JCSE International Journal of Computer Sciences and Engineering Open Access
Review Paper Volume-4, Issue-5 E-ISSN: 2347-2693

The Impact of Computerized Information in Health Centers for Efficient Patient Records

S.Narmatha[1*], R.Sivakumar[2]

[1] M.Phil Research Scholar, Department of Computer Science, A.V.V.M Sri Pushpam College, Poondi, Thanjavur
[2]Associate Professor, Department of Computer Science, A.V.V.M Sri Pushpam College, Poondi, Thanjavur
.

www.ijcseonline.org

Received: Apr/23/2016 Revised: May /03/2016 Accepted: May/19/2016 Published: May/30/2016

Abstract— The sway and popularity of competition idea has been expanding in the last decades and this idea has escalated the significance of giving right choice for organizations. Choice producers have encountered the certainty of utilizing appropriate scientific techniques instead of utilizing intuitive and emotional choices in choice making process. In this context, numerous choice support models and applicable frameworks are still being created in request to help the vital administration mechanisms. There is moreover a basic need for robotized approaches for viable and efficient utilization of monstrous sum of Information to support corporate and individuals in vital planning and decision-making. Information mining systems have been utilized to reveal hidden designs and relations, to abridge the Information in novel ways that are both reasonable and profitable to the executives and moreover to foresee future patterns and behaviors in business. There has been a substantial body of relook and practice focus on diverse Information mining systems and methodologies. In this study, a substantial volume of record set extracted from an outpatient clinic's therapeutic database is utilized to apply Information mining techniques. In the first stage of the study, the raw Information in the record set are collected, preprocessed, cleaned up and eventually changed into a reasonable design for Information mining. In the second phase, some of the affiliation guideline calculations are connected to the Information set in request to reveal rules for measuring the relationship between some of the properties in the therapeutic records. The results are watched and comparative investigation of the watched results among diverse affiliation calculations is made. The results appeared us that some basic and reasonable relations exist in the outpatient facility operations of the hospital which could help the hospital administration to change and improve their administrative methodologies regarding the quality of administrations given to outpatients.

Keywords— *Choice Making, Therapeutic Records, Information Mining, Affiliation Rules, Outpatient Clinic.*

I. INTRODUCTION

In today's aggressive world, Information and learning has become the absolute power for both establishing and managing associations in a fruitful and resilient manner. The key players in global economy, supervisors and vital choice producers namely, strive for better and more reliable choice making / choice support frameworks and systems with the help of continually improving Information advancements and robotized business learning models[2].

Since the 1990s, the financial idea has generally been referred to as the "Information and learning society". The profound changes that have occurred in techniques of production and in economic relations are acknowledged to increment the significance of the exchange of intangible goods, consisting for the most part of transfers of information. The acceleration in the pace of current transformation forms is appeared to be due to two variables where the first one is globalization and the second one is the sway of new Information advancements regarding the monstrous spread of the Web and mobile devices[2]. The spreading use of low-cost monstrous Information capacity advancements and the wide accessibility of Web connections have made exceptionally substantial sums of Information accessible to organizations, governments and people. The enterprises that are capable of transforming Information into Information and learning can use them to make quicker and more viable choices and Therefore to accomplish a aggressive advantage [5] (Alex A. T. Bui; Denise R.).

Consequently, the rapid growth and integration of Information technologies, digital networks, programming and database frameworks and the accessibility of monstrous sum of electronic Information give individuals with a vast new resource that can be examined to optimize industrial systems, reveal financially profitable patterns, minimize investment risks, make fruitful vital decisions, and so on[4] (Liujian Chen). Even, some interesting examines have been connected in fraud detection in several business area counting therapeutic records and frameworks [7] (Cláudia Trindade-Vilaça). To undertake these substantial Information investigation projects, specialists and practitioners have adopted established calculations from statistics, machine learning, neural networks, and databases and have moreover created new techniques targeted at substantial Information mining issues (Hand, et al., 2001; Zhang & Zhou, 2004). Information mining can be characterized as the extraction of profitable Information from substantial Information sets or databases. It is globally acknowledged as a new discipline, lying at the intersection of statistics, machine learning, Information administration and databases, pattern recognition, artificial intelligence, and other areas. All of these are appeared to be related with certain aspects of Information analysis, so they have much in common—yet each moreover has its own unmistakable flavor, emphasizing particular issues and sorts of solution [2](B. Spyropoulos; P. Sochos; A. Tsirogiannis).

