BIDM: THE BUSINESS INTELLIGENCE DEVELOPMENT MODEL

Keywords: Business Intelligence, Maturity Modelling.

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: BI & MATURITY MODELING

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 Business Intelligence (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 some literature about BI in general can be found, there is not much scientific research done regarding the evolution of BI and each of its development stages. A starting point for our framework is represented by the 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 characterised 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). The former identifies five stages and analyzes them from three perspectives: people, technologies and organization, but both the model and the paper are in German. This model is definitely a source of inspiration for our model, but we took another approach regarding the BI maturity stages and their characteristics. The latter seems to be more company oriented as it shows the trajectory most organizations follow when evolving their BI infrastructure from a low-value, cost-center operation to a high-value, strategic utility that drives market share. However, this model merely shows a couple of curves that make it rather difficult for a company to assess its current position in the BI maturity evolution.

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. This will be the foundation for a more elaborate future BI maturity model that might be designed like the focus-area based maturity matrix developed by (van de Weerd, 2009). 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 the literature until now and how are they related?

2 RESEARCH MOTIVATION AND METHODOLOGY

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). Most of the available literature is about data warehousing (Inmon, 2002; Kimball et al., 2008), online analytical processing (OLAP) (Chaudhuri & Dayal, 1997; Thomsen, 2002) and data mining (Fayyad et al., 1996; Holsheimer & Siebes, 1994; William et al., 1992). However, in the last couple of years, new concepts such as real-time business intelligence (Azvine et al., 2006; Panian, 2007), data analytics (Seufert & Schiefer, 2005; Eckerson, 2007), embedded BI (Azvine et al., 2006; Davis & White, 2008) and business performance management (Golfarrelli, 2005; Nagpal & Krishan**,** 2008) have developed as research interests in this field.

But, even if there are so many concepts and perspectives on BI, there is not too much structure among them. There are many papers containing redundant information and using different names for the same concepts. Also, most of the papers focus on one or maybe two concepts (e.g: data warehousing and OLAP, OLAP and data mining, etc), but there are not many articles that 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. It could be applied in organizations in order for them to analyze their current situation and see what requirements they have to accomplish to get to the next stage.

Our BI development model will be developed using a design research approach is used (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 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. However, most organizations are not aware of all the possibilities that BI offers and how they can achieve great benefits from having a mature BI insight. In order to solve this problem, we developed the BI development model. Its stages and characteristics will be described in section 3. The evaluation step will be done in future research case studies within several organizations. Finally, section 4 contains conclusions regarding our model and future research agenda.

3 THE BI DEVELOPMENT MODEL (BIDM)

Even though the available literature on BI is very broad, there is only one paper that describes a BI maturity model and it is in German (Chamoni & Gluchowski, 2004). It considers five BI maturity stages and analyzes them from three perspectives: people, 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, sage). However, the TDWI model presents different perspectives of BI adoption by drawing several graphs: BI Adoption Curve, Local Control versus Enterprise Standards curves, BI Usage, BI Insight and BI Business Value curves. 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. Nevertheless, these concepts are not clearly explained and they cannot be depicted very easily from the model. 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 BI development model is shown in the table below and will be discussed in the remainder of this paper.

Characteristics	Stages	Predefined Reporting	Data Marts	Enterprise -wide DW	Predictive Analytics	Operational BI		BPM
						Data Analytics	Embedded BI	
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

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

3.1 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.

3.1.1 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 that would help creating the reports. However, even if nowadays most companies create the reports on computers, the majority of users are casual or without experience and prefer the predefined type of reporting. It is characterized by rigid evaluations of business facts that are presented in periodic static reports. Hence, further analysis is impossible as the information cannot be changed and in order to create new reports or their own personalized spreadsheet, users have to copy and paste parts from multiple reports (Ekerson, 2009). The Data Warehousing Institute uses the terms *paper report* and *briefing book* to characterize the first two stages of their BI maturity model. However, we consider that the two notions imply common characteristics that could be described in a single stage. Moreover, in (Chamoni & Gluchowski, 2004), we can find the first stage to be called *vordefiniertes Berichtswesen, i.e. predefined reporting*. We decided to choose the second name for our first stage of the BI maturity model as it is very representative for its characteristics: static deductive reports, usually restricted to certain departments or transactions and visualized by casual users. These reports are quite rudimentary as they might have redundant information, they offer rather limited capability to analyze data and they do not have any common semantics. This is why more recent new reporting capabilities were developed and a new stage of BI maturity was reached.

