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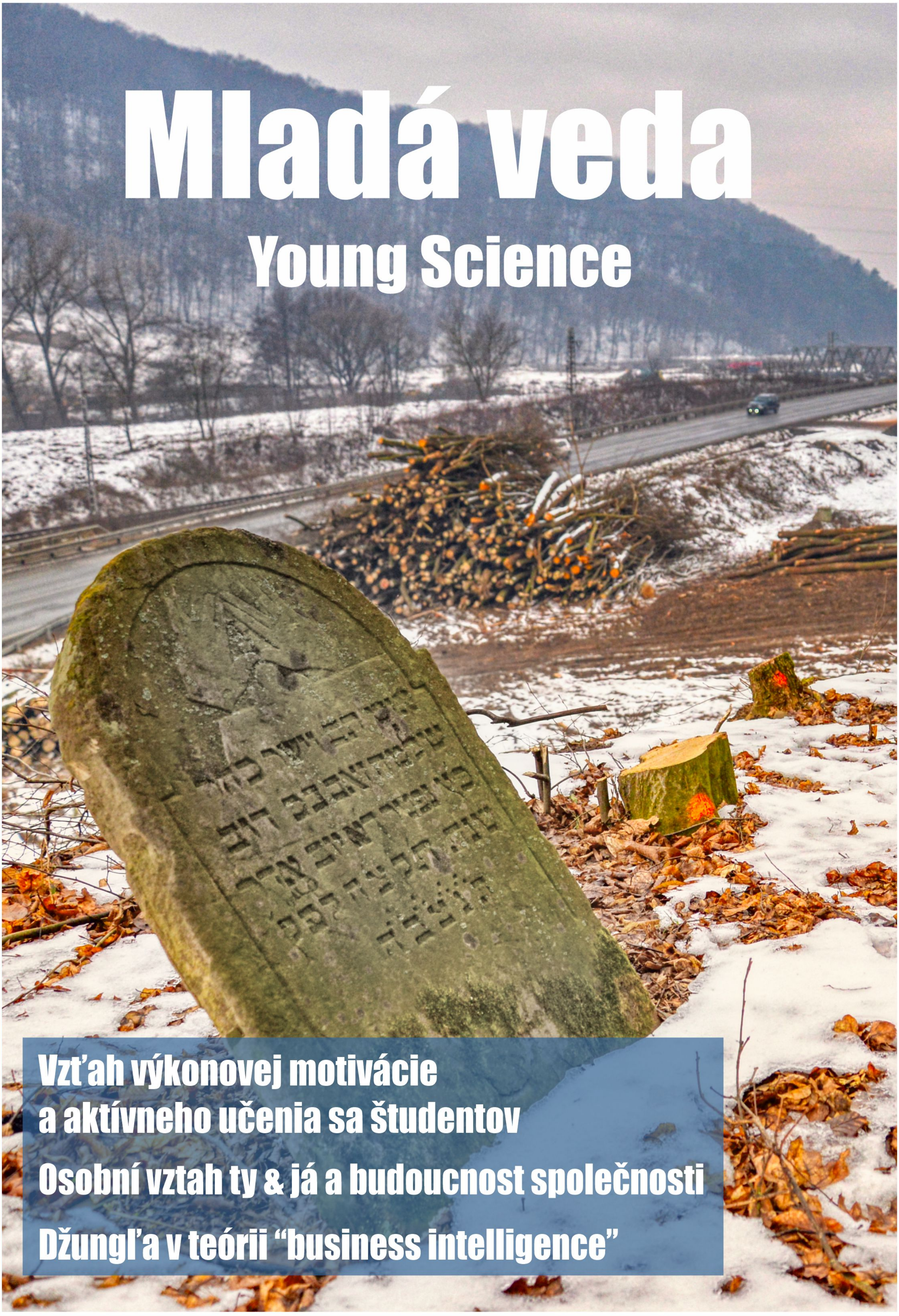

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DŽUNGĽA V TEÓRII "BUSINESS INTELLIGENCE"

THE BUSINESS INTELLIGENCE THEORY JUNGLE

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Marián Halaj studies as a part-time doctoral student at Faculty of Management of the Comenius University in Bratislava. His research work is focused on advanced methods of managerial data analyses particularly in the field of business intelligence.

