MEDINFO 2019: Health and Wellbeing e-Networks for All
L. Ohno-Machado and B. Séroussi (Eds.)

doi:10.3233/SHTI190339

Performance Evaluation of Clinical Decision Support Systems (CDSS): Developing a Business Intelligence (BI) Dashboard

Vania Teixeira[a], Analía Mori[a], Andres Usera[a], Juan Carlos Bacigalupo[a], Daniel Luna[b]

[a] *Department of Biomedical Informatics, Universal Soluciones Tecnológicas, Montevideo, Uruguay,*
[b] *Department Biomedical Informatics, Hospital Italiano de Buenos Aires, Buenos Aires, Argentina.*

Abstract

This document describes the development of a Business Intelligence (BI) dashboard for tracking the drug-drug interaction (DDI) alerts implemented as Clinical Decision Support Systems (CDSS) in Electronic Health Records (EHR). CDSS are known for their potential to reduce medical error. The use of requirements in the development of BI dashboards is crucial to obtain successful software. In this work, the requirements were analysed using a score methodology, considering the relevance of the indicators and visualization methods. CDSS effectiveness and acceptance have been questioned, so it is fundamental to monitor their behaviour and performance. The dashboard was designed in order to satisfy the needed indicators. Using BI as a tool for monitoring the CDSS performance made it possible to operationalize the EHR content repository, maximizing the understanding in relation to the override and, by inference, to optimize the CDSS system by opening new lines of work.

Keywords:

Decision Support Systems, Clinical; Drug Interactions, Software

Introduction

Medical errors are a serious problem for the health system. The stages defined in the medication cycle are prescription, transcription, dispensation, administration, and monitoring. It is known that at least 50% of errors are generated during prescription. This can be due to lack of information about the medication used or the patient's background [1,2].

Clinical Decision Support Systems (CDSS) are recognized as a significant contribution to structured electronic prescription. They provide information about a specific need and responses that are similar to human reasoning. While there are no clear short-term benefits, previous work has shown that warning systems could reduce medical errors by 81% [3]. CDSS are able to identify up to 89% of medication-related errors and prevent 23% of them [4].

Despite providing warnings about potential harm and the initial promising outcomes, users often do not adhere to CDSS messages, overriding 49% to 96% of the time [5–7]. Reasons for nonaderance are diverse and reflect the complexities of clinical practice, where usually there is more than one correct decision when managing a specific case. Moreover, design and implementation could lead to ineffective alerts. Redundant alerts and those with lack of scientific evidence or usability are usually overridden and cause alert fatigue [8].

It is widely recognized that CDSS are based on rigorous scientific evidence, so that the advice they provide is equal or superior to the average in a health care system. However, contrary to other analytic decision software that is part of a medical device (for example, automatic infusion pumps), CDSS have no regulatory standards, and like any other software, they have flaws [9].

In this context, it is necessary to deploy a monitoring system during the implementation and ongoing use of CDSS. Not only would such monitoring allow design validation, detection usability problems, and inconsistencies in the knowledge base and rules, but it also grants a cycle of continuous improvement in order to optimize the tool.

In the last decade, there has been significant growth in the literature on the use of Business intelligence (BI) in the healthcare field. Electronic Health Records (EHR) contain massive clinical datasets. BI emerged as a technological tool with the potential to collect, manipulate, and analyse the dataset in the EHR repository in order to improve the evidence-based decisions and quality practices [10–12].

As was explained in our previously published report, CDSS of drug-drug interaction (DDI) alerts have been implemented in a Uruguayan healthcare network [13].

The purpose of this paper is to describe the development of a CDSS-DDI dashboard for a federated Health Information System (HIS) in Uruguay using Business Intelligence (BI) tools.

Methods

Definition of Key Progress Indicators

Previous to the availability of BI tools, CDSS alerts were manually monitored by the medical informatics staff. Manual monitoring was based on the team objectives, the literature and their knowledge of CDSS use. Different Key Progress Indicators (KPI) of that manual monitoring using Microsoft Excel where then the basis for the initial BI dashboard.

