Business Intelligence

Chapter · January 2012

DOI: 10.4018/978-1-61350-050-7.ch001

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Business Intelligence and Agile Methodologies for Knowledge-Based Organizations:

Cross-Disciplinary Applications

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BUSINESS SCIENCE Reference

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Published in the United States of America by
Business Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com

Library of Congress Cataloging-in-Publication Data

Business intelligence and agile methodologies for knowledge-based organizations: cross-disciplinary applications / Asim Abdel Rahman El Sheikh and Mouhib Alnoukari, editors.
p. cm.
Includes bibliographical references and index.
Summary: "This book highlights the marriage between business intelligence and knowledge management through the use of agile methodologies, offering perspectives on the integration between process modeling, agile methodologies, business intelligence, knowledge management, and strategic management"--Provided by publisher.
ISBN 978-1-61350-050-7 (hardcover) -- ISBN 978-1-61350-051-4 (ebook) -- ISBN 978-1-61350-052-1 (print & perpetual access) 1. Business intelligence. 2. Knowledge management. I. El Sheikh, Asim Abdel Rahman. II. Alnoukari, Mouhib, 1965-
HD38.7.B8715 2012
658.4'72--dc23

2011023040

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

Chapter 1
Business Intelligence:
Body of Knowledge

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ABSTRACT

This chapter attempts to define the knowledge body of Business Intelligence. It provides an overview of the context we have been working in. The chapter starts with a historical overview of Business Intelligence stating its different stages and progressions. Then, the authors present an overview of what Business Intelligence is, its architecture and goals, and its main components including: data mining, data warehousing, and data marts. Finally, the Business Intelligence 'marriage' with knowledge management is discussed in details. The authors hope to contribute to the recent discussions about Business Intelligence goals, concepts, architecture, and components.

INTRODUCTION

Business Intelligence is becoming an important IT framework that can help organizations managing, developing and communicating their intangible assets such as information and knowledge. Thus, it can be considered as an imperative framework in the current knowledge-based economy era.

Business Intelligence applications are mainly characterized by flexibility and adaptability in which traditional applications are not able to deal with. Traditional process modeling requires a lot of documentation and reports and this makes traditional methodology unable to fulfill the dynamic requirements of changes of our high-speed, high-change environment (Gersten, Wirth, and Arndt, 2000).

DOI: 10.4018/978-1-61350-050-7.ch001

An important question raised by many researchers (Power, 2007; Shariat & Hightower, 2007) as to what was the main reason pushing company to search for BI solutions, and what differentiates BI from Decision Support System (DSS) systems? In fact, over the last decades, organizations developed a lot of Operational Information Systems (OIS), resulting in a huge amount of disparate data that are located in different geographic locations, on different storage platforms, with different forms. This situation prevents organization from building a common, integrated, correlated, and immediate access to information at its global level. DSS have been evolved during the 1970s, with the objective of providing organization's decision makers with the required data to support decision-making process. In the 1980s, Executive Information System (EIS) was evolved to provide executive officers with the information needed to support strategic decision-making process. in 1990s BI was created as data-driven DSS, sharing some of the objectives and tools of DSS and EIS systems.

BI architectures include data warehousing, business analytics, business performance management, and data mining. Most of BI solutions are dealing with structured data (Alnoukari, and Alhussan, 2008). However, many application domains require the use of unstructured data (or at least semi-structured data), e.g. customer e-mails, web pages, competitor information, sales reports, research paper repositories, and so on (Baars, and Kemper, 2007).

Any BI solution can be divided into the following three layers (Alnoukari, and Alhussan, 2008): data layer, which is responsible for storing structured and unstructured data for decision support purposes. Structured data is usually stored in Operational Data Stores (ODS), Data Warehouses (DW), and Data Marts (DM) while unstructured data are handled by using Content and Document Management Systems. Data are extracted from operational data sources, e.g. SCM, ERP, CRM, or from external data sources, e.g. market research data. Data extracted from data sources are then transformed and loaded into DW using ETL tools. The second layer is the analytical layer which provides functionality in order to analyze data and provide knowledge including OLAP and data mining. The third layer is the visualization layer which can be realized using some sort of software portals (BI portal).

