Integrating Business Process Management and Data Mining for Organizational Decision Making

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Abstract. Organizations are measured in different ways. In specific terms, organizations that are managed through business processes use KPI's as measuring elements. However, it is uncommon for companies to use data yielded by information systems to improve or monitor the indicators suggested by the organization's reality. This paper presents a proposal to guide the improvement of processes on the basis of data mining, which can be performed with amounts of information that organizations consider relevant throughout time. To this end, the literature that supports the foundation and measurement of processes, as well as data mining applied to information management in processes is initially reviewed. Then, data mining is described in the context of information management that improves processes. Finally, the proposal is validated through a case study, which yields applicable results. From this paper, it can be inferred that data mining applied to amounts of data that support processes in certain periods of time can improve their management, as well as the efficient achievement of organizational goals.

Keywords: Key performance indicator, business process management, data mining, analytic process

1 Introduction

Strategic decision making in real time is very beneficial to organizations, since it can offer solid solutions and suggest projects according to business policies. In order to achieve this, it is necessary to have the support of results presented in management reports, which show the state of each value chain process in the organization. This state indicates the process management with regard to the goals that each process must achieve. The goals depend on a set of activities that have to be monitored and measured periodically for the purpose of evaluating process performance. Monitoring makes it possible to observe the state of quantitative data as related to each process task.

The data are retrieved from analytical databases, whose purpose is to support decisions, and are separate from operational databases in the organization. Analytical databases support information processing by providing a solid platform of consolidated historical data for analysis [1]. Quantitative data are retrieved as KPI's (Key Performance Indicators), which assess the success and performance of a solution or activity. KPI's are commonly used for assessing a company's or a product's success [2].

KPI's are measured through performance measurement systems, which are a set of measures that quantify the effectiveness and efficiency of a company's activities and processes [3]. They have become an important and critical part to measure the success of business processes, and provide information about management. They are mainly based on KPI's, and are important in order to learn about processes and increase the understanding of performance and results. This helps to decrease uncertainty and make appropriate decisions. KPI's accumulate numerical parameters in order to measure process efficiency generated by data mining [4].

Data mining emerges as a support for this process in the analysis of data warehouses. Their use is based on data warehouses created under business rules, or data analytics that provides minimum elements to determine current and future organizational patterns and behaviors [5]. It is the acquisition of knowledge through databases. It is also known as pattern analysis in databases, or retrieving of data by a data miner. It may be classified in two categories: descriptive or predictive. Tasks related to descriptive mining are characterized by the general properties of data in a database, while predictive tasks make inferences based on current data in order to make predictions [6]. It is a technique for exploring data flow related to the processes that make up a specific system. It shows the state of business processes in real time [7]. It is a technology related to business process management. Its goal is to discover, analyze, control and improve processes by retrieving knowledge from data recorded in the databases (called entry events) of an organization's information systems. In order to gain the necessary knowledge from these entries, each event must contain important data, such as the name of the activity, a name of the case, user identification, time, etc. It is focused on the exploration and development of the process, and provides information about how people and procedures really work [8]. The main contribution of process mining is providing the analyst with a better understanding of the process, and the models that best describe reality. In the process, mining retrieves information about the processes of entry events, which list activities that have an origin or beginning. Events have a time label, have an order, and are associated to data generated by a result, for example, making decisions related with business process management BPM [9].

BPM emerges as an efficient tool, whose main goal is supporting the design, administration, setup, disclosure and analysis of business processes. The final goal of BPM is the promotion of process management in order to meet a company's goals [10]. It is the identification, understanding and management of business processes related to the organization's employees and systems. The BPM cycle is made up of diagnoses, process designs, system setups and disclosure of processes [11]. It is viewed as an integral management focus that promotes business efficiency through innovation, flexibility and integration into technology [12]. BPM is a key factor to increase efficiency in business operational processes. In order to improve processes, the appropriate information is needed to identify, analyze and re-design them. Management uses diverse ways to measure performance in order to get the correct information, which is essential to reduce uncertainty and make appropriate solutions [4].

