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The Boundaries and Difference between business intelligence, big data analytics, and big data: A review

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Abstract: The Business Intelligence (BI) field is about 55 years old, starting with decision support systems in the '60s, which used computer-assisted quantitative modeling to assist in decision-making. Thus, BI is a new field that needs good study and understanding of the expansion of its use within business. So, using a search for BI within target databases and publications for this research, the databases, namely (Web of Science, EBSCO host, IS publications, IS conference proceedings, and Google search engine), from 1986 to 2022, 37 years of searches have been selected to view more details about BI in the literature base with custom queries searching for a keyword. Various keywords are used, such as "Big Data Analytics", "Business Intelligence", "Business Analytics", "Big Data", and "Business Intelligence & Analytics", among others. The main criteria used were the number of citations and definition repetitions used in the latest documents. Then, view the definition, boundaries, differences, limitations, and relationship between BI, Big Data (BD), and Big Data Analytics (BDA). As a result of the review.

Keywords

Big Data Analytics BDA, Business Intelligence BI, Business Analytics BA, Big Data BD, and Business Intelligence & Analytics

Abbreviation

Key	Meaning
ABI	Analytics and Business Intelligence
BD	Big Data
BDA	Big Data Analytics
BI	Business Intelligence
ETL	Extract, Transform, and Load
ODS	Operational Data Sources

Introduction

In the 21st century, technology reached the pinnacle of use and overpowered our lives, which appears clearly with the amount of enormous data exchanged. That gigantic numbers of data are daily collected and stored where the traditional tools process cannot deal with it. So, refer to that huge amount of transferred data like Big Data (BD). Also, most organizations depend on BD to improve the information, and facts about customers, which introduces new knowledge about the customers for the design makers. Thus, Big Data Analytics (BDA) occurs as a mechanism for deriving the information and extracting meaning from such raw BD. Concerning the fact that the traditional computing tools and techniques are disabled to deal with BD. So, that issue supports the development of tools used for BDA, which view in the recent past. Moreover, BDA has found several applications in different industries. Thus, that leads to better knowledge about the organization's customers and the customer's preferences. But that improves the extremely advantageous of techniques.

The definition of business intelligence and boundaries

The Business Intelligence (BI) field is about 55 years old, starting with decision support systems in the '60s, which used computer-assisted quantitative modeling to assist the decision-making. But the term BI was not used in its current meaning until 1989 (Power, 2007). There are many definitions for the concepts of BI, some broad and others more narrow in their concept. Within academic's documents review, there are a lot of different approaches to viewing the entitlement meaning of BI. And each scheme has its subjects like press groups, information technology vendors, and business consultants. To get the differences in BI definitions, we should follow the changes of the BI definitions over time. Like 37 years. Moreover, there are many definitions per year. So, the most reused definition in the later publications is the best one over that year, which is a token from late publication. The definition in table 1 is collected carefully with back to numerous articles, theses, and books. Also, depending on the author's accessibility of documents, that is one of the limitations in this side of work.

Table 1: The BI definitions over selected (37) years from 1986 till 2022

Order	BI definition	Reference (s)	Year
1	"The collection of systems and products that have been implemented in various business practices, but not the information derived from the systems and products"	(Tikait, 2022)	2022
2	"A responsible for bringing technological solutions that correctly and effectively manage the entire volume of necessary and important information for companies"	(Velosa, et al., 2021)	2021
3	"A set of processes, architectures, and technologies that convert raw data into meaningful information that drives profitable business actions"	(Nordeen, 2020)	2020
4	"A data visualization tool, which gathers, process and produces data that could be used to evaluate the performance of higher education"	(Jamiu, et al., 2020)	2020
5	"A set of processes, applications and technologies designed to support the decision-making processes in the enterprise efficiently"	(Bestman, et al., 2019)	2019
6	"That technology with a great potential of extracting valuable information from mass data that exist within an organization"	(Combita Niño, et al., 2018)	2018
7	"A set of skills, technologies and application systems used to collect, store, analyze and create effective access to the task to help organizations better understand the business context and make accurate decision timely and respond quickly toward inflation, rate fluctuations and the market price"	(Radmehr & Bazmara, 2017)	2017
8	"A set of integrated strategies, applications, technologies, architectures, processes and methodologies used to collect, store, retrieve and analyze data in order to	(Mashingaidze & Backhouse,2017)	2017