3.1.2 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. This implies that data marts are limited to specific subject areas. For example, a data mart for the marketing department would have subjects limited to clients, articles, sales, etc. The data from a data mart are usually aggregated to a certain level. 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). It is usually easier to build a data mart as in this case, the implementation cycle is measured in weeks or months rather than in years. Also, the costs and the investment necessary for a data mart are much lower than those needed for building a data warehouse. However, even if from a short-term perspective a data mart seems a better investment than a data warehouse, from a long-term perspective, the former is never a substitute for the latter. One of the reasons is that the structure of the data found in a data mart is shaped by the particular requirements of the department. Hence, each department will have its own data structure for the data mart, making it difficult to build a data warehouse from more data marts. Also, the data will be denormalized based on the department's need for information.

But, this stage also has its 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 is possible due to the fact that they are served by online analytical processing (OLAP) technology that automates the updates of the data cubes and makes possible different operations such as roll-up (increasing the level of aggregation) and drill-down (decreasing the level of aggregation or increasing detail) along one or more dimension hierarchies, slice and dice (selection and projection) or pivot (re-orienting the multidimensional view of data) (Inmon, 2002). This enforces clear commitment to a common semantic for the department and the possibility of accessing ad-hoc reports anytime a user requires one. The same stage exists in the BI maturity model developed by (Chamoni & Gluchowski, 2004) under the name of *BI pro Fachbereich* which means *BI per department*. In this paper, we'll adhere to the more common terms of *data marts or departmental data warehouse*.

3.1.3 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. Such a data warehouse collects information about all the subject areas involved in the whole organization. The volume of data is large and it usually contains detailed data, but also aggregated data and its size varies from a few gigabytes to hundreds of gigabytes, terabytes or more. Of course, this involves higher costs for modelling than in the case of data marts and a longer period of time (even years) for design and actual development. However, an enterprise-wide data warehouse could accomplish various useful objectives (Airinei, 2002):

- the possibility of accessing historical, summarized and consolidated organizational data;
- a single version of truth because the data from a data warehouse are consistent as they been previously cleaned, transformed and integrated;
- combined summarized/detailed access to data – OLAP technology and other reporting 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.

These goals can be accomplished due to the data warehouse architecture that can be seen in figure 1 (Chaudhuri & Dayal, 1997).

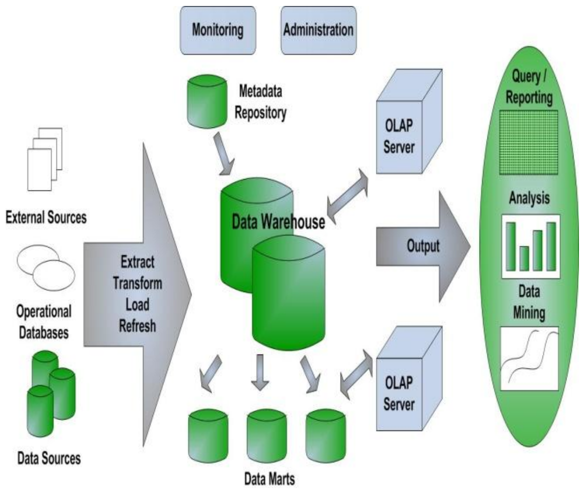

Figure 1: Data Warehouse Architecture (Chaudhuri & Dayal, 1997).

As can be seen from figure 1, the architecture includes tools for extracting data from multiple operational databases and external sources; for cleaning, transforming and integrating this data; for loading data into the data warehouse; and for periodically refreshing the warehouse to reflect updates at the sources. In addition to the main warehouse, there may also be several data marts. However, contrary to the previous stage described in 3.1.2, the warehouse is created first for the whole organization and then, the data marts are developed which makes a shared data infrastructure possible. Data in the warehouse and data marts are stored and managed by one or more warehouse servers, which present multidimensional views of data to a variety of front end tools: query tools, report writers and analysis tools. Finally, there is a repository for storing and managing metadata and tools for monitoring and administering the warehousing system.