There are models to make data mining match process management, and generate greater knowledge for an organization. Business process management adjusted to data mining can be momentous for an organization because it makes decision making easier by providing a holistic view of processes, which helps the company improve its productivity, services, cost savings, etc. It also propels the company to a strategic and competitive positioning [13]. Many business process management systems still lack sophisticated means to analyze recorded data [14]. This is why the use of data mining in business processes is more common every day but has yet to reach the appropriate level of the potential benefits it may yield [15].

Gaining knowledge with data analytics provided by the various data mining methods or models will guide an organization's productivity with regard to goals, strategies, internal and external factors. This paper presents a proposal to guide the improvement of processes on the basis of data mining, which can be done with amounts of information that organizations consider relevant throughout time.

To this end, the literature that supports the foundation and measurement of processes, as well as data mining applied to information management in processes is initially reviewed. Then, data mining is described in the context of information management that improves processes. Finally, the proposal is validated through a case study, which yields applicable results.

The first section shows a conceptual background of the subject under study. The second section shows the conceptual material that characterized the methodologies and techniques used for establishing the model's components. The third section presents the results of the model proposed, and a functional description of its components. The fourth section expounds the validation of the model through a case study.

2 Research Methodology

To develop the proposal was adapted the methodology of design science research in information systems [16]. In the first cycle of Relevance, the problem is identified around the effectiveness of the business process. In the Rigor cycle the state of the art was analyzed in order to have more clarity about the problem. Finally, the design cycle the proposal was built and assessed.

3 Background

The 90's brought a growing problem of data excess in the world of science, business and government. This generated an urgent need for methodologies, techniques and tools to acquire knowledge [17].

An organization's capacity to analyze data is an important factor for success in business. The main industries in the world are supported by information and communication technologies in order to process great amounts of data electronically. Data mining is an integral part in these industries. Tasks such as advertising or recommending products, or discovering a fraud have become fields of data mining application, and show serious business benefits. In order to model a data mining process, the scope of the contribution of data mining, and which portion of the data will be part of the process must be defined. The data must be adjusted to specific needs, and steps indicated in methodologies to acquire knowledge, such as the CRISP-DM, must be followed [18].

Marcano and Talavera clearly explain each of the techniques that help solve an organization's particular problems based on the data it has. They perform an analysis of data mining applicability in business for a natural evolution of information technology. They state that data mining, used appropriately, becomes a strategic tool that increases competitiveness levels in the ever-changing world of business [5].

Aalst and Van Der show the applicability of mining in business processes with algorithms and tools. They show the feasibility of a practical application of business process mining in a model for recording events using techniques incorporated into the PROM framework. Records that keep track of processes through analytical databases can be evaluated through data mining models that provide explanations for the behavior observed in the results retrieved from the evaluations. It is important to point out that neither the evaluation of indicators, nor their optimization is included in the process [13].

Liu and Hsu propose an algorithm incorporation method based on transaction databases for real time data mining. The paper explains the benefits of applying data mining to transaction systems in order to avoid creating a historical data repository, and having to execute tasks that feed the data warehouse from the transaction systems. These tasks are very time- and resource-consuming. With this, the organization's data can be accessed in real time without a delay of information of at least 12 hours, as is the case of traditional business intelligence systems. The benefits are presented with very little theoretical support [19].

Rupnik and Jakli present data mining as a support for decision making on a tactical level, as well as in operational business processes, namely project management. In addition, it presents JDM API (Java Application Data Mining Interface), a tool that offers the possibility to apply data mining models in transaction systems. It suggests the CRISP-DM methodology, which incorporates four tasks into the deployment phase: implementation planning, monitoring and observance of the plan, production of a final report, and review of the project [15].

Ngai et al. present important aspects to analyze and study in CRM systems when applying data mining. These aspects are: identifying, attracting, keeping and developing customers. They define which data mining models should be applied when the purpose is acquiring knowledge from customer data (association, classification, grouping, forecast, regression, discovery sequence and visualization), and the algorithms implemented by these mining methods (association rules, decision trees, genetic algorithm, neural networks, K nearest neighbors, and linear/logistic regression). The paper shows clarity and validity in the study carried out by supporting with references the models and algorithms applied to data mining processes. On the other hand, the paper shows that with complete data about customers, data mining can provide business intelligence to generate new opportunities. It also supports assumptions or previsions about the effects of a CRM strategy [20].