The objective of the KPI is to monitor the user's alert fatigue and alert adequacy, as well as design and usability aspects.

DDI alerts provided by the Buenos Aires Italian Hospital (HIBA) web service have been used in our system for more than two years and have allowed us to successfully collect valuable data. However, due to the amount of information generated, conventional tools are inefficient for data analysis and reporting.

In 2018 with already defined indicators, we incorporated a BI tool, Tableau, for the CDSS dashboard construction.

CDSS Dashboard Requirements

The CDSS dashboard requirements were established in agreement with the BI developer. The requirements were designed regarding priority levels from 0 (not a priority) to 5 (very high priority).

System Architecture

Our Healthcare Data Warehouse (DW) was built using Pentaho Data Integration (PDI) to extract the relevant data from the EHR and Enterprise Resource Planning (ERP). Both use DB2 as a transactional database. For the DW a combination of Postgres and MySQL was used.

The DataMart for CDSS alerts is a subset of this Data Warehouse. Each service, databases or Extract-Transform-Load (ETL) tools, runs as a Docker Container in a cluster. This allows optimizing resource allocation during the ETL process. For the consumption of this DataMart, Tableau was chosen, which is based on VizSQL, a proprietary language that integrates SQL data consumption with graphical visualization grammar. This allows postponing the actual specification of the final use of a specific element. The advantages of Tableau Hyper were used in the memory data engine to speed up analytical query processing. A Drug ID could be used as a dimension or measure filter (distinct count) by the end user in a very intuitive way. No SQL, no MDX, no extra burden and no need to wait for a new logical cube modification.

The validation of the cube and its data were carried out in iterative cycles with the medical informatics team and the BI developer, based on the comparison of previous results with some of the basic KPI obtained by queries and processed in Microsoft Excel.

As an initial stage, it was defined that the dashboard should not be integrated with the Electronic Medical Record (EMR) application or in other medical management tools but that it would be accessed from Tableau by the medical informatics team.

Results

Definition of Indicators

Some Key Progress Indicators (KPI) were previously defined and manually measured twice a year to monitor the clinician's behaviour and CDSS performance. The established KPI were:

- Number of CDSS-DDI alerts per 1000 prescriptions
- Number of CDSS-DDI per 1000 patients
- Number of CDSS-DDI per 1000 medical consults
- % of overridden CDSS-DDI alerts

Definition of Requirements

Considering the KPI and other possible data to be retrieved such as medical specialities, alert incidence per DDI pair and override justifications, a list of requirements for the BI dashboard was developed. The requirements with priority level over 3 where covered in the dashboard. Table 1 shows a description of the requirements with their priority assessment.

Table 1– BI dashboard requirements

Priority (0 – 5)	Requirement	Description
5	EHR as a source of information	Exporting data from EHR of three healthcare centres in Uruguay.
4	Automatic update	Real-time update.
5	Remote access	Provide access to specified dashboards.
4	Ad-Hoc Calculations	Related to the predefined indicators and metric.
5	Information retrieval	Data reporting based on dates.
4	KPI visualization	Real-time display of KPI evolution.
4	Advanced Chart Types	Ad-Hoc report with the selection of multiple dimensions and metrics: number of alerts, override justifications, DDI pairs, override, medical specialities.
5	Dataset exploration	Explore one CDSS case to audit the EMR.
5	Data security	Sensitive patient data should remain confidential.

Data Validation

Data architecture issues such as semantics, integrity, and security were analysed. A semantic standard was established to define, for example, what was understood by "Consult," what type of health professionals could be responsible for the consult, if it included a prescription or not, and if there was an alert or not. Regarding data integrity, all the components were evaluated, leading to the detection of some initially incomplete logs. For example, when the clinician decided to override the alert, the active drug information was not recorded in the data warehouse. For data security, data items that should be visible or editable according to the user´s profile and license duration were assessed.