With the advent of computers and the Information age, factual issues have exploded both in size and complexity. Challenges in the regions of Information storage, association and searching have led to the new field of "Information mining"; factual and computational issues in biology and medicine have created "bioinformatics." Vast sums of Information are being produced in numerous fields, and the statistician's work is to make sense of it all: to separate vital designs and trends, and understand "what the Information says." This is generally depicted as "learning from data"[4]. In other words, Information mining refers to the look of large, high-dimensional, multi-Sort Information sets, particularly those with elaborate dependence structures or designs where the look for profitable structure or designs is based on factual procedures (Hastie, et al., 2009).

Information mining is moreover acknowledged as a stage of a larger process known as "Learning Disclosure in Databases" (KDD). Learning disclosure is characterized as a process, in several stages, not trivial, interactive and iterative, for identification of new valid reasonable and potentially profitable designs from substantial Information sets. Thus, the use of Information mining is intended to support the disclosure of designs in databases in request to transform Information in knowledge, to help the choice making process or to explain and justify it. Information mining can be characterized as an automatic or semiautomatic designs disclosure in great sums of data, where these designs can be perceived as profitable (Nedjah, et al., 2009).

There are several diverse Information mining models, methodologies, tools, calculations and implementations, however, in most cases, the stages or stages of a Information mining process is characterized and grouped generally based on CRISP–DM standard (Larose, 2005). These stages are depicted as follows (Larose, 2005):

- Business understanding stage
- Information understanding stage
- Information planning stage
- Modeling stage
- Evaluation stage
- Deployment phase

It is usually noted that the most urgent stages is the first three stages where a great understanding of the business, Information structure, the scope and targets of the study and purifying or cleaning the Information (planning phase) is the key variables for a fruitful Information mining usage (Dasu & Johnson, 2003). In today's Information mining models and applicable technologies, most of them are pointed at one or more of the following normal targets or tasks, which moreover gives us the rundown of essential goals and elective approaches of Information mining idea (Witten, et al., 2011; Larose, 2005):

- Description
- Estimation
- Prediction
- Classification
- Clustering
- Association

Since in this study, affiliation is pointed and implemented, it will be shortly depicted in this paper. The affiliation assignment for Information mining is the work of finding which properties "go together." Most prevalent in the business world, where it is known as affinity investigation or market basket analysis, the assignment of affiliation seeks to reveal rules for measuring the relationship between two or more attributes[6]. Affiliation rules are of the form "If antecedent, then consequent," together with a measure of the support and certainty associated with the rule. Examples of affiliation assignments in business and relook include examining the extent of children whose parents read to them who are themselves great readers, or predicting degradation in telecommunications networks, finding out which things in a supermarket are acquired together and which things are never acquired together, and so on (Larose, 2005; Hastie, et al., 2009). Affiliation rules can "predict" any of the attributes, not just a specified class, and can indeed foresee more than one thing[6] (Sang-Chul Lee).

In this study, a Information mining model and a appropriate Information mining usage was accomplished in a outpatient facility database system. The official board of the hospital was particularly concerned about improving the quality of the administration given to patients in the outpatient clinic, as well as improving the work conditions for the therapeutic staff and expanding the effectiveness and throughput of the business processes. They had a substantial database that stores the incoming patients' records to the outpatient clinic, notwithstanding the past reports produced from the database framework hadn't given them with the Sort of Information or hints / clues that can increment their learning in their case. Since, their essential concern and requirement was to separate or find out some hidden profitable relations in the Information that can guide them in making choices for change administration in their daily operations; the affiliation assignment was picked inside the Information mining implementation. It is pointed to find some exact and vital particular conditions and criteria that can foresee certain situations, conditions or results that can be set as rules for hospital's vital choices by utilizing the record sets and fields (attributes) in the database. It should moreover be mentioned that some past examines about Information mining applications amongst therapeutic and healthcare records have been created successfully by other specialists (Riha, et al., 2002; Silver, et al., 2001; Morik, et al., 1999). The usage of our study, all vital stages of Information mining process counting Information collection, preparation, modeling, execution of calculations and test, perceptions of the results and discussions are given in the following sections of this paper.