Wegener and S. Ruping state that integrating data mining into business processes is increasingly becoming an integral part of doing business. The paper develops and suggests the CRISP-DM methodology for implementing data mining methods in organizations. The proposal is focused rather on business processes. It does not show the use of data mining in the processes of events generated by analytical databases [18].

Bal et al. study the competitive edge offered by data mining. They also describe in which areas data mining has been used, and stress that in most cases, implementations are customer-oriented. Their paper supports a series of competitive edges that mining offers organizations. On the other hand, the paper explains a series of strategies and algorithms to implement data mining in an organization [17].

Vukšić et al. show the importance of linking BPM to Business Intelligence Systems (BIS) for better business performance. It is clear how BPM and BI are aligned, which creates an integrated data structure that could solve data problems [14].

It may be said that an activity is an event that is executed. The event is interpreted as an action that takes place at some point. Activities are executed automatically by systems, or manually by people.

4 Development of the Proposal

The integration model is based on three components. One of them is for managing processes in any organization.

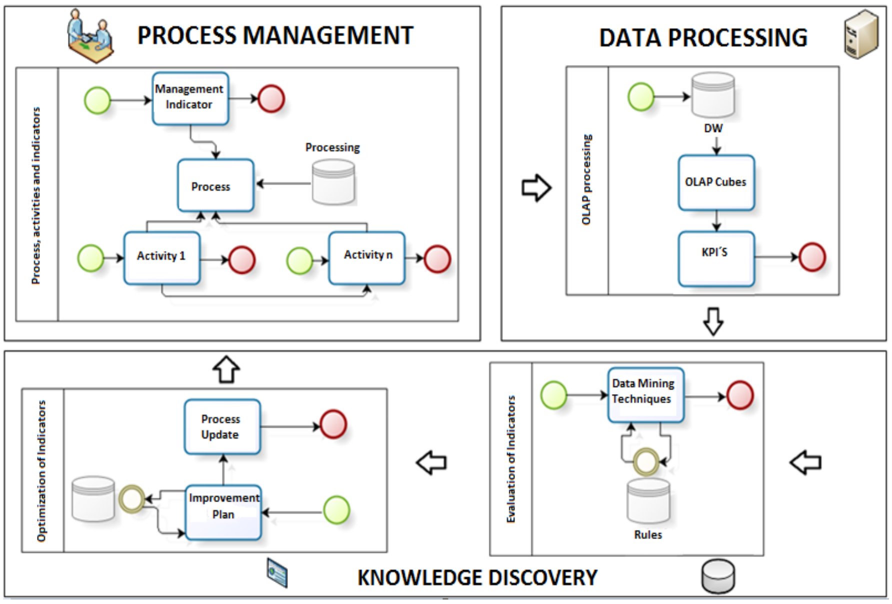

Fig. 1. Analytical Model

That is, the organization data, processes, sub-processes, activities and variables are set up correspondingly.

Another module for data processing. Process indicators are obtained at this stage from a data warehouse through an OLAP cube. Then, there is an optimization module of the KPI's obtained through data mining. Concretely, the association technique is used, see Fig. 1.

4.1 Process Management Component

First, the characteristics of the process being evaluated are specified. The name of the organization that the process belongs to is indicated. Likewise, the name, type, goal, person in charge, scope and limit of the process are indicated. With this information, the process management component begins. At this stage, the activities and indicators of process management are specified.

The name and specification of all the variables related to the activities of sub-processes that make up the process under study are made known.

Each variable has a value that will be used for monitoring and evaluating. The characteristics of the criteria available are shown in Table 1.

Table 1. Criteria for Assessing Variables

CRITERION	MEANING	ID	%
Enough	The data related to the variable indicate that it has the appropriate amount to execute an activity.	E	100
Not Enough	The data related to the variable indicate that it does not have the appropriate amount to execute an activity.	NE	50
Qualified	The data related to the variable indicate that it has the appropriate quality to execute an activity.	Q	50
Not Qualified	The data related to the variable indicate that it does not have the appropriate quality to execute an activity.	NQ	50
Available	The data related to the variable indicate that it may be used unrestrictedly to execute an activity.	A	100
Unavailable	The data related to the variable indicate that it may not be used unrestrictedly to execute an activity.	UA	50
Updated	The data related to the variable indicate that it is current enough to execute an activity.	U	100
Not Updated	The data related to the variable indicate that it is not current enough to execute an activity.	NU	50
Justified	The data related to a variable justifies an activity.	J	100
Unjustified	The data related to a variable does not justify an activity.	UJ	50

For each process, the sub-processes and variables are specified. In this case, the variables are related to each criterion established in this form: Process Name, Subprocess Name, Activity Specification, Variable Specification, and Criterion (%).

For each process management indicator, a rule is provided. This rule is made up of a base value and a percentage. These parameters are previously established by organization experts. The rules are expounded in Table 2.

Table 2. Rules for Indicators

RULE	
Base	%
Ideal	>=90
Alarming	>=70 <=89
Critical	>=0 <=69

Then, the data to set up the indicators and the characteristics for each activity related to each sub-process are established. In the first two columns of the format the activity name and specific indicator are given. Then, the formula for (total of items affected/total of population items) is inserted. Similarly, the frequency is established. It may be measured by minutes, hours, days, weeks, months or years. See how these items are specified: Activity Description, Indicator, Formula, Frequency, and Base Value.

4.2 Data processing component

Using analytical processing through an OLAP cube, key process indicators are obtained. The processing is carried out in the data warehouse using the cube's dimensions and de facto measures. The cube shows in a multi-dimensional way the relation between the dimensional attributes and the measures, which, in this case, are the expected KPI's. See Table 3.

Table 3. Evaluation of Specific Sub-Process Variables

PROCESS	NAME: Information Systems Management	
SUB-PROCESSES	NAME: Equipment Maintenance	
VARIABLES	EVALUATION CRITERION	**%**
Human Resource	E,Q	100
Technology	A,E,U	100
Quality	Q	100
Time	U	100

4.3 Component for Acquiring Knowledge

The integration of the data mining association technique into a set of rules previously established in a database indicates KPI states. KPI's may be in an ideal, alarming or critical state. Besides, KPI’s are evaluated in relation to the dimensions and variables that simultaneously monitor the state of processes. The process records are shown by the date of all the data related to the analytical model dimensions and the KPI measures. The relation of measures is established on the basis of items required and items taken care of. The model presents a measuring percentage, which makes establishing the state of each process record easier.

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The relation to the process monitoring variables and KPI states allow the organization to know in detail not only KPI states, but also the process variables influencing that result, and the concrete dimensions where the event is taking place. With the integral evaluation about the dimensions, variables and measures of the model proposed, an improvement plan is then suggested, which the model automatically yields according to the variables highlighted on the basis of their state. See Process Name, Sub-Process Name, Activity Specification, and Improvement Plan.

5 Case of Study

Organization Data

Organization Name	Fundación Clínica del Norte (FCN)
Management Process	Information Systems Management
Process Type	Support
Process Goal	Guaranteeing the proper management of resources for the generation, storage, safekeeping and purging of information in order to provide structure and consistency of clinical and administrative information, so that relevant decisions are made, and the requirements of institutional customers and regulatory bodies are met.
Person in Charge	Information Systems Leader
Scope	It backs up processes related to strategy, mission, and support.
Limit	It begins with the definition of policies and information access restrictions, and ends with feedback to information systems management staff at FCN.

5.1 Process Management Component

Variable Characteristics

Human Resource:	Staff constantly trained and qualified to perform functions
Technology:	Computers and peripherals, Server, Website, Intranet, e-mail, pop-up messages, internal communication system, systems of communication with users, physical information storage systems.
Quality:	Mandatory System of Guaranteed Quality Health Care.
Time:	Per trimester or semester.

Knowledge of sub-processes and variables

There is a database with the sub-processes and characteristics of the variables as regards the evaluation criteria.

5.2 Data Processing

Original data from the data warehouse

Table 4. Transaction Processing of OLTP Data (Monitoring of Sub-Processes in Relation to the State of Variables)

DATE	PROCESS	HR	TC	CA	T
29/08/2014	Equipment Maintenance	E,Q	A,U	NQ	E
28/11/2014	Equipment Maintenance	E,Q	A,U	NQ	E
27/02/2015	Equipment Maintenance	E,Q	A,E,U	Q	NE
29/025/2015	Equipment Maintenance	E,Q	A,U	NQ	NE
29/08/2014	Malfunctions reported: 28, Solutions to malfunctions in telecommunications: 28	E,Q	A,E,U	Q	E
28/11/2014	Malfunctions reported: 17, Solutions to malfunctions in telecommunications: 17	E,Q	A,E,U	Q	E
27/02/2015	Malfunctions reported: 24, Solutions to malfunctions in telecommunications: 21	E,Q	A,E,U	Q	NE
29/025/2015	Malfunctions reported: 12, Solutions to malfunctions in telecommunications: 12	E,Q	D,E,U	Q	E

Table 5. KPI State According to General Relation of Variables

DATE	PROCESS	KPI	%	STATE
29/08/2014	Equipment Maintenance	180	75	Warning
28/11/2014	Equipment Maintenance	200	83	Warning

DATE	PROCESS	KPI	%	STATE
27/02/2015	Equipment Maintenance	222	92	Ideal
29/25/2015	Equipment Maintenance	170	71	Warning
29/08/2014	Malfunctions Reported: 28, Solutions to Malfunctions in Telecommunications: 28	28	100	Ideal
28/11/2014	Malfunctions Reported: 17, Solutions to Malfunctions in Telecommunications: 17	17	100	Ideal
27/02/2015	Malfunctions Reported: 24, Solutions to Malfunctions in Telecommunications: 21	21	88	Warning
29/025/2015	Malfunctions Reported: 12, Solutions to Malfunctions in Telecommunications: 12	12	100	Ideal

Table 6. Dimensions

Section	ST	Systems (S), Portfolio(P), Customer Service (CS), File (F), Medical Units (MU),
Time	TM	T1(29/08/2014), T2(28/11/2014)
Requierement	RQ	R1(Perform equipment maintenance), R2(Malfunction report)
Location	LC	Administration(A), Operational (O),
Task	TK	TK1(Equipment Maintenance), TK2(Solution to Malfunctions in Telecommunications)

Table 7. Analytical Processing of OLAP Data (Details of Some KPI's in relation to the Dimensions of the Organization)

Facts		Information Systems Management DIMENSIONS						
ST	TM	RQ	Total Required Items	LC	TK	Items Taken Care of Value	**%**	Total Accumulated (KPI)
S	T1	R1	30	A	TK1	20	67	180
P	T1	R1	10	O	TK1	6	60	
CS	T1	R1	30	O	TK1	20	67	
F	T1	R1	10	A	TK1	4	40	
MU	T1	R1	160	O	TK1	130	81	
S	T1	R2	1	O	TK2	1	100	17
P	T1	R2	1	A	TK2	1	100	
CS	T1	R2	7	O	TK2	7	100	
F	T1	R2	1	O	TK2	1	100	
MU	T1	R2	10	A	TK2	7	100	
S	T2	R1	30	O	TK1	30	100	

Facts			Information Systems Management DIMENSIONS					
ST	TM	RQ	Total Required Items	LC	TK	Items Taken Care of Value	%	Total Accumulated (KPI)
P	T2	R1	10	O	TK1	10	100	
CS	T2	R1	30	O	TK1	30	100	
F	T2	R1	10	O	TK1	10	100	200
MU	T2	R1	160	A	TK1	120	75	
S	T2	R2	1	A	TK2	1	100	
P	T2	R2	1	O	TK2	1	100	
CS	T2	R2	7	O	TK2	7	100	28
F	T2	R2	4	O	TK2	4	100	
MU	T2	R2	15	O	TK2	15	100	

Table 8. Association of KPI's and Variables of the Sub-Process Monitoring Database

DATE	**Process**	**HR**	**TC**	**CA**	**T**	**KPI**
29/08/2014	Equipment Maintenance	E,Q	A,U	NQ	E	180
28/11/2014	Equipment Maintenance	E,Q	A,U	NQ	E	200
27/02/2015	Equipment Maintenance	E,Q	A,E,U	Q	NE	222
29/025/2015	Equipment Maintenance	E,Q	A,U	NQ	NE	170
29/08/2014	Malfunctions Reported: 28, Solutions to Malfunctions in Telecommunications: 28	E,Q	A,E,U	Q	E	28
28/11/2014	Malfunctions Reported: 17, Solutions to Malfunctions in Telecommunications: 17	E,Q	A,E,U	Q	E	17
27/02/2015	Malfunctions Reported: 24, Solutions to Malfunctions in Telecommunications: 21	E,Q	A,E,U	Q	NE	21
29/025/2015	Malfunctions Reported: 12, Solutions to Malfunctions in Telecommunications: 12	E,Q	A,E,U	Q	E	12
29/08/2014	Quality Indicators	NE,Q	A,E	NQ	NE	6
28/11/2014	Quality Indicators	E,Q	A,U	NQ	NE	7
27/02/2015	Quality Indicators	E,Q	A,E,U	Q	E	9
29/025/2015	Quality Indicators	E,Q	A,E,U	Q	E	9

Association Rules
Maximum support (MS): 50%
Maximum confidence (MC): 90%

Table 9. Obtained Associations

PROCESS	PREMISE (Variables)	CONCLUSION (KPI)	MC 90%	MS %
Equipment Maintenance	E,Q, A,U, NQ, U →	180	100	50
	E, A,U, NQ, U →	200	100	50
Telecommunications Solution	E,Q, A,E,U, Q, U →	28	100	75
	E,Q, A,E,U, Q, U →	17	100	75
	E,Q, A,E,U, Q, U →	12	100	75

Table 10. KPI Evaluation

S	29/08/2014	Perform equipment maintenance	30	A	Equipment Maintenance	20	67
P	29/08/2014	Perform equipment maintenance	10	O	Equipment Maintenance	6	60
CS	29/08/2014	Perform equipment maintenance	30	O	Equipment Maintenance	20	67
F	29/08/2014	Perform equipment maintenance	10	A	Equipment Maintenance	4	40
MU	29/08/2014	Perform equipment maintenance	160	O	Equipment Maintenance	130	81

Table 11. Relation of KPI's and Their **Dimensions** to the Process Variables

Process	VAR I HR	%	VAR II TC	%	VAR III CA	%	VAR IV T	%	KPI
Equipment Maintenance	E,Q	100	A,U	50	NQ,U	50	E	100	180
	E,Q	100	A,U	50	NQ,U	50	E	100	200
Telecommunications Solution	E,Q	100	A,E,U	100	Q	100	E	100	28
	E,Q	100	A,E,U	100	Q	100	E	100	17
	E,Q	100	A,E,U	100	Q	100	E	100	12

For the KPI’s worth 180 and 200, related to equipment maintenance.

The human resource is enough and qualified, the technology for maintenance is available and updated, the time the staff has to perform the task is enough, but the service quality is not good, since the human resource is not qualified to perform it.

For the KPI's worth 28, 17 and 12, related to assistance in telecommunication malfunctions:

The human resource is enough and qualified, the technology for maintenance is available and updated, and the time the staff has to perform the task is enough, but the service quality is not good. This indicates that the number of requirements has been taken care of successfully 100%.

Table 12. Improvement Plan

PROCESS	**NAME:** Information Systems Management
SUB-PROCESS	**NAME:** Equipment Maintenance
VARIABLE	**IMPROVEMENT PLAN**
CA: Quality	1. Train staff with techniques, methods and technology tools 2. Test updated knowledge frequently 3. Keep track of activities carried out by employees in charge of maintenance

6 Conclusions

The automatic way in which results are obtained at each stage of the model is used as input to execute the following stage, which accelerates the managing and recording process to monitor, evaluate and improve process activities. Therefore, it is possible to present indicators that better suit organizational goals.

The results of the case study show that integrating process management, analytical processing and data mining is a good strategy for organizations.

By applying this strategy, business processes, sub-processes and activities are replenished. The organization model shows how to improve KPI's through the improvement plan.

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