

Business Intelligence Platform for Nosocomial Infection Incidence

Jose Machado*, Eva Silva and Antonio Abelha

University of Minho, ALGORITMI Research Center, Portugal; jmac@di.uminho.pt, evaalexandra.psilva@gmail.com, abelha@di.uminho.pt

Abstract

Background/Objectives: Nosocomial infection prevention is essential for patients' safety and well-being. It can be efficiently performed through the analysis of the information available. With this analysis, it is possible to build knowledge that helps to identify the risk factors and the activities related to the nosocomial infection occurrence and it also allows characterizing the infection. **Methods/Statistical Analysis:** This paper presents a Business Intelligence (BI) system built to allow the study of nosocomial infection incidence in the Medicine Units of Centro Hospitalar do Porto (CHP), a hospital center in the north of Portugal. This BI platform is responsible for presenting nosocomial infection indicators. **Findings:** This platform enables to query important information and to analyze it, supporting healthcare professionals in their decisions. The knowledge obtained by this analysis allows preventing, monitoring and reducing nosocomial infections. So, the system acts as a Clinical Decision Support System (CDSS) capable of increasing patient safety and well-being. The platform developed shows that, for example, in 2013 the rate of nosocomial infection in CHP Medicine Units varied between 9.43% and 12.95% and the respiratory and the urinary tract infections were the most frequent nosocomial infections. **Application/Improvements:** This work and the platform developed demonstrate that BI technology can be applied to healthcare with utility.

Keywords: Business Intelligence, Clinical Decision Support System, Data Warehousing, Nosocomial Infection, On-Line Analytical Processing

1. Introduction

A nosocomial infection is an infection that occurs during the 48 hours after the patient's hospitalization, during three days after his discharge or during the 30 days that follow a surgery and it was not present or in incubation in the moment of the patient's admission^{1,2}. These infections also include healthcare institutions' occupational infections³.

There are several factors that contribute to the acquisition of a nosocomial infection, for example the patient's age, his/her immune status, the hospitalization time, the administration of antibiotics, the diagnostic methods used, etc.². Moreover, great amounts of microorganisms exist in healthcare units and, thus a small fail in the

infection prevention programs can easily contribute to the occurrence of an infection.

Nosocomial infections have a great impact on patients' morbidity and mortality, especially in intensive care units where the nosocomial infection rate is significantly higher because of the compromised immune systems of the patients hospitalized in these units and the invasive procedures performed there^{1,2}. Apart from that, a patient with a nosocomial infection stays a longer time in the hospital, resulting in additional costs for the healthcare organization^{1,2}. Thus, the control and prevention of nosocomial infections is essential for healthcare institutions.

These infections can be used to evaluate the quality of the care delivered in the healthcare organizations and can be effectively controlled, prevented and treated through

*Author for correspondence

the application of specific measures. According to¹, it is proved that about one third of nosocomial infections can be prevented with the implementation of appropriate infection control measures. Besides the implementation of these measures, healthcare institutions must monitor continually the results associated with the infection control programs, through systematic data collection and Key Performance Indicators (KPIs) analysis⁴.

These KPIs should help to summarize and understand important factors present in the data, such as the nosocomial infection rate and the factors that contribute to its occurrence. The analysis of these indicators is then capable of helping healthcare professionals in the identification of critical processes and activities that occur in the healthcare environment, clinical specialties where the infection rate is higher and where the implementation of infection control measures is essential and urgent for patients' safety. Therefore, these KPIs allow healthcare professionals to plan and implement specific and efficient infection control measures in order to reduce nosocomial infection incidence in these processes and activities in order to improve the quality of the health care^{5,6}.

BI technology can be applied to healthcare to generate and present indicators for the nosocomial infection incidence study because it allows the efficient treatment and analysis of data. Thus, the information presented by a BI system can be used to support decision-making in the healthcare organization.

The present work arises from the need to constantly monitor the healthcare environment to apply specific measures to prevent and reduce nosocomial infection rate, and from the possibility of using BI technology to treat and analyze clinical data. The motivation of this work is also related to the healthcare professional's need to take fast and reasoned decisions to improve the productivity and efficiency of the healthcare organization and the quality of the rendered care.

This work is capable to help healthcare professionals in the nosocomial infection study and infection related decision-making through data analysis. The main goal is to develop a BI platform for the study of nosocomial infection incidence in the Medicine Units of CHP. This platform is part of a BI system that extracts data from CHP databases and stores them in a Data Warehouse (DW). After that, a BI tool extracts KPIs from the DW and it presents the extracted information in the BI platform.

Besides the introduction, this article includes five more sections. The first is related to the background and pro-

vides an overview of the BI technology and BI systems. The second section shows the benefits of the implementation of BI in healthcare. The third section explains the case study of this work, the study of nosocomial infection incidence in the Medicine Units of CHP, as well as the motivation and the expected benefits of this work. It discusses the utilization of BI in the study of nosocomial infection. The solution proposed to explore the case study, the methodology used to implement that solution are presented and discussed in this section. The fourth section discusses the main results obtained by the implemented BI system. The fifth section suggests some future work measures and the last section presents the main conclusions of the work.