Abstract
Although the topic of business intelligence (BI) and business analytics (BA) has gained an increasing amount of interest among researchers and management practitioners over the last ten perhaps twenty years, there is still an unbelievable disagreement among those people what the BI really is and is not. The aim of this article is to define and understand the BI from the management perspective based on a decision process chain from a raw data collection to actionable decision making allowing a business performance improvement, with the consideration of available technologies and business particularities. This is enabled by a literature review on a current state of knowledge within the BI area published by authors from various disciplines, including but not limited to math and statistics, data science, information technology, business performance management, organizational behaviour, psychology and project management.
Key words: business intelligence, analysis, data science, knowledge

Abstrakt
Hoci oblasť business inteligencie (BI) and business analytiky (BA) získala v posledných desiatich, možno dvadsiatich rokoch výraznú pozornosť, ako u výskumníkov, tak u manažérov z praxe, v tom čo BI je a nie je panujú medzi týmito ľuďmi až neuveriteľné rozpory. Cieľom tohoto článku je preto definovať a pochopiť BI z manažérskej perspektívy, a to cez celý rozhodovací proces - od zberu "surových dát" po realizáciu rozhodnutia, umožňujúceho zlepšiť obchodné výsledky spoločnosti alebo efektivitu vykonávaných pracovných úloh, a to s použitím dostupných technológií a s prihliadnutím na odvetvové špecifiká. Prakticky sú tieto úlohy spracované analýzou súčasného stavu poznania BI cez

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práce od autorov z rôzneho spektra disciplín, vrátane matematiky a štatistiky, dátových vied, informačných technológií, manažmentu výkonnosti organizácií, organizačného správania, psychológie či projektového manažmentu.

Kľúčové slová: business intelligence, analytika, dátové vedy, znalosti

Introduction

294 billion emails sent, 5 billion searches made, 500 million tweets, or 4 terabytes of data created from each connected car – these are just some of daily statistics on data flow (WEF, 2019). As per the same report 44 zettabytes of data are expected to be generated by 2020 which is 40 times more bytes than there are stars in the observable universe. But how efficiently can we use these data?

Concepts and techniques for coping with a large data sets grow rapidly with the increasing data volume, velocity and variety of new data. Some of them notably known are advanced analytics, big data, business analytics, business intelligence, etc.

Within the last years, perhaps within the last decades the term Business Intelligence (BI) became widely spread over numbers of disciplines. Unfortunately, even within a small portion of this "bunch" (in management field) the meaning of this term varies. The aim of this article is to present the literature review and analyze on what is believed the BI is, define it and its relation to other terms like data science, analytics, data mining; as well as to briefly describe the tools and techniques used by BI.

From Information to Actionable Knowledge

The terms data and information are often used people as synonyms but there is actually a significant difference in its meaning as shows the Data Knowledge Information (DIK) pyramid (Fig. 1) where the data stand at the bottom of this pyramid making a solid base for higher layers. They are used as an input for the information that is extracted from them.

Fig. 1 – Data pyramid
Source: knowledge-management-tools.net

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(Sherman, 2015) sees data as a raw, random, and unorganized and suggests raw data needs integration, design, modeling, architecting, and other work before it can be transformed into accountable information). (Rao, 2018) defines data as a collection of facts, signals, or symbols. He states in this form, it might be raw, inconsistent, or unorganized and claims as such, it is not useful while the data in the form of information becomes more useful because storage and retrieval are easy. Data can be obtained from a variety sources (Fig. 2) i.e from the business process itself, from clients and suppliers, social networks, external databases, etc. from the information processing point of view the special case are so called unstructed data like printed documents, sms messages or emails.

Information is data that has been organized, structured, and processed. Information is the one used to gain the knowledge (Sherman, 2015). (Rao, 2018) defines in Information is a collection of data that is arranged and ordered in a consistent way. As per (Laursen, 2010) the information is a data that is aggregated to a level where it makes sense for decision support in the shape.

The Knowledge (Davenport, 1998) is a fluid mix of framed experience, values, conceptual information, and expert insight that provides a framework for evaluating and incorporating new experience and information. It originates and is applied in the minds of knowers.

Fig. 2 – Data sources
Source: Sharman, 2015

Over the years the basic concept of DIK pyramid has been evolved and extended by many authors. One example of this extension is a DIKW pyramid developed by adding a Wisdom to this model (Fig. 3).