	support decision making”		
9	“A set of methodologies, processes, architectures and technologies that transform raw data into significant and useful information which are used to build perspectives and make efficient strategic, tactic and operational decisions”	(Ackermann, et al., 2016)	2016
10	“The integration of the data, strategy, process and analytic components of an organization to support decision making”	(Fekete & Vossen, 2015)	2015
11	“A tool that makes higher education business run smoothly, successfully and profitably”	(Clavier, et al., 2014)	2014
12	“An umbrella term that includes the applications, infrastructure and tools, and best practices that enable access to and analysis of information to improve and optimize decisions and performance”	(Gratner, 2013)	2013
13	“A mechanism for intelligence exploration of data, aggregation, and integration of data from multiple sources”	(Anjariny, et al., 2013)	2013
14	“An information system that helps managers make the right decisions at the right times, it is used across business units”	(Chen, et al., 2012)	2012
15	“The process of transforming raw data into useful information for more effective strategic, operational insights and decision-making purposes”	(Duan & Xu, 2012)	2012
16	“A collection of decision support technologies for the enterprise aimed at enabling knowledge workers such as executives, managers, and analysts to make better and faster decisions”	(Chaudhuri et al., 2011)	2011
17	“Broad category of technologies, applications and processes for gathering, accessing and analyzing data to help its users make better decisions”	(Wixom & Watson, 2010)	2010
18	“Is a system which generates analyzes and reports on trends in the business environment and on internal organizational matters”	(Jalonen & Lonnqvist, 2009)	2009
19	“A broad category of applications, technologies, and processes for gathering, storing, accessing, and analyzing data to help business users make better decisions”	(Watson, 2009)	2009
20	“Both a process and a product, that is used to develop useful information to help organizations survive in the global economy and predict the behavior of the general business environment”	(Jourdan et al., 2008)	2008
21	“A combination of products, technology and methods to organize key information that management needs to improve profit and performance”	(Williams & Williams, 2007)	2007
22	“A managerial philosophy and a tool used to help organizations manage and refine business information with the objective of making more effective business decisions”	(Lonnqvist & Pirttimaki, 2006)	2006
23	“The use and analysis of information that enable organizations to achieve efficiency and profit through better decisions, management, measurement and optimization”	(Burton &Hostmann, 2005)	2005

24	"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"	(Negash , 2004)	2004
25	"A system designed to help individual users manage vast quantities of data and help them make decisions about organizational processes"	(Watson et al.2004)	2004
26	"Systems combine data gathering, data storage, and knowledge management with analytical tools to present complex and competitive information to planners and decision makers"	(Negash,& Gray, 2003)	2003
27	"An architecture and a collection of integrated operational as well as decision support applications and databases that provide the business community easy access to business data"	(Moss &Atre, 2003)	2003
28	"Organized and systemic processes which are used to acquire, analyze and disseminate information to support the operative and strategic decision making"	(Hannula & Pirttimaki, 2003)	2003
29	"A set of concepts, methods and processes that aim at not only improving business decisions but also at supporting realization of an enterprise's strategy"	(Olszak & Ziemba, 2003)	2003
30	"A critical component for the success of a modern organization is its ability to take advantage of all available information"	(Cody et al., 2002)	2002
31	"System regards as a kind of strategic information system aiming to enhance decision making and competitive advantages of organizations"	(Thomas, 2001)	2001
32	"A term encompasses a broad range of analytical software and solutions forgathering, consolidating, analyzing and providing access to information in a way that is supposed to let an enterprise's users make better business decision"	(Adelman & Moss,2000)	2000
33	"A process of acquiring and processing of information in order to support an organization's strategy"	(Vriens& Philips, 1999)	1999
34	"An umbrella term to describe the set of concepts and methods used to improve business decision-making by using fact-based support systems"	(Dresner, 1989)	1989
35	"The activity of monitoring the environment external to the firm for information that is relevant for the decision-making process in the company"	(Gilad & Gilad, 1988)	1988
36	"The ability to access and analyses information as needed and to utilize this information to make sound business decision"	(Ghoshal,1987)	1987
37	"A system that assists organizations to manage and transfer data into useful business information in order to make more effective business decisions, considered as an activity within which information about competitors, customers, markets, new technologies, and broad social trends is gathered and analyzed"	(Ghoshal& Kim, 1986)	1986

While understanding table 1 about the changing in the meaning of BI over the selected years shows that BI is increasing area and becomes bigger. As in 1986, the BI was defined as a system that assists organizations to manage the organization, and in 2022 BI defines as a collection of systems and products implemented for business. So, the BI props changed too. That means the BI limitations are decreasing over time and introducing new knowledge. Also, the BI introduces new problems, which become new limits over time till got all paths in business. Moreover, at the appendix I there are another list of definition which is appears with different web pages or white papers.

