Using Performance Measurement in Healthcare Analytics

Fadi L. Nammour[1], Nashat Mansour[2], and Konstantinos Danas[1]

[1] School of Computing and Information Systems, Kingston University, London, UK
[2] Department of Computer Science and Mathematics, Lebanese American University, Beirut, Lebanon

Abstract— **Electronic Health Records (EHR) embody a large volume of measured values and records of clinical encounters. Data is produced in healthcare settings at a large rate. Medical researchers find themselves facing massive volumes of data that should be reviewed and analysed before making clinical decisions that affect the lives of patients. The aim of this study is to apply the performance measurement approach used in finance and engineering to the EHR systems and develop a new system that allows clinicians who are not computer experts to analyse and query the EHR for better clinical decisions. Sources of healthcare data are numerous: nurses, doctors, technicians, patients, pharmaceutical companies, and third-party payers. Data is collected and stored from different sources such as computerised patient files, laboratory and diagnostic machinery, wired and wireless monitoring devices attached to patients across the various care-giver encounters, and many other electronic files and databases. Decision-support is critical in management of healthcare organizations. Data is collected for analysis, but requires organization of structure, design of systems to analyse the data, and technical knowledge from the management. This study aims at developing a novel system for the analysis of EHR data through the application of Performance Measurement and Management (PMM). This is achieved through investigation of the current situation and the state-of-the-art in clinical analytics, and then modifying the solutions to take advantage of PMM.**

Keywords— **Clinical Decision Support, Electronic Health Record, Performance Measurement, Analytics, Data Warehousing, Cloud Computing.**

I. Introduction

The electronic health record (EHR) is now the defining term for the recording, storage, retrieval, and analysis of patient-related information in healthcare centres and points-of-care such as clinics, diagnostic centres and specialized treatment centres throughout the lifetime of the patient. The EHR can be described as the set of information repositories located in data stores in multiple points of care that are securely accessed and updated by authorized users. Patient information in the EHR spans historical, current and possibly expected results of patient encounters [12]. The growing adoption of EHR systems along with components that target special services at healthcare and clinical centres, and the needs for detailed management of patient records in the various healthcare specialties created an opportunity for dedicated or specialized modules to track every detail of the patient interaction with the point of service.

Clinical decisions are a daily challenge for medical researchers [1], [2]. As an example, in the prescription process, the effectiveness of the drug on the patient's current diagnosis is critical to minimize the healing time and reduce complications and interactions [5]. There is no one system for managing a healthcare organization. Data is produced and consumed in isolated systems. In addition, interchange of information between systems is minimal and at the data-level only. Interchange of data requires schema adaptation and integration. Such queries need information from different components of the EHR system and need to be executed in part against each component separately, then their results joined together and analyzed. The more data structures available, the harder the interchange between systems.

To summarize, the problem in clinical decisions through EHR systems is that patient data is stored on multiple devices and databases, where different components of the EHR system might have different components of the patient records. Decision-support requires a unified data experience. This study propose a methodology for enhancing the efficiency of clinical decision support through encapsulating the EHR component schemas within a unified identification structure to serve as the basis for such queries, reducing errors and standardizing information access and representation. The aim of this study is to improve the efficiency of clinical decisions by analyzing EHR data aquired through the application of PMM methods.

The objectives are to:

1. Investigate the current situation and produce a case study exposing current problems
2. Study the state of the art solutions that have been applied to solve similar problems and identify the most appropriate for the local current situation
3. Modify that solution in order to be able to be applied locally and improve the current situation
4. Propose a solution that could improve the current situation.

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II. The state of the art in clinical decision support

A. Current Situation

Clinical decision support uses sets of techniques and tools [6] that provide access to electronic data and optimize the accuracy of decision results. Currently systems exist that collect data from different sources. Special databases are constructed to host this data, either as data warehouses or as graph databases. Data warehouses store de-normalized data structures. New schemas require re-design of analytical reports.

In the United States clinical systems benefit from the interchange of data among care-givers and the network of data sources that exchange data for clinical management [13], [14]. The use of EHR data in the US greatly contributed to the interchange of patient data securely and through standard structures [15], [16].

In the UK, national health data is interchangeable in a networked system that exposes patient health records to clinicians and treatment purposes [5]. The system allows the interface with EHR data from the national health records, and clinicians can securely provide treatment plans form patients [17].

In Canada, the integration of national-wide data improved the exchange of health data for clinical purposes. Clinicians can consume patient historical data and attempts exist to fully connect pharmacies nation-wide [18]. In Europe challenges exist for some countries where interchange of secure data is a problem, however in other countries where EHR data is connected from clinical points of care, electronic prescription is used in many places [19], [20].