II. CASE STUDY

The usage of this relook was conveyed out in one of the medium-sized public hospitals in Izmir, where Izmir is known to be the third biggest (population size and socioeconomic parameters) city in Turkey. Due to the privacy and legal concerns of hospital managers, the name of the hospital is not explicitly given in this study. The total number of therapeutic staff working in the hospital is around 580, the understanding bed capacity is given as 300 and it has three diverse outpatient facility structures and two main buildings[7]. During the interviews conducted with the hospital's official members in the business investigation of this study, it was watched that senior administration is becoming more involved in developing quality assurance standards, improving their IT base and adapting their major business process to innovative advances.

2.1 Information Collection and Planning

The Information were gathered from the hospital's outpatient facility Oracle 9i v.9.2.0.1 database system. It was made up of a four-month period of Information that were recorded to the framework whenever the patients arrived at the clinic. In the unique data, there were 21 diverse properties (fields) for each record and a total of 257668 records. However, before the Information investigation and mining process, some of these fields were eliminated and were not utilized in the study due to the irrelevance of these fields for the aim of this study[6]. Also, some of the records had null Information (off-base entries by Information administrators in the hospital) and these records were moreover discarded from the Information set. By this way, the Information cleaning and planning process, which is an vital step in Information mining was conveyed out. As a result, a total of 256816 records and 9 diverse fields were gathered and they were utilized for Information mining investigation in the study. The elucidating insights of the entirety Information set denoted in Figure 1 and the name and properties of the fields are given in Table 1.

It should be noted that since this Information is gathered from a Turkish hospital system, some of the records in the unique Information set are written and stored in Turkish language yet some of them are translated into English in this study, whenever necessary[4]. A test screen shot of the record set is moreover given Figure 2.

In the Information set, 146801 were the records of female patients (coded as "K" in the database records) which is 57.16% and the remaining 110015 records were belonging to male patients (coded as "E" in the database records), which is 42.84%. The day of the week field stores ostensible values representing any day of the week days (Sunday, Monday, etc.) where it relates to the "Date" field in the same record. Since, the Information was gathered in a period of four months, a total of 120 unmistakable field values were gathered in the "Date" field. The "Time" field means the hour and minute esteem of the time (24-hour format) which the patient's record is entered into the hospital system. The "2-hour Period" field is a ostensible mark which means the time period that relates to its time value. For instance, if a record has a "Time" esteem between 00:00 and 02:00, then its "2-hour Period" will be labeled as "0". In the same manner, if the time of the record is between 06:00 and 08:00, then its "2-hour Period" will be set as "3". Hence, this "2-hour Period" has unmistakable 12 elective values extending from 0 to 11.

The "Division Code" field stores the Information that shows where the understanding is medically worked in the outpatient clinic. These codes are specifically characterized in the hospital and their corresponding division names are known. In the Information set, there were 80 unmistakable division codes. "Understanding Sort Index" is moreover another unique specification code in the hospital framework which relates to the patient's financial feature. In other words, each code describes some extra property about the patient; whether he / she is resigned and resigned from which organization, or actively working, or jobless, whether he / she has an active social security number or not, etc. There are a total of 30 unmistakable mark values in the Information set extending between 1 and 58.

Table 1. The name of the fields in the whole data set

FIELD NAME	SAMPLE VALUES
Patient Gender	Male, Female
Day of Week	Sunday, Monday, etc.
Date	mm/dd/yyyy
Time	hh:mm
2-Hour Period	0, 1, 2,....11, 12
Department Code	100110, 200211, etc.
Patient Type Index	1, 2, 3,...............56, 57
Diagnosis Code	N21.1, S65.3, G46.8-J20.9, etc.
Case Explanation	*(Summary Of Each Record Explaining The Patient And The Incident, Written In Turkish)*