As a remark, while the BI expands in uses, the BI definition would be changing to be more generalized, and that definition will be more globalized to include the organization's goals and supports the decision with enough information. Now, the BI can be defining as a set of methodologies, technologies and architectures that transform raw data into meaningful insights applied to enable more effective strategic and operational decision-making to ultimately create business value. Farther, analytics and business intelligence (ABI) is a canopy style that contains the applications, tools, and infrastructure, with a good training that enable access to and Data quality is an important prerequisite for a well-functioning BI environment.

The variance of BI bounders is a lot. As an example, that implementing BI within the health care domain brings with it extra challenges (Leitheiser, 2001). Thus, BI requests to answer complex questions around business process and accomplishment. Analysis the useful data to optimize and improve both performance and decisions.

The definition of big data analytics and boundaries

BDA is the analysis process of a large volume of a diverse data set, using higher analytic abilities. The supply chain analytics becomes more useful with depending on BD. And use quantitative methods and BD with big supply series analytics, which enhance decision-making processes over the supply series methods. Also, that gives an opportunity from BDA for organizations by arising pivotal; BD is described as, "the mother lode of disruptive change in a networked business environment" (Baesens et al., 2014).And from a perspective of "technology-push", the BDA becomes piece of the vast family of digital technologies, and the creativeness ideas increasingly believes on this technology (Nambisan et al., 2017). Also, “Data analytics is the science of examining raw data to reach certain conclusions" (Monnappa, 2022). Additionally, BDA is a form of advanced analytics related to complex applications with elements such as analysis supported by analytics systems, statistical algorithms, and predictive models. Thus, this application is one of the limitations and boundaries. Moreover, BDA is a complicated operation of testing BD to extract pieces of information; such as market trends, hidden patterns, customer preferences, and correlations, which help organizations make business decisions depending on the information.

BD processing starts with raw data that hasn't been aggregated and is nearly hard to keep in a single computer's memory. Existing technologies have a hard time processing BD (Constantiou & Kallinikos, 2015). And data analytics entails using an algorithmic or mechanical approach to draw insights and looking for relevant correlations across multiple data sources. Organizations also employ analytics technologies to extract valuable insights from a stack of raw and unstructured data, such as hidden patterns, unknown correlations, market trends, customer preferences, and other interests. Furthermore, little is understood about how businesses design and implement digital innovation plans, and many businesses are unsure how to effectively invest in BDA skills to drive their innovation agenda (Bean, 2016). However, results from many surveys of BI users, developers, and managers indicated that varied perspectives of these stakeholders must be considered when implementing metadata management for BDA (Dinter et al., 2015).

BD is being used to evaluate data so that better judgments and corporate strategic actions can be made. Thus, the analysis of big data (BDA) is the way to get information from that BD which service the organization's decision maker. As a result, BDA and related knowledge management are fast gaining traction as a critical component of business innovation culture and ideals (McAfee et al., 2012). The usefulness of BDA for urban planning, according to the OECD report, comes from the convergence of high-resolution geographic data with information about residents' observed or interpreted usage of urban space (OECD, 2015).Also, the process as ("Data mining", "Predictive analytics", "machine learning", "deep learning", "text mining and statistical analysis software", "artificial intelligence", "mainstream BI software", "data visualization tools", "In-memory data fabric", "Data virtualization", "Data integration software", "Data quality software", "Data preprocessing software", "Spark, Key BDA technologies and tools", "Hadoop", "NoSQL", "databases", ...) are used to analysis the BD.