Our main focus in this chapter is to provide an overview of Business Intelligence by focusing on its body of knowledge. The authors start by providing a historical overview of Business Intelligence explaining the evolution of its concepts, followed by a brief discussion about different definitions and concepts of this field. The authors will describe the different layers and components of Business Intelligence application. Finally, the core body of knowledge, and the marriage between Business Intelligence and Knowledge Management will be discussed in details.

HISTORICAL OVERVIEW

In his article "A Business Intelligence System." Which have been published in IBM Journal, Luhn had defined intelligence as: "the ability to apprehend the interrelationships of presented facts in such a way as to guide action towards a desired goal.", (Luhn, 1958).

Business Intelligence is considered as a result of Decision Support Systems progression (DSS). DSS was mainly evolved in the 1970s. Model-driven DSS was the first DSS models that use limited data and parameters to help decision makers analyzing a situation (Power, 2007).

Data-driven DSS was also introduced as a new DSS direction by the end of the 1970s. It focused more on using all available data (including historical data) to provide executives with more insights about their organization's current and future situation. Executive Information Systems (EIS) and Executive Decision Support (ESS) are examples of data-derived DSS (Power, 2007).

In the late of 1980s, the client/server era has helped BI concept to evolve specially when Business Process Reengineering became the main trend of the industry, and the implementations of relational technologies – especially SQL skills - were transported between systems (Biere, 2003). During this period, the new idea of information warehousing was raised. Although the concept itself was brilliant, the data was never converted into clear information, the idea was simply to leave the data as it was and where it was but to have an access to it from anywhere using the early Business Intelligence tools.

In the 1990s, after the information warehousing quickly vanished, the data warehousing era takeover. This era introduced a way to not only reorganize data but to transform it into a much cleaner and easier to follow form. Data Warehousing is actually a set of processes designed to extract, clean, and reorganize data, enabling users to get a clearer idea of exactly what kind of data they are dealing with and its relevance to the issue they are addressing.

In this era, DSS was pushed notably by the introduction of Data Warehousing (DW) and On-Line analytical Processing (OLAP) which provide a new category of data-driven DSS. OLAP tools provide users with the way to browse and summarize data in an efficient and dynamic way (Shariat, and Hightower, 2007). In other word, OLAP tools provide an aggregated approach to analyze large amount of data (Hofmann, 2003). Data Warehousing is mainly composed of two components, data repository, or data warehouse, and metadata. Data warehouse is a logical collection of integrated data gathered from various operational data sources. Metadata is a set of rules that guide all data preparation operations (Shariat, and Hightower, 2007).

In the year 1989, Howard Dresner, the member of the Gartner group, was the first who introduced the term "Business Intelligence"(BI) as an umbrella term that "describe a set of concepts and methods to improve business decision making by using fact-based support systems" (Power, 2007).

Taking common BI concepts with data warehouse technologies, well developed enterprise application tools and on line analytical processing (OLAP) assists in faster collection, analysis or data research (Flanglin, 2005). Hence, BI technology assists in extracting information from the available data and using them as knowledge in developing innovative business strategies. But the growing competition in market is forcing small to large organizations to adopt BI to understand economic trends and have an in depth knowledge about the operation of a business.

Those years has considered a new era for BI, where packaged Business Intelligence solutions are provided on demand. Golfarelli had described a new approach of BI called "Business Performance Management (BPM)" which "requires a reactive component 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, Stefano, and Iuris, 2004).

Colin in her paper " The Next Generation of Business Intelligence: Operational BI" describes the term "Operational BI", that is used to react faster to business needs and to anticipate business problems in advance before they become major issues, (Colin, 2005).

Similarly, many researchers were talking about the term "Real-time Business Intelligence" which has a very close relationship with the Operational BI, and targeting to reach the almost real-time decision making and a much higher degrees of analytics involved within business intelligence (Azvine, Cui, and Nauck, 2005).

Many other concepts had appeared in many areas: Ad-hoc and Collaborative BI (Berthold, et al., 2010), BI networks, Portals and thinner clients (Biere, 2003).

BUSINESS INTELLIGENCE: CONCEPTS AND DEFINTIONS

Decision support is aimed at supporting managers taking the right decisions (Jermol, Lavrac, and Urbancic, 2003). It provides a wide selection of decision analysis, simulation and modeling techniques, which include decision trees and belief networks. Also, decision support involves software tools such as Decision Support Systems (DSS), Group Decision Support and Mediation Systems (GDSMS), Expert Systems (ES), and Business Intelligence (BI) (Negash, 2004).

Decision makers depend on accurate information when they have to make decisions. Business Intelligence can provide decision makers with such accurate information, and with the appropriate tools for data analysis (Jermol, Lavrac, and Urbancic, 2003; Negash, 2004). It is the process of transforming various types of business data into meaningful information that can help, decision makers at all levels, getting deeper insight of business (Power, 2007; Girija, and Srivatsa, 2006).

In 1996, the Organization for Economic Cooperation and Development (OECD) redefined "knowledge-based economies" as: "Economies which are directly based on the production, distribution and use of knowledge and information" (Weiss, Buckley, Kapoor, and Damgaard, 2003).

According to the definition, Data Mining and Knowledge Management, and more generally Business Intelligence (BI), should be the foundations for building the knowledge economy.

BI is becoming vital for many organizations, especially those have extremely large amount of data (Shariat, and Hightower, 2007). Organizations such as Continental Airlines have seen investment in Business Intelligence generate increases in revenue and cost saving equivalent to 1000% return on investment (ROI) (Watson, Wixom, Hoffer, Anderson-Lehman, and Reynolds, 2006).

Business Intelligence is becoming an important IT framework that can help organizations managing, developing and communicating their intangible assets such as information and knowledge. Thus it can be considered as an imperative framework in the current knowledge-based economy era.

BI is an umbrella term that combines architectures, tools, data bases, applications, practices, and methodologies (Turban, Aronson, Liang, and Sharda, 2007; Cody, Kreulen, Krishna, and Spangler, 2002).

Weiss defined BI as the: "Combination of data mining, data warehousing, knowledge management, and traditional decision support systems" (Weiss, Buckley, Kapoor, and Damgaard, 2003).

According to Stevan Dedijer (the father of BI), Knowledge management emerged in part from the thinking of the "intelligence approach" to business. Dedijer thinks that "Intelligence" is more descriptive than knowledge. "Knowledge is static, intelligence is dynamic" (Marren, 2004).

For the purpose of this dissertation the following definition of BI applies: "The use of all the organization's resources: data, applications, people and processes in order to increase its knowledge, implement and achieve its strategy, and adapt to the environment's dynamism" (Authors).

THE GOAL OF BUSINESS INTELLIGENCE

The goal for any BI solution is to access data from multiple sources, transform these data into information and then into knowledge. The main focus of any BI solution is to improve organization's decision making capabilities. This can be done using the knowledge discovered from the data mining phase for the purpose to support decision makers by explaining current behavior, or predicting future results (Kerdprasop, and Kerdprasop, 2007).

The main complex part in any BI system is in its intelligence ability. This is mainly found in the post data mining phase where the system has to interpret its data mining results using a visual environment. The measure of any business intelligence solution is its ability to derive knowledge from data. The challenge is to meet the ability of identifying patterns, trends, rules, and relationships from large amount of information which is too large to be processed by human analysis alone.

BUSINESS INTELLIGENCE ARCHITECTURE

Any Business Intelligence application can be divided into the following three layers (Azvine, Cui, and Nauck, 2005; Baars, and Kemper, 2007; Shariat, and Hightower, 2007):

1. Data layer: responsible for storing structured and unstructured data for decision support purposes. Structured data is usually stored in Operational Data Stores (ODS), Data Warehouses (DW), and Data Marts (DM). Unstructured data are handled by using Content and Document Management Systems. Data are extracted from operational data sources, e.g. SCM, ERP, CRM, or from external data sources, e.g. market research data. Data are extracted from data sources that are transformed and loaded into DW by ETL tools.
2. Analytics layer: provides functionality to analyze data and provide knowledge. This includes OLAP, data mining, aggregations, etc.
3. Visualization layer: realized by some sort of BI applications or portals.

Data Warehouse and Data Mart

During the last two decades, data warehouses have gained a great reputation as a part of any decision support systems. Data warehouse came as a result of the failure of the mainframe systems to support enterprise decision making, those systems clustered the business entities across many production databases, aiming to enhance the performance level, but due to nature of the complex quires, the load generated create the need to separate the operational data from the data required to generate the DSS reports.

Ralph Kimball has defined the data warehouse as "A copy of transaction data, specifically structured for query and analysis" (Kimball, 2002). Barry Devlin defined it as: "A data warehouse is a simple, complete and consistent store of data obtained from a variety of sources and made available to users in a way they can understand and use it in a business context" (Devlin, 1997). Bill Inmon (the father of the data warehouse) defined data warehouse as: "a collection of integrated, subject-oriented databases designed to support the DSS (Decision Support Systems) function, where each unit of data is relevant to some moment in time. The data warehouse contains atomic data and lightly summarized data…" (Inmon, 2005).

Data marts were viewed as limited alternatives to fully populated enterprise data warehouses. Today, data marts have surged in popularity. Frequently, they serve as more manageable, cost-effective stepping-stones to the data warehouse. A data mart is a collection of subject areas organized for decision support based on the needs of a given department. Inmon defines Data Mart as follows: "a departmentalized structure of data feeding from the data warehouse where data is de-normalised based on the department's need for information" (Inmon, 2005).

The union of business process data marts is not a data warehouse, as Ralph Kimball and his collaborators suggest because this union doesn't necessarily provide management decision support for departments, or for departmental interactions among themselves and with the external world. (Kimball, Reeves, Ross, and Thornthwaite, 1998).

Data warehousing, in practice, focuses on a single large server or mainframe that provides a consolidation point for enterprise data coming from diverse production systems. It protects data production sources and gathers data into a single unified data model, but does not necessarily focus on providing end-user with an access to that data. Conversely data mart ignores the practical difficulties of protecting production systems from the impact of extraction. Instead it focuses on the knowledge needed from one or more areas of the business.

Data Mining

It is noted that the number of databases keeps growing rapidly because of the availability of powerful and affordable database systems. Millions of databases have been used in business management, government administration, scientific and engineering data management, and many other applications. This explosive growth in data and databases has generated an urgent need for new techniques and tools that can intelligently and automatically transform the processed data into useful information and knowledge, which provide enterprises with a competitive advantage, working asset that delivers new revenue, and to enable them to better service and retain their customers (Stolba, and Tjoa, 2006).

Data mining is the search for relationships and distinct patterns that exist in datasets but they are "hidden" among the vast amount of data (Jermol, Lavrac, and Urbancic, 2003; Turban, Aronson, Liang, & Sharda, 2007). Data mining can be effectively applied to many areas (Alnoukari, and Alhussan, 2008; Watson, Wixom, Hoffer, Anderson-Lehman, and Reynolds, 2006) including: marketing (direct mail, cross-selling, customer acquisition and retention), fraud detection, financial services (Srivastava, and Cooley, 2003), inventory control, fault diagnosis, credit scoring (Shi, Peng, Kou, and Chen, 2005), network management, scheduling, medical diagnosis and prognosis. There are two main sets of tools used for data mining (Corbitt, 2003; Baars & Kemper, 2007): discovery tools (Wixom, 2004; Chung, Chen, and Nunamaker jr, 2005), and verification tools (Grigori, Casati, Castellanos, Dayal, Sayal, and Shan, 2004). Discovery tools include data visualization, neural networks, cluster analysis and factor analysis. Verification tools include regression analysis, correlations, and predictions.

Data mining application are characterized by the ability to deal with the explosion of business data and accelerated market changes, these characteristics help providing powerful tools for decision makers, such tools can be used by business users (not only statisticians) for analyzing huge amount of data for patterns and trends. Consequently, data mining has become a research area with increasing importance and it involved in determining useful patterns from collected data or determining a model that fits best on the collected data (Fayyad, Piatetsky-Shapiro, and Smyth, 1996; Mannila, 1997; Okuhara, Ishii, and Uchida, 2005). Different classification schemes can be used to categorize data mining methods and systems based on the kinds of databases to be studied, the kinds of knowledge to be discovered, and the kinds of techniques to be utilized (Lange, 2006).

A data mining task includes pre-processing, the actual data mining process and post-processing. During the pre-processing stage, the data mining problem and all sources of data are identified, and a subset of data is generated from the accumulated data. To ensure quality the data set is processed to remove noise, handle missing information and transformed it to an appropriate format (Nayak, and Qiu, 2005). A data mining technique or a combination of techniques appropriate for the type of knowledge to be discovered is applied to the derived data set. The last stage is post-processing in which the discovered knowledge is evaluated and interpreted.

The most widely used methodology when applying data mining processes is named CRISP-DM. It was one of the first attempts towards standardizing data mining process modeling (Shearer, 2000). CRISP-DM has six main phases, starting by business understanding that can help in converting the knowledge about the project objectives and requirements into a data mining problem definition, followed by data understanding by performing different activities such as initial data collection, identifying data quality problems, and other preliminary activities that can help users be familiar with the data. The next and the most important step is data preparation by performing different activities to convert the initial raw data into data that can be fed into modeling phase. This phase includes tasks such as data cleansing and data transformation. Modeling is the core phase which can use a number of algorithmic techniques (decision trees, rule learning, neural networks, linear/logistic regression, association learning, instance-based/nearest-neighbor learning, unsupervised learning, and probabilistic learning, etc.) available for each data mining approach, with features that must be weighed against data characteristics and additional business requirements. The final two modules focus on the evaluation of module results, and the deployment of the models into production. Hence, users must decide on what and how they wish to disseminate/deploy results, and how they integrate data mining into their overall business strategy (Shearer, 2000).

THE KNOWLEDGE DIMENSION OF BUSINESS INTELLIGENCE

Knowledge was defined as "justified true belief" (Nonaka, 1994), which is subjective, difficult to codify, context-related, rooted in action, relational, and is about meaning. Knowledge differs from information as the later is objective and codified in any explicit forms such as documents, computer databases, and images.

Knowledge is usually identified to have two types: tacit and explicit (Nonaka, and Takeuchi, 1995). Tacit knowledge is personal, context-specific, and resides in human beings minds, and is therefore difficult to formalize, codify and communicate. It is personal knowledge that is embedded in individual experience and involves intangible factors such as personal belief, perspective, and value system. Tacit knowledge is difficult to communicate and share in the organization and must thus be converted into words or forms of explicit knowledge. On the other hand explicit knowledge is the knowledge that is transmittable in formal, systematic languages. It can be articulated in formal languages, including grammatical statements, mathematical expressions, specifications, manuals and so forth. It can be transmitted across individuals formally and easily.

Knapp defined Knowledge Management (KM) as "the process of making complete use of the value generated by the transfer of intellectual capital, where this value can be viewed as knowledge creation, acquisition, application and sharing", (Knapp, 1998).

Business Intelligence is a good environment in which 'marrying' business knowledge with data mining could provide better results (Anand, Bell, and Hughes, 1995; Cody, Kreulen, Krishna, and Spangler, 2002; Weiss, Buckley, Kapoor, and Damgaard, 2003; Graco, Semenova, and Dubossarsky, 2007). They all agree that knowledge can enrich data by making it "intelligent", thus more manageable by data mining. They consider expert knowledge as an asset that can provide data mining with the guidance to the discovery process. Thus, it says in a simple word, "data mining cannot work without knowledge". Weiss et al. clarifies the relationships between Business Intelligence, Data Mining, and Knowledge Management (Weiss, Buckley, Kapoor, and Damgaard, 2003).

McKnight has organized KM under BI. He suggests that this is a good way to think about the relationship between them (McKnight, 2002). He argues that KM is internal-facing BI, sharing the intelligence among employees about how effectively to perform the variety of functions required to make the organization go. Hence, knowledge is managed using many BI techniques.

Haimila also sees KM as the "helping hand of BI" (Haimila, 2001). He cites the use of BI by law enforcement agencies as being a way to maximize their use of collected data, enabling them to make faster and better-informed decisions because they can drill down into data to see trends, statistics and match characteristics of related crimes.

Cook and Cook noted that many people forget that the concepts of KM and BI are both rooted in pre-software business management theories and practices. They claim that technology has served to cloud the definitions. Defining the role of technology in KM and BI– rather than defining technology as KM and BI – is seen by Cook and Cook as a way to clarify their distinction (Cook, and Cook 2000).

Text mining, seen primarily as a KM technology, adds a valuable component to existing BI technology. Text mining, also known as intelligent text analysis, text data mining or knowledge-discovery in text (KDT), refers generally to the process of extracting interesting and non-trivial information and knowledge from unstructured text. Text mining is a young interdisciplinary field that draws on information retrieval, data mining, machine learning, statistics and computational linguistics. As most information (over 80 percent) is stored as text, text mining is believed to have a high commercial potential value.

Text mining would seem to be a logical extension to the capabilities of current BI products.

However, its seamless integration into BI software is not quite so obvious. Even with the perfection and widespread use of text mining capabilities, there are a number of issues that Cook and Cook contend that must be addressed before KM (text mining) and BI (data mining) capabilities truly merge into an effective combination. In particular, they claim it is dependent on whether the software vendors are interested in creating technology that supports the theories that define KM and providing tools that deliver complete strategic intelligence to decision-makers in companies. However, even if they do, Cook and Cook believe that it is unlikely that technology will ever fully replace the human analysis that leads to stronger decision making in the upper echelons of the corporation.

The authors provide the following findings:

- BI focuses on explicit knowledge, but KM encompasses both tacit and explicit knowledge.
- Both concepts promote learning, decision making, and understanding. Yet, KM can influence the very nature of BI itself.
- Integration between BI and KM and makes it clear that BI should be viewed as a subset of KM.
- Fundamentally, Business Intelligence and Knowledge Management have the same objective - to focus on improving business performance. If we agree that Business Intelligence is comprised of Customer, Competitor and Market Intelligence and that the purpose of Business Intelligence is to support strategic decision-making, grow the business and monitor the organization's competitors,
- The business intelligence concern of DSS in company and deal with customers and competitors where as knowledge management concern about employees

CONCLUSION

There are people who think that BI encapsulates KM and they do believe so because they argue that BI is the mean to manage the different knowledge in any organization "Share the knowledge". actually it is a good way to see it, but if we are trying to look deeper into the different types of knowledge including tacit and explicit knowledge. Actually, KM can be seen as a boarder notation than BI because BI deals mainly with structured data, while KM deals with both structured and unstructured data.

Conceptually, it is easy to understand how knowledge can be thought of as an integral component of BI and hence decision making. This chapter argued that KM and BI, while differing, they need to be considered together as necessarily integrated and mutually critical components in the management of intellectual capital.

In this chapter, the authors provide a detailed overview of Business Intelligence including: definitions, concepts, goals, architecture, components, and mainly its body of knowledge.

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KEY TERMS AND DEFINITIONS

Body of Knowledge (BoK): The sum of body of all knowledge elements in a particular field.

Business Intelligence (BI): An umbrella term that combines architectures, tools, data bases, applications, practices, and methodologies. It is the process of transforming various types of business data into meaningful information that can help, decision makers at all levels, getting deeper insight of business.

Data Mining (DM): The process of discovering interesting information from the hidden data that can either be used for future prediction and/or intelligently summarizing the details of the data.

Data Warehouse (DW): A physical repository where relational data are specially organized to provide enterprise-wide, cleansed data in a standardized format.

Decision Support System (DSS): An approach (or methodology) for supporting making. It uses an interactive, flexible, adaptable computer-based information system especially developed for supporting the solution to a specific nonstructured management problem.

Knowledge: About meaning. It is subjective, difficult to codify, context-related, rooted in action, and relational.

Knowledge Management (KM): The acquisition, storage, retrieval, application, generation, and review of the knowledge assets of an organization in a controlled way.