UNIVERSIDAD DEL ROSARIO

BUSINESS INTELLIGENCE: FROM CONVENTIONAL TO COGNITIVE

ASISTENTE DE INVESTIGACIÓN

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ABSTRACT

Technological systems enhance organizations since 1958 and are the ground basis of a strong managerial operation in today´s business competition. Based on a literature review that identifies past, present and future applications of technology from business intelligence to artificial intelligence. This article offers an understanding of which technological advances are applied in organizations to adapt and survive within an ever-changing environment in business world today. Business intelligence´s definition and key divisions are described to carry on a wide explanation due to its scope. Based in a state-of-the-art literature revision and going through several definitions, BI it is analyzed as a process and as technological aid. From key divisions in its application such as: reporting, analysis, monitoring and prediction to its extensions based on time frames in operational and strategic bids. BI is the starting point to excel why having a decision support making tool is key to hedge the risk from failure to be an outstanding tool to increase profits. How can systems create for themselves prediction modules that optimize and later adapt to future scenarios based on historic data and how its adaptivity is key. Therefore, new technologies are emerging at a neck breaking speed. Hence, this article explains and help to understand their scope and importance within the world we live in and why companies must innovate and cope with them when building their industry to new horizons. Internet of things, machine learning and artificial intelligence are the new emerging and disruptive technologies that are being implemented in all industries creating new trends and challenges to manage.

Key words: Business Intelligence, analytics, cognitive, Internet of things, machine learning, artificial intelligence.

1. INTRODUCTION TO BUSINESS INTELLIGENCE

Nowadays working in fluctuating, fast phased, dynamic and ever-changing environments are making managers, analysts, executives, analyze past information in a more detailed way to enhance and faster their decision-making process for future scenarios (Michalewicz, Schmidt, Michalewicz, & Constantine, 2010). Mentioned as early as in 1958 by IMB´s researcher Hans Peter Luhn who described it as an automated method to bring awareness services to scientists and engineers (Luhn, 1958) coined as a term for data analysis tools, it´s understanding of what it is widened towards being considered as: The sum of components of a decision support infrastructure (Lahrmann, Marx, Winter, & Wortmann, 2011). *Business Intelligence* (BI) could be define in several ways depending on the industry, application and author.

BI´s literature absences a general definition (Pirttimäki, 2007). A definition could be made in function of how BI is viewed from a multidimensional point of view where It could be seeing it as a process: BI has as a result creating knowledge in function of how we transform raw data into information. Knowledge is normally gained to improve everything costumer related: Needs, decision making process, competition, conditions in the industry, general economic, technological and cultural trends (Golfarelli, Rizzi, & Cella, 2004, pág. 1)

Or as a set of technologies:

> Business intelligence (BI) is a broad category of technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help its users make better decisions. (Wixom & Watson, 2010, pág. 14)

It gained overall importance due to Information Technologies (IT) since the arise of organizational behavior systems (OBS) like enterprise resource planning (ERP) or customer relationship management (CRM). Overall BI is a system comprised of both technical and organizational elements that presents its users with historical information for analysis to enable effective decision making and management support, with the overall purpose of increasing organizational performance measured in financial results (Jones, Sidorova, & Isk, 2012).

It is likewise seeing as a: Organizational decision-making process, information and knowledge management, decision flows and processes, and human interaction. BI´s definition was used several times to cover other kind of different processes. E.g. It was used to convey the term *Competitive intelligence* (CI) at the late 90´s to talk about the collection of internal and external information to find business opportunities (Richard G. Vedder-, 1999). Further terms such as: decision support systems, executive information systems, management support systems and Business/Corporate performance management are used to talk about BI as well (Thomas D. Clark, 2007)

BI responds to the fact that predicting the exact future is impossible, yet we could make a good speculation about it. BI is implemented to build a forecast enhanced by an accurate detail technology-aid analysis of past data presented in front end applications such as: reports, summaries, dashboards, graphs, charts, maps and Key performance index. For whoever is needed, it might be a very useful tool to reduce hesitation and estimate which is the most likely event to happened in the future. Once this analysis has been made, which decision should be the best one to make in the present time? BI will not decide itself what to do, it´ll describe the past and current state of things, what was and what is, to excel trends and derive insights.

Accessing to data in an organize way at any given time helps to discover inefficient business processes & hidden patterns, identify areas of strength and weakness, and new opportunities to better understand a company´s operations and challenges. BI is basically accurate, understandable, actionable information on demand. An example about BI application could be well explain in a retail chain that has both stores and on-line sales. The manager could track his or her costumers purchase behavior through a loyalty card that has a unique ID which can be swipe at both sales platforms. The card associates everything they buy into the company´s data base through they ID number. Managing purchase tracks of costumers empowers the managers to run analytical reports on massive amounts of data to understand how loyal they are to a certain brand, purchase frequency, and preferred purchase platform. Hence, managers could create targeted marketing campaigns and predict how a certain product rotation will be performed in the future (Hitachi, 2014). BI is a source of decision support and not decision making. BI process shows a relation between data and knowledge which is further turned into decision making support.

1.1. Key divisions into BI

Since BI itself is a very wide concept it cannot be encapsulated in just a few definitions nor uses. There are several uses, applications and types. Normally, they all look very similar, however they have slightly but important differences. This article will review just a few, so the reader can build up an image upon how diverse BI could be. To understand this concept let´s take a closer look into a couple of BI uses, applications and types.