Design and Development of the Dashboard

The requirements were embedded in the software as three modules:

1. KPI
2. Overall CDSS performance
3. Detailed CDSS performance

Module 1 was deployed as line charts. Module 2 (Figure 1) was developed in order to monitor the rate of prescriptions with DDI alerts, the rate of overridden or accepted alerts and the quantity and type of justifications for the override. Module 3 (Figure 2) was designed as an advanced chart to combine and visualize multiple dimensions and their relation (quantity of alerts, override percentage, medical specialities and DDI pairs involved).

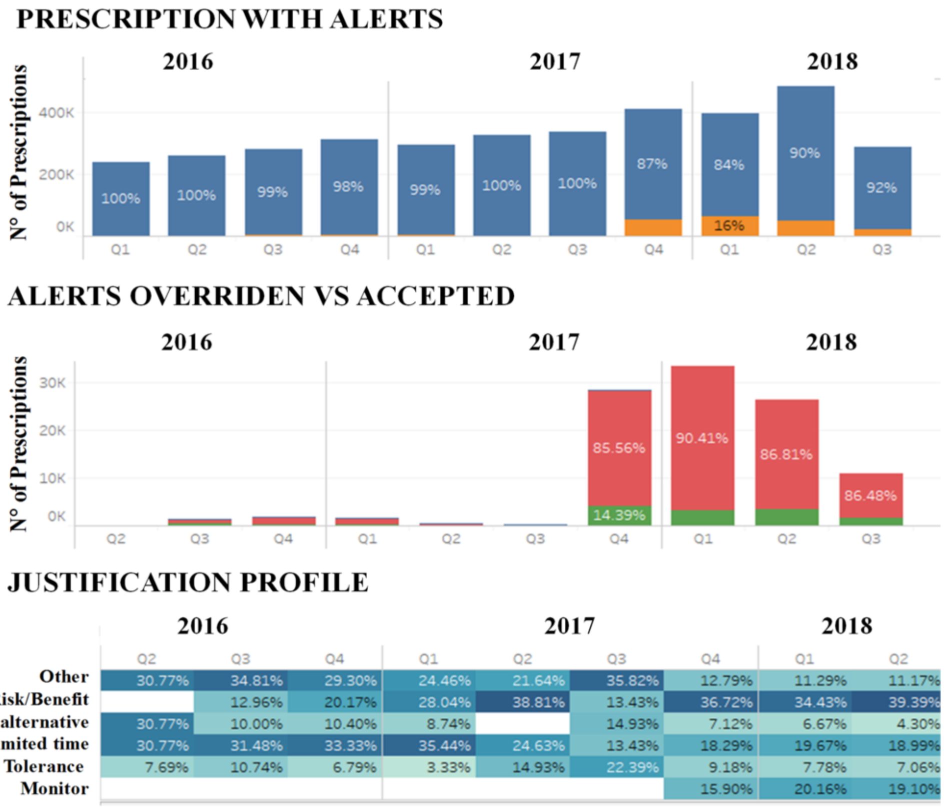

Figure 1- Module 2: The figure shows prescriptions with (orange) and without (blue) CDSS alerts, overridden (in red) vs accepted (in green) alerts and the justification profile for clinician alert override (higher percentages in darker tones).

