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Integrated Insurance & Health (Medical) Sensors Data Sharing

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Abstract: **In this paper the main focus is on the of integration of health organizations with insurance companies. It provides an analysis of shared models of health insurance premium based on data collected by human body sensors in a hospital. Health insurance arrangements are based on the methods of risk calculations associated with health of an individual. These risks are computed on the basis of multiple health related frameworks. The implementation of the system uses health standards which will provide the interaction between virtual insurance industries and various multiple Health virtual organization.**

Keywords: Health insurance, insurance models Digital Ocean, Django, Restful API, JSON, Body Sensors, Big data analytics.

I. Introduction

Health insurance is a contract between an individual and the insurance company that says that the insurance company will pay a portion of medical expenses if the patient get sick or hurt and have to visit a doctor or hospital. Some Contracts also specify that the insurance company will pay a portion of your medical expenses to ensure you don't get sick, such as paying for annual physicals or immunizations. Here, In this paper work, a common Data models between Health Care Industry and insurance companies has been proposed. The Insurance companies are integrated with health care providers for getting information on fitness of their client. Such, input from medical industry helps the insurance companies to build Pre health insurance premium models based on individuals health data. The traditional underwriting process was designed for a world of information scarcity and is trying to adapt now to information super-abundance. There is a building of system beyond simple client-server architecture and layered application that integrates with multiple medical and insurance vendors. There is an Integration of all of medical things with sensors with multiple competing standards in health and standardization in medical system. Data models are shared for health care and insurance. With which Patients tracking systems for medical treatment and insurance is overcome. The health insurance companies create profiles of customer health and develop individual scores accordingly, insurers are now casting the information net very wide indeed. Information is collected by following ways.

- Transactional data from credit card describes about where and what a customers buy like junk food etc.
- Body sensors devices monitors the consumption or alert the wearer to early signs of illness
- Exterior monitors devices collect the data from workout machines
- Social media can collect the information from tweets about one’s personal health or state of mind.

II. Literature survey

There are many researchers who had worked on Health insurance and the health Informatics by using their technologies and learning approaches. In this paper, the major focus is to reduce the work of hospitals and the companies regarding gathering of data about potential risks. Their work is reviewed and defined here:-

R.C sato et al. (2010**)** represented a clinical structure with using of Markov models. Markov models consider the patients in discrete state of health and events from one state to another. Simulation cohort model by Markov chain is used for the comparison of stages of diseases

Abidoy A.P(2011) and many others used the Medical sensors to collect physiological data from patients band transmit it to IPDA using ZigBee/Ieee802.15.4 standard to medical server. They used Architecture of wearable sensors composed 3-tier for healthcare. Simulation model were used to analyze array of public policy.

Edward W.Jetal.(2013) Predicative analytics are used by health care, physicians. In which models were compared on an out of sample basis and Examined frequency and premiums. Calculated results are of predictive distribution for models by simulation.

G.Omar Et gayar et al.**(2014)** presented a research for business intelligence and big data analytics and examines how analytics are used. Outcomes tracked by analytics. Examined the modes b/w health insurer i.e. HMO and health insurance They used of vertical integration in health insurance. ROC curve report of analysis used to compare models like Laplacian. Comparison b/w Hadoop and Analytics results in implementation. Developed a prototype using Map Reduce that demonstrates how Cloud Infrastructure can analyze a sample set of open data.

Ying he, F Richard Yu et al. (2016) stated that big data analytics improves the performance in various fields of network. Big data analytics improve the performance in various fields of network. A unique data model and machine learning approach described. Here in this paper connection b/w big data and cellular n/w is explored and compared.

III. Scope of work

In this paper, the motive is on Health insurance integration with hospitals. As the work is done on the basis health sensors models that calculates the output as per circumstances. Companies are combining the connection of customers on individual profile basis e.g., email, call center, adjustor reports, etc with indirect sources like social media, blog comments, website and click stream data so to create a 360 degree that is complete profile of each individual. That gives employees a consolidated view of each customer for understanding their finances hence there is urgent need for building integrated insurance and hospital Data models.