1.1.1 Uses and Applications: Reporting, analysis, monitoring and prediction

BI has four main categories and they are applied in different BI uses that data analysis related companies should be acquainted with: *Reporting*, *analysis*, *monitoring* and *prediction* (Apex, 2018)

Reporting is used by professionals as a record of past activities and data written in any front desk application (Word, excel, power point, etc.). The scope could be the whole company´s activities or it could be a simply as a weekly report about a specific department or task.

Data itself is worthless without a proper *analysis*. It becomes useful when it becomes into something we can interpret and understand. Basically, it has to be analyzed in order to know why something happened. Numerous ways to analyze information exist. e.g. Spreadsheet analysis is used with the goal to assess or anticipate performances. Ad-Hoc Query is to build up a solution for an exact specific problem in function of many variables in a software program, saving resources. Finally, Visualization tools, in order to have an easier way to digest information, e.g. A bar chart showing the augmentation of costumers through discounts program over time or underpin a market share gain/loss in a pie chart. Among others.

A thermometer of how things are going on in between reports and one of BI´s main functions to support any decision-making process is to *monitor* organized data in real-time or in a close frame time to it. There are several to monitor your data. A Dashboard are graphically presented so people can easily read them and understand them. *Key performance Indicators* (KPI´s) are normally based on some weighted average of many variables (Like an index) or it could just be the performance of a specific task or action. Finally, Business performance management is a way of measure your company´s overall performance in function of meeting established goals in the past.

As we spoke before, one of the main reasons (if not the most important one) of why companies decide to invest millions of dollars in BI technologies is to try to predict (*Prediction*) the future based on past data. The so-called Historic data have provoked new technologies to emerge to better manage information (Gandhi & Armstrong, 2016). Since, this is not only complex but tedious, outsourcing this kind of procedures to software specialized companies that automates the process (SAP, Oracle, IBM, etc.) is becoming more popular. The two main procedures to do this are *Data mining* (DM) which is the method of locating relationships among large sets of data and extract it for further understanding and use and predictive modeling which is the process of creating a mathematical tool that generates an accurate prediction or forecast in function of many variables the probabilities of a certain outcome (Kuhn & Jhonson, 2016)

1.1.2. Real applications

BI and it´s techniques have real life benefits and applications in crossover industries for multiple purposes.

The mobile industry for example uses BI to predict when a costumer could probably stop using their services to get their phone, gas or other things from a different company by collecting billing information, costumer services interactions, web site visits and other metrics then they rate costumers with a low or high risk and offer them incentives for not leaving (Thelwell, 2018)

Data analysis tools are now available to help both subjective and objective decisions. For example: Decisions such as employee recruitment or product branding are now based on data-driven analysis and costumer risk analysis or financial/ logistic scenario planning are using more advanced analysis based on complex data that is more accessible than it has ever been (Weldon, 2018) .

A BI solution system implanted by Universidad de Magdalena in Colombia found relevant benefits for a more smooth and efficient operation at their university, such as: Aline daily operations with a global strategy and its goals, access to information and specific functions of users and assigned tasks, easier understanding of BI output through spread sheets and front desk apps and monitor business KPI in real time (Triana, Hernández, Martínez, Lista, & Flórez, 2013).

Continental airlines are a world leader in offering air transport services and in real-time BI use application for its company. A self-made study designed to review the outcome of how real-time BI increased the revenue and decreased costs after applying it in several departments such as: Revenue management and accounting, Customer relationship management, Crew operations and payroll Security and fraud Flight operations BI management. The study showed that after a 30M investment in hardware, software and personnel the company generated revenue enhancements and cost savings for 500 Million USD resulting in a *return of investment* (ROI) greater than 1000% (Hugh J. Watson, 2009).

2. BUSINESS INTELLIGENCE EXTENSIONS

2.1. Operational vs Strategic Business Intelligence

Operational Business Intelligence (OBI) and *Strategic Business Intelligence* (SBI) are vastly used in companies for the same purpose: to optimize. Although this might sound obvious and redundant through the article, it is not. Since they do not optimize in-between the same time frame nor department, which is fundamental to consider when shining the difference. SBI is used when managers want to gain strategic advantages through improving a business process. Analyzing a certain relevant data-set to that offers historical context trends and patterns are found. Additionally, it investigates the future by forecasting, setting goals, and creating: planning, direction and execution in whatever industry they are in (UJ, 2018). By the other hand, time wise OBI it´s applied in a shorter almost immediate time frame. It means that any analysis Is used for real time decision making. Critical factors emerge from that because data must be reachable in a mobile and accessible tool in order to be intimate and interactive since decisions must be taken fast, even seconds before events happen. It´s often called as well *Real-Time Business Intelligence* (RTBI) (Techopedia, 2018).

2.2. Business Intelligence vs Business analytics and Big data

Organizations look mainly after successful business function when they hire top managers and invest in any kind of services and talent to answer questions such as: How to compete in the market? How to increase market share and growth profit? How to reach and keep more costumers? and so on. BI, *business analytics* (BA) and *big data* (BD) are collecting, analyzing and reporting techniques that bring value out of the data that has being stored historically or in the present to enable good decision-making process in critical moments that lead to a more efficient operation, a more profitable enterprise or perhaps a more satisfied costumer. The aim is simple: More business benefits.

