BIDM
The Business Intelligence Development Model

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Abstract: Business Intelligence (BI) has been a very dynamic and popular field of research in the last few years as it helps organizations in making better decisions and increasing their profitability. This paper aims at creating some structure in the BI field of research by creating a BI development model that relates the current BI development stages and their main characteristics. This framework can be used by organizations to identify their current BI stage and provide insight into how to improve their BI function.

1 INTRODUCTION

In nowadays economy, organizations have a lot of information to gather and process in order to be able to take the best decisions as fast as possible (Misner et al., 2002). One of the solutions that can improve the decision making process is (BI).

According to (Gray & Negash, 2003), BI systems "combine data gathering, data storage, and knowledge management with analytical tools to present complex and competitive information to planners and decision makers". Another interesting definition is the one given by (Eckerson, 2007) who believes that BI represents "the tools, technologies and processes required to turn data into information and information into knowledge and plans that optimize business actions." We can see in both definitions that BI helps the decision making process by transforming data into knowledge by using different analytical tools. But, throughout time, BI has evolved from rather simple, fixed reports to real-time analysis. However, even if BI seems to play an important part in the present economy, scientific research in this field is limited, though research possibilities are many (Gray & Negash, 2003). Some literature about BI in general can be found, but there is not much scientific research done regarding the evolution of BI and each of its development stages. Moreover, there are lots of redundant information, concepts and perspectives on BI, but there is not too much structure among them and not many articles give an overall insight into the BI field and its development. This is the gap that our paper is trying to narrow down by developing a model that structures the most important stages of BI maturity and their most representative characteristics.

A starting point for our framework is represented by maturity models. Essentially, they describe the development of an entity over time, where the entity can be anything of interest: a human being, an organizational function, an organization, etc. (Klimko, 2001). Maturity models are characterized by a number of sequentially ordered levels with certain requirements that the entity has to achieve on that level. Moreover, two models that can be a starting point in assessing the BI maturity in a company would be the BI Maturity Model developed by (Chamoni & Gluchowski, 2004) and the Data Warehousing Institute's BI Maturity Model (2009). More details about them will be given in section 2.

Hence, this paper tries to develop a framework that presents different BI development stages and their characteristics that will make it possible for a company to assess its current BI maturity and see the next steps it has to take in order to become an intelligent organization. In order to develop our framework, this paper will address and try to answer the following research question: *What Business Intelligence development stages have been defined in literature until now and how are they related?*

Our BI development model will be created using a design research approach (Vaishnavi & Kuechler, 2007). Hence, our research is structured into the following steps: awareness of the problem, suggestions for the problem solution, development of an artifact – a problem's solution, evaluation and

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conclusion. The first step was accomplished by doing a thorough BI literature research and examining professional magazines and websites. Based on this review, we realized that the BI field is very broad and it involves constant evolution, but many organizations are not aware of all the advantages that BI provides. In order to solve this problem, we developed a BI Development Model (BIDM). Its stages and characteristics will be described in section 2. The evaluation step will be done in future research case studies within several organizations. Finally, section 3 contains conclusions regarding our model and future research. A preliminary version of this research has been published in (Sacu & Spruit,2010).

2 THE BI DEVELOPMENT MODEL (BIDM)

Even though the available literature on BI is very broad, there are not many papers that deal with developing a BI maturity model. One of the most representative ones is (Chamoni & Gluchowski, 2004), but it is in German. It considers five BI maturity stages and analyzes them from three perspectives: business content, technologies and organization. The basic idea for our framework is inspired by (Chamoni & Gluchowski, 2004) and by the BI maturity model developed by The Data Warehousing Institute (TDWI, 2009). The latter six-stage model shows the trajectory that most organizations follow when evolving their BI infrastructure (i.e: prenatal, infant, child, teenager, adult and sage). However, the TDWI model presents different perspectives of BI adoption by drawing several graphs and providing concepts that are not clearly explained and cannot be easily depicted from the model. For each of the stages, there is interesting information provided such as necessary architecture, scope, system type, analytics, users, BI focus and executive perception about the role of BI. Moreover, there are more characteristics that could be determined in order to create a better insight on the BI field. This is what our model tries to do. It involves six stages (i.e: predefined reporting, data marts, enterprise-wide data warehouse, predictive analytics, operational BI, business performance management) with several characteristics categories. Each characteristic can be assigned to one or more stages depending on the maturity of a certain stage. In this way, a company can assess its BI maturity as some characteristics are typical for lower maturity stages, whereas others are met only in very mature BI infrastructures. The BIDM is shown in figure 1 and will be discussed in the remainder of this paper.