2. Background

2.1 Business Intelligence

The term BI was introduced by Howard Dresner in 1989 that described it as a set of concepts and methods used to improve the decision making process on a business by using computerized systems^{7,8}.

A BI system is a data-driven Decision Support System (DSS) that includes a set of methodologies and tools capable to collect, integrate, analyze and present data about the activities and processes that happen inside an organization. Its main goal is to promote more informed, faster and consequently, better decisions⁹⁻¹². A BI system must integrate huge amounts of data coming from different heterogeneous data sources and provide the tools for the analysis of those data¹³. Therefore, these systems integrate data coming from different disparate sources and convert them into a unified format. After that, the data are loaded to a DW and can be explored, analyzed and presented with BI tools.

BI technology improves the quality and the quickness to obtain the information in order to consider it in decision-making process¹⁴. Thus, BI systems provide timely and relevant information to help the decision-making process^{15,16}. So, they are a competitive advantage for the organization that implements them.

A typical BI system is composed by a DW and software tools to implement the Extract Transform Load (ETL) process, On-line Analytical Processing (OLAP) data analysis, querying and reporting tools and Data Mining tools^{9,17}.

2.2 Data Warehousing

The DW is the core component of a BI system. This component is a repository of data coming from different

sources that is used to store information about the activities of an organization¹⁸.

The integration of relevant data coming from different sources in a single location and format contributes to improve the speed and efficiency of the knowledge discovery process and that contributes to better, faster and more reasoned decisions¹¹.

A DW is a collection of data that is subject-oriented, integrated, non-volatile, varies in time and is capable supporting decision-making¹⁸. It is important to note that these properties distinguish DWs from operational databases. As opposed to operational databases, a DW is non-volatile and, thus its data are not modified or deleted, but they are added to the DW when they enter the system. In this way, DWs vary in time. They allow the temporal storage and analysis of data. Consequently, the temporal analysis of data allows the presentation of information about the evolution of the activities and processes that occur inside the organization in a certain period of time. Moreover, normally DWs are bigger than operational databases and are specially developed for decision support and it is because of that they can be seen as decision support databases^{19,20}.

The data existent in a DW are available to be explored, analyzed and presented with BI tools, OLAP tools, data mining tools, querying and reporting tools or dashboard tools, just to refer a few²¹.

Data can also be stored in smaller subject-oriented repositories known as data marts. These data marts are structures that have smaller amounts of data than DWs. They allow an analysis more oriented to their goals because they have only data about a certain subject²². So, the data marts performance in queries can be much higher than the one from DWs.

In the data warehousing field two different and equivalent approaches for building a DW exist: Ralph Kimball's paradigm and Bill Inmon's paradigm. According to Inmon's paradigm, the DW is built following a top-down approach where the data are extracted from operational data sources and stored in a single database. Data extractions from this database allow the creation of data marts. On the other hand, Kimball paradigm states that the DW is built considering a bottom-up approach because operational data is used to feed the individual data marts and the DW is the aggregation of these data marts²³.

Normally a DW stores data in a dimensional model and it allows a more efficient representation of the data used

by BI tools for decision support^{22,24}. Dimensions and fact tables compose a dimensional model. The fact tables store facts and each fact is associated with a set of dimensions through foreign keys^{25,26}. The dimensions characterize the facts, give them context and make them unique and they are composed by a set of attributes related in a hierarchical fashion and that are used to constrain facts²⁷.

Usually the dimensional model is organized in a star schema in which the fact table is at the center of the model and it is associated with several dimensional tables. There are also more complex schemas such as the snowflake schema, where a dimension can have sub-dimensions, or the constellation schema, where several fact tables can share one or more dimensions²⁷.

DW's are periodically refreshed through ETL and the frequency of the application of ETL depends on the needs of each organization²⁴. ETL is the process used in data warehousing to extract data from different operational data sources, integrate them and convert them into an unified format according to the schema defined for the DW, and load them into the DW¹⁹. ETL is a critical stage for the efficient loading of huge amounts of data to the DW and to find and correct data quality related problems, ensuring, so, the quality of the data stored in the DW²⁷. This is the most complex and time consuming activity in the implementation of a DW^{19,28}. Interoperability is essential to allow for an efficient and complete ETL process. Intelligent agents play also an essential role in interoperability in general, and ETL in particular²⁹.

2.3 On-line Analytical Processing

OLAP is one of the most used techniques to access and analyze data stored in a DW or data mart²⁸. According to the OLAP Council³⁰, OLAP technology "enables analysts, managers and executives to gain insight into data through fast, consistent, interactive access to a wide variety of possible views of information". The data to analyze with OLAP are organized in OLAP cubes that allow the visualization of the information according every dimension of the data model²². This format allows the fast analysis of data⁹.

OLAP tools support real-time analysis, allowing the user to make more structured and faster searches to generate graphs and tables⁹. According to user's analysis needs, these tools allow him/her to perform operations on data such as drill-down, roll-up, slice and dice and pivot to perform a deeper data analysis^{24,26,27}.