Indeed, research has demonstrated that if not effectively handled, high data structure can pose hazards, such as the creation of cognitive models, which can encourage homogenization and constrain, rather than drive, creativity and innovation (e.g. Kwon et al., 2014; Choi et al., 2017). Executives' adoption of BDA in strategic decision-making is frequently hampered by a lack of competencies or awareness of the benefits (Merendino et al., 2018). Organizations can benefit from BD while continuing to operate in a similar manner, albeit more successfully and efficiently:"incremental enhancements to established business models through increased digitization and BDA may replace less efficient business models (and thereby companies) in the long run" (Loebbecke & Picot, 2015). The analytics data are used to make more decisions pieces of information. As well as verify and disprove existing theories or models. The major of data analytics is by deriving conclusions. Those conclusions are exclusively based on BD. Offering customers customized products and services based on BDA poses a number of issues, unfair classification, identity theft, including privacy, and illegal discrimination (Alshboul et al., 2015; Markus, 2015; Clarke, 2016; Ekbia et al., 2015), and even "exploitation of the vulnerable" (Newell &Marabelli, 2015). Many legal and ethical debates center on the social hazards that arise when certain ecosystem actors (usually businesses) use BDA to exercise and exploit power over others (usually individuals) (Zuboff, 2015; Greenaway et al., 2015). However, empirical IS research has just scratched the surface of how businesses cope with legal and ethical issues in acceptable and creative ways. To answer the limitations of BDA would be with answer (Kouropalatis et al., 2019) question as;"Which capabilities are required to embrace a successful digital transformation based on BDA?"

BDA may aid decision-makers by assisting them in comprehending existing and future client demands, market trends, and market demand (Peteraf et al., 2013; Coussement et al., 2015; Jin et al., 2016; Bresciani et al., 2018). According to several research, BDA are becoming increasingly important in strategic and innovative management decision-making. (LaValle et al., 2011; Chen et al., 2012). By adopting advanced analytics technologies, organizations can use BD for developing products, services, and innovative insights (Davenport et al., 2012). There needs of an effective strategy, that improves business-related outcomes, by BDA systems and software to driven decisions include more effective marketing, improved operational efficiency, customer personalization and, new revenue opportunities these benefits can provide competitive advantages over rivals.

The definition of big data and boundaries

BD is a database that includes different data properties and dissimilar data. Which also could hinder the workflows. Due to the randomness of data sorting and making, the process spends more time. And because of the urgent business needs, it must be developed and improved to a higher level because data is the cornerstone of decision-making and analysis reports. Also, data cleansed improves the data quality by fixing. And Gartner defined the BD as "Big data is high-volume, and high-velocity or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision-making, and process automation" (Sicular, 2013).As a result, information is prepared and processed. Data experts must organize, arrange, and split suitable data for analytical queries once it has been acquired and stored in a data warehouse or data lake. In addition, BD refers to large amounts of data that make it impossible to process adequately with present applications (Monnappa, 2022). Furthermore, the term "big data" is a catchphrase that refers to massive amounts of data. In addition, both unstructured and structured data may inundate a company on a daily basis. This means that BD is a word for data sets that are too large or too complex for standard rotating databases to capture, manage, and process. The database required to handle BD should not be a typical database with minimal latency. Furthermore, the BD necessitates preparation and processing, resulting in faster analytical queries. Additionally, data cleansing enhances information quality by removing any flaws or inconsistencies, such as duplicates or formatting issues, as well as organizing and cleaning the data.

The Difference between business intelligence, big data analytics, and big data

Concerning previous sections, BD is the base of BI. As many studies have emphasized that BDA take a more active role as a cornerstone of organization competitive success and performance (Wamba, 2017; Ferraris et al., 2018; George et al., 2014) and asserted that an organization's ability to use BDA, which is a dynamic skill (van Rijmenam et al., 2018; Giudici & Reinmoeller, 2012; Teece, 2018). Moreover, Günther, et al. (2017) At various levels of analysis, identify six debates that are fundamental to how businesses achieve value from BD. They highlight two socio-technical aspects of BD that have an impact on value realization (portability and interconnectivity). In order to realize the benefits of BD, firms must continually realign work methods, organizational structures, and stakeholder interests, according to the authors. As a result, the wealth of information accessible has aided the development of novel BDA methods (Carillo et al., 2019; Mashhadi et al., 2018). As a result, BDA are critical since they improve a company's capacity to connect customers and technology (Dobusch & Kapeller, 2018; Brown et al., 2011), and enable the collection of a vast quantity of data concerning technological development and expected client demand (Papadopoulos et al., 2017). (Bresciani et al., 2018). Furthermore, "Intelligence" models are being re-defined to give greater weight to the web dimension and strategic viewpoint (Lanzolla & Giudici, 2017; Reinmoeller& Ansari, 2016). Information management models and methods have emerged to meet the demand for strategic decision support based on the identification of the primary aspects of analysis (LaValle et al., 2011; Kuosa, 2011; Garzella & Fiorentino, 2014). Scholars have combined contributions from numerous managerial disciplines that tackle this topic in different ways to develop a complete and systematic picture (Popovic et al., 2012; Wagner, 2004). The relationship needs to view the dynamic capabilities between the digital innovation process and BDA with properly clarify (Prange et al., 2018; Dixon et al., 2014).