IV. Proposed methodology

Step 1:-Integration of hospital and insurance organization using shared model.

Step 2:-Clinical data accumulator sends and receives data for both insurance and hospital.

Step3:-Patient data statistics are computed with biosensors.

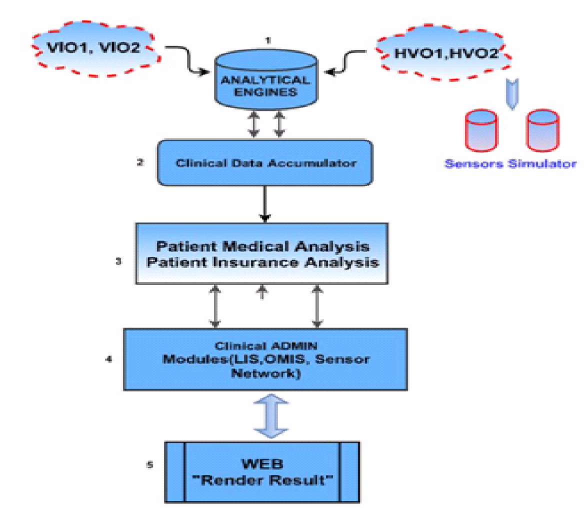

Fig4.1- Building an virtual insurance Organisation

Step4:- Restful API provides the interaction with multiple HVO's and VIO virtual insurance organization.

Step5:-Sensor module facilitates to add, delete sensors and sensor data sets.

Step6:-This module provides the interface between users and all technologies for Big Data Analysis.

Step7:-Performance of system is checked using experts from insurance and health industry.

V. Calculating Insurance Cost Using Shared Model

Followings are the factors involved in computing insurance costs

Table-5.1 Workout Risk Factors

Risk Factors	Work out (Mins)	Mean	Reward Points
Low risk	30-40	35	5
Ideal Risk	60-120	90	10
Pre-High	10-20	15	3
High risk	0-10	5	2

***Considering Reward 5=Lower Risk, 10=Normal/Ideal, 0=Higher Risk**

According to the data given in an above table[5.1]. This shows the following risk factors and conditions. On the behalf of these risk factors, the rewards are assigned to all the patients respectively. In case of reward system a simple rule is followed as *lesser the risk, Higher is the Rewards points* so in the above table[5.1] our results depends upon time of work out a person does in his daily life. Suppose if we say that Person A's workout time is 35 min & Person B's workout time is hardly 10 min, then according to the range series person A is under low risk category so he/she will be awarded with 5 points and person B is under High risk will be awarded with minimum 2 points. Same fundamental rules will be applied in all the cases of low, high and ideal risks.

Table-5.2 Sleep Risk Factor

Risk Factors	Sleep durations (hours)	Mean	Reward Points
Low risk	5-7	6	5
Ideal risk	8-11	10	10
Pre-High	3-5	4	3
High risk	1-3	2	2

***Considering Reward 5=Lower Risk, 10=Normal/Ideal, 0=Higher Risk**

In this table[5.2] the given data represents the risk factors, sleep duration time periods and reward points. Whereas four conditions are mentioned that is low risk, ideal risk, pre-high risk and high risks, in above table rewards are assigned according to the sleep duration time. *Lesser the sleep time higher is the risk* and lower is the reward points. In short conclusion *lesser is the risks, higher is the reward.* If person A is taking sleep of approximately 9 hours and person B is taking sleep of 3 hours, then person A will be awarded with more reward that is equals to 10 so this is the case of Ideal risk. Ideal risk case is awarded more than other cases. But person B is rewarded with less point =2

Table-5.3 Age (Male) Risk Factor

Risk Factors	Age(years) MALE	Mean	Reward Points
Low risk	25-35	30	5
Ideal risk	20-30	25	10
Pre-High	40-50	45	3
High risk	50-70	60	2

***Considering Reward 5=Lower Risk, 10=Normal/Ideal, 0=Higher Risk**

In this table[5.3] the reward depends upon the age factors of male. *Lesser will be the Age; more/higher is the reward points*. As the age grows on their rewards points goes down. So the ranges of 50-70 yrs of age will get less reward as compare to range of male age 25-35. Age range in between 20 to 30 is the ideal case with highest reward of 10.