Finally, the enterprise-wide data warehouse stage offers the possibility of setting standards and defining an overall semantics for the whole organization which leads to consistent information that is the source for standard reporting and simple forecasts. This stage is called *unternehmensweite BI or company-wide BI* in (Chamoni & Gluchowski, 2004). We decided to choose the name *enterprise-wide data warehouse* for this stage in order to differentiate it from the previous stage to a greater extent. More advanced BI capabilities can be found in the next stage.

3.1.4 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*. However, 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). We decided to choose the name *predictive analytics* as it seems to be the most popular term nowadays and it is the most representative for the data analysis it involves.

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 about the database and the objects in the database. 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 useful and understandable patterns in data; whereas data mining refers to a particular step in this process that consists of "applying data analysis and discovery algorithms that, under acceptable computational efficiency limitations, produce a particular enumeration of patterns over the data" (Fayyad et al., 1996).

A better understanding of the difference between knowledge discovery and data mining can be seen in figure 2 where all the steps of the process are drawn. The most challenging phase of the process is the preparation of data – data research, selection, cleaning, enrichment and transformation. Only by having valuable input data can we get significant results. Usually, this phase is handled by having a well-designed data warehouse. Once the input data is ready, we can apply the data mining methods (i.e: classification, regression, clustering, summarization, dependency modeling or change and deviation detection (Fayyad et al., 1996) and algorithms in order to identify meaningful patterns in data, interpret them and gain the desired knowledge.

Figure 2: Knowledge Discovery Process Steps (adapted from 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.

3.1.5 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. The overnight updates extract operational data in batch, transform the data into a format for analysis (e.g.: denormalized data, multidimensional OLAP cubes) and load them into the data warehouse. Then, users can run ad-hoc queries and apply predictive analytics in order to do their analysis. However, as the conditions and environments in which business operate are in a constant state of flux and change, 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 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 (Davis et al., 2009). Real time BI offers the same functionality as the traditional BI, but it operates on data extracted from operational data stores with zero-latency and provides means to propagate actions back into business processes in real time.

In order to better understand operational BI, it is also important to take a look at the other two types of BI analytics:

- strategic BI – helps executives and business/financial analysts develop and assess progress in achieving long-term enterprise goals. It depends on historical data that may span months or even years. It is data centric as it is typically supported by a data warehouse that serves as the source for data and user driven as it is initiated on demand by a business user;
- tactical BI – helps achieving strategic goals by analyzing shorter-term data and is valuable to operational and line-of-business managers in addition to executives and analysts. It uses historical data that is one day to a few months old. Like strategic BI, it is also data driven and user centric.

All the previous stages of the BIDM are part of the strategic and tactical BI. However, unlike them, operational BI has a much narrower scope as it tries to support data collection, analysis and decision making that is closer to real time. 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. It achieves this by integrating BI analytics into business processes and creating a "closed loop" environment (Davis et al., 2009):

- collect data, transactions and business events generated by operational and external systems;
- integrate the data where appropriate;
- apply analytics to produce appropriate results for faster decision making and better insights that inform the business;
- incorporate the results back into the operational systems to help people and processes continue to make better business decisions.

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. However, refreshing the data warehouse limits the update frequency and that is why new methods for getting the data were developed: data propagation – copies only changed data between systems, data federation – provides real-time access to current data via virtual integration or "ELT (extract, load, transform)" approach – transform operational data after they are loaded into the data warehouse. But this approach seems not be enough for getting real-time information. And this brings us to the second approach.

It is called *event analytics or embedded BI* and it refers to analyzing business and system events as they flow into the organization. Embedded BI services provide analytical and data services to operational applications that might be directly embedded in operational processes or may be called at specific points in an operational process workflow (Davis et al., 2009). A better image on how embedded BI works can be depicted in the figure below.

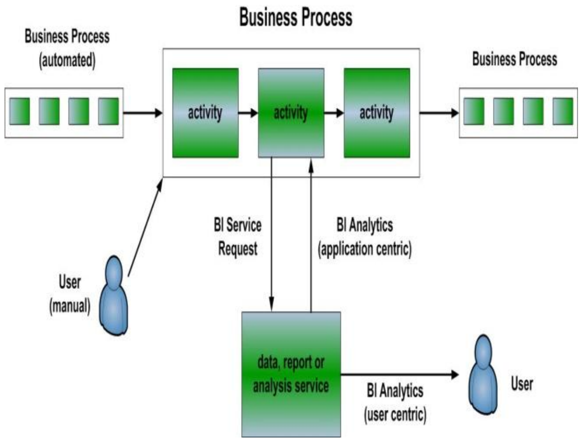

Figure 3: Embedded BI Analytics (Davis & White, 2008).