With the advancement in EHR connectivity worldwide, several approaches were taken to reduce medical errors and improve the efficiency of clinical decisions leading to reduced treatment time [4], [7]. Using Decision-Support systems (DSS) to suggest treatment plans in healthcare settings [3] improved the dependency on patient data to short-list the treatment options. Query tools [8], [10], [11] help clinicians examine patient data and construct efficient treatment plans through analysis of similar data from other patients.

Graph databases attempt to overcome this limitation by representing data in graph structures, avoiding schema limitations. Graph databases are the basis of NoSQL databases. Binary relationships are detected among data entities. As technology advances, cloud-based solutions [9] reduce both cost of ownership [5] and technical difficulties to enable clinicians easy access to patient data for better decision-support and efficient patient treatment plans.

B. Continuous Analysis

Clinicians ask questions regarding the history of the patient through queries against the EHR. These questions, when answered, lead to other questions that need answers. This interactive approach is critical to identifying the proper treatment plan and thus prescribing the correct medication. The continuous analysis of the EHR is thus the iterative and progressive enquiry of patient-centric information leading to the proper judgement of the case. Once a decision is made, the clinician will have to monitor the progress of the treatment and its success or failure. This monitoring requires a repetition of previously executed queries to compare results.

III. Current situation in Lebanon and problems

A. Limitations

The adoption of custom coding structures for data in points of care reduces the ability of researchers and clinicians to analyse historical data in EHR systems and forces them to consume much of their time in the correlation of data or in discontinued enquiries. Particularly in treatment plans where the order is of months rather than days as is the case with inpatient treatment, the need for a continuous and progressive recording of patient data is critical. While current approaches work for specific structured patient data, clinician's and medical researchers always need to introduce new data sources into their analysis to support their decisions in patient treatment plans. Continuously "plugging" new data schemas into analytical systems requires the restructuring of queries to adjust to this new data. The ability to seamlessly introduce new sources such as new monitoring devices or data coming from the adoption of a new medical surveillance system is a frequently occurring task in clinical settings.

B. Case Study

In order to describe the current situation in Lebanon healthcare, a survey was conducted where four hospitals were surveyed and key people were chosen and interviewed to answer a questionnaire. The selection criteria were based on the nature of interaction between the subject and the EHR in terms of information retrieval, decision support and clinical findings/research. The personnel selected were unit/department managers, statisticians, decision support managers, doctors, executives in the financial, medical and business domains, information analysts and in some cases experienced EHR personnel.

Ideas from a focus group of analytical staff in the healthcare organizations were put together to further identify the limitations and problems of the local situation. The group emphasized that data from current EHR systems cannot be analysed without some sort of intervention from technical specialists, either in the preparation of data or in the execution of queries against the databases.

Organizations dealing with researchers, such as hospitals with specialized cancer centres or diagnostic facilities sometimes need to provide analysis from similar centres to improve the quality of care and performance of the organization. In such a situation the availability of aggregated analytics is subject to requesting it from the technical departments across these organizations.

There are technical and legislative barriers that prevent the secure and private exchange of aggregated healthcare information among researchers and doctors nationwide.

C. Problems

The following problems were identified following the case study and literature review:

a) Integration: The EHR is not integrated with all systems used. As a result it cannot serve complete analysis of the different parts of the patient information

b) Privacy: EHR cannot be used for statistical data analysis without compromising the security and privacy of patient information.

c) Analysis: Continuous analysis of EHR systems is not easy, therefore resulting in low user (management and decision takers) satisfaction.

In Lebanon, the EHR system is not present, and therefore the local situation is summarized as a group of independently maintained electronic patient record (EPR) systems across multiple points of care, but with no centralization

D. The Need for a New System

Based on limitations of the approaches in the leading countries, a new approach is needed to insure the completeness, security, privacy of shared patient information, and the possibility of the implementation of continuous analysis on the shared data.

The new approach is based on lessons learned from the adoption of the performance measurement approach in other industries where key performance indicators enabled the analysis of aggregated data without compromising the privacy of industry secrets.

Integrating this approach with the distributed analytical techniques will insure completeness of shared patient information while maintaining the security and privacy of this information, benefiting from the continuous analytics possibilities.

IV. Proposed Solution

A. Performance Measurement and Management

As organizations started facing financial challenges and spending problems, the adoption shifted to budgetary control, where the focus was on how to properly manage the existing financial resources rather than how good the performance of the organization was.

Recently, organizations started shifting to the integrated performance management approach, where they would have to manage performance in a changing environment with global challenges.

When applied to the healthcare setting, the same concepts can be used, in that the healthcare environment is changing and social networking challenges exist in the organization, and thus the adapted integrated performance management approach is suitably applied.