All three concepts begin with an ETL (Extracting, transforming loading of data) process, it allows data to be dumped in Datawarehouse, then data is retrieved through querying and finally displayed in forms of report in front desk apps.

As we showed above, one way to differentiate what type of analysis is being made in a certain process is to observe the time frame and the kind of analytical approaches being used. Basic Business intelligence is used to:

> BI tends to provide reports, dashboards, and queries on business questions for the current period or in the past. BI systems make it easy to answer questions related to quarter-to-date revenue, progress toward quarterly targets, and understand how much of a given product was sold in a prior quarter or year, for example (Dietrich, Heller, & Yang, 2015, pág. 12).

It focusses on the ability to comprehend presented information and then use it to successfully guide business actions to achieve planed strategic goals. By the other hand, BA is built up to aiming a different goal: To help predict the future. BA is completed to spot weakness in current procedures and accentuate important data that will help a company prepare for future progress and trials (Techopedia, 2018).

BI and BD are correlated in a closer way than BI and BA. BI is part of BD and BD is fundamental for BI. BD has big potential to influence society and science (Viktor Mayer-Schönberger, 2014).

BD is a popular concept we have already hear of, but most of us don´t really know what it is about. BD is one of the most discussed topics in business today across industry sectors and is normally related with other concepts such as BI or DM which is not entirely wrong since they all analyze data. The main difference is the size of data volumes, number of transactions and number of data sources since they are outrageous big and require special methods and technologies in order to draw insight out of data (Su, 2018). Prior to enlighten the differences between BI and BD, is important to distinguish it. BD is high in several aspects such as: volume, velocity and variety of information assets that demand profitable and innovative forms of information processing that allow improved vision, decision making and process automation (Gartner, 2018).

BD is a larger and more complex data sets from several sources. Traditional processing software like the one BI use can´t manage voluminous data sets. Normally, these massive volumes of raw data are address business problems companies were never able to attack before. BD is explained in Three Vs: Volume, Velocity and Variety (Oracle, 2018)

The main differences among both concepts rely on the amount of data they can handle, the speed at which they can process it. BI works upon structured data sets and BD desires and differentiate structures, unstructured or semi structured data sets, BI can handle terabytes of data while BD handles Petabytes or exabytes of data (Stefan Debortoli, Müller, & Brocke, 2014)

2.3. Challenges

Although BI is nowadays essential in most companies regardless of their industry some challenges have been identified in its implementation. Challenges in the technology, organizational, cultural and infrastructure, issues lead to a fail use to the end user: Managers, analysts, and decision making responsible (Wong, 2011).

Malliton a Software company which offers cloud data platforms solutions to power companies through building precise insights, recently made a survey among 10.000 managers, from 150 different countries and 18 different industries, where they identified five main problems when building up BI tool at organizations: Delivered self-service reported analysis, Reporting/analyzing among multiple systems, Unblocking data buried in systems, reducing the cost of producing reports and delivering mobile BI (Thewell, 2018)

2.4. Trends

In a fast-paced world, markets environments nature changed completely, this dynamic requires that businesses either adapt or lose market by their competitors. Outsourcing technological systems has increasingly become the way of companies to implement business intelligence tools to cut fixed cost where only the services are paid avoiding huge investments. Therefore, Industry trends shows an increasing growth in the BI implementation in companies in the last decade. An article published in April 2012 by Gartner Inc (one of the biggest tech consulting companies in the United States) presented through a survey that analytics and BI is the No. 1 technology priority for CIOs in 2012, as well Worldwide business intelligence (BI) platform, analytic applications and performance management (PM) software revenue reached $12.2 billion in 2011, a 16.4 percent increase from 2010 revenue of $10.5 billion (Gartner, 2012). Gartner four years later exposed again a promising forecast about this industry forecasting that by 2016 The Global revenue in the business intelligence and analytics market is to reach $16.9 billion which means an increase of 5.2 percent from 2015 (Gartner, 2016)

3. ADAPTIVE BUSINESS INTELLIGENCE MODEL

BI has been used as an umbrella term to describe concepts and methods to improve business decision making by using fact-based support systems (Chiang, Chen, & Storey, 2010). After reviewing the concept of business intelligence and it`s applications we might now want to take a step further. Since managers responsibility is to come up with strategies that answer questions such as: how to reduce costs, optimize profits or gain market share? a gap between knowledge and decision making has been found. The concept of Adaptive business intelligence emerged after understanding that decisions are not evaluated in a periodic manner and non-accurate decisions of the past might happened again (Abdelkerim Rezgui, 2016). Therefore, using prediction and optimization techniques to build self-learning decision systems that recommend near optimal decisions and an adaptability module for improving future recommendations when taking a decision solve this uncertainty. The adaptability behind the proposed solution is achieved through the evaluation, tracking and recommendation of decisions in any BI system. Figure 1 shows the *Adaptive Business Intelligence* (ABI) process.