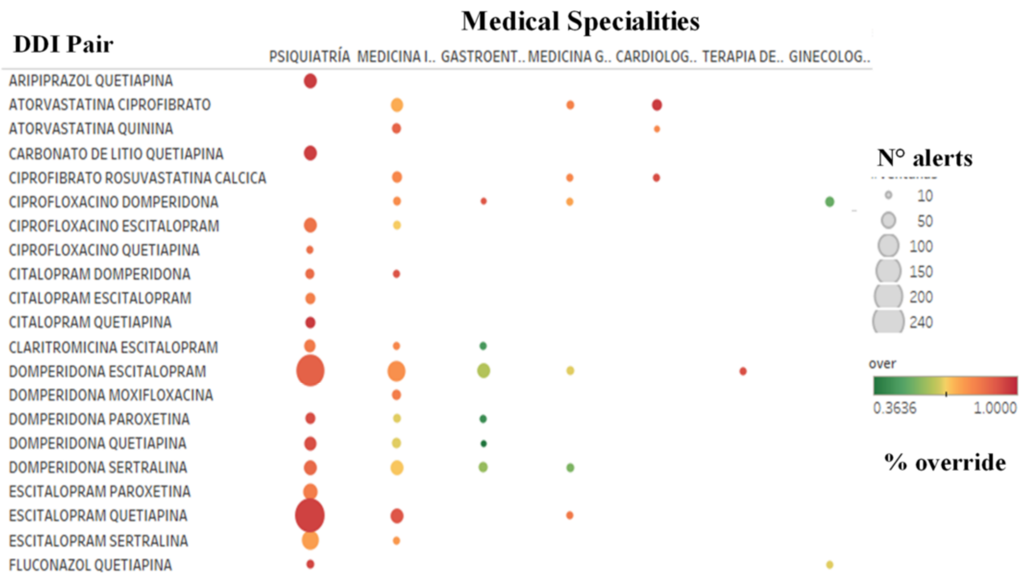

Figure 2- Module 3: medical specialities are in the x-axis and DDI pairs in the y-axis.The quantity of alerts is represented in the size of the spheres. The override percentage is represented in a colour range from green (lower override %) to red (higher override %

Discussion

CDSS can reduce errors and prevent the harm caused by them by alerting the clinicians. However, their effectiveness and acceptance have been questioned. The recommendation to improve these issues respecting the five rights is: "CDSS should be designed to provide the right information to the right person in the right format through the right channel at the right time" [14,15]. In order to achieve the five rights, it is fundamental to monitor CDSS behaviour and performance.

The EHR is a repository where the clinical data is stored, some structured and others unstructured. Data mining technologies are necessary to extract quality data and inference rules from the information stored in order to provide CDSS real-time monitoring. The benefit in employing BI is that it works with unstructured data while other tool doe not [16].

According to the literature, the use of BI technology with EHR allowed operationalizing the data warehouse of the EHR to improve the quality and safety delivered by the healthcare system [11,12,17,18]. This improvement is due to the potential of BI to support evidence-based practice and decision-making process [12].

To the best of our knowledge, there is no study regarding the use of BI for tracking CDSS. However, BI seems like a valid alternative to efficiently and effectively monitor CDSS. To test the integration of these technologies on a first pilot scale, a BI dashboard was developed for the previously implemented DDI alert system [13].

The BI dashboard for CDSS-assisted DDI alerts was developed as customized software. It was designed in order to satisfy the needed KPI. Before the dashboard, KPI were measured once or twice a month through a manual process that included Microsoft Excel spreadsheet calculations dependent on data requests to the engineer. The KPI were defined to track the prevalence of CDSS alerts and overrides. In order to have the number of alerts independent of the number of prescriptions, persons, and consults, CDSS prevalence was settled in relation to these attributes. The acceptance of the CDSS alerts was determined by the override percentage.

The use of requirements in the developing of BI dashboards has been reported as a crucial issue to obtain successful software [19,20]. In this work, requirements were analysed using a score methodology [20], considering the relevance of the indicators and visualization methods. The requirement analysis was outlined with a mixed approach that considered the goal of the tool, the characteristics of the user, and the nature of the information. The chart types were selected to visualize several variables in the same chart in order to obtain a process behaviour overview. At the same time, it enables the evaluation of data below or above the specified threshold.

BI is only useful if the information provided is built on quality-assured data. Otherwise, logic and inference rules can be flawed [12,21]. Hence, data validation is a critical issue even though it is not always considered by software developers. During data validation for this project, incomplete logs in the data warehouse were detected, caused by the lack of knowledge of their relevance by the EHR developers. Semantics and security were also reviewed. When CDSS-DDI are implemented in multiple healthcare centres, it important to recognize that one data field can have several meanings, especially if the EHR has several types of users. Unless the data field has the same meaning, it is impossible to integrate or communicate efficiently across the organization(s). Regarding data security, it is relevant to consider that the information managed is related to the patients and, in this way, it is sensitive information. Previous reports have described techniques to adopt secure barriers for EHR [22]. For this dashboard, we adopted techniques such as access control and data encryption.