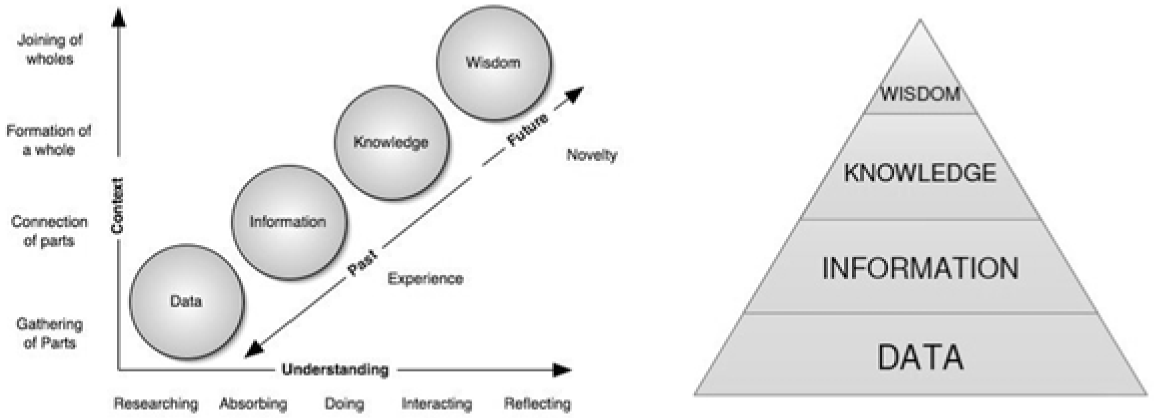

Fig. 3 – Two perspectives on data-information-knowledge-wisdom
Source: Flood, 2014

Wisdom as it is defined in (Cambridge Dictionary) is the ability to use your knowledge and experience to make good decisions and judgments. (Rao, 2018) defines the wisdom as the outcome of experience from or knowledge of earlier attempts to reach a successful outcome and explains it as follows: while knowledge is the most valuable distillation of data, and although knowledge gives you the means to solve a problem, it doesn't necessarily show you the best way to do so. He considers wisdom as ability to pick the best way to reach the desired outcome comes from experience gained in earlier attempts to reach a successful solution. As majority of reviewed authors puts BI into relationship with the the effective decision making the wisdom seems to be the BI driver.

Building the business case for BI

The context of BI is with the term analytical edge, a window in time where competitive advantages will be gained from companies making increasingly more advanced use of information while the others will fail and falter as infosaurs, and takes the BI beyond reporting (Laursen, 2010). These information are either internal data from the organization, officially traded once, or a publicly accessible data sets, that are further processed by analytics. As per (Sherman, 2015) the enterprises with the most advanced analytics capabilities outperformed competitors by wide margins, with the leaders showing these results:

- Twice likely to be in the top quartile of financial performance within their industries
- Five times as likely to make decisions much faster than market peers
- Three times as likely to execute decisions as intended
- Twice as likely to use data very frequently when making decisions

Let’s present some more statistics: 58% companies claim they will make a bigger investment in Big data over the next 3 years, two-thirds of executives consider their organizations as “data driven” (Sherman, 2015). The vast majority (92%) of all users report they are satisfied with business outcomes, 94 % feel their big data implementation meets their needs (accenture). Larger companies are more likely than others to regard big data as extremely important and central to their digital strategy (accenture).

Capturing data, however is just the beginning (Sherman, 2015). Contrary to the numbers above the 42% executives say that data analysis has slowed down decision-making and 85% believe the main challenge is to analyse and act on growing volume of data (Sherman, 2015). The use of analytics is not just growing in volume; it is also growing more complex. Advanced analytics is expanding to include predictive analytics, data visualization, and data discovery (Sherman, 2015). Along with that a plenty of new disciplines, ofter overlapping, has arisen over the last years.

One possibility to look at the analytics and data analyses is from the data analytist perspective. (Laursen, 2010) illustrates how business analytics is a layered and hierarchical discipline (Fig. 4). Arrows show the underlying layers that are subject to layers above. Information requirements move from the business-driven environment down to the technically oriented environment. The subsequent information flow moves upward from the technically oriented environment toward the business-driven environment. There are many competencies, people, and processes involved in the creation of BA. In the top layer of the model the management specifies or develops an information strategy based on the company's overall business strategy. In the second layer, the operational decision makers' need for information and knowledge is determined in a way that supports the company's chosen strategy. In the middle layer of the model, analysts, controllers, and report developers create the information and knowledge to be used by the company's operational decision makerswith the purpose of innovating and optimizing their day-to-day activities. A business (data) analyst are understood those performing business analysis and they work as a liaison among stakeholders in order to elicit, analyze, communicate and validate requirements for changes to business processes, policies and information systems; he understands business problems and opportunities in the context of the requirements and recommends solutions that enable the organization to achieve its goals (BA BoK, 2006). In the second layer from the bottom, in the technically oriented environment in the data warehouse. In the bottom layer the business's primary data generating source systems are run and develop by IT professionals. These five layers therefore represents a repeated process starting by data creation / collection up to decision making and again.