3. Benefits of Business Intelligence in Healthcare

Nowadays, with the implementation of Information Technologies in healthcare institutions, the amount of data collected has exponentially increased³⁰. These data contain huge amounts of relevant and useful information, essential to support the clinical and administrative decision making process^{30,31}. So data management is essential for healthcare organizations. Besides that, the amount and complexity of these data makes them hard to process and analyze in useful time without using automated methods. Thus, the utilization of automated methods to extract information from data has become a necessity.

The implementation of BI systems is an efficient and adequate method to integrate and explore clinical data collected by healthcare institutions. This technology gives utility to healthcare data using it to decision support. The information extracted from data by these systems may be very relevant to identify, characterize and monitor the activities and processes that happen in the healthcare environment. Therefore, it is possible to identify problems and improvement opportunities.

So, BI implementation in healthcare institutions may improve the quality and the safety in the delivered care. It also allows efficiency and financial performance improvements of the healthcare organization. In addition, it contributes to the adoption of evidence-based practice, once this technology helps managers and healthcare professionals to make better decisions, giving them access to relevant information about the activities and processes that occur inside the organization^{9,31}.

Moreover, the healthcare environment is very complex and it is always in constant change, so the utilization of BI tools to support the decision making process is crucial for making good and more reasoned decisions.

For patient's safety and well-being, it is crucial to prevent and control nosocomial infections. Data analysis is an efficient method to characterize the nosocomial infection incidence. It identifies activities and risk factors with great impact on the occurrence of these infections. So, BI concepts and tools can be applied to nosocomial infection data to extract relevant information for nosocomial infection in order to facilitate the decision making process.

4. Case Study: Nosocomial Infection Incidence in CHP

In this work a BI platform is implemented in CHP to study of nosocomial infection incidence in the Medicine Units of this hospital center. The platform presents relevant KPIs that are extracted from CHP's data. It helps healthcare professionals to identify important risk factors and parameters that allow the characterization of the nosocomial infection incidence in CHP's Medicine Units.

4.1 Motivation and Benefits of the Nosocomial Infection BI Platform

The motivation for the development of the BI platform comes from the need to help healthcare professionals to perform their jobs in the analysis of data for the study of nosocomial infection incidence. Through the platform they can understand better, monitor and analyze the evolution of nosocomial infections. Thus, they can take better and more reasoned nosocomial infection related decisions. They also can define specific nosocomial infection control measures, more focused on the real needs of CHP's Medicine Units.

Besides that, the platform also gives utility to the great amount of data collected in CHP. It allows the creation of useful knowledge with that data, optimizes and automates the process of extracting information from data. It ensures that the information be available in the decision making moment.

Therefore, the BI platform benefits CHP in the study of nosocomial infection because it allows:

- the analysis and monitoring of nosocomial infection incidence and consequently the identification of processes and activities with great impact on the occurrence of nosocomial infections;
- the definition and implementation of specific and adequate infection control programs and the evaluation of the measures implemented with those programs;
- a stronger support in decision making, by organizing and providing dispersed and relevant information;
- to perform simple and faster clinical data analysis and gives healthcare professionals a bigger autonomy and flexibility in data analysis.

For the development of the BI platform the implementation of a whole BI system in CHP was needed. The BI system applies BI methods and tools to extract and

treat data, generate a set of nosocomial infection KPIs and present these indicators in the platform.

4.2 Kimball's Methodology to Implement the BI System

To implement the BI system Ralph Kimball's methodology for the implementation of data warehousing and BI systems was used (Figure 1). This methodology is the most widely known methodology for this type of system and it indicates the flow of activities necessary for the implementation of these systems.

According to Kimball and Ross²⁵, a set of parallel and sequentially activities must be followed:

- **Project Planning:** at this stage the scope of the project was defined as the study of nosocomial incidence in CHP through the implementation of a BI platform; the activities to execute during the implementation of the project were also defined and planned.
- **Project Management:** this activity was performed during the entire project in order to identify eventual problems in its implementation.
- **Business Requirements Definition:** at this stage the nosocomial infection KPIs to present in the BI platform were defined according to the needs of the study.

This last activity originates three parallel tracks:

- **Technology track:**
 1. **Technical Architecture Design:** at this stage the system architecture was designed considering the defined business requirements and the needs of its users.
 2. **Product Selection and Installation:** this activity corresponds to the selection and installation of the software needed and most suitable to implement the system. In this work, an Oracle Database Management System was used. Oracle SQL Developer was used to

mediate the access to data in the database. As BI tool the Pentaho Community Edition, an open source tool, was used to extract and present information.

- **Data Track:**

1. **Dimensional Modeling:** at this stage the dimensional model for the DW was designed through the identification of the facts and dimensions necessary to obtain the desired KPIs.
2. **Physical Design:** this activity corresponds to the physical implementation of the dimensional model in the database.
3. **ETL Design and Development:** ETL procedures were created to populate and refresh the DW with CHP database data. These procedures include the transformation and cleaning of data in order to make them suitable for the schema defined for the DW that will be accessed by the BI tool.