In the current work, a modular approach was used to develop the DDI dashboard. Since it was important to have rapid visualization of the system behaviour, three modules were designed. The modules varried based on their level of specificity: the first is aimed for large-scale CDSS monitoring with KPI, the second provides in-depth analysis, and the last module mixes several variables in one chart to simultaneously convey large-scale and granular information. The indicators previously tracked manually, new indicators, and measurements that were previously unable to be processed manually were included in the development of the dashboard.

The increased autonomy and flexibility of users to get information and the efficiency and quality of the reports are only some of the benefits of using the developed dashboard. For example, the dashboard enables detection of trends in alerts overridden by the clinicians so the usefulness of these alerts can be analysed.

On the other hand, several challenges have been described in the literature for the appropriate integration of BI with the EHR. These were mainly non-technical factors such as organizational issues and lack of governance [23,24]. In this work, the most noticeable challenges were those related to data architecture.

Limitations

The current work has faced limitations related to data architecture. As mentioned above, initially, some crucial information for the dashboard was incomplete in the data warehouse. A second issue was to join data that, historically, were in separate data silos.

Future Lines

Considering the benefits obtained with this initial dashboard, the scope will be extended to other CDSS alerts and implemented in the EHR. Furthermore, based on the findings of this work, the data integrity of the EHR repository is being thoroughly reviewed. Based on last year's monitoring, a work line was initiated to optimize some drug pair rules in order to reduce the rate of overrides. Finally, the application of BI to other issues related to healthcare decision-making processes has been triggered.

Conclusion

The development of a BI dashboard for tracking CDSS-assisted DDI alerts in an EHR was described throughout this document. Alongside the definition of indicators and requirements, data architecture was crucial, the latter being the most challenging issue during development.

Using BI as a tool for CDSS performance monitoring made it possible to operationalize the EHR content repository, to maximize understanding of overrides, and to optimize the CDSS.

Acknowledgements

We would like to thank Jose Abadie and Rodrigo Martinez for their assistance with the data warehouse in the EHR and Álvaro Tamborindeguy for supporting the development of the Business Intelligence area at Universal Soluciones Tecnológicas. We would also like to thank all the members of the Biomedical Informatics Department of Hospital Italiano de Buenos Aires.

References

[1] L.L. Leape, D.W. Bates, D.J. Cullen, J. Cooper, H.J. Demonaco, T. Gallivan, R. Hallisey, J. Ives, N. Laird, and G. Laffel, Systems Analysis of Adverse Drug Events. ADE Prevention Study Group., *JAMA* **274** (1995) 35–43.

[2] L. Daniel, H. David, G. Schpilberg, Mónica Hernandez, E. Soriano, M. Martinez, A. Gomez, G. Cifarelli, and F. Bernaldo de Quiros, Validación de la base de conocimiento de un sistema notificador de interacciones farmacológicas, *V Simp. Informática En Salud* ***31*** (2002).

[3] D.W. Bates, J.M. Teich, J. Lee, D. Seger, G.J. Kuperman, N. Ma'Luf, D. Boyle, and L. Leape, The Impact of Computerized Physician Order Entry on Medication Error Prevention, *J Am Med Inform Assoc* **6** (1999) 313–321.

[4] D.W. Bates, A.C. O'neil, D. Boyle, J. Teich, G.M. Chertow, A.L. Komaroff, and T.A. Brennan, Potential Identifiability and Preventability of Adverse Events Using Information Systems, *J Am Med Inform Assoc* **1** (1994) 404–411.

[5] H. Van Der Sijs, J. Aarts, a Vulto, and M. Berg, Overriding of Drug Safety Alerts in Computerized Physician Order Entry, *J Am Med Inform Assoc* (2006) 138–148.

[6] A.B. McCoy, E.J. Thomas, M. Krousel-Wood, and D.F. Sittig, Clinical Decision Support Alert Appropriateness: A Review and Proposal for Improvement, *Ochsner J* **14** (2014) 195–202.