B. System Design

The system is designed with several functioning components that manipulate the consumed data with reference to the original data in their existing data silos. The system functions independently of the original data silos. Based on this, the system is divided into separate functioning components that independently control the input and process the output.

Using a conventional data-warehouse scenario to perform the required analysis involves loading data from different patient health data silos through an Extract-Transformation-Loading (ETL) process. The tabular data is then consumed inside the warehouse in the form of cubes that construct dimensions and measures and finally the data is visualized and presented to the user. Any change in the structure of the analysis requires a re-write of the computations in the form of queries against the data warehouse.

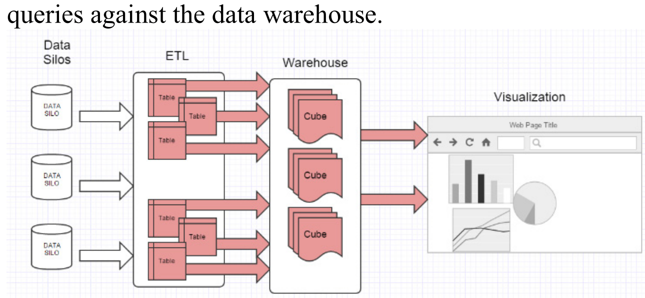

Fig 1: Conventional Data-warehouse Analytics

In the solution proposed in this paper, during the loading process performance measures are loaded instead of tabular data. The performances are multi-key tuples with a performance value and a date stamp. The tuples represent any set of identities in the data that contribute to the measure. For example, a doctor performing an operation on a patient in an operating room, or a nurse taking the blood pressure of a patient. The loaded performances are then presented to the user who builds the enquiries with no technical requirements. The enquiries are executed against the performance tuples inside the analytics data warehouse and the results are visually presented to the use. The user can then go back to the enquiries and change them as needed to gain further insight into the performance of the sub-systems. This process is detailed in the sections below.

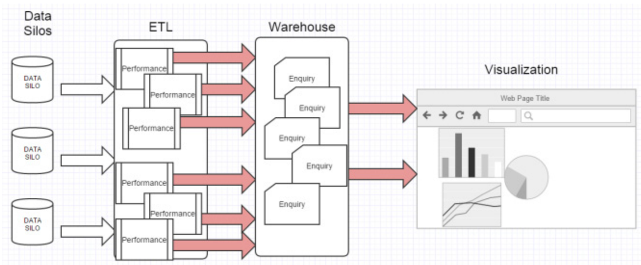

Fig 2: The Proposed Solution:

C. Data Loading Module

Loading starts at the data silo end, and a transformation mechanism exists that fits the loaded data to the framework's data schema. The data loading mechanism starts with an interpretation of the existing data silo structure, and then identify the tables that hold the required data. A schema matching transformation generates loading scripts that read data from the client's database and loads it into the data warehouse.

The data loading component is not intrinsic to the framework, and it is the actual manipulation of the data that is the starting point of the component line.

D. Analytics Engine

The analytics engine is responsible for hosting, manipulation, integrating and executing user-defined analytics in the framework. The operating system manages these programs' executions, and so will do the analytics engine with the analytics hosted.

The output of analytics changes as the data changes, so a data-independent analytics engine exist that ensures the ability to re-execute such analytics at different times and on different data sets.

The outputs of analytics are identity sets, list of identity instances that explain the situation under investigation and contribute to the decision process. Analytics can be composite, in that smaller analytics can be embedded within bigger ones.

In the case of analytics, a rights-management component exists that ensures client analytics exhibit unaltered behaviour whether the service analytics can be executed or not. When a user authors an analytic for comparing the body mass index of patients to the diabetes diagnoses, the engine shows identities such as patients, diagnoses, and laboratory glucose tests.

E. Relation to Problems

The suggested solution addresses the integration problem by collecting data from different sources and storing it in an integrated point in a standard structure. The privacy problem is addressed by hiding patient information details keeping only patient records to reduce deduction. Finally, the analysis problem is addressed through an open architecture for analytical design based on clinicians' algorithms and not on hard-coded pre-defined rules.

F. Data Visualization

Business Intelligence suits offer a multitude of data presentation and visualization tools that help explain the output of analysis in a human-readable language. It is the role of the data visualization component to link to the outcomes of analytics seamlessly, not only connecting to not persistent data in database tables, but also to temporally changing data and on-the-fly data manipulation outputs.

The data visualization engine will also need to operate in a manner instructed by the analytics author. Following from out previous example, the author of the diabetes study might instruct the framework to present the data in the form of pie-charts and email PDF versions of the output to specific identities.

G. Continuous Auditing

The continuous auditing module will be responsible for applying audits to the output of analytical executions. These audits are special analytics created in the same way other analytics have been created, but possess the ability to change the context of the audit and expand it whenever certain criteria are achieved. In the analytic presented above, a special audit can be created that will identify inconsistency in the analytic output by comparing patterns over periods of time.

H. Application Scenario

In order to explain the difference between the approach used in this paper and those commonly used in analytics engines currently adopted, an application scenario from real-world requirements is described.

A medical committee clinician in a local hospital wants to measure the effectiveness of the treatment plan from several doctors for inpatients over average length of stay. The clinician will use three analytical data warehousing approaches – the classical approach, the modern state-of-the-art cloud-based approach, and the approach of this paper.

a) The Classical Approach: The steps leading to the proper identification of patients is expressed below, with reference to the executing party:

1. The clinician identifies in the requirement the needed data records.
2. The clinician identifies in the requirement the aggregations and comparison conditions to be evaluated against data from step (1).
3. The clinician submits the information from steps 1 and 2 to the Information team.
4. The information team loads the required data from time periods into medical research data warehouse.
5. The information team prepares the deduced fields and defines the queries to execute against the data
6. The information team loads the results to the visualization software to send to the clinician.

b) The Cloud Analytics Approach: The modern cloud analytics approach is based on loading the data needed for analysis to the private cloud computing service, and applying the analysis*:*

1. The clinician identifies in data schemas required to create the data in the cloud platform
2. The analytics system generates the structure of files to load the data offline, or requires that the information team create local queries to upload the data to the cloud.
3. The clinician identifies in the requirement the aggregations and comparison conditions to be evaluated against the data from step 2.
4. The information team prepares the deduced fields and defines the queries to execute against the data
5. The analytics system generates the visualizations of the results and makes them available for the clinician.

c) The Proposed Approach: The approach proposed in this paper is based on loading (both continuously and intermittently) the performance measures from the environment through standard key-value-date time records. The steps required to perform the analytic are:

1. The clinician creates the analytic using the online cloud-based system in the form of selection of measurement and conditions
2. The clinician executes the analytic by filling in the parameters for the drug, diagnosis and surgery and gets a list of patients as a result

The clinician finds that the analytic just created can be used later on for different diagnosis, drug, and surgery pairs and decides to save it. Another co-researcher later uses this analytics as a starting point for a different diagnosis but adds the gender filtration to show female/male responses to the same treatment.

I. Implementation Methods

The first design principle of the system involves loading continuously produced performance measurements into the core database. The data coming from different measurements is consolidated and identified by its source, measures and performance values and date/time taken. The primary keys for the measurements are labelled as identities in the system, with respective grouping. For example, a patient is an identity, the group is “Patients”, similarly for doctors, diagnoses, surgical operations, etc…

The integration of the various identities into one table results in a comprehensive data loading procedure, but complicates the internal analytical processing of the user queries. To solve the complexity problem, a special query engine was designed to create the complex queries from user input and aggregate the data to produce a solution data-set.

User queries are stored and executed in two phases. The first phase creates the query with variable parameters. The second phase fulfils the query at execution time with parameters input from the user. This provides other users with the ability to re-use existing queries that are solutions to pervious problems, thus achieving collaboration and speeding problem-solving time.

J. Results

The results of the using the system can be divided into three parts.

First in the loading of data, the system was able to incorporate new data groups (identity definitions) without the need to modify its structure.

Second, the ability of researchers to define and implement standard KPI’s cannot be immediately proven without further integration of data-aggregating function into the analytics engine. Advanced functions can be used for solving more complicated KPI's, and this is left for future improvements.

Third, the system was able to produce the data output in a manner that can be consumed by most visualization and charting tools. Advanced toolkits that enrich the experience of users with the resulting data can be integrated into the system, and this also will be done in future enhancements.

V. Conclusion

Integrating disparate EPR systems through a securely available EHR system improves the ability of clinicians to prescribe drugs to patients based on reliable data. However, when new data from patient encounters is added to the EHR, a performance measurement approach improves the linking of data providers to produce a clear analytical view of patient performance, thus leading to a more reliable clinical decision-support.

VI. Discussion

The system can be run in a cloud computing platform. Based on current technology in research trends [3], [4], big-data and cloud-based platforms allow the collaboration of researchers in a secure and reliable computing model. This removes the dependency on local hardware and configurations, and gives researchers the ability to share information in an analytical framework.

VII. Future work

The system should be adapted to the needs of healthcare medical researchers, and for this purpose it will be subjected to extended and daily use by such users in the coming period. The system should be able to enable such users to answer most basic questions regarding their data. KPI's need to groups by complexity, and the ability of the system tested against the more complicated KPI's.

Conflict of Interest

The authors declare that they have no conflict of interest.

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