- **BI Applications Track:**

1. **BI Application Design:** the BI platform features were defined considering the healthcare professionals' needs and the desired results with the implementation of the system.
 2. **BI Application Development:** at this stage the platform was developed with Pentaho Community Edition.
- **Deployment:** the three parallel tracks converge to this activity. It is necessary to plan this activity in order to have a good integration of all system components.
 - **Maintenance and Growth:** the system was implemented considering the eventual need of its expansion or modification to keep it actual and adequate to CHP reality. These two activities ensure that and they are performed to keep the system performing optimally.

4.3 Data Characterization

In this study data from 2013 recorded with the nosocomial infection forms used CHP are used. So the analysis includes only the year of 2013. Moreover, the study only considers data from the Medicine Units of CHP, which means that only data from the medical specialties Medicine A, Medicine B and Medicine C are used.

The nosocomial infection forms used in CHP are filled by physicians at the moment of discharge and collect important information to understand and study the incidence of nosocomial infection in this healthcare

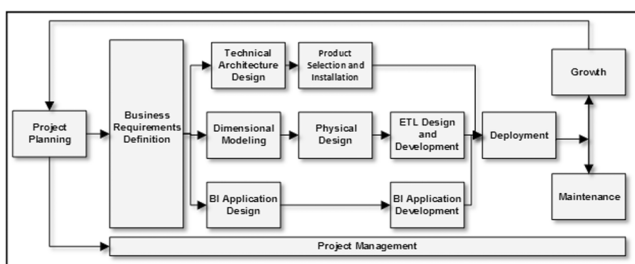


Figure 1. Kimball's methodology for implementing data warehousing and BI systems (adapted from²⁵).

institution, such as the occurrence of a nosocomial infection, the period of hospitalization, the invasive devices used at that time, the treatments applied to the patient, the antibiotics administered, the health status of the patient, the diagnosis made, etc.

During the studied year and for the medical specialties considered in the analysis 2118 forms of nosocomial infection were recorded in CHP's databases. From that 2118 forms only 1669 were correctly finished and, thus, contain information about the occurrence or not of a nosocomial infection. From that 1669 forms only 173 are effectively associated with the occurrence of an infection.

4.4 Nosocomial Infection Key Performance Indicators

In this work nosocomial infection KPIs were used. They allow the identification of risk factors and important parameters to characterize nosocomial infection incidence. Three groups of indicators were used. The group of indicators Studied Population allows the characterization of the population in the study. It analyses a set of general information about the nosocomial infection forms, such as the capacity of the service (number of beds available), average of hospitalization days, discharged patients, total of started nosocomial infection forms and percentage of nosocomial infection forms correctly filled and finished. The indicators Intrinsic Risk Factors per Service evaluate the relationship between certain risk factors such as coma, diabetes, alcoholism, malnutrition, and the occurrence of nosocomial infections. The number of patients with each risk factor, the number of patients with the risk factor and a nosocomial infection and the percentage of nosocomial infections for each risk factor are estimated. Moreover, Extrinsic Risk Factors per Service is a group of nosocomial infection indicators that studies the influence of certain extrinsic risk factors, *i.e.*, invasive devices, in the occurrence of nosocomial infections. The invasive devices considered in this work are some forms of catheterization (peripheral catheter, urinary catheter and central catheter) and some forms of intubation (nasogastric intubation and nasotracheal intubation). The number of patients with each invasive device, the number of infections related to each device and the percentage of infections for each device are calculated. The group of indicators Infections per Type and Service characterizes the nosocomial

infection incidence through the calculation of nosocomial infections per type of infections, the number of nosocomial infections and estimates the rate of nosocomial infection. The types of infection considered are sepsis, respiratory tract infection, urinary tract infection and others.

4.5 Business Intelligence System for Nosocomial Infection Study

The BI system developed for the study of nosocomial infection incidence in CHP (Figure 2) follows an architecture composed of three levels. In the first level are the databases that store the relevant data for the study. The second level is the DW of nosocomial infection, composed by two data marts that are populated with ETL procedures executed on the data sources from the first level. The third level is a BI platform that presents the nosocomial infection KPIs extracted from the data of the data marts.

4.5.1 Data Warehouse

The nosocomial infection DW was implemented considering Ralphs Kimball paradigm. It is formed by two data marts: one to represent the indicators that characterize the population in study and the other to represent all the other indicators. These data marts are implemented using a dimensional model that was defined considering the needs of the system and the KPIs to extract from it. Both data marts follow a star schema configuration.

After the definition of the dimensional model, the different fact and dimension tables defined were created in the database and populated. Before being loaded to the

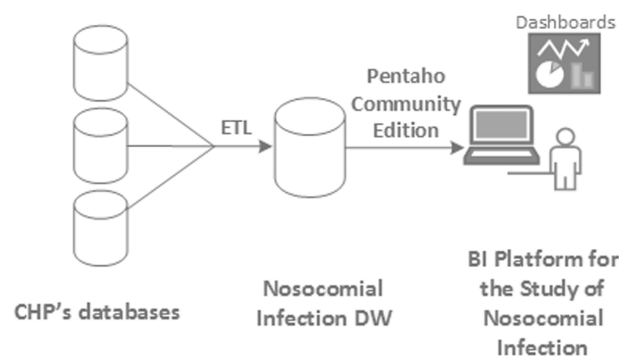


Figure 2. BI system for nosocomial infection incidence study.