Embedded BI analytics are an integral component of a business process. The embedded analytics component delivers data, BI reporting and/or BI analytics services to the process. Embedded BI is dynamic because we can have access to what is happening now as data comes from the business process or application and, in this way, we can be aware of all the events taking place. It relies on an "analyze and store" model as the events are analyzed as they happen in the organization and then, the results are stored in a data warehouse. There are two main scenarios that can do this type of processing (Davis et al., 2009):

- simple event processing – process and analyze one or more streams of events associated with a specific operational business process;

- complex event processing – process and analyze multiple event streams associated with multiple business processes.

3.1.6 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 is a key business initiative that enables companies to align strategic and operational objectives with business activities in order to fully manage performance through better informed decision making and action (Ballard et al., 2004).

BPM 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. 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. In this way, managers can ensure that all processes are effective by continuously measuring their performance through KPIs (key performance indicators) and scorecards. A process can be defined as "a set of logically related tasks performed to accomplish a defined goal" (Golfarelli et al., 2004). 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. That is why BPM involves a closed-loop approach where (Golfarelli et al., 2004):

- the strategy and the corresponding targets on indicators are influenced by the enterprise performance as inferred from the information system;
- the actions and decisions taken at the tactical and operational levels are aimed at matching current and target values for indicators;
- the actions and decisions fulfil the company strategy and determine its performance.

The BPM closed-loop approach can be seen in figure 4. Any BI implementation is aimed at turning available data into information and putting it into the hands of decision makers. However, BPM is focused on a subset of the information delivered by a BI system. It is the information that shows business performance and indicates business success or failure. This information subset enables organizations to focus on the important task of optimizing business performance.

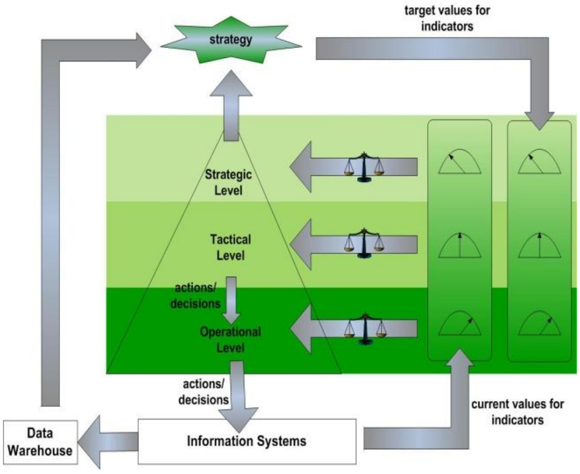

Figure 4: The Closed-loop in the BPM Approach (Golfarelli et al., 2004).

3.2 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 some characteristics related to the BI field that we consider important after doing the literature research and discovering all the BI maturity stages. We decided to include twenty characteristics that we consider most appropriate for our model. 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. Each attribute can fit one or more BI development stages. Some attributes are more appropriate for the less mature stages, whereas others characterize the stages with higher maturity. All six characteristics categories are summarized below.

3.2.1 Temporal Characteristics

This category refers to some characteristics regarding the focus of our data and data analysis. As we have seen, time is very important in nowadays economy and it is very important to have real-time access to the information we need in order to take immediate action. But, sometimes, in order to do a better analysis, we also need insight to historical information. 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).

3.2.2 Data Characteristics

This category refers to the data types and data sources used for doing the data analysis. Of course, the more mature the BI development is, the more diverse and unconventional the data are:

- 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).

3.2.3 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. All the attributes can be found in the information we presented so far:

- 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).

3.2.4 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).

3.2.5 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.

3.2.6 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).

4 CONCLUSIONS AND FURTHER RESEARCH

This paper has presented a framework that connects BI maturity stages and corresponding characteristics. In this way we attempted to answer our research question: *What Business Intelligence development stages have been defined in the literature until now and how are they related?*

By doing a thorough literature study, we came up with six BI maturity stages (i.e: predefined reporting, data marts, enterprise-wide data warehouse, predictive analytics, operational BI, business performance management) 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, our current framework, 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) in which the columns will represent the BI maturity stages and the rows will include the necessary steps in order to reach each one of the stages. Moreover, case studies as well as expert interviews or surveys may help validate how our framework works in practice.

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