been done with high accuracy. The study showed that the degree of appropriateness of identifying planning problems in the health care sector with manpower challenges by



DBSCAN model in different parts of participatory refining network except programming configuration, centralized management and traffic management has been done with high accuracy. . The data accuracy of KMEANS clustering model is higher than DBSCAN clustering model and therefore KMEANS clustering model has higher power for controlling participatory refining network. The demographic information of this group of experimental people, which was provided to the research team of this research, which included the researcher and his research colleague, was examined separately and by determining the field related to each person. MATLAB participatory refinement entered.

References

1. Zhu S, Fan W, Yang S, Pei J, Pardalos PM. Operating room planning and surgical case scheduling: a review of literature. *J Combi Opt.* 2019;37(3):757–805.
2. Ahmadi-Javid A, Jalali Z, Klassen KJ. Outpatient appointment systems in healthcare: A review of optimization studies. *Euro J Oper Res.* 2017;258(1):3–34.
3. Sigurpalsson AO, Runarsson TP, and Saemundsson RJ. Stochastic master surgical scheduling under ward uncertainty. In *International Conference on Human-Centred Software Engineering*, pages 163–176. Springer, 2019.
4. Turhan AM, Bilgen B. Mixed integer programming based heuristics for the patient admission scheduling problem. *Comp Oper Res.* 2017;80:38–49.
5. Guido R, Solina V, Mirabelli G, and Conforti D. Offline patient admission, room and surgery scheduling problems. In *New Trends in Emerging Complex Real Life Problems*, pages 275–283. Springer, 2018.
6. Bolaji AL, Bamigbola AF, Shola PB. Late acceptance hill-climbing algorithm for solving patient admission scheduling problem. *Knowledge-Based Systems.* 2018;145:197–206.
7. Doush IA, Al-Betar MA, Awadallah MA, Hammouri AI, Raed M, Mustafa S, and Alkhraisat H. Harmony search algorithm for patient admission scheduling problem. *J Intel Sys,* 2018;29(1):540–553.
8. Bastos LS, Marchesi JF, Hamacher S, Fleck JL. A mixed-integer programming approach to the patient admission scheduling problem. *Euro J Operational Res.* 2019;273(3):831–40.



9. Hammouri AI. A modified biogeography-based optimization algorithm with guided bed selection mechanism for patient admission scheduling problems. *J King Saud Univ-Comp Info Sci*, 2020.
10. Zhu YH, Toffolo TA, Vancroonenburg W, Berghe GV. Compatibility of short and long term objectives for dynamic patient admission scheduling. *Comp Operations Res.* 2019;104:98–112.
11. Diamant A, Milner J, Quereshy F. Dynamic patient scheduling for multi-appointment health care programs. *Prod Operations Manage.* 2018;27(1):58–79.
12. Zhu S, Fan W, Liu T, Yang S, Pardalos PM. Dynamic three-stage operating room scheduling considering patient waiting time and surgical overtime costs. *J Combinatorial Opt.* 2020;39(1):185–215.
13. Molina-Pariente JM, Hans EW, Framinan JM. A stochastic approach for solving the operating room scheduling problem. *Flex Serv Manu J.* 2018;30(1–2):224–51.
14. Kroer LR, Foverskov K, Vilhelmsen C, Hansen AS, Larsen J. Planning and scheduling operating rooms for elective and emergency surgeries with uncertain duration. *Oper Res Healthcare.* 2018;19:107–19.
15. Xiang W. A multi-objective aco for operating room scheduling optimization. *Nat Comp.* 2017;16(4):607–17.
16. Ansarifar J, Tavakkoli-Moghaddam R, Akhavizadegan F, and Amin SH. Multi-objective integrated planning and scheduling model for operating rooms under uncertainty. *Proceedings of the Institution of Mechanical Engineers, Part H: J Eng Med*, 232(9):930–948, 2018.
17. Akbarzadeh B, Moslehi G, Reisi-Nafchi M, Maenhout B. There is a diving heuristic for planning and scheduling surgical cases in the operating room department with nurse re-rostering. *J Sched*, pages 1–24, 2020.
18. Varmazyar M, Akhavan-Tabatabaei R, Salmasi N, Modarres M. Operating room scheduling problem under uncertainty: Application of continuous phase-type distributions. *IIE Transactions.* 2020;52(2):216–35.
19. D. Clavel, D. Botez, C. Mahulea, and J. Albareda. Software tool for operating room scheduling in a Spanish hospital department. In 2018 22nd International Conference on System Theory, Control and Computing (ICSTCC), pages 413–420. IEEE, 2018.



20. Belkhamsa M, Jarboui B, Masmoudi M. Two metaheuristics for solving no-wait operating room surgery scheduling problem under various resource constraints. *Comp Ind Eng.* 2018;126:494–506.
21. Khaniyev T, Kayış E, Güllü R. Next-day operating room scheduling with uncertain surgery durations: Exact analysis and heuristics. *Euro J Oper Res.* 2020.
22. Lin TK, and Chou YY. A hybrid genetic algorithm for operating room scheduling. *Health Care Management Science*, pages 1–15, 2019.
23. Timucin T, and Birogul S. Implementation of operating room scheduling with genetic algorithm and the importance of repair operator. In 2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), pages 1–6. IEEE, 2018.