DW, the relevant CHP data were extracted from the databases, manipulated and cleaned, in order to make them adequate to the dimensional model previously defined. In this work all the ETL procedures were executed and automated with PL/SQL procedures.

Since the KPIs presented on the platform are extracted from the DW, it is very important for the data in the DW to have high quality. So, it is important to spend time in the analysis and transformation of data.

4.5.2 Business Intelligence Platform

The BI platform for nosocomial infection KPIs presentation is a web application that, through a BI tool, makes OLAP data analysis and queries to generate indicators and present them in pivot tables and graphs. Pentaho Community Edition is an open source BI tool that allows the creation of reports and dashboards, the implementation of Data Mining and OLAP and other features to help its users to visualize and analyze data. In this work only the main component of Pentaho Community Edition, the Business Analytics Platform, was used.

To create this platform, Community Dashboard Editor (CDE) module of Pentaho Business Analytics Platform was used. CDE allows and simplifies the development of powerful, interactive and visually attractive dashboards, making information interpretation easier for the user.

The BI platform is composed by a set of dashboards that contain all the indicators and make possible the navigation between them. In the main dashboard a set of graphs that summarize the most important indicators for each group of indicators are presented. This dashboard is connected with the other dashboards and it allows the exportation of each graph data to XLS. The other dashboards contain more detailed information about the different groups of indicators previously presented. These dashboards implement OLAP in order to explore data.

To implement OLAP, OLAP cubes were created with Pentaho Community Edition. The OLAP cubes contain the dimensions and facts to generate each group of indicators and they allow the definition of the hierarchy of the attributes in the dimensions. The OLAP analysis dashboards are composed of pivot tables created with OpenI, an OLAP tool. OpenI is plug-in for Pentaho Community Edition that provides a simple interface to explore data in OLAP cubes. The user can explore the pivot tables created with OpenI in real-time, through operations such as drill-down.

5. Results and Discussion

Some of the indicators presented in the BI platform are shown and discussed in this section. The overall BI system is also analyzed and discussed.

Analyzing at first the Studied Population indicators (Figure 3), it can be seen that in the year of 2013 Medicine A was the specialty with the highest average capacity (49 beds).

During the same period, Medicine B had the highest average number of hospitalization days (15.43 days). The lowest value was 12.23 days and belongs to Medicine C.

Medicine A had the highest number of discharges and the highest number of patients. The difference between these values in this clinical specialty and in the others is high and may be justified by the highest capacity verified in this specialty.

In spite of having a lower average capacity than Medicine B, Medicine C had a higher number of discharges and patients. This fact can be related to the lower average number of hospitalization days verified in Medicine C.

Medicine C had the highest percentage of nosocomial infection forms (85.94%). In general, the percentage of nosocomial infection forms was 78.80%. So, in every 100 hospitalized patients only 78.80 nosocomial infection forms were correctly filled.

In relation to the indicators Infections per Type and Service, the rate of nosocomial infection in the year of 2013 was homogeneous in the Medicine Units of CHP (Figure 4). Medicine A had the lowest rate (9.43%) and Medicine B had the highest rate (12.95%).

It can also be observed that a relationship between the rate of nosocomial infections and the average hospitalization days exists, because Medicine B has the highest rate of nosocomial infection and it also has the highest average hospitalization period. This fact is justified by the longer exposure to the hospital environment that is a risk for acquiring an infection.

Dates	Specialties	Measures				
		Capacity	Hospitalization Days	Number of Discharges	Number of Patients	% of Forms Correctly Filled
All Dates	All Specialties	41,54	14,07	1669	2118	78,80%
2013	All Specialties	41,54	14,07	1669	2118	78,80%
	Medicine A	49,00	14,30	1018	1318	77,24%
	Medicine B	32,78	15,43	278	366	75,96%
	Medicine C	26,26	12,23	373	434	85,94%

Figure 3. Pivot table for the nosocomial infection indicators group studied population.

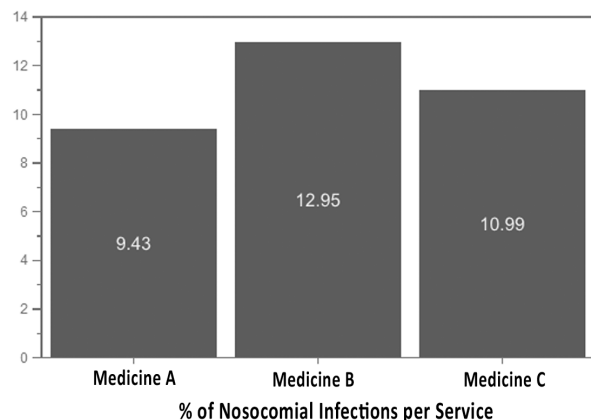


Figure 4. Nosocomial infection rate per service in 2013.