Table-5.4 Age (Female) Risk Factor

Risk Factors	Age(Years) FEMALE	Mean	Reward Points
Low risk	30-40	35	5
Ideal risk	25-35	30	10
Pre-High	45-55	50	3
High risk	55-75	65	2

***Considering Reward 5=Lower Risk, 10=Normal/Ideal, 0=Higher Risk, Higher cost**

Same is the case of female table[5.4] the reward depends upon the age factors of female. *Lesser will be the Age; more/higher is the reward points*. As the age grows on their rewards points goes down. So the ranges of 55-75 yrs of age will get less reward as compare to range of female age 30-40. Age range in between 25 to 35 is the ideal case with highest reward.

Table-5.5 Family Size Factors

Risk Factors	No. of Family Size	Mean	Reward Points
Low risk	2-4	3	5
Ideal risk	1	1	10
Pre-High	5-6	5.5	3
High risk	6-8	7	2

***Considering Reward 5=Lower Risk, 10=Normal/Ideal, 0=Higher Risk**

Here is the above table[5.5] in which our reward based system depends on family size. *More is the members in the family lesser is the reward.* Their results are computed according to the risks it depends on, suppose if the number of family size increases by 5 than that case will be considered under high risk factors and will be reward with low points 2. Family size of 1 person is rewarded with high points 10.

Table-5.6 Marital Status Factors

Risk Factors	Age	Marital Status	Mean	Reward Points
Ideal Risk	20-30	Single	25	10
High Risk	30-40	Married	35	2
Low Risk	30-50	Other case	40	5

***Considering Reward 5=Lower Risk, 10=Normal/Ideal, 0=Higher Risk**

In the above table[5.6] the data shows the following risk factors and conditions. On the behalf of these risks, the rewards are assigned to all the patients respectively. In case of reward system a simple rule is followed as *lesser the risk, Higher is the Rewards points* so in the above table our results depends upon marital status of person. Suppose if we say that Person A's marital status is unmarried & Person B's marital status is married , then according data, person A is under low risk category so he/she will be awarded with 9 or 10 points and person B is under High risk will be awarded with minimum 2 points. Same fundamental rules will be applied in all other cases.

Table-5.7 Tobacco Risk Factors

Risk Factors	Condition	No. of Cigarette	Mean	Reward Points
Low risk	Occasionally	5-7	6	5
Ideal risk	Never	0	0	10
Pre-High	Weekly	3-5	4	3
High risk	Daily	1-3	2	2

***Considering Reward 5=Lower Risk, 10=Normal/Ideal, 0=Higher Risk**

In this Tobacco table[5.7] there are 5 risk factors defined that are High, Pre-High, Low and last is the Ideal/ Normal case. Our results output of reward based system depends upon the tobacco consumer according to the type of condition like daily consumer, weekly consumer, occasionally consumer or never. Never is an ideal case with highest reward points =10 because in case never there is no risk. So other cases are assigned with less rewards points depending upon its condition weather a low risk or high. Here in this above table number of cigarettes will define its condition. Suppose if the No. of drinks are =3 Daily then that will comes under high risk with very less reward= 10.

Table-5.8 Alcohol Risk Factor

Risk Factors	Condition	Alcohol consumption(No. of Drinks)	Mean	Reward Points
Low risk	Occasionally	5-7	6	5
Ideal risk	Never	0	0	10
Pre-High	Weekly	3-5	4	3
High risk	Daily	1-3	2	2

***Considering Reward 5=Lower Risk, 10=Normal/Ideal, 0=Higher Risk**

In this Alcohol table[5.8] there are 5 risk factors defined that are High, Pre-High, Low and last is the Ideal/ Normal case. Our results output of reward based system depends upon the Number of drinks a person taking according to the type of condition like daily consumer, weekly consumer, occasionally consumer or never. Never is an ideal case with highest reward points =10 because in case never there is no risk. So other cases are assigned with less rewards points depending upon its condition weather a low risk or high.