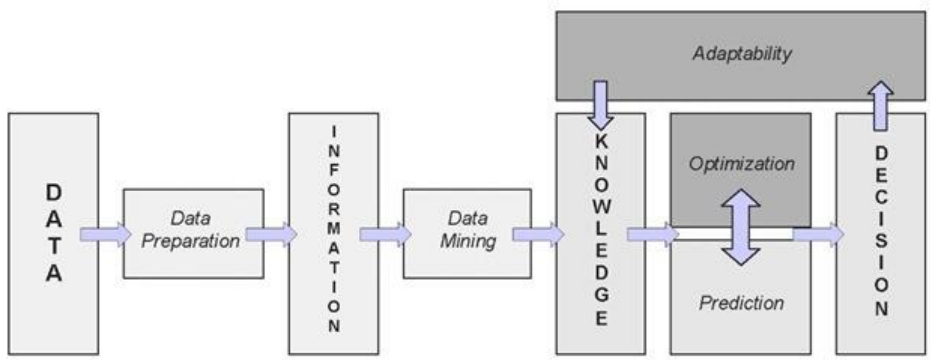

Figure 1: Decision making process based on prediction and optimization
Taken from: http://what-when-how.com/artificial-intelligence/adaptive-business-intelligence-artificial-intelligence/

knowledge is transformed into decisions through optimization and prediction which is further adapted in function of future scenarios with the aim of helping organizations to make better decisions. We will explain briefly what is behind the process as the figure 1 shows.

3.1.Data

The Cambridge dictionary define Data as:

> Information, especially facts or numbers, collected to be examined and considered and used to help decision-making, or information in an electronic form that can be stored and used by a computer (Cambridge D. , 2018).

Gathering, store and analyze huge amounts of data was a lift for managers to apply the scientific method in their practices. As we have already excelled several times through the article, the primary basis for BI´s output into decision-making is that data will turn into information, later knowledge and finally to making better decisions (Shollo & Kautz, 2010).

Nowadays, collecting massive amounts of organized information is affordable due to the declining cost of acquiring and storing very large amounts of data from many sources like banks, retails and e-commerce (Surajit Chaudhuri, 2011). Data are collected in the form of bits, numbers, symbols and objects, which is later prepressed, cleaned and arranged into structures and stripped of redundancy to become information. Knowledge is merely the identification, discover and learning of facts, trends and relationship among organized information.

3.2. From data preparation/cleaning to Information

Data cleaning (DC) is a huge step towards DM since it needs noiseless data to be mined. Bi is the process of how we manage raw data into something useful. As the figure 1 shows prior to find trends and patterns we must have accessible and organized data or most known as: Information. DC will measure from the beginning how high quality our process will be. DC could be defined as:

> Data cleaning, also called data cleansing or scrubbing, deals with detecting and removing errors and inconsistencies from data in order to improve the quality of data (Rahm & Do, 2015, pág. 2).

And it´s participation within BI process could be explained as crucial since DC is the ground basis for an effective DM process because information storage in warehouses is massive and cleanness. Improving data´s quality consist in removing errors and inconsistencies, this process is also known as Data cleansing or scrubbing (Devi & Kalia, 2015).

Most frequently problems are misspelling, contradictory values, duplicates, naming conflicts, scheme conflicts that lead to overlapping and inconsistent data. DC is an exhausting work when doing manually, despite de fact that many software that automatizes the process it still must be reviewed by a human being to find overlaps or inconsistencies. The need to build a process is imperative. Global managing website Geotab suggest six steps to reach goals at your company when cleaning data: Monitor errors, standardize the process, validate accuracy, scrub for duplicate data, analyze and communicate with the team (Geotab, 2018). Since data has not a physical product is harder to assess its quality for companies and dirty data costs billions of dollars annually to companies, for deep understanding on how to enhance your data cleaning processes in complex process check, Fixing Rules for Data Cleaning based on Conditional Functional Dependency (Rashed K. Salem, 2016)

3.3. From data mining to knowledge

Cleaned raw data is now called information and saved in data warehouses in order to become knowledge. Now is safe to proceed with the DM process which is basically find relationships and patterns among variables. DM is the extraction of implicit, previously unknown and potentially useful information from data and Machine Learning (ML) normally provides the technical basis of DM (H.Witten & Frank, 2005). As a complementary discipline for BI data mining is described as a discovery phase in data bases (KDD: Knowledge discovery in data bases), which is a methodology that gather non-common processes in potentially usable patterns (Gorbea & Madera, 2017). DM is based on math, statistics and computational sciences, it gathers huge data exploring techniques to diagnose patterns and identify relationships to classify and predict tendencies that might happened in the future (Hazen, Boone, Ezell, & AllisonJones-Farmer, 2014). Prior to execute any DM process is very important to trace a clear path towards the target and direction to reach research´s final goal (PaulaGonzález, JesúsLorés, & AntoniGranollers, 2008)

3.4. From knowledge to Optimization, Prediction and Adaptability

In a real scenario companies operate in an ever-changing environment full of many internal and external variables that makes them either adapt and adjust or let their competition run them out of business. An ABI system must have three main functions: To predict, to take near optimal decisions and to adapt the last two to changes in the environment. Nowadays it has many other names and technologies. For now, we´ll explain ABI´s insight.