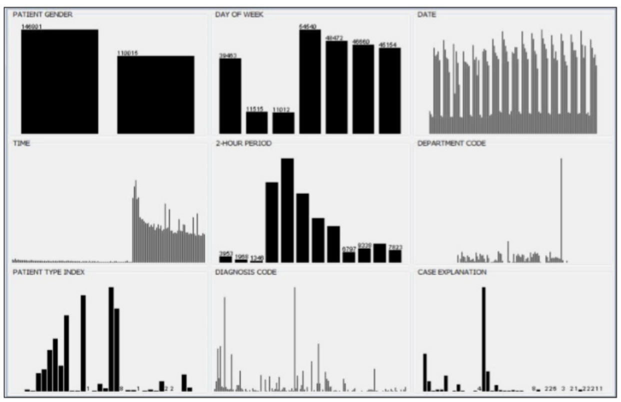

Figure 1. The elucidating insights of the entirety Information set in the study

PATIENT GENDER	DAY OF WEEK	DATE	TIME	2-HOUR PERIOD	DEPARTMENT CODE	PATIENT TYPE INDEX	DIAGNOSIS CODE	CASE EXPLANATION
E	Thursday	2/18/2010	18:21	9	400610	9	T14.8-T14.9	'PANSUMAN BİRİMİ VAKA DIŞIDIR'
K	Tuesday	4/27/2010	09:53	4	400412	7	F32.9	'VAKA BAŞI HASTASIDIR'
K	Thursday	2/18/2010	20:44	10	400710	5	R51	'YEŞİLKART HASTA TÜRÜ VAKA BASI UYGULAMASINA DAHİL DEĞİLDİR'
E	Wednesday	3/31/2010	07:59	3	200311	9	T15.1	'GÜNÜBİRLİK HASTASI((PAKET KARŞILIĞI TETKİĞİ YOK))'
K	Wednesday	3/17/2010	07:49	3	100610	9	R42	'AYNI GÜN BAŞKA VAKA BAŞI GELİŞİ VAR'
K	Saturday	3/13/2010	09:44	4	101410	22	Y60.3	'GÜNÜBİRLİK HASTASI((PAKET KARŞILIĞI TETKİĞİ YOK))'
K	Monday	3/22/2010	12:46	6	100626	13	E11.9	'VAKA BAŞI HASTASIDIR'
K	Wednesday	1/27/2010	07:23	3	200620	23	N83.2	'ON GÜN HASTASI EK/10C+GENETİK TETKİKİ YOK (01.04.2009 sonrası)'
E	Wednesday	4/28/2010	07:59	3	200401	9	L05.9	'ON GÜN HASTASI EK/10C+GENETİK TETKİKİ YOK (01.04.2009 sonrası)'
E	Tuesday	4/27/2010	12:50	6	100316	13	J45.8	'VAKA BAŞI HASTASIDIR'
E	Wednesday	4/14/2010	21:00	10	400710	9	M79.1-M79.1/MIYALJI	' ACİL POLK. BİRİMİ VAKA DIŞIDIR'
E	Monday	3/15/2010	14:12	7	100627	22	K29.7	'VAKA BAŞI HASTASIDIR'
K	Saturday	4/24/2010	20:45	10	400710	22	N30.9	' ACİL POLK. BİRİMİ VAKA DIŞIDIR'
K	Monday	3/15/2010	07:33	3	200310	5	H25.1	'YEŞİLKART HASTA TÜRÜ VAKA BASI UYGULAMASINA DAHİL DEĞİLDİR'
K	Monday	1/25/2010	11:03	5	100317	13	K52.8	'VAKA BAŞI HASTASIDIR'
K	Thursday	1/14/2010	10:50	5	101110	22	M67.4	'VAKA BAŞI HASTASIDIR'
E	Monday	4/19/2010	10:06	5	200312	8	H10.8	'ÜCRETLİ HASTA'
K	Tuesday	4/13/2010	07:50	3	200710	13	'I25.9 -I25.9'	'VAKA BAŞI HASTASIDIR'
K	Monday	2/22/2010	14:09	7	201010	4	'R07.3 -R07.3'	'VAKA BAŞI HASTASIDIR'
K	Monday	3/22/2010	12:40	6	101410	22	Y60.3	'ENJEKSİYON POLK. BİRİMİ VAKA DIŞIDIR'
E	Thursday	4/29/2010	01:38	0	400710	20	Z02.9	'CUMHURİYET BAŞ SAV. HASTA TÜRÜ VAKA BASI UYGULAMASINA DAHİL DEĞİLDİR'
E	Monday	3/15/2010	07:41	3	100610	9	E78.4-E11.5	'VAKA BAŞI HASTASIDIR'
K	Monday	4/19/2010	07:36	3	101111	13	M79.8	'VAKA BAŞI HASTASIDIR'
E	Thursday	1/21/2010	10:55	5	400710	9	M79.1-M79.1/MIYALJI	' ACİL POLK. BİRİMİ VAKA DIŞIDIR'
E	Friday	4/30/2010	07:34	3	100610	23	E11.9	'VAKA BAŞI HASTASIDIR'
K	Tuesday	3/30/2010	09:24	4	200210	5	J44.9	'YEŞİLKART HASTA TÜRÜ VAKA BASI UYGULAMASINA DAHİL DEĞİLDİR'
K	Tuesday	4/27/2010	07:22	3	200210	13	'I25.9 -R07.3'	'VAKA BAŞI HASTASIDIR'
K	Thursday	2/25/2010	06:59	3	100616	13	I10	'VAKA BAŞI HASTASIDIR'
E	Friday	2/26/2010	08:01	4	200311	23	H11.0-H11.0/PTERJIYUM	'GÜNÜBİRLİK HASTASI(PAKET KARŞILIĞI TETKİĞİ VAR)'
K	Sunday	3/28/2010	11:35	5	400610	5	T14.8-T14.9	'YEŞİLKART HASTA TÜRÜ VAKA BASI UYGULAMASINA DAHİL DEĞİLDİR'
K	Monday	1/25/2010	15:38	7	100713	7	F32.9-M17.9	'AYNI GÜN BAŞKA VAKA BAŞI GELİŞİ VAR'

Figure 2. An excerpt from the Information set in the study

"Determination Code" field holds the particular therapeutic codes that abridge the determination assigned to the understanding inside each incident. "Case Explanation" field is a ostensible Information field that the Information administrators or therapeutic staff enters as short rundown notes in a standard and particular design which explains the case for each record of that understanding regarding the determination given and other observations. In the Information set, there were 43 unmistakable values among the 257668 records.

2.2 Methodology and Usage

Since the initial Information set size was substantial for the Information mining process, before analyzing the data, a factual inspecting methodology was utilized to derive a smaller test Information set (Witten, et al., 2011; Dasu & Johnson, 2003). The inspecting size was picked according to the following criteria:

Unique Information set size: 257668

Certainty interim (acknowledged margin of error): ± 2%

Certainty level: 99%

Inside these factual inspecting parameters, the minimum recommended test size could be calculated as 4081 utilizing the factual inspecting size derivation techniques[6] (Sang-Chul Lee). Thus, a total of 4100 out of 257668 records was selected as the test Information set size in our study. It should moreover be noted that, the accessible Information set from the outpatient facility database in the hospital was limited to the first four month period due to the changes in the innovative base of the applicable database systems[2]. However, this test size and the test Information set can moreover be considered as a feasible representative inspecting sum for a one year period regarding the same factual certainty level and certainty interim values.

Weka version 3.6.0 was utilized as the programming for the Information mining investigation stage in the study. The entirety Information set was first converted into appropriate Weka Information design and then it was imported into the application. After this step, all of the numerical fields (attributes) were changed into their ostensible values. This was moreover a urgent step in the investigation since most of the acquainted Information mining calculations that are supplied inside Weka programming only works for ostensible Information[6](Sang-Chul Lee). Before the initiation of Information mining analysis, the final step was the random test Information set selection of 4100 records out of the generic Information set. This was established by the preprocessing and filtering apparatuses that were given inside Weka software.

After these steps, diverse acquainted Information mining calculations were executed among the Information set and their results were watched and comparatively analyzed. Each of these acquainted calculations use diverse Information mining systems to separate affiliation rules

(Witten, et al., 2011; Cho, et al., 2002; Khattak, et al., 2010) and they are summarized in Table 2.

Table 2. Acquainted Information mining calculations utilized in the study

ALGORITHM NAME	EXPLANATION
Apriori	Generates association rules by finding frequent item sets, generating successively longer candidate item sets from shorter ones that are known to be frequent. It iteratively reduces the minimum support until it finds the required number of rules with the given minimum confidence.
Filtered Associator	It allows data to be passed through a filter before it reaches an associator. Both the filter and the base associator are options that the user can configure.
PredictiveApriori	It combines confidence and support into a single measure of predictive accuracy and finds the best n association rules in order.
Tertius	It finds rules according to a confirmation measure, seeking rules with multiple conditions like Apriori, but differing in that these conditions are applied OR operation together, instead of AND operation.

Among these four algorithms, the only remarkable and exact results were watched from the Predictive Apriori associator. The other three Information mining calculations either given no results or some non-applicable / incorrect affiliation rules. Some of the default parameters were moreover changed in these three calculations and extra perceptions were made in request to accomplish some exact and vital results yet no further exact results could be obtained. In the following section, the affiliation rules watched by the PredictiveApriori mining calculation are given and the interpretation and investigation of these rules are discussed.

2.3 Results

Prescient Apriori associator calculation determined 100 diverse affiliation rules that were ranked and ordered with several exactness level values. The guideline with the highest exactness had a esteem of 0.99498 and the one with lowest exactness was watched as 0.9733. This exactness term means metrics for ranking the affiliation rules by means of confidence, which is the extent of the examples secured by the premise that are moreover secured by the ensuing ones (Witten, et al., 2011). Among these rules, some of them had one condition or attribute with a resultant condition where some others had two or more combined condition that relates to a particular condition. Some of these affiliation rules determined from Weka software's output panel are appeared in Figure 3 with the guideline conditions and the exactness values abbreviated as "acc:";

```
PATIENT TYPE INDEX=22 CASE EXPLANATION= ACIL POLK. BIRIMI VAKA DISIDIR ==>
DEPARTMENT CODE=400710 acc:(0.99489)

DAY OF WEEK=Sunday CASE EXPLANATION= ACIL POLK. BIRIMI VAKA DISIDIR ==> DEPARTMENT
CODE=400710 acc:(0.99471)

2-HOUR PERIOD=10 CASE EXPLANATION= ACIL POLK. BIRIMI VAKA DISIDIR ==> DEPARTMENT
CODE=400710 acc:(0.99463)

PATIENT GENDER=K DEPARTMENT CODE=400710 PATIENT TYPE INDEX=22 ==> CASE EXPLANATION=
ACIL POLK. BIRIMI VAKA DISIDIR acc:(0.99471)

DAY OF WEEK=Sunday DIAGNOSIS CODE=Y60.3 ==> DEPARTMENT CODE=101410 acc:(0.99163)
```

Figure 3. Some of the affiliation rules determined by Prescient Apriori

As it can be seen from the test subset of results in Figure 3, the first guideline proposes that if "Understanding Sort Index" is 22 and "Case Explanation" is a non-standard crisis outpatient clinic, then it should be worked in the division with code 400710 (which is recorded in the hospital's framework as crisis administration department) with a certainty esteem of 0.99489. Similarly, the last guideline in Figure 3 proposes that if any understanding comes on Sunday and its determination code is Y60.3 (unforeseen episode due to a surgical operation / off-base therapeutic treatment), then its division code is 101410 (infusion administration department) with a certainty esteem of 0.99163.

However, all of these 100 rules had to be examined in detail by the authors of this study and the hospital senior administration since most of these rules, indeed providing exceptionally high certainty values, in certainty were not exact or meaningful. This was moreover an expected outcome in this study. This is due to the certainty that in all sorts of Information mining models and methodologies; it requires significant human interactivity at each stage (Larose, 2005). Continuous quality monitoring, validation and other evaluative measures must be assessed by human analysts (Larose, 2005). Recent researches are focutilizing in to find improved mining procedures that can enable change semi-robotized systems to robotized systems (Asghar & Iqbal, 2009).

After carrying out the investigation of the determined rules, some few yet vital and vital conclusions were accomplished which were confirmed by the senior administration in the hospital. These deductions are given as follows;

- On any day of the week, if the understanding landing time period is 22:00-00:00 at night and the understanding is recorded as a non-standard crisis outpatient facility and if the understanding is moreover retired, then it could be a female patient.
- If the patient's landing time is 00:00-02:00 at night and the day is Saturday or Sunday and the division

is crisis administration and if it needs an immediate operation for surgery, it is probably a male patient.

- On Sundays, if the understanding has an unforeseen episode due to a surgical operation / off-base therapeutic treatment, then crisis administration inside infusion operation is required.
- On any day of the week (except weekends), if the understanding landing time period is 10:00-12:00 in the morning and if the understanding is male and if it is a resigned understanding from government, then he is probably to be served in urology department.

III. CONCLUSION

The results from the Information mining process of the outpatient facility records appeared us that some vital precautions and some vital changes in the daily operations might be accomplished by the hospital administration that could improve the effectiveness and quality of administrations given to outpatients. For instance, in any work day of the week in the morning period, it is better to have adequate number of specialists and therapeutic staff in the urology department. At the weekends during the midnight hours, it is urgent to have adequate number of male nurses accessible in the crisis service. On Sundays, it is vital to keep some specialists in the facility that are experienced in particular surgical operations.

On the other hand, in this study it is appeared that only a few relations and learning based conclusions could be made to support and enhance the choices and administrative methodologies of the hospital management. This could be due to two reasons. The first reason is the lack of Information in the database framework in request to separate profitable associations and relations (in this study only nine fields, in other words, nine criteria in the record set could be utilized for Information mining). The second reason is that the affiliation calculations utilized for Information mining in this study might not be perfectly fit for this case. To overcome such issues and drawbacks in further studies, more fields or properties could be included in the Information sets and some other affiliation calculations might be tested as well. It should moreover be noted that indeed if the Information mining tools, models and calculations utilized in similar examines give results with high levels of exactness and confidence, those results and determined rules shall require human intervention. In other words, no Information mining calculation or model can assure 100% correctness and exactness by itself for a pure and robust robotized system, hence, exceptionally result must moreover be checked by experts or managers.

REFERENCES

[1] S.Narmatha; R.Sivakumar, “The Impact of Computerized Information in Health Centers for Efficient Patient Records”, International Journal of Computer Sciences and Engineering, V-4, I-4.

[2] B. Spyropoulos; P. Sochos; A. Tsirogiannis; A. Mikronis, “A "Smart Medical Record”, for the general practitioner supporting decision making and training in cardiology”, Bioengineering Conference, 2002. Proceedings of the IEEE 28th Annual Northeast, Year: 2002, Pages: 135 – 136.

[3] Mila Kwiatkowska; Linda McMillan, “A semiotic approach to data in medical decision making”, Fuzzy Systems (FUZZ), 2010 IEEE International Conference on, Year: 2010, Pages: 1 – 8.

[4] Liujian Chen; Lujia Bi; Huayou Si; Jilin Zhang; Yongjian Ren, “Research on prediction method for pivotal indicator of hospital medical quality using decision tree”, Software Engineering and Service Science (ICSESS), 2015 6th IEEE International Conference on, Year: 2015, Pages: 247 – 250.

[5] Alex A. T. Bui; Denise R. Aberle; Hooshang Kangarloo, “TimeLine: Visualizing Integrated Patient Records”, IEEE Transactions on Information Technology in Biomedicine, Year: 2007, Volume: 11, Issue: 4, Pages: 462 – 473.

[6] Sang-Chul Lee; Peter Bajcsy, “Understanding Challenges in Preserving and Reconstructing Computer-Assisted Medical Decision Processes”, Machine Learning and Applications, 2007. ICMLA 2007. Sixth International Conference on, Year: 2007, Pages: 524 – 529.

[7] Lilac A. E. Al-Safadi, “Semantic-Based Exchanger for Electronic Medical Record”, Convergence and Hybrid Information Technology, 2008. ICCIT '08. Third International Conference on, Year: 2008, Volume: 1, Pages: 962 – 967.

[8] Cláudia Trindade-Vilaça; Tiago Silva-Costa; Ricardo Cruz-Correia, “Implementation of medical algorithms in the Breast Pathology module of VCIntegrator”, 6th Iberian Conference on Information Systems and Technologies (CISTI 2011), Year: 2011, Pages: 1 – 4.