Table-5.9 Profession Risk Factor

Risk factors	Profession Type	Reward Points
Low	Govt. employee	5
Ideal	Retired	10
Pre-high	Business/Student/Private	3
High	Defence	2

***Considering Reward 5=Lower Risk, 10=Normal/Ideal, 0=Higher Risk**

This table[5.9] of profession will gives the reward points according to the type of profession, the person he/she belongs to. Suppose person A is of profession type Army and person B is of profession type Government. Then person B will awarded with more points =10 than person A because risk factors in person A is very high as compare to others.

VI. Partial List of Subjects/Insured

S.NO	NAME	AGE	GENDER	D.O.B	MARITAL STATUS	EMAIL ID	CONTACT
1	Mona Pathania	23	Female	04.11.1991	Single	Pathaniamona786@gmail.com	09780417141
2	Raghubir Singh	62	Male	01.01.1954		Prince.thakur@gmail.com	9888191004
3	Manmohan Jamwal	23	Male	26.09.1987	Single	pathaniamona@ymail.com	9780417141
4	Geeta Pathania	52	Female	16.09.1964	Single	geeta.pathania7@gmail.com	09417423633
5	Shubam Sharma	24	Male	31.03.1993	Single	Shubam.sharma67@gmail.com	07837413224
6	Puneet Arora	42	Male	31.12.1974	Married	puneet@ecologic.co.in	9872856485

Table-6.1 Partial list of subjects

Medical data of Mona Pathania

Risk Factors	Time Frequency (Mins)	Time Frequency (Hours)	Years (Female)	No. of Persons	Married/Unmarried/ Other	No. of Cigarettes	No. of Drinks 1 drink=30 ml	Type
Workout	20 mins							
Sleep		9 hrs						
Age			25 Y					
Family Size				4				
Marital					Unmarried			

Status								
Tobacco						0		
Alcohol							0	
Profession								Student

Table-6.2 Medical Report of Mona Pathania

Followings are the details of Mona's medical report describing all the risk factors like workout, *sleep, family size, marital status, tobacco, and Alcohol and profession type.* These details are collected by the survey of individual personalities so that we can get an make an actual outcomes for each.

Applying the Implemented systems

NAME	***Workout***	***Sleep***	***Age***	***Family Size***	***Marital status***	***Tobacco***	***Alcohol***	***Profession***
MONA PATHANIA	High	Ideal	Ideal	Low	Ideal	Ideal	Ideal	Pre-High
RAGHUBIR SINGH	Low	Ideal	High	Low	High	High	High	Ideal
MANMOHAN JAMWAL	Ideal	Low	Ideal	Low	Ideal	Ideal	Ideal	High
GEETA PATHANIA	Ideal	Pre-High	Pre-High	Low	High	Ideal	Ideal	Ideal
SHUBAM SHARMA	High	Ideal	Ideal	Low	Ideal	Ideal	Ideal	Pre-High
PUNEET ARORA	Low	Pre-High	Pre-High	Low	High	Ideal	Ideal	Pre-High

Table-6.3 Overall Subject's Data

Now in this above table[6.3] It has actually obtained an overall data for all 6 patients and then after that we had made a comparison by risk wise depending upon the type of risk he/she suffering from. If anyone among them will be given *HIGH* value that means he/she is under *high risk,* in same manner if any one comes under ideal category then its automatically an out of risk or at normal condition. The following rule is applied in this table that is *low=less risk, ideal=no risk, pre-high=below high risk, high=more risk.*

Acknowledgement

I owe a grateful thanks to all the doctors who had helped in obtaining these medical results.