In respect to the types of infection associated with nosocomial infections (Figure 5), most of nosocomial infections are associated with urinary infections and respiratory infections in all services.

The group of indicators Extrinsic Risk Factors per Service (Figure 6) shows that, for all services in the analysis, the peripheral catheter was the most used invasive device in 2013 and the nasotracheal intubation was the less frequent. For all services, the peripheral catheter was also associated with the highest number of nosocomial infections and the nasotracheal intubation had the lowest number of infections.

With regard to the percentage of patients who used the invasive device and had a nosocomial infection, it can be observed that the percentages are relatively high, being the highest 50% (utilization of nasotracheal intubation in Medicine B). The lowest percentage is 10.90% (utilization of peripheral catheter in Medicine A). In spite of being associated with the highest number of nosocomial infections, the peripheral catheter is also the most frequently used invasive device, so, its percentage of nosocomial infections is not very high for all the specialties. Nasotracheal intubation has the opposite behavior.

When giving health care, healthcare professionals must consider the relationship between the utilization of invasive devices, especially nasotracheal intubation, and the occurrence of nosocomial infections.

The BI system presented in this chapter allows the user to analyze nosocomial infection data in a fast and simple manner. It benefits the CHP because improves healthcare professional autonomy and flexibility in data analysis. It gives utility to the data stored through the use of auto-

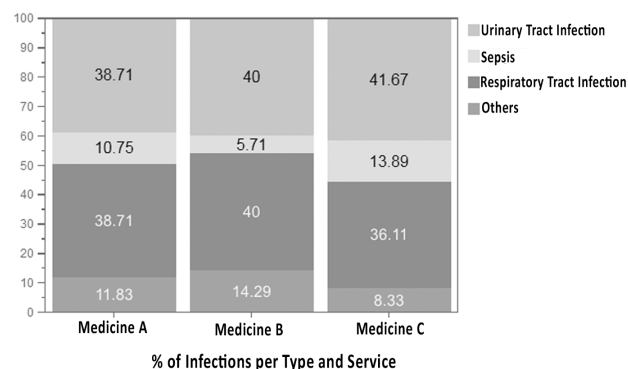


Figure 5. Percentage of infections per type of infection and service in the year of 2013.

Dates	Specialty	Invasive Device	Measures		
			Patients	Nosocomial Infections	% of Nosocomial Infections
All Dates	All Specialties	All Invasive Devices	2118	333	15,72%
2013	All Specialties	All Invasive Devices	2118	333	15,72%
	Medicine A	All Invasive Devices	1276	187	14,66%
		Central Catheter	39	8	20,51%
		Peripheral Catheter	789	86	10,90%
		Urinary Catheter	352	67	19,03%
		Nasogastric Intubation	85	22	25,88%
		Nasotracheal Intubation	11	4	36,36%
	Medicine B	All Invasive Devices	363	60	16,53%
		Central Catheter	11	3	27,27%
		Peripheral Catheter	213	26	12,21%
		Urinary Catheter	111	26	23,42%
		Nasogastric Intubation	26	4	15,38%
		Nasotracheal Intubation	2	1	50,00%
	Medicine C	All Invasive Devices	479	86	17,95%
		Central Catheter	17	7	41,18%
		Peripheral Catheter	288	35	12,15%
		Urinary Catheter	126	31	24,60%
		Nasogastric Intubation	42	11	26,19%
		Nasotracheal Intubation	6	2	33,33%

Figure 6. Extrinsic risk factors per service group of indicators per service and for the year of 2013.

rated methods, supports decision making and allows the study and monitoring of nosocomial infections.

The information presented by the BI platform helps healthcare professionals to characterize, analyze and monitor nosocomial infections in CHP's Medicine Units. Infection control programs must consider this information in order to plan, evaluate and implement adequate and customized infection control measures according to Medicine Units' real needs. Thus, the system is capable of helping in the prevention and reduction of nosocomial infections.

The implementation of a DW facilitates the querying of data and allows OLAP, because it stores quality data in a format that simplifies its access and the application of BI tools. OLAP tools such as OpenI pulg-in, allow real-time *ad hoc* data exploitation, allowing the user to explore data rapidly and interactively according to different

dimensions. The user can explore the pivot tables created by these tools in real-time.

The hierarchical structure of the OLAP cube's dimension attributes allows drill-down on data. In this work the dimension Date, for example, is composed by a set of attributes that are organized in a hierarchal structure (day, month, trimester, semester and year). Thus, data can be explored through this hierarchy according to user needs. Figure 7 presents an example of drill-down on Date dimension. This figure allows the visualization of the Studied Population indicators per month.

The utilization of a web platform to present the indicators makes user's accessibility simpler, allowing them to access the platform at any time and place if they have access privileges and a network connection. Therefore, the web platform ensures that data are always available to support healthcare professionals' nosocomial infection related decision-making.