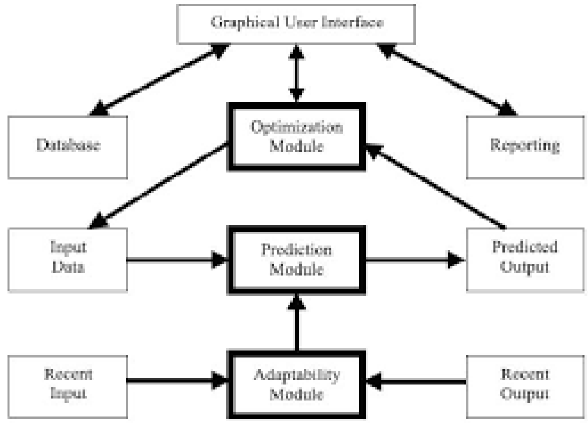

Figure 2: The structure of an adaptive business intelligence system
Taken from: http://zeus.inf.ucv.cl/~jrubio/docs/AIABICP.pdf

Knowledge is the basis from where predictions are built. Predictions are directly applicable to decision making, whereas knowledge discovery is closer to decision support. The basic function of a prediction module is to produce an output based in some input. Prediction models are trained with historical data in order to learn, this process could be developed in a mathematical, distance, logic or modern heuristic way (Michalewicz, Schmidt, Michalewicz, & Constantine, 2010). Let´s not forget that BI is a support technology for decision making process. Optimization modules have the main function to recommend a best answer which is based on prediction´s output module and it generates a distribution solution that serves as input data for the prediction module and the cycle repeats again and again.

Both optimization and prediction modules are insufficient by themselves for today´s ever changing environments. The concept of adaptability has far reaching consequences, the most important one is to learn from its own mistakes and adapt again and again for *n* amount of time. The detection process occurs when the systems finds a gap between the real value of the variable in real time with the one the prediction and optimization module suggested. If an error exist the adaptability module will tune the prediction module to decrease the prediction error (Michalewicz, Schmidt, Michalewicz, & Constantine, 2010). Finally, Adaptive module: its objective is that predictions can be modified if the environment changes, so that the prediction module can learn and adapt to the change. The adaptation module must compare the predictions made with reality. If there are differences, the adaptation module reconfigures the prediction module to reduce the differences (Rubio & Crawford, 2014).

4. NEW TECHNOLOGIES

Disruptive technologies are maturing and being a game changer for companies. From Internet of things to artificial intelligence technology is nowadays beyond than a trend, is the new way to do business at any industry (Heltzel, 2018). As we started this article scientific analysis data tools have been Game-changer technologies and their applications to real organization enhancement and industry to have a better ERP managing. A brand-new technology for this would be SAP leonardo which at the moment in the current market offers cloud integrations to embrace all these emerging technologies such as machine learning, advanced analytics, blockchain and Artificial intelligence for simple business (SAP, 2018). Therefore, we will review some of the most trending technologies for companies.

4.1. Internet of things (ITO)

The Internet of Things (IoT) denotes to the daily interconnection of everyday objects, it embraces a universal connection around a variety of objects to the internet by using wireless/wired technologies (Yang, 2014). The word *internet* covers different realities from a networking point of view to data and services and the word *things* which is more subjective to interpretation covering anything we might use to collect this data to any application, although the IoT normally refers to network-able things. A more scientific approach could define and explain its application as:

> The connection of physical things to the Internet makes it possible to access remote sensor data and to control the physical world from a distance. The mash-up of captured data with data retrieved from other sources, e.g., with data that is contained in the Web, gives rise to new synergistic services that go beyond the services that can be provided by an isolated embedded system. The Internet of Things is based on this vision. A smart object, which is the building block of the Internet of Things, is just another name for an embedded system that is connected to the Internet (Kopetz, 2011, pg. 307).

The IoT is changing in many aspects the world we live sophisticated chips are embedded in the things that surround us each to transmit valuable data that allow us to identify patterns among our most inmate daily life gadgets. So, now that we know what IoT is, how does it work? Basically, you take things (Gadgets, devices, apparats, etc.) and then you add the ability to sense, touch, communicate, control and so on creating the opportunity to interact and collaborate with other things (Hougland, 2014). The process starts with the devices themselves that communicate with an IoT platform that integrates the data from many devices and applies analytics tools to address industry specific needs (IBM, 2015).

Back in 2010 an article called *Internet of things: a survey* published by the scientific magazine computer networks concluded that IoT offers numerous applications that could be grouped in four main domains: Transportation and logistics, healthcare, smart environment and, personal and social domains. applied in the upcoming decade that were unviable back in the day due to the lack of connectivity among our devices (Atzori, Iera, & Morabito, 2010). As well some intrinsic factors where identified for IoT to grow at exponential phases in the last decade such as: The internet of everything, services and networks which can control, trace and identify trillions of objects (Ning & Wang, 2011). It is not a surprise that numbers predict an increased number connected things in use will hit 14.2 billion in 2019 and to grow to 25 billion by 2021 (Paul, 2018).