The Relationship between Business Intelligence, Big Data analytics and Big Data

Scholars state that BI, BD, and BDA are related because BI offers the methodological and technological skills needed for data analysis (e.g. Llave, 2018; Sun, et al., 2015). BDA may be considered a portion of BI because it assists establishments in making decisions based on valuable data, information, and expertise (Alnoukari & Hanano, 2017). (Sun, et al., 2015). In addition, both BI and BDA use certain standard decision-making tools. Similarly, BI and BDA both emphasize the importance of valuable data, information, and expertise. Also, interactive visualization is used in BI and BDA for data discovery and disquisition. Furthermore, business intelligence is today founded on four slice-age technological pillars: pall, mobile, business intelligence, and social technologies, all of which are successfully supported by BDA as a service and technology (Sun, et al., 2015; Passlick, et al., 2017). Sun et al. (2015) go on to say that BDA is a vital tool for expanding BI in terms of both data and technology. BDA is data-driven and business-driven from a technology approach. acquainted practices, which makes it easier for businesses to make decisions and enhances BI. Knowledge discovery is at the heart of BDA and BI schemes (Sun, et al., 2015). Jin& Kim (2018) believe that BI's "raw data" has been expanded into "Big Data." As a result, it's reasonable to assume that BI, BD, and BDA aren't independent generalizations.

As a result, combining them all into a single DSS that covers all processes is advantageous, from data gathering to data analytics and perception to decision-making (Jin, & Kim, 2018). According to Fan et al. (2015), BDA helps marketers by allowing them to mine social media for user input on a product, service, or company. According to Fan et al. (2015), Client opinion mining is an important component of strategic marketing choices that may be based on a variety of data sources, including social media, offers, checks, and detectors, and can be used to find marketing information (Fan, et al., 2015). Perceptivity may be limited in analytical models based on a single data source. Which can lead to skewed business decisions. Using numerous data sources can help you get a more holistic view of your organization and make better decisions (Fan, et al., 2015). BD and its operations on BI, according to Fan et al. (2015), have a better likelihood of producing business outcomes. Kimble & Milolidakis (2015) in a similar line, we argue that BI produced from BD might be tremendously helpful. According to Sun et al. (2015), As a consequence of the remarkable rise of BD technologies, BI is presently experiencing new challenges and possibilities, with how to leverage BDA to improve BI becoming a critical problem for organizational success (Sun, et al., 2015). Others, on the other hand, point out a number of BI drawbacks as compared to BDA and BD. (examples: Marn-Ortega, et al., 2014;Llave, 2018; Ram, et al., 2016).

In the 2000s, business and technology executives helped BI gain a strategic orientation (Faroukhi, et al., 2020; Marn-Ortega, et al., 2014) BI is based on technology-driven data analytics that pulls actionable data. The logical conclusions supplied by reports, dashboards, and data visualizations may be used by decision-makers with these tools. Basically, BI focuses on organized and internal firm's data, on the other hand ignoring the buried valuable information which unstructured and external data (Marn-Ortega et al., 2014).This might lead to a skewed perception of reality and skewed business judgments (Marn-Ortega, et al., 2014; Llave, 2018; Ram, et al., 2016).

Scholars have identified some of the drawbacks of BI perpetration (As: Marn-Ortega et al., 2014), such as new BI model have a high time costs perpetration, a poor conjunction of information technology and between business, and the focusing lack on the personalities requirements.

Traditional business intelligence (BI) data analytics are inappropriate for gaining significant business information (Saidali, et al., 2019). The information and temporal gaps in traditional styles are filled by BD perceptivity (Walls & Barnard, 2020).According to Marn-Ortega et al. (2014),because data operation is time consuming, it is the most important and difficult phase in BI development. The majority of BI solution providers are more concerned with the technological aspects of data operations than with the availability of all necessary data (structured and unstructured) to create a satisfactory result. Faroukhi et al. (2020) recognized some of the differences between BI, BD, and BDA, such as the fact that BI uses Train-Grounded or Object-Grounded storehouse models, whereas BD uses Block-Grounded storehouse models.