[7] K.C. Nanji, D.L. Seger, S.P. Slight, M.G. Amato, P.E. Beeler, Q.L. Her, O. Dalleur, T. Eguale, A. Wong, E.R. Silvers, M. Swerdloff, S.T. Hussain, N. Maniam, J.M. Fiskio, P.C. Dykes, and D.W. Bates, Medication-Related Clinical Decision Support Alert Overrides in Inpatients, *J Am Med Inform Assoc* **25** (2017) 476–481.

[8] J.S. Ancker, L.M. Kern, E. Abramson, and R. Kaushal, The Triangle Model for Evaluating the Effect of Health Information Technology on Healthcare Quality and Safety, *J Am Med Inform Assoc* 19 (2012) 61–5.

[9] E.H. Shortliffe, and M.J. Sepúlveda, Clinical Decision Support in the Era of Artificial Intelligence, *JAMA*. **320** (2018) 2199–2200.

[10] M. Reimers, Leveraging Business Intelligence to Make Better Decisions: Part I, *J Med Pract Manage* **29** (2014) 327–30.

[11] W. Zheng, Y.-C.J. Wu, and L. Chen, Business Intelligence for Patient-Centeredness: A Systematic Review, *Telemat Inform* **35** (2018) 665–676.

[12] W. Bonney, Applicability of Business Intelligence in Electronic Health Record, *Procedia - Soc. Behav Sci* **73** (2013) 257–262.

[13] V. Teixeira, L. Rubin, R. Rebrij, A. Tamborindeguy, R. Martinez, J.C. Bacigalupo, and D. Luna, Implementation of an Outsourced Transnational Service of Clinical Decision Support System, *Stud Health Techno. Inform* **245** (2017) 1384.

[14] G.L. Alexander, Issues of Trust and Ethics in Computerized Clinical Decision Support Systems, *Nurs Adm Q* **30** (2006) 21–29.

[15] C.B. Byrne, D.S. Sherry, L. Mercincavage, D. Johnston, E. Pan, and G. Schiff, Advancing Clinical Decision Support - Key Lessons in Clinical Decision Support Implementation, 2010.

[16] J. Lamont, Business Intelligence: The Text Analysis Strategy, *KM World* **15** (2006) 8–10.

[17] P. Brooks, O. El-Gayar, and S. Sarnikar, A Framework for Developing a Domain Specific Business Intelligence Maturity Model: Application to Healthcare, *Int J Inf Manage* **35** (2015) 337–345.

[18] R. Gaardboe, T. Nyvang, and N. Sandalgaard, Business Intelligence Success Applied to Healthcare Information Systems, *Procedia Comput Sci* **121** (2017) 483–490.

[19] N.H.Z. Abai, J.H. Yahaya, and A. Deraman, User Requirement Analysis in Data Warehouse Design: A Review, *Procedia Technol* **11** (2013) 801–806.

[20] P. Rezaei-hachesu, T. Samad-Soltani, S. Yaghoubi, M. GhaziSaeedi, K. Mirnia, H. Masoumi-Asl, and R. Safdari, The Design and Evaluation of an Antimicrobial Resistance Surveillance System for Neonatal Intensive Care Units in Iran, *Int J Med Inform* **115** (2018) 24–34.

[21] J. Jordan, and C. Ellen, Business Need, Data, and Business Intelligence, *J Digit Asset Manag* **5** (2009) 10–20.

[22] C.S. Kruse, B. Smith, H. Vanderlinden, and A. Nealand, Security Techniques for the Electronic Health Records, *J Med Syst* **41** (2017) 127.

[23] J. Glaser, and J. Stone, Effective Use of Business Intelligence, *Healthc Financ Manage* **62** (2008) 68–72.

[24] W. Yeoh, and A. Koronios, Critical Success Factors for Business Intelligence Systems, *J Comput Inf Syst* **50** (2010) 23–32.

Address for correspondence

vania.teixeira@universal.com.uy