Currently, IoT has applications all throughout many industries and are used by companies to enhance their products experience, especially when they are related with our lifestyle. We will go through some real-life applications at a multi-sectorial level. The healthcare industry with IoT monitors our daily movements in order to control and enhance our health. In the healthcare industry wearables have become at the hearth of every discussion IoT related since the requirement for self-health monitoring and preventive medicine is increasing due to the projected dramatic increase in the number of elderly people until 2020 (Mostafa, Thurow, Habil, Stoll, & Habil, 2017). A recent study published by the Nagoya journal of medical science used wearable monitoring devices loaded with IoT systems to determine lifestyle interventions that resulted in lowering Hemoglobin A in elderly Japanese population during a 6 month period to prevent and control diabetes mellitus type 2 (T2DM) in patients (Kato, y otros, 2018). In addition, a hybrid real-time device that remote-monitor patients helps to predict real health statuses by using context awareness through IoT and cloud computing technologies helping to develop healthcare services that have very precise prediction capabilities for patients with chronic diseases (Hassan, El Desouky, Elghamrawy, & Sarhan, 2019). Likewise, the urban context has IoT applications to improve the quality of lifestyle of residents using smart buildings applications using information and communication technology:

> A customized Internet of Things (IoT) enabled Wireless Sensing and Monitoring Platform to monitor the temperature, relative humidity and light in the context of building automation. In developed system, data is sent from the transmitter node to the receiver node through a customized hopping method. The data received at the receiver node is monitored and recorded in an excel sheet in a personal computer (PC) through a Graphical User Interface (GUI), made in LabVIEW (Shah & Mishra, 2016, pág. 256).

Applications of IoT are seeing in massively in the sports industry achieving breakthrough results by bridging the physical to the digital world when combining strategically data and connectivity they can provide real time personalization, increasing venue efficiency, enhancing the fan experience and creating additional profit (Giorgio, Marzin, Lee, & Vonderhaar, 2018).

Due to the wide scope IoT has some issues have emerged with it, as it would and have with promising technology. Three main aspects to evaluate are society, privacy and regulatory standards. Customers demand change constantly, new devices emerging at breakneck speeds and lack of understanding by costumers of best IoT practices is a challenge for companies to understand customer's needs. Privacy issues are becoming more predominant in consumer devices since they can track our location and recognize our voice thus integrating our private conversations to a dataset where it could be analyzed by a third party. Most of these issues face with data protection and privacy law issues, some regulatory standards must be created for data brokers (Banafa, 2017).

4.2. Machine Learning

Due to the exaggerated surrounding of IoT, emerging technologies have experienced a boost among industrial companies. For instance, ML is well used to find answers among IoT data. The ability to learn and get better at tasks out of experience is an intrinsic part of being human. When we were born, we were almost able to do absolutely nothing for ourselves and we got better over time through repetition. ML functions under the same idea. ML satisfy the need to build up a computer system that automatically improve through experience, challenging the computer, human and organizations statistical computational theoretic laws that govern learning systems. It is a field within the artificial intelligence since it is operating in an ever-changing environment where having the ability to adapt requires intelligence. ML has the main goal to give computers the ability to self-learn without further human intervention (Being programed) based on statistics and computer sciences (Sparks, 2017). ML works based upon an algorithm which is a step by step method of solving a problem for data processing, calculation and other related computer and mathematical operations that should be carried out to transform the input in some output (Techopedia, 2018). A computer programmed before to learn will seek statistical patterns within the data (Input) that will enable to recognize a certain thing, but it is crucially the computer and not the programmer that identifies those patterns and stablishes the algorithm by which future data will be sorted (output). Since it could be mistakes in the future the quality of the outcome will be measured by the amount of data the computer receives which can enhance the quality of its predictions. In a more scientific way, we could explain it, as follows:

> Machine learning is programming computers to optimize a performance criterion using example data or past experience. We have a model defined up to some parameters, and learning is the execution of a computer program to optimize the parameters of the model using the training data or past experience. The model may be predictive to make predictions in the future or descriptive to gain knowledge from data, or both (Alphaydin, 2010, pág. 3)

One of the most common applications of ML is DM. ML provides the technical basis for DM through an abstraction process, it takes the data to later infer whatever structures is underneath exceling patterns and trends to later be converted in knowledge (H.Witten & Frank, 2005). ML is main divided by to types: *Supervised* and *Unsupervised* learning. *Supervised machine learning* (SML) is used in the context of classification, to map input to output labels, it includes logistics regressions, naïve bays, support vector machines, artificial neural networks and random forests. The main goal is to find specific relationships or structure in the input data that avoids mistakes producing a high-quality output (Soni, 2018). By the other hand, *unsupervised machine learning* (UML) without the need to know references or labels, it can infer patterns from dataset which cannot be applied to regression or a classification problem since output values are unknown, is a better tool to discover the underlying structure of data (DataRobot, 2018).

Currently, new technologies permeate everywhere in real life creating and collecting massive amounts of data. For instance, Facebook, Alibaba, Amazon and Tencent collect massive data to further take advantage through some advanced techniques such as machine learning to conduct big data analytics, to analyze and predict in order to take market decisions and improve their services (Zhao, Yu, Li, Han, & Du, 2018). Applications score a wide range of daily applications that we might not be aware are conducted by ML. For example: Virtual assistants led by Siri, Alexa and Google which feed themselves with previous giving instructions to render future results that are tailored based on your preferences. Predictions while commuting like: Traffic predictions, where a map that shows current traffic is build thanks to the data created when we use our GPS to save our velocities (Daffodil, 2017).