BI, like SQL databases and data storages, is based on a conventional database data model. Traditional databases, on the other hand, are incapable of addressing BD difficulties such as storing and recycling large amounts of unstructured data; as a result, distributed storage and NoSQL databases are often used in BD data models (Faroukhi, et al., 2020). Similarly, BI's conventional storehouse structure is mainly reliant on storehouse bias, but BD requires novel storehouse structures, such as storehouse network structure and storehouse virtualization. In order to exchange data, computations, and processing among numerous connected bumps, BD also requires a distributed processing architecture. Traditional BI, on the other hand, lacks a comparable distributed processing infrastructure (Faroukhi, et al., 2020).

Finally, and from a logical perspective, BI traditional systems significantly developed descriptive and predictive analyses; while, BD gives the potential to successfully construct and employ new analytics capabilities comparable to conventional and individual analysis (Faroukhi, et al., 2020). One option proposed is to fix the ETL (Load, Transfigure, and Extract) stage tailback (Marn-Ortega et al., 2014). In a typical BI structure, the ETL process begins with the extraction of raw data from Operational Data Sources (ODS), followed by the transubstantiation of the raw data into a regularized form, and finally the loading of the reusable data into the data storehouse. During the transformation period, it is vital to process raw data.

A data warehouse frequently consolidates a large number of different ODS with heterogeneous schemas, necessitating the regularization of the raw data. The ODS may also contain faulty, erroneous, or missing data, necessitating the sanctification and data consolidation process (Alnoukari, et al., 2012). According to Marn-Ortega et al. (2014), Data warehousing hasn't been beaten by ETL technology solutions in terms of scalability and performance. As a result, the majority of BI architectures are experiencing significant bottlenecks; data cannot be processed and fed into Data Warehousing in a timely manner, but decision makers want real-time information. One recommended strategy to addressing the ETL substantial tailback is to move the metamorphosis phase following the loading phase to the conclusion of the ETL. As a result, ETL is becoming ELT. ELT allows for initial data rooting and loading, which is a major benefit of this transfer, as well as on-demand metamorphoses based on business requirements.

Furthermore, ELT enables data transformation to be applied and reapplied in response to changes in the landscape. This gives ELT the rigor it needs to respond to modification requests. As a result, ELT tackles the difficulty of developing BI solutions in less time while also allowing the BI to react to changes in the environment. Passlick et al. (2017) created a BI and BDA armature model that enables both traditional BI logical reports and BDA. Both BI and BD bones are included in the suggested armature model. The typical ETL approach is used by the data processing sub caste, which is augmented with the capacity to do BD and ELT procedures. Additionally, data integration may be performed in the warehouse and analysis structure sub castes. Besides that, data integration in the storehouse and analysis structure subcaste can be done using traditional Data Warehousing as well as other BD technologies such as Hadoop clusters orin-memory databases (Passlick, et al., 2017). Assimilation of Data Lakes with BI is another option that has been presented (Llave, 2018). According to Llave (2018), BI can now gather data independent of its structure thanks to Data Lakes. It's a fantastic feature to be able to store limitless quantities of raw data without any data transformation. Data metamorphosis is considered a tailback when utilizing the ETL technique to link data sources to Data Warehousing. As a result, it's similar to ELT, in which the transformation occurs in the final phase (Llave, 2018). Data monetization is one of the broad categories that has progressed significantly from the BD to the BI age (Faroukhi, et al., 2020).Data monetization is a revolutionary concept that relies on the profitable exploitation of association data. Unambiguous data monetization is actively dealing with data for cache or participation in the data, whereas implicit data monetization is a cyclical way of depending on data to create value by developing own data-based commodities (Faroukhi, et al., 2020). Throughout the BI era, descriptive analytics made data monetization seem natural. In most cases, product data was only used internally. Data monetization gained fissionability and crucial elaboration over time over the BD era. During the BD period, data monetization becomes more tempting (Faroukhi, et al., 2020). Data is incorporated from both external and internal sources, resulting in increased logical capacities through data-driven goods and services. This allows for clear data monetization as well as the dexterity needed to produce and sell knowledge. Thus, according to Faroukhi et al. (2020),value of BD appears based on the following business model articulated directions; starts with data extractors which is a rooting guests based conditioning data, then data providers which is collecting and processing data, then data aggregators which aggregating data services, lastly, specialized platform providers which furnishing specialized platforms with supports processing, participating data, and consuming the information. Businesses may unlock value and maximize their data-driven capabilities by monetizing BD (Faroukhi, et al., 2020).