2.1 BI Maturity Stages

The BI maturity stages and their most representative characteristics were derived from the literature study. In this way we decided that the BIDM should comprise of the following maturity stages: predefined reporting, data marts, enterprise-wide data warehouse, predictive analytics, operational BI and business performance management (BPM). Each of the stages will be described and analyzed further in this paper.

2.1.1 Predefined Reporting

A few years ago before the development of data warehouses, predefined reporting was the only way a company analyzed their financial results and their general development. At first, reports were only on paper, but then different software programs were developed for creating them. However, even if nowadays most companies create the reports on computers, the majority of users are casual or without experience and prefer this type of reporting. The Data Warehousing Institute and (Chamoni & Gluchowski, 2004) have similar stages. We decided to choose this name for our first stage of the BI maturity model as it is very representative for its characteristics: static deductive reports that present rigid evaluations of business facts, with common semantics, usually restricted to certain departments or transactions and visualized by casual users. These reports are quite rudimentary, containing redundant information and they offer rather limited capability to analyze data or change information.

2.1.2 Data Marts (Departmental Data Warehouse)

The next BI maturity stage is represented by the development of data marts or departmental data warehouses. A data mart contains a subset of the data volume from the whole organization specific to a group of users or department, also called specific subject areas. There is an argument in the IT community whether it is better to build more data marts instead of a unified data warehouse (Inmon, 2002).
Even if it is usually easier and cheaper to build a data mart rather than a data warehouse, from a long-term perspective, the former is never a substitute for the latter. The structure of the data found in a data

	Stages / Characteristics	Predefined Reporting	Data Marts	Enterprise-wide DW	Predictive Analytics	Operational BI: Data Analytics	Operational BI: Embedded BI	BPM
Temporal Characteristics	Focus:							
	-historical	x	x	x	x			x
	-near real-time					x		x
	-real-time						x	x
	Refreshing period:							
	-periodically		x	x	x			x
	-near real-time					x		x
	-real-time						x	x
	Action type:							
	-static	x	x	x	x	x		x
	-dynamic						x	x
Data Characteristics	Data types:							
	-structured	x	x	x	x	x		x
	-unstructured						x	x
	Data sources:							
	-files & databases	x	x	x	x	x		x
	-application tools		x	x	x	x		x
	-web based & others					x		x
	-processes						x	x
	Granularity level:							
	-aggregated	x	x	x	x			x
	-low					x	x	x
Decision Insights	Analysis:							
	-standard reporting	x						
	-ad-hoc analysis		x	x				x
	-trends analysis			x	x			x
	-data mining			x	x			x
	-predictive modeling				x			x
	-exception handling					x	x	x
	Orientation:							
	-deductive	x	x	x	x			x
	-inductive				x	x	x	x
	Decision making:							
	-manual	x	x	x	x	x		x
	-automatic						x	x
Output Insights	Output:							
	-analyses	x	x	x				x
	-recommendations				x	x	x	x
	Visuals:							
	-tables, charts, reports	x	x	x	x			x
	-dashboards, scorecards							x
	-alerts					x	x	x
BI-Process Approaches	Initiation:							
	-user driven	x	x	x	x	x		x
	-process driven						x	x
	Process Integration:							
	-data centric	x	x	x	x	x		x
	-process centric						x	x
	Processing model:							
	-"store & analyze"	x	x	x	x	x		x
	-"analyze & store"						x	x
	Event stream processing						x	x
	"Closed-loop" approach					x	x	x
Other Characteristics	Users:							
	-specialized	x	x	x	x	x		x
	-casual						x	x
	Implementation:							
	-departmental	x	x					
	-enterprise-wide			x	x	x	x	x
	Semantics:							
	-not common	x						
	-common		x	x	x	x	x	x

Figure 1: The Business Intelligence Development Model (BIDM).

mart is shaped by the particular requirements of the department, making it difficult to build a data warehouse from more data marts.But, this stage offers some advantages. Even if valid only for departments, these local data silos have a multi-dimensional data structure supported by multi-dimensional databases that make navigation and visualization easy for the user. This enforces clear commitment to a common semantic for the department and the possibility of accessing ad-hoc reports anytime a user requires one by using online analytical processing (OLAP) technology that automates the updates of the data cubes and makes possible different operations (Inmon, 2002). The same stage exists in (Chamoni & Gluchowski, 2004) under a different name.

2.1.3 Enterprise-wide Data Warehouse

The third stage from our BI maturity model involves the development of an enterprise-wide data warehouse with high availability and integration, common standards and an overall semantic.It collects information about all the subject areas involved in the whole organization. Even if the volume of data is large and the costs and time for modelling and development are higher than in the case of data marts, an enterprise-wide data warehouse could accomplish various useful objectives (Airinei, 2002): access historical, summarized and consolidated organizational data; a single version of truth because the data from a data warehouse are consistent as they have been previously cleaned, transformed and integrated; combined summarized/detailed access to data – OLAP technology and other front end tools such as query tools, report writers and analysis tools offer the possibility of visualizing the information at different hierarchical levels through operations like roll-up, drill-down, slice, dice and pivot; separation of the operational and decisional or analytical processing as they have a very different architecture; monitor and administer the warehousing system; and store and manage metadata.

In addition to the main warehouse, there may also be several data marts. However, contrary to the previous stage described in 2.1.2, the warehouse is created first for the whole organization and then, the data marts are developed which makes a shared data infrastructure possible. This stage also exists in (Chamoni & Gluchowski, 2004). We decided to choose the name *enterprise-wide data warehouse* in order to differentiate it from the previous stage to a greater extent.

2.1.4 Predictive Analytics

The fourth stage of our BI maturity model is called *predictive analytics* and it involves more advanced methods for data analysis which include discovering different patterns in data. Predictive analytics has been around for a long time, but it has commonly been referred to as *data mining* or *knowledge discovery.* Vendors and consultants have recently started using other names such as *predictive analytics, advanced analytics* or just *analytics* to describe the nature of the tools or services they offer (Eckerson, 2007).

However, there are some differences between the names. Data mining is defined by (Holshemier & Siebes, 1994) as being "the search for relationships and global patterns that exist in large databases, but are 'hidden' among the vast amount of data"; these relationships can then offer valuable knowledge. But, some researchers such as (Fayyad et al., 1996) consider that actually knowledge discovery refers to the overall process of discovering useful knowledge from data by identifying valid, novel, potentially understandable patterns in data; whereas data mining refers to a particular step in this process (Fayyad et al., 1996).

Note that unlike other BI technologies, such as different reporting tools or OLAP, that are deductive in nature as they examine what happened in the past, predictive analytics is inductive as it employs statistics, machine learning, neural computing, robotics, computational mathematics and artificial intelligence techniques to explore all the data, instead of a narrow subset of it, and to ferret out meaningful relationships and patterns.

2.1.5 Operational BI

The previous stages of the BI maturity model refer to out-of-date analyses made by using a data warehouse and/or data marts updated overnight (within the traditional "batch window") with data from operational systems. However, over the past few years, organizations have explored technology to support more real-time data collection, analysis and decision-making in a BI environment in order to reduce latency in the decision process.

According to (Azvine et al., 2006), *real-time BI* or *operational BI* can have several meanings such as:

The requirement to obtain zero-latency within a process; the possibility that a process has access to information and provides it whenever it is required; the ability to derive key performance indicators (KPI's) that relate to the situation at the current point in time and not just to some historic situation.

Hence, we can say that *operational BI* is the ability to manage more effectively and optimize daily business activities by integrating BI analytics within operational processes and by propagating actions back into business processes in real time (Davis et al., 2009). All the previous stages of the BIDM are part of the strategic (long-term goals; historical data – months or even years old) and tactical BI (shorter-term goals; historical data – one to a few months old). The overall goal is to reduce latencies in the decision process in order to make faster and better decisions. It is process centric and user and process driven as it can be initiated by a business user or a process. Moreover, two approaches for implementing operational BI solutions can be defined.

One approach that is more often pursued is called *data or traditional analytics*. It is typically based on data stored in a data warehouse and it involves reducing the latency of the data by updating the data warehouse more frequently. The second approach is called *event analytics or embedded BI* and it refers to analyzing business and system events as they flow into the organization. These operational applications might be directly embedded in operational processes or may be called at specific points in an operational process workflow (Davis et al., 2009).

2.1.6 Business Performance Management (BPM)

The last stage from our BI maturity model is called *Business Performance Management (BPM)*. It can also be found under different names such as *Corporate Performance Management* or *Enterprise Performance Management*. So far, each stage referred to a stage of the BI process. This last stage refers to a new way of thinking and of managing an organization that involves BI, but other fields also. BPM can be defined as “a set of processes that help organizations optimize business performance by encouraging process effectiveness as well as efficient use of financial, human, and material resources” (Golfarelli et al., 2004).

BPM takes a closed-loop approach as it includes data warehousing, but it also requires a reactive component (usually called Business Activity Monitoring – BAM) capable of monitoring the time-critical operational processes to allow tactical and operational decision-makers to tune their actions according to the company strategy (Golfarelli et al., 2004). One could say that BPM is the combination between data warehousing, data mining and operational BI. It ensures the collaboration between the strategic, tactical and operational levels in an organization. BPM is an enabler for businesses in defining strategic goals and then measuring and managing performance against these goals by tracking the evolution of KPI’s and scorecards. In the case of BPM, the focus is on the global business goals rather than on the single tasks. Of course, employees involved in processes must share the business strategy in order to synchronize their behavior.

2.2 BI Maturity Model Characteristics

Now that we have surveyed the overall range in BI development capabilities as depicted in the columns of the table, it is the moment to turn our attention to the rows of the model. They represent twenty characteristics related to the BI field that we consider important after doing the literature research and discovering all the BI maturity stages. Each attribute can fit one or more BI development stages, some of them being more appropriate for the less mature stages, whereas others characterize the stages with higher maturity. These characteristics are grouped into the following six categories: temporal characteristics, decision insights, data characteristics, output insights, BI-process approaches, miscellaneous, each having several attributes and are summarized below.

2.2.1 Temporal Characteristics

This category refers to some characteristics regarding the focus of our data and data analysis, whether the data analysis is done in real-time or in a longer period of time. Hence, the characteristics in this category are: focus (historical, near-real time (seconds to minutes old data), real-time (current data)); refreshing period (periodically, near-real time, real-time); action type (static, dynamic).

2.2.2 Data Characteristics

This category refers to the data types and data sources used for doing the data analysis: data types (structured (e.g: relational), semi-structured (e.g: XML) unstructured (e.g: documents, web pages, etc.); data sources (files and databases, application tools and packages (e.g: Excel spreadsheets, Word documents, etc.), web based, uncommon data sources that require custom a interface, processes); granularity level (low; aggregated, summary data).

2.2.3 Decision Insights

As the main scope of BI is to make faster and better decisions, this category comprises of several characteristics of the necessary analysis and the resulting decisions: decisions (strategic, tactical, operational); analysis (standard reporting, ad-hoc analysis, trends analysis, data mining, predictive modeling, exception handling); orientation (deductive, inductive); decision making (manually, automatically).

2.2.4 Output Insights

Once we have the data, it is important to have more possibilities of doing the analysis and showing the results. Also, the ways in which this is possible can differentiate a maturity stage from another: output (analyses, recommendations and actions); visuals (tables, charts and reports, dashboards and scorecards, alerts).

2.2.5 BI-Process Approaches

As can be seen throughout the paper, whether BI analytics is integrated or not in the business process can strongly affect the decision making process.

Hence, we consider this category to be a very important one when delimiting a maturity stage: initiation (user driven – activity initiated by the user, process driven – activity initiated by a process); process integration (data centric – BI analytics is usually supported by a data warehouse, process centric – BI analytics is integrated in the business processes); processing model (store and analyze; analyze and store); event stream processing; "closed-loop" environment.

2.2.6 Other Characteristics

This last category contains some characteristics that can distinguish a maturity stage from another, but do not fit in the other categories and they refer to: users (specialized, casual); implementation (departmental, enterprise-wide); semantics (common, different).

3 CONCLUSIONS AND FURTHER RESEARCH

This paper has presented the Business Intelligence Development Model (BIDM). By doing a thorough literature study, we came up with six BI maturity stages and a selection of twenty characteristics that best describe and differentiate these stages. Each of the characteristics has several attributes that might fit one or more of the development stages. This is how BIDM can help determine which characteristics are necessary for reaching a desired BI maturity stage. Furthermore, we would like to refine our framework in the future to include support for companies to assess their BI capability. One promising approach might be to apply the type of maturity matrix model developed by (van de Weerd, 2009). Moreover, case studies as well as expert interviews or surveys may help validate how our framework works in practice.

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