6. Future Research Directions

It would be interesting to present the indicators considered in this work with other BI tools, namely other OLAP tools or other tools to create dashboards. This would allow the comparison of features between different tools and conclude which one is the most adequate to the reality presented in this chapter.

To explore more deeply the potential of the methodology proposed here, it is considered interesting and relevant to extend the study to other years, clinical specialties and/or other relevant KPIs for nosocomial infection study. This can be done, for example, through the addition of new data marts to the DW, modification of the existing ones or integration of new dashboards in the BI platform.

It is also important to evaluate the usability and functionality of the platform to find improvement opportunities related to the performance of the system or with important features to its users.

Dates	Specialties	Measures				
		Capacity	Hospitalization Days	Number of Discharges	Number of Patients	% of Forms Correctly Filled
All Dates	All Specialties	41,54	14,07	1669	2118	78,80%
2013	All Specialties	41,54	14,07	1669	2118	78,80%
1st Semester	All Specialties	41,79	13,92	1030	1272	80,97%
1st Trimester	All Specialties	42,06	13,82	623	797	78,17%
January	All Specialties	41,90	13,74	200	241	82,99%
	Medicine A	49,00	13,28	121	137	88,32%
	Medicine B	36,00	15,02	35	59	59,32%
	Medicine C	28,00	13,47	44	45	97,78%
February	All Specialties	42,32	13,27	218	311	70,10%

Figure 7. Excerpt of drill-down on date dimension.

7. Conclusions

The prevention and control of nosocomial infections is crucial because these infections can put at risk the security and well-being of patients and healthcare professionals. Data analysis is an efficient method to characterize nosocomial infection and identify risk factors with great impact on the occurrence of these infections.

In this work a BI system for the study of nosocomial infection incidence was implemented in CHP. The system was developed through the application of BI concepts and tools. It is composed by a DW and a BI platform. The BI tool Pentaho Community Edition is applied to the DW and extracts from it several nosocomial infection KPIs. These KPIs are then presented on the platform, allowing the user to analyze them interactively and in real-time. The information presented by the system has high quality because it is based on clinical data that were carefully extracted and transformed.

The solution presented is an efficient automated method to treat, analyze and explore nosocomial infection data and it allow the study of nosocomial infection in the Medicine Units of CHP.

With the platform the nosocomial infection incidence study is performed through the presentation of relevant nosocomial infection indicators, such as the percentage of nosocomial infection per service or the percentage of infections associated with nosocomial infections per type and service. Through the analysis of these indicators, it was verified that, for example, Medicine Units' nosocomial infection rate in 2013 varied between 9.43% and 12.95% and the most frequent infections associated with nosocomial infections were urinary infections and respiratory infections.

As expected, the BI platform gives more autonomy and flexibility for healthcare professionals in the analyses of nosocomial infection data, allowing them to analyze data and interpret information extracted from data in a quicker and simpler manner. Healthcare professionals can apply the information presented on the platform to monitor nosocomial infection incidence, identify risk factors and plan specific and customized infection control measures according to the real needs of each clinical service. So, the platform helps these professional performing their jobs.

To prevent and reduce the rate of nosocomial infections in an efficient manner, the infection control programs must consider the information presented on the BI platform.

The BI systems consider only data from 2013, but in the future the system can be expanded for other years. This will allow monitoring nosocomial infections in long-term, compare information from different years and evaluating the effects of infection control programs. The solution proposed here can be also applied to other healthcare data or to generate other nosocomial infection KPIs because the system was implemented considering the eventual need of its expansion. The methodology is also valid for data of other healthcare institutions.

Open source BI tools allow the creation of new knowledge through data exploitation without representing additional costs for healthcare organizations.

The BI system is capable of presenting relevant and useful information for nosocomial infection related decision-making, allowing to monitor and study nosocomial infections and, so, it is capable of acting as a CDSS for healthcare professionals.

The work presented in this chapter is of great worth to society because the developed BI system is capable of helping in the prevention and reduction of nosocomial infections in healthcare institutions because it promotes an evidence-based clinical practice, decreasing the risk of complications to patients and improving their safety and well-being.

8. Acknowledgement

This work has been supported by COMPETE: POCI-01-0145-FEDER-007043 and FCT – Fundação para a Ciência e Tecnologia within the Project Scope: UID/CEC/00319/2013.