ML is still a young field with many research opportunities that should be explored despite its practical and commercial successes. A new approach to new research opportunities is being discovered by differentiating current machine learning approaches from the types of learning observed in nature. While most ML algorithms learn a specific function from a single data source, humans clearly learn many skills and types of knowledge, from years of diverse training experience, supervised and unsupervised, in a sequence simple to more difficult. Considerations like these suggest that machine learning is one of the most transformative technologies of the 21st century (Jordan & Mitchell, 2015).

4.3. Artificial Intelligence

Researchers has always strived to implement in computers a more efficient way for them to think and recognize information since learning is a many-faceted phenomenon. ML is indeed one of the greatest advances since it doesn´t need further human input to enhance. Although it´s limited by its own algorithm ML is just a part within the real and wider technology behind it.

Mostly known as a famous term listened in science fictions movies and linked with machines dominating the world or robots with human-like characteristics rather than being a helpful technology for humanity, AI is everywhere, from personal device assistants like Siri or Google search engines to self-driving cars or autonomous weapons to debating machines that solve better moral and ethical matters of human kind than humans. AI is probably the most revolutionary technology in the past century. Contraire to public believe AI´s concept is not as recent as people believe it is, the term Artificial Intelligence was first coined by its pioneer PhD in mathematics

John McCarthy at a conference on the campus of Dartmouth College in the summer of 1956 when he defined it as: The science and engineering of making intelligent machines (Peart, 2017). In 1950 pioneer advances were made regarding AI: A British scientific called Alan Turing created the Turing test which is a test to measure whether a machine is capable or not to think like a human being, he claimed that it can be concluded that if a machine can mimic human thinking (Reasoning, processing and decision making) under specific conditions it is consider AI or Isaac Asimov's three laws of Robotics (Anderson, 2008) for are more known reference. Through time it´s definition has been changing at the technological advancement phase of it. In the 90´s AI was seeing as the study of agents that exist in an environment and perceive and act (Nilsson, 1996) this definition was a ground base of its application field. Prior to get into a more recent and general definition, let´s try to understand what the artificial intelligence means by decomposing it. Artificial means everything that is not natural but made by the people (Cambridge, 2018) and intelligence defines it as the ability to learn and understand things (Cambridge, 2018) and AI is mainly complex human-task solving related therefore in the early 50´s one of its main applications were at board games like chess (Brown, y otros, 2018). AI does not have a universal definition mainly because in the scientific community people do not agree on what intelligence is. Nonetheless, for this article purpose matters, it´ll be defined from a field perspective, as:

> Artificial intelligence (AI) is the field within computer science that seeks to explain and to emulate, through mechanical or computational processes, some or all aspects of human intelligence. Included among these aspects of intelligence are the ability to interact with the environment through sensory means and the ability to make decisions in unforeseen circumstances without human intervention. Typical areas of research in AI include game playing, natural language understanding and synthesis, computer vision, problem solving, learning, and robotics (Enciclopedia, 2018)

AI has types and applications that can vary depending on the complexity of their tasks and whether or not they have been fully developed yet (Hintzed, 2016). There are mainly two ways to differentiate them Type I and Type II AI. Type I suggests two sub groups *weak* or *narrow AI* and *strong AI.* The first one states that machines are not too intelligent to perform their programmed task, yet they are built in a way to look sufficient smart and the second one is machines that can have a self-learning process through experience and are able to deliver tasks even better than a human being, a set of type I AI contributes to a type II AI (GN, 2018).

Type II is a way to divide them according to their functionalities where four sub-groups exits. *Reactive machines* do not possess the ability to create memories or go through past experience to develop themselves in function of some previous impute that allows them to perform the task they were create for, a great example of this type of AI is the Deep blue machine that beat world famous chess player Garry Kasparov in a six game match in 1997 (Campbell, Jr, & Feng-hsiung, 2002). *Limited memory* AI has the ability to look into past experiences to take future decisions like self-driving cars. *Theory of mind* is the one that gets closer to what being a human being is about because it should be able to understand people´s emotions, believes, thoughts and expectations in order to interact socially which is a breakthrough when reconsidering what is intelligence (Erb, 2016) and last one is *self-awareness* where machines will completely be like human beings, this one is far from reach to present technologies and many ethical and moral conflicts will exist.

AI is wide implemented in many industries, is a technology that is taking over most of economic sectors because now it is the way to innovate in business. AI is indeed taking over the way we live our life since technology became essential for our daily function from waking up to watch a movie to drive our car, for instance, companies like Amazon builds most of its business based on machine-learning systems to improve customer experience and selection through optimizing logistic speed and quality. Google tops AI´s priority is to create smarter, more useful technology and help as many people as possible through machine and *deep learning* (DP), Facebook is using it to find better ways to communicate and IBM´s three areas of focus include AI engineering, building scalable AI models and tools (Bernad, 2018). An article of IBM clearly states the focus on what AI is moving forward:

> Artificial intelligence (AI) is moving beyond the hype cycle, as more and more organizations seek to adopt AI-related technologies. These organizations are focusing on prioritizing functional areas and use cases, placing a stronger emphasis on topline growth, taking up a renewed interest in their data infrastructure and articulating greater unease about the skills of their knowledge workers (IBM, 2018)

As well ONG´s have emerged to develop a responsible AI development, the biggest one who is a joint venture of more than 80+ of the most relevant, powerful and advanced tech companies on earth, including: Apple, Amazon, Accenture, Facebook, Google, Intel and so on, called: Partnership on AI whose mission is to:

> Benefit people and society, the Partnership on AI intends to conduct research, organize discussions, share insights, provide thought leadership, consult with relevant third parties, respond to questions from the public and media, and create educational material that advances the understanding of AI technologies including machine perception, learning, and automated reasoning (AI, 2018)

Research and dialog on ethical and social implications of AI are as important as the technological development itself, most conclusions converge with the same idea and conclude that AI should only be used in the real world when there are no mayor consequences if it fails e.g. Uber cancels its self-driving cars project after having a fatal casualty in what would be consider the first accident in history involving autonomous vehicles (Price, 2018). Job-risk ethical problems have been addressed as well since the beginning of the 21st century:

> The ethical issues related to the possible future creation of machines with general intellectual capabilities far outstripping those of humans are quite distinct from any ethical problems arising in current automation and information systems. Such superintelligence would not be just another technological development; it would be the most important invention ever made and would lead to explosive progress in all scientific and technological fields, as the superintelligence would conduct research with superhuman efficiency. To the extent that ethics is a cognitive pursuit, a superintelligence could also easily surpass humans in the quality of its moral thinking (Bostrom, 2003, pág. 1)

These systems are built and created in order to solve problems in ways humans solve problems, to close the gap as much as possible while avoiding and enhancing the human factor and therefore, error. ML and AI are steps to reach the ultimate goal which is to create machines capable to sense, act and adapt based on learned experience in a more efficient and powerful way than humans.

4.4.Cognitive computing

Cognitive computing (CC) refers to the process simulation of human thinking by machines, more specific computers. It uses an autolearning systems based on pattern recognition, data mining and natural language processing to imitate human brian function. The main target of CC is to create automatized systems to solve, anticipate and model problem solutions without human help (Raona, 2018). IMB´s writer Peter Sommer, described it as:

> Cognitive Computing are systems that learn at scale, reason with purpose and interact with humans naturally. It is a mixture of computer science and cognitive science – that is, the understanding of the human brain and how it works. By means of self-teaching algorithms that use data mining, visual recognition, and natural language processing, the computer is able to solve problems and thereby optimize human processes (Sommer, 2017)

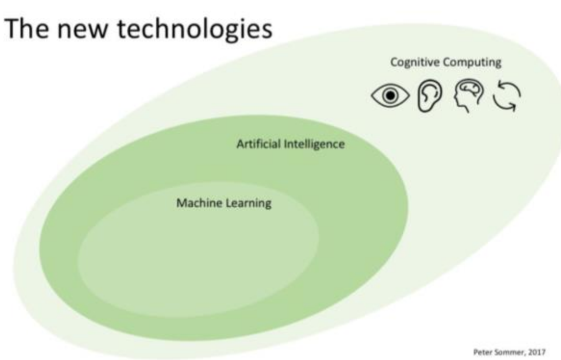

Figure 3: The new technologies
Taken from: https://www.ibm.com/blogs/nordic-msp/artificial-intelligence-machine-learning-cognitive-computing/

CC is considered the third era of computing, at the beginning we started with computers that could tabulate sums in 1900, then we moved forward with programmable systems in the 50´s and now we have computers that simulate human brain processing (Marr B. , 2016) Therefore, it embraces many sub-subjects we might have hear about such as: Machine learning and Artificial Intelligence. These technologies use as well self-learning mechanism to create results at different phases and levels. Cognitive solutions are made to solve technical, industry-specific content and use advanced reasoning, predictive modeling, and machine learning techniques to advance research faster (Chen, Argentinis, & Weber, 2016).

World class scientific and celebrities have addressed this issue as well, people like Stephen Hawking, Elon Musk, Steve Wozniak, Bill Gates have expressed their concern in the media and via open letters about AI´s risk (Tegmark, 2018). Elon musk claimed that it is very uncertain what will happened when AI is developed enough and is substantially smarter than a human being and people do not understand the ethical dangers involved in it (CNN, 2016).

5. CONCLUSIONS

Business intelligence is a wide concept that embrace everything related with storage, processing and analyzing data from several sources and in different times frames with the ultimate goal to be a decision support tool for companies. Several stages are involved prior to arrive to useful data, from collecting unprocessed data to finding patterns and trends. Several key divisions and applications where found which are mainly used in function of an amount of data, time frame, department and technology involved. Prediction and optimization are key words to underling the main use of BI hence, it´s adaptive business model shows and excels the importance of a self-feed systems that, in function of an in-put creates an out-put which evolves over time as long as it´s feed with new in-put. Introducing adaptive business intelligence model is the start point to introduce and explore the many wonders and limitless benefits of emerging technologies which basically depending on its initial sequence of algorithms may have a larger scope wherever implemented. DM is a part of ML that finds patterns and trends from sources like IoT which at the same time enhance the user experience with AI. Finally, trends show that humanity are paddling towards the same direction which is called cognitive computing. Dehumanizing technology that is intended to behave, think and perceive as humans with the purpose of enhancing organizations and daily human life avoiding mistakes which ironically is the biggest human factor.

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