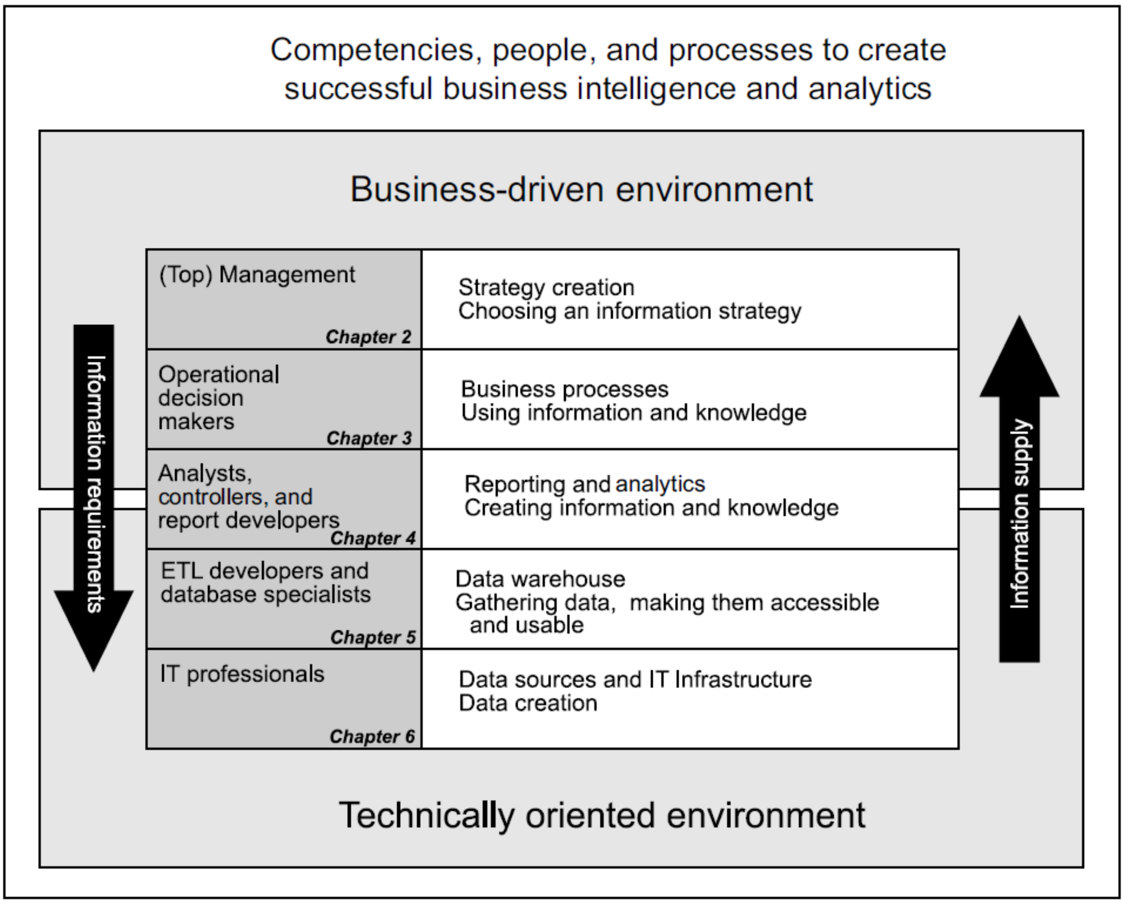

Fig. 4 – The Business Analytics Model
Source: Laursen, 2010

The BI Theory Jungle

The title of this sub-chapter was inspired by the famous article of Dr. Harold Koontz (Koontz, 1961) describing the confusion comming from the variety of schools of management theory. „The noteworthy absence of academic writing and research in the formative years of modern

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management theory is now more than atoned for by a deluge of research and writing from the academic halls“ (Koontz, 1961, p.174). While many organizational theorists could argue sixty years later it is even worse in management the same situation actually happens in the so called data science discipline. The aim of this section is to specify the Business Intelligence (BI) area from the process point of view (not the IT one) and its relationship with other similar data driven disciplines.

Let's go a little bit back in history. The earliest known use of the term "Business Intelligence" is in Richard Millar Devens' in the „Cyclopædia of Commercial and Business Anecdotes“ from 1865 (Bentley 2017). Devens used the term to describe how the banker, Sir Henry Furnese, gained profit by receiving and acting upon information about his environment, prior to his competitors. "Throughout Holland, Flanders, France, and Germany, he maintained a complete and perfect train of business intelligence. The news of the manybattles fought was thus received first by him, and the fall of Namur added to his profits, owing to his early receipt of the news.". The ability to collect and react accordingly based on the information retrieved, an ability that Furnese excelled in, is today still at the very heart of BI. Much later, in a 1958 IBM researcher Hans Peter Luhn described BI as an automatic system for encoding documents and the updating of desired points of interest to accommodate all information problems of an organization. In 1989, Howard Dresner (later a Gartner analyst) proposed "business intelligence" as an umbrella term to describe "concepts and methods to improve business decision making by using fact-based support systems." It was not until the late 1990s that this usage was widespread (Bentley 2017). Nowdays, however, as described further in this chapter there many more definitions of BI.