9. References

1. Inweregbu K, Dave J, Pittard A. Nosocomial infections. Continuing Education in Anaesthesia, Critical Care and Pain. 2005; 5(1):14–17. Crossref
2. Rigor H, Machado J, Abelha A, Neves J, Alberto C. A web-based system to reduce the nosocomial infection impact in healthcare units. Proceedings of the WEBIST- International Conference on Web Information Systems, Funchal, Madeira, Portugal; 2008.
3. Clean care is safer care team. Report on the burden of endemic health care-associated infection worldwide: Clean care is safer care, World Health Organization; 2014.
4. Hospital do Futuro. Infecção hospitalar: Um problema do mundo. um problema de todos, Blog of Hospital do Futuro (in Portuguese); 2014.
5. Silva E, Cardoso L, Portela F, Abelha A, Santos MF, Machado J. Predicting nosocomial infection by using data mining technologies. New Contributions in Information Systems and Technologies, Advances in Intelligent Systems and Computing. 2015; 354:189–98. Crossref
6. Faria R, Vicente H, Abelha A, Santos M, Machado J, Neves J. A case-based approach to nosocomial infection detection. Artificial Intelligence and Soft Computing, Lecture Notes in Computer Science. 2016; 9693:159–68. Crossref
7. Ghazanfari M, Jafari M, Rouhani S. A tool to evaluate the business intelligence of enterprise systems. Scientia Iranica. 2011; 18(6):1579–90. Crossref
8. Power DJ. Understanding data-driven decision support systems. Information Systems Management. 2008, 25(8):149–54. Crossref
9. Bonney W. Applicability of business intelligence in electronic health record. Procedia - Social and Behavioral Sciences. 2013; 73:257–62. Crossref
10. Glaser J, Stone J. Effective use of business intelligence. Healthcare Financial Management: Journal of the Healthcare Financial Management Association. 2008; 62(2):68–72.
11. Prevedello LM, Andriole KP, Hanson R, Kelly P, Khorasani R. Business intelligence tools for radiology: Creating a prototype model using open-source tools. Journal of Digital Imaging. 2010; 23(2):133–41. Crossref
12. Portela F, Santos M, Machado J, Abelha A, Silva A. Pervasive and intelligent decision support in critical health care using ensemble. Lecture Notes in Computer Science - Information Technology in Bio- and Medical Informatics. 2013; 8060:1–16. Crossref
13. Popović A, Hackney R, Coelho PS, Jaklič J. Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. Decision Support Systems. 2012; 54(1):729–39. Crossref
14. Mettler T, Vimarlund V. Understanding business intelligence in the context of health care. Health Informatics Journal. 2009; 15(3):254–64. Crossref
15. Shahraki A, Dezhkam A, Dejkam R. Developed model of management of successful customer relationship in the context of business intelligence. Indian Journal of Science and Technology. 2015 Dec; 8(35):1–8. Crossref
16. Hasan HM, Lotfollah F, Negar M. Comprehensive model of business intelligence: a case study of nano's companies. Indian Journal of Science and Technology. 2012 Jun; 5(6):1–9.
17. Dehkordi MN. A novel association rule hiding approach in OLAP data cubes. Indian Journal of Science and Technology. 2013 Feb; 6(2):1–13.
18. Inmon WH. Building the data warehouse (3rd ed.). John Wiley & Sons Inc, USA; 2002.
19. El-Sappagh SHA, Hendawi AMA, Bastawissy AHE. A proposed model for data warehouse ETL processes. Journal

- of King Saud University - Computer and Information Sciences. 2013; 23(2):91–104. Crossref
20. Thangaraju G, Rani XAK. Multi user profile orient access control based integrity management for security management in data warehouse. *Indian Journal of Science and Technology*. 2016 Jun; 9(22):1–7. Crossref
21. Portela F, Veloso R, Oliveira S, Santos MF, Abelha A, Machado J, Silva A, Rua F. Predict hourly patient discharge probability in intensive care units using data mining. *Indian Journal of Science and Technology*. 2015; 8(32):1–11.
22. Loshin D. *Business intelligence: The savvy manager's guide*, (2nd ed.). Morgan Kaufman Publishers Inc, USA; 2012.
23. Kimball R. *The data warehouse toolkit: practical techniques for building dimensional data warehouses*. John Wiley & Sons; 1996 Feb.
24. Thalhammer T, Schre M, Mohania M. Active data warehouses: Complementing OLAP with analysis rules. *Data and Knowledge Engineering*. 2001; 39 (3):241–69. Crossref
25. Kimball R, Ross M. *The data warehouse toolkit: The definitive guide to dimensional modeling*, (3rd ed.). John Wiley & Sons Inc, USA; 2013.
26. Chaudhuri S, Dayal U. An overview of data warehousing and OLAP technology. *SIGMOD Rec*. 1997; 26(1):65–74. Crossref
27. Chaudhuri S, Dayal U, Narasayya V. An overview of business intelligence technology. *Communications of the ACM*. 2011; 54(8):88. Crossref
28. Machado J, Alves V, Abelha A, Neves J. Ambient Intelligence via Multiagent Systems in Medical arena. *International Journal of Engineering Intelligent Systems, Special issue on Decision Support Systems*. 2007; 15(3):167–73.
29. Cardoso L, Marins F, Portela F, Santos M, Abelha A, Machado J. The next generation of interoperability agents in healthcare. *International Journal of Environmental Research and Public Health*. 2014; 11(5):5349–71. Crossref
30. Spruit M, Vroon R, Batenburg R. Towards healthcare business intelligence in long-term care. *Computers in Human Behavior*. 2014; 30:698–707. Crossref
31. Foshay N, Kuziemy C. Towards an implementation framework for business intelligence in healthcare. *International Journal of Information Management*. 2014; 34(1):20–7. Crossref