The Methodology & Analysis

In terms of the research's search technique, target databases, and publications. The most important databases are: (Web of Science, EBSCO host, IS publications, IS conference proceedings, & google search engine). The years 1986 to 2022 were chosen as the study period. A specified literature base on BI was systematically examined with keyword queries as well as backward and forward searches in order to provide further information insights into the issue. Several keywords were used such: "Business Intelligence & Analytics", "Business Intelligence", "Big Data Analytics", "Business Analytics", "Big Data", among others. The quantity of citations and the usage of definition repetition in the most recent papers were the major criteria employed. Using the classification guidelines (Jorgensen &Shepperd, 2007), based on our experience of the domain (Corte-Real, et al., 2012). Some of the studies are examples of how BI technologies are used (Abbasi, et al.,2012; Lau, et al., 2012; Sahoo, et al., 2012; Park, et al., 2012; Hu, et al., 2012).Finally, the studies are compiled and the contents are classified using the BI definitions. Scholars have emphasized the relevance of data analysis and management in promoting creativity and innovation processes across a variety of literary streams (Perry-Smith &Mannucci, 2017; Markides& Anderson, 2006; Olszak&Kisielnicki, 2016). As a result, studies have underlined the need of analyzing millions of data points in order to increase customer satisfaction and develop new approaches to customers, such as developing creative goods, processes, or business models (Mahmoud et al., 2018; Levine et al., 2017; Shipilov et al., 2017).

The Decision& Limitations

After a deep looking at the changing in the meaning of Business Intelligence definition over the period from 1986 until now, shows that the extent of BI expansion over the business fields and the applications of BI with a diversity of business and services which, leads to further expansion of the meaning to become more general and of greater value. Also, with the increasing amount of big data to transform into more complex and more data-intensive types. Therefore, the constant need to find appropriate tools to deal with it, as these tools are divided into two types (ideas, methods, algorithms, and schemes) for analysis and technological capabilities (computer equipment, and software that can deal with the volume of BD quickly and with appropriate performance) and these are the main features of the shape of the determinants related to all the terms and concepts under study, but with limited impact for each separately.

Starting with BD, the ability to store and save data, as well as the speed of data transmission from the storage environment to the analysis environment, as well as the diversity of storage methods for this data and the diversity of storage forms, especially when it comes to BD.

Secondly, BD analysis which depends on the data appears, the technological ability to process BD, and deal with all forms of data on the diversity of them (audio, images, texts, etc…). Moreover, the processing time is one of the main determinants of benefiting from data analysis, as well as the capacity of the storage unit, RAM size as it contributes to reducing the analysis time, and therefore the material part at its various points is one of the determinants.

Not only that. Also, there are other determinants related to the algorithms and methods of analysis, which contribute more to the form of results and outputs. Which affect all the following from findings and recommendations based on it.

Thirdly comes the role of BI, which is in an applied manner by making decisions based on information from various sources. But at this point, the interest in the information received from the results of BDA; which meaning that decisions based on the results are more accurate and closer to the specific goals within each institution.

But in the end, without the driving ingredients for this meaning, the expansion would be limited. So, BD is the most important of these ingredients, which is collected based on a specific orientation and goals; But the crude data needs to be arranged, and initial processing such as (eliminating redundancy, correcting errors, identifying contradictions, and initially treating them, etc...) and this processing transforms BD into organized data which allows simple analytical processes to work under the condition of ability to deal with BD. That was previously, but with the emergence of methods, methods, and tools for analysis dedicated to BD, the concept of BDA emerged, which takes the spotlight during the current period.

One of the most confuse while searching over the definition of BI that the meaning of BI as abbreviation of different words like “Basic Income (BI) I understand a minimal income received by everyone, regardless of whether one has any additional income” (Nooteboom,1987). Moreover, the title of “Basic Income as a Basis for Small Business”.