VII. <u>RESULTS OBSERVATION</u>

NAME	Workout	Sleep	Age	Family Size	Marital Status	Tobacco	Alcohol	Profession
Mona Pathania	3	10	10	5	10	10	10	3
Raghubir Singh	5	10	2	5	2	2	3	10
Manmohan	10	5	10	5	10	10	10	2
Geeta Pathania	10	5	3	5	2	10	10	5
Shubam Sharma	3	10	10	5	10	10	10	3
Puneet Arora	5	3	3	5	2	10	10	3

Table-7.1 Reward Card of the Subjects

This is table[7.1] of reward card for all the patients who are represented in the above table[7.1]. These rewards are calculated on basis of risk factors[7.2]. The rules which are used in this is *higher the risk, lesser is the reward*, so these reward based systems are mainly in the case of health insurance systems in which rewards are assigned according to wellness and sickness insurance. The term 'wellness insurance' means high rewards are assigning to the one who keep him/her self safe and healthy risk free throughout the life. But in case of sickness insurance less rewards is given to the patients due to the sickness or the type of risk they suffering from. Rewards are given by assigning the points like 2, 3, 5, and 10 where reward 2 is for those who are amongst the higher risks, 3is for those who are among the pre-high risk and 5 is for the case of low risk patients. For ideal case the maximum high points are assigned that is 10 (*high reward*).

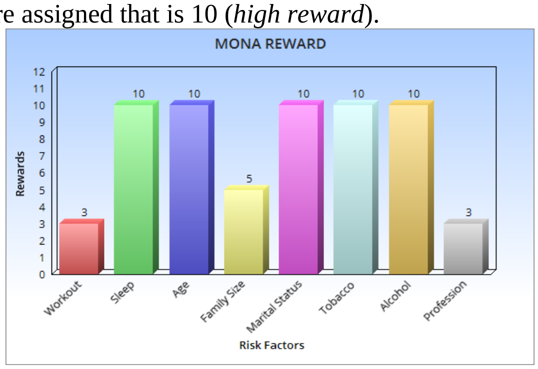

Fig-8.1 Reward Result graph of Risk factors

This is the result figure where the results of the patient Mona are represented in form of *Bar chart*. This bar chart shows how rewards are depicted in above graph according to their risks where as in Y-axis there is Rewards column and in X-axis Risk factor Block is in the horizontal manner.

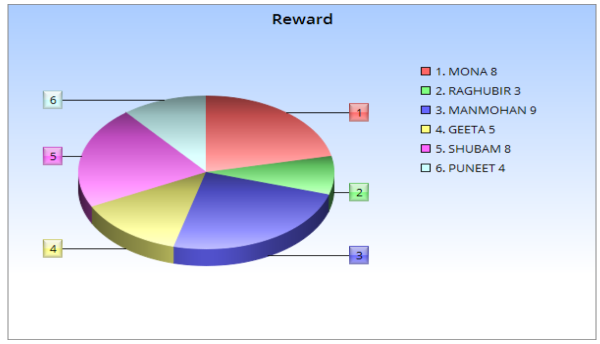

Fig-7.2 Comparable Results Pie-Chart of the Patients

The final overcome of this figure [7.2] is represented in the form of pie-chart comparing their overall results on the basis of rewards. A reward is computed by the risk factors, lesser the rewards means more the patient is under risk category. Suppose from the above data Ms.Mona, Mr. Manmohan & Mr. Shubam's rewards is 8 and 9 that is higher rewards as compare to other subjects Mr. Raghubir, Mr. Puneet having very low rewards so those who are having very low rewards are more to risk prone. Mrs. Geeta's reward is 5 which are less prone to risk.

VI. CONCLUSION AND FUTURE

In this work a system is build as n-tier server architecture in a layered application that integrates with multiple virtual medical and insurance vendors. The above system helps in building insurance premium models. The patient's statistics is computed and analyses for building customized health insurance plans and premium models. This system is build on Python based technology stack that provides facilities for integrating the data streams coming from human subjects.

Future Scope: In this research work we have used insurance hospital shared model for computing the cost of insurance to the customer using reward points system for future scope, however It is suggested that the use of time series analysis along with calculus may be used for building one to one insurance products.

VII. EXPERIMENTAL SETUPS

Software Requirements:

Operating System	Software Packages
Linux / Window Ubntu Or Window 7	1. Java 2. Python 3. Pycharm 4. JavaScript 5. GitHub 6. Digital Ocean

Hardware Requirements:

Processors	Disk Space	RAM	Graphics

Intel CORE i5	500 GB	4 GB	32 bit OS

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