One of the few common aspects across the review literature is the BI reading in context with a Data Science. Fig. 5 shows the data science as an overlapping of computer science (IT), math including statistics and the domain knowledge. The main message here is the overlapping of all three paradigms, therefore machine learning, traditional research or software development are not considered here as a part of data science.

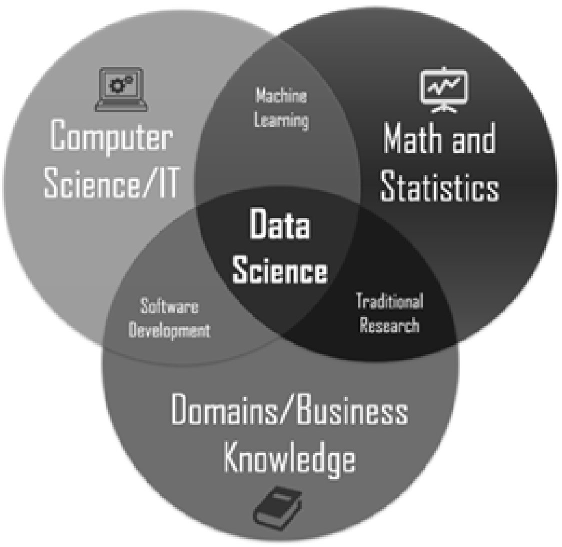

Fig. 5 – Data Science Model
Source: Luellen, 2018

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Business intelligence systems combine operational data with analytical tools to present complex and competitive information to planners and decision makers. The objective is to improve the timeliness and quality of inputs to the decision process. Business Intelligence is used to understand the capabilities available in the firm; the state of the art, trends, and future directions in the markets, the technologies, and the regulatory environment in which the firm competes; and the actions of competitors and the implications of these actions (Negash, 2004). This specification is clearly focused on the domain / business knowledge. (Bentley, 2017) adds the essential aspects of business intelligence are context analysis (a method to analyze the environment of any business), business performance management, business process discovery, information system, organization intelligence and process mining.

Second point of view is the IT. According to (Schniederjans, 2014) one function that is generally accepted as a major component of BI involves storing an organization's data in computer cloud storage or in data warehouses. BI encompasses data warehousing, business analytics and knowledge management (Graham, 2004).

Third is the math or statistics point of view. (Negash, 2004) categorizes the BI into reactive and proactive ones and recognize several essential components of proactive BI, i.e. real-time data mining, automated anomaly and exception detection, proactive alerting with automatic recipient determination, automatic learning and refinement, etc. Particularly data mining is significantly represented in reviewed data analytics related literature (Cao, 2008), (Shmuelli, 2017) (McCue, 2006). It refers to business analytics methods that go beyond counts, descriptive techniques, reporting, and methods based on business rules (Shmueli, 2017). He writes data mining stands at the confluence of the fields of statistics and machine learning (also known as artificial intelligence) and suggest several statistic tools like linear regression, k-nearest neighbors or neural nets.

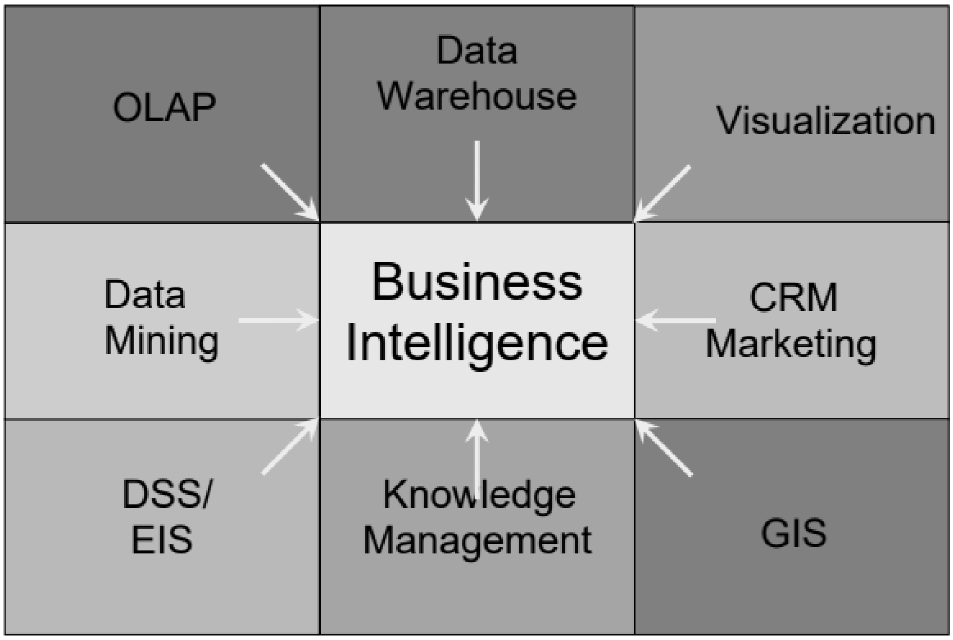

Fig. 6 – BI Relation to Other Information Systems
Source: Negash, 2004

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Fig. 6 presents how the other IT and data systems support the BI. According to this picture the BI is a core (brain) that pulls and process information from many other systems and converts data into useful information and, through human analysis, into knowledge.

Based on the above assumptions and thoughts the BI is seen as a huge knowledge area widely referred to across the various data sources. Therefore, this topic can be seen from various points of view, i.e. BI as a data science, applied math, while the practical one is represented by the business itself. There is a variety of definitions what the BI is and the same is valid for so called BI systems. Some of these definitions are:

BI can be described as a set of techniques and tools for the acquisition and transformation of raw data into meaningful and useful information for business analysis purposes (Bentley 2017).

The processes, technologies and tools needed to turn data into information and information into knowledge and knowledge into plans that drive profitable business action (Graham, 2004).

Another terms often used in context with BI are Analytics, Business Analytics (BA) and Data Mining (DM). From the literature review is it obvious the processes and analytical tools are very similar, the disputes are just in what their mutual relationships are, i.e. superiority or subordinality. In summary, BA includes the same procedures as in plain analytics but has the additional requirement that the outcome of the analytic analysis must make a measurable impact on business performance (Sniederjans, 2014). (Bull, 2017) defines the three main types of business analytics: BI, predictive analytics, and prescriptive analytics.

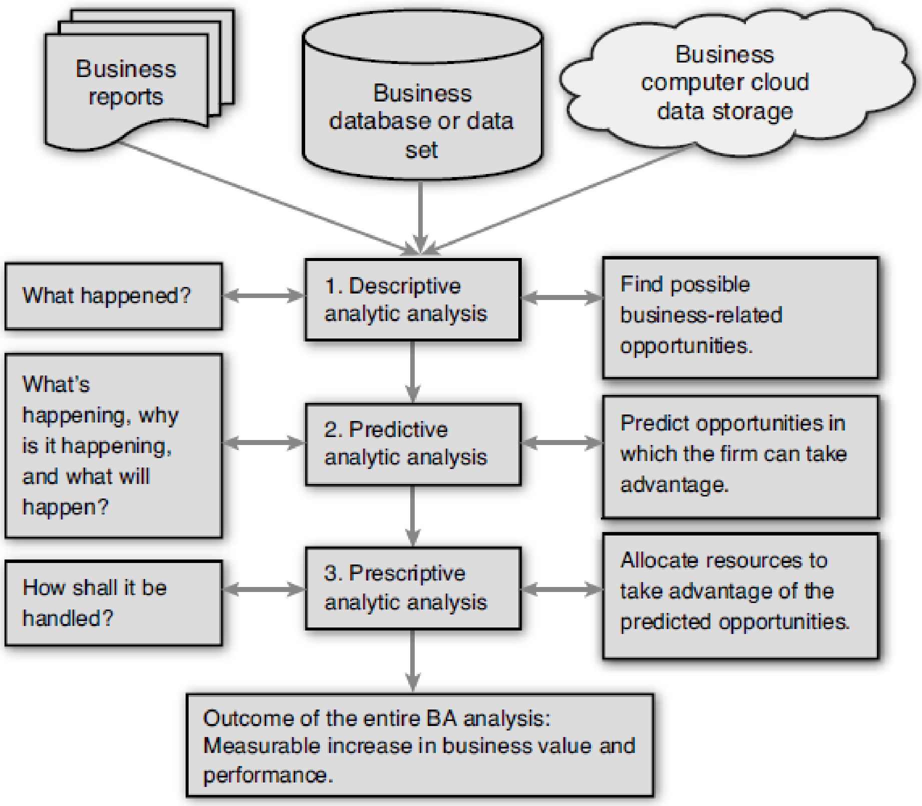

Fig. 7 – BA Process
Source: Schniederjans, 2014

As per (Laursen, 2010) the analytics is an advanced discipline within business intelligence. He clains the BI as a term is today heavily associated with large software vendors that offer only simple technical reporting solutions for the end users, therefore the term business analytics in order to put extra focus on this missing element of the business intelligence equation, and which is by now the most exciting one. He suggests if mastered, this element will be what drives your company into a prosperous future. Schniederjans (Fig. 8) defines BA as a process beginning with business-related data collection and consisting of sequential application of descriptive, predictive, and prescriptive major analytic components, the outcome of which supports and demonstrates business decision-making and organizational performance. (Bentley, 2017) by BA refers to the skills, technologies, practices for continuous iterative explo-ration and investigation of past business performance to gain insight and drive business planning.

As shows Fig. 7 the complete business analytics process involves the three major component steps (Schniederjans, 2014) applied sequentially to a source of data and describes 3 types of analytics: descriptive, predictive and prescriptive. The outcome of the business analytics process must relate to business and seek to improve business performance in some way.

Within the review literature the BA has generally been described as a math-based field, where data experts use quantitative tools to make predictions and develop future strategies for growth. For example (Smueli, 2017) in BA puts emphasis on using quantitative tools to bear on decision making who claims Business analytics includes more sophisticated data analysis methods, such as statistical models and data mining algorithms used for exploring data, quantifying and explaining relationships between measurements, and predicting new records. (Adair, 2018) also recognize the BI as diagnostic and descriptive analytics against the predictive and prescriptive BA.

(Laursen, 2010) suggests to understand of BA as a holistic information discipline with links to business's strategy, as a combination of IT technology, strategy, human competencies, and organizational processes which he believes, in the near future will be aimed at optimizing individual human behavior. Similar approached by several other authors.

Basis for comparison	Business Intelligence	Business Analytics
Definition	Analyses past and present to drive current business needs	Analyses past data to drive current business
Usage	To run current business operations	To change business operations and improve productivity
Ease of operations	For current business operations	future business operations
Applications	Apply to all large-scale companies to run current business operations	Applies to the companies where future growth and productivity as its goal
Field	Comes under Business Analytics	Contains Data warehouse, information management, etc.

Tab. 1 – Business Analytics vs. Business Intelligence
Source: Educba

As per Harvard Business Analytics Staff (HBS, 2018) BI is use of data to manage day-to-day operational management while BA make predictions and develop future strategies for growth. (Bentley, 2017) claims BA focuses on developing new insights and understanding of business performance while traditionally focuses on using a consistent set of metrics to both measure past performance and guide business planning. BA includes reporting results like BI but seeks to explain why the results occur based on the analysis rather than just reporting and storing the results, as is the case with BI (Schniederjans, 2014).

The summary of differences between BI and BA performed via business focus perspective arepresented in Tab. 1 and Tab. 2.

Characteristics	Analytics	Business Analytics	Business Intelligence
Business performance planning role	What is happening and what will be happening?	What is / will be happening, what is the best strategy to deal with?	What is happening now, and what have we done in the past to deal with?
Use of descriptive analytics as a major component	Yes	Yes	Yes
Use of predictive analytics as a major component	Yes	Yes	No
Use of prescriptive analytics as a major component	Yes	Yes	No
Use all three above in combination	No	Yes	No
Focus to improve business value and performance	Maybe	Yes	No

Tab. 2 – Characteristics of Analytics, Business Analytics, and Business Intelligence
Source: Schniederjans, 2014

Revealing its origins and widespread use in business, data mining goes by many names, including knowledge management, knowledge discovery, and sense making (McCue, 2006). It is an integrated process of data analysis that consists of a series of activities that go from the definition of the objectives to be analysed, to the analysis of the data up to the interpretation and evaluation of the results (Giudici, 2009). From this definition it seems to be a well defined process. On the other hand, is a highly intuitive, visual process that builds on an accumulated knowledge of the subject matter, something also known as domain expertise (McCue, 2006). As per (Shmueli, 2017) the data mining refers to business analytics methods that go beyond counts, descriptive techniques, reporting, and methods based on business rules, which indicates it forms a part ob BA. These definitions of DM are similar to the definition of BA. Taking into account the strong emphasis on analyzing techniques that part of DM dealing with business related issues might be considered as a part of BA.

Advanced analytic methods and techniques

Analytical methods and techniques form are a core of the reviewed business analytics literature which is reflected in a number of them in use. These methods might be either business specific (often taylor made for a specific situation) or imported from other disciplines like statistics, informatics, artificial intelligence or psychology. For example (Marr, 2016) describes 18 analytic tools (in fact these are methods) to analyze data and extract actionable and commercially relevant information that you can use to increase results or performance: Business experiments, Visual analytics, Correlation analysis, Regression analysis, Scenario analysis, Forecasting/time series analysis, Data mining, text analytics, sentiment analysis, image analytics, video analytics, voice analytics, Monte Carlo Simulation, linear programming, cohort analysis, factor analysis, neural network analysis, meta analytics/literature analysis.

(Albright, 2015) distinguishs three themes addressed within the methods that can be used to analyze data and help make business decisions: data analyses, decision making and uncertainty and describes them as follows:

- Data analysis includes data description, data inference, and the search for relationships in data.
- Decision making includes optimization techniques for problems with no uncertainty, decision analysis for problems with uncertainty, and structured sensitivity analysis.
- Dealing with uncertainty includes measuring uncertainty and modeling uncertainty explicitly

(Giudici, 2009) notes several analytical techniques used in data analytics, including cluster analysis, linear regression, logistic regression, tree models, neural networks or k-nearest-neighbour.

(Schniederjans, 2014) adopts the three categories (descriptive, predictive, and prescriptive) for grouping the types of analytics and those defines as follows:

- Descriptive - application of simple statistical techniques that describe what is contained in a data set or database.
- Predictive - application of advanced statistical, information software, or operations research methods to identify predictive variables and build predictive models to identify trends and relationships not readily observed in a descriptive analysis.
- Prescriptive - application of decision science, management science, and operations research methodologies (applied mathematical techniques) to make best use of allocable resources.

As we can see these tools mainly involve statistical and data mining methods. Quite exhaustive description of data mining has been published by (Shmueli, 2017) and (Albright, 2015) who mentions five primary methodologies of data mining: clasification analysis, prediction, cluster analysis, market basket analysis, and forecasting. In order to get a helicopter view of DM techniques we can use a scheme presented by (Shmueli, 2017). In his model the DM as a process of discovering hidden facts may be reallized using two types of methods: supervised or unsupervised. Supervised learning, where we actually assist in the teaching of the algorithms by providing examples / training data, are those used in classification and prediction. The methods here are mainly linear and logistic regression, neural nets and k-nearest-neighbour (Shmueli, 2017).

Unsupervised learning algorithms are those used where there is no outcome variable to predict or classify. Hence, there is no "learning" from cases where such an outcome variable is known. Association rules, dimension reduction methods, and clustering techniques are all unsupervised learning methods (Shmueli, 2017).

Among the reviewed techniques there are some listed by almost all authors, particularly linear regression, k-nearest-neighbour or clustering.

Conclusion

The study is based on the on the exhaustive literature review on a current state of knowledge within the BI area published by authors from various disciplines, including but not limited to math and statistics, data science, information technology, business performance management, organizational behaviour, psychology and project management. This literature was balanced to include books, dissertations, articles, another literature reviews, as well as surveys and reports from internationally recognized management consultants.

Study found the BI definition itself represents the most complex part of literarture review as there is a huge disagreement amont the authors on the definition, components and even features of BI. There are three streams of defining the BI depending whether the emphasis is put on the domain, IT or math and statistics. Domain paradigm (looking at BI from the business process perspective) in BI definition is presented within the majority of conference articles. Contrary to the articles the books split these three perspectives almost equally. A typical IT focused literature is (Sherman, 2015), (Schniederjans, 2014), (Graham, 2004). The BI focus on statistics is highlighted by authors dealing with predictive and advanced analytics, like data mining, knowledge discovery (Cao, 2008), (Shmueli, 2017).

However, the major issue with BI definition is to bound the relationships between business analytics (BA) and BI. Some authors consider the BA as a subset of BI (advanced analytics part of BI), while other consider the BI as that part of BA allowing for the technical feasibility of BA algorithms. There is also another stream considering BA and BI as a separate disciplines, one representing the analytics and the second represents the technology and hardware. This thesis is, however aligned with the first category of those authors, i.e. the BI is considered here as an integrated and (in some extent) automated system or process consisting of technology (hardware), tools (operation systems and applications) and techniques (analytical content) with the interface to people operating these systems and based on that operations allowing them to make the qualified and actionable decision towards business needs. This system should be also equipped with the automation of the data collection, sourcing and extracting from another systems and databases. The practical interpretation of this developed definition is that BI user may not necessarilly require an expert knowledge unless he makes a business decisions, as all the other BI processes may be routine or even fully automated.

This paper has adopted for the concept of three analytics types: descriptive, predictive and prescriptive presented by several authors, notably (Schniederjans, 2014), where the descriptive one describes the past (what is contained in a data set), predictive models identify the future trends and prescriptive models for best use of allocable resources. This categorization is critical to define the purpose of BI system, i.e reporting of past data to run current business operations, predictive business modelling to change business operations or project resources allocation to improve productivity. As a conclusion the author suggests to recognize a reporting, predictive and optimizing BI rather than use terms business intelligence, business analytics and data mining in business context.

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