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Appendix

Order	BI definition
1	It is a set of tools used to manipulate a mass of operational data and to extract essential business information from them.
2	A new concept in the public sector that uses advanced analytical tools such as data mining to provide insights into organization trends, patterns, and decision making.
3	An umbrella term that includes the applications, infrastructure and tools, and best practices that enable access to and analysis of information to improve and optimize decisions and performance.
4	Deployment of (usually artificial intelligence-based) techniques such as online analytical processing (OLAP) and data mining to analyze information in the operational data sources.
5	The process of building the capacity for an organization to make informed decisions based on historical data of its operations and of its operating context in order to achieve greater competitiveness.
6	It includes technologies, techniques and methods for data analysis and knowledge presentation for facilitation the business decision making process.
7	The foundation for a green information system network that supports an organization's ability to manage, communicate and develop its intangible assets sustainably. As interactions with other developed countries intensifies, so does the need to share information and knowledge. These intangible assets serve as a new commodity for business intelligence.
8	The process of gathering information in the field of business. The goal is to gain competitive advantage. Information gathered usually refers to customers (their needs, their decision making processes), the market (competitors, conditions in the industry), and general factors that may affect the market (the economy at large, technology, culture).
9	Process of collecting, treating and using information to assist managers in the decision-making process.
10	The process, technologies, and tools needed to turn data, patterns into information, information into knowledge, and knowledge into plans that help for forensic decisions.
11	Broad category of applications and technologies for gathering, storing, analyzing, and providing access to data to help enterprise users make better business decisions
12	Getting the right information to the right people at the right time so they can make decisions that ultimately improve performance.
13	The ability of an organization to collect, maintain, and organize knowledge in order to develop new business opportunities and mitigate existing threats.
14	A set of theories, methodologies, architectures, and technologies that transform raw data into meaningful and useful information and knowledge for business purposes, by handling large amounts of both structured and unstructured data.
15	A corporation's ability to access and employ information usually contained in a data warehouse. With the information, the corporation can analyze and develop insights and understanding that lead to improved and informed business decision making.
16	This results from information systems that combine data with analytical tools in order to provide information relevant to decision making, while seeking to improve the quality and availability of this information to decision makers.
17	The process of gathering and transforming raw data into actionable insights yielding better decisions.
18	Includes the tools, practices, and infrastructures necessary for the organization, management and analysis of information, in a visual and customized way, to improve business decision making.
19	A group who usually works within the Information Technology area of an institution and is responsible for curated and enriched data, as well as reports and visualizations. This group is focused more around operational reporting.
20	The ability of an organization to collect, maintain, and organize knowledge. BI technologies provide historical, current and predictive views of business operations. Common functions of business intelligence technologies are reporting, online analytical processing (OLAP), analytics, process mining, complex event processing, business performance management, benchmarking.

21	A broad category of applications, technologies, and processes for integrated acquisition, interpretation, collation, analysis, and exploitation of data to help business users make better decisions in order to improve business operations, reduce uncertainty & apply past experience to develop an exact understanding of business dynamics.
22	The process of using advanced applications and technologies to gather, store, analyze and transform overloaded business information into knowledge that provides significant business value in improving the effectiveness of managerial decision making.
23	It is a collection of processes, architectures, and technologies that turn raw data into useful knowledge driving productive business behavior. To turn data into actionable knowledge it is a suite of tools and services.
24	Is a set of theories, methodologies, processes, architectures, and technologies that transform raw data into meaningful and useful information.
25	An umbrella term that includes the applications, infrastructure and tools, and best practices that enable access to and analysis of information to improve and optimize decisions and performance.
26	Tools and techniques to transform data to information for business purposes.
27	The methodology for the acquisition and transformation of raw data into useful information for business analysis.
28	A set of tools and technologies for gathering, storing, accessing, and analyzing data to aid in managerial decision-making.
29	A set of tools, techniques, and methodologies for managing and analyzing large quantities of operational data for obtaining aggregated, highly relevant strategic information.
30	The information technology used by decision makers.
31	A corporation's ability to access and employ information usually contained in a data warehouse. With the information, the corporation can analyze and develop insights and understanding that lead to improved and informed business decision making.
32	A general term that refers to a range of capability and tools used to analyze an organization's raw data and transform them to actionable knowledge by data mining, online analytical processing, querying, reporting and so on.
33	A set of different theories, methods and technologies which transform raw data of different sources into information or knowledge relevant for business decisions.
34	The process, technologies, and tools needed to turn data, patterns into information, information into knowledge, and knowledge into plans that help for forensic decisions.
35	A collection of tools, methods, technologies, and processes needed to transform data into actionable knowledge.
36	Umbrella term that includes the applications, infrastructure and tools, and best practices that enable access to and analysis of information to improve and optimize decisions and performance.
37	Getting the right information to the right people at the right time so they can make decisions that ultimately improve performance.
38	The ability to collect, integrate, and organize the data in a way which received by the right source, at the right time, and via the right tool. It provides basic insights about the data by regenerating reports, queries, alerts, etc.
39	Software tools that can analyze large data quantities and retrieve information to reach knowledgeable conclusions.
40	It is a combination of processes, products, and technologies that have the ability in supporting organization, and can have a direct key role in data management by storing, and analyzing the data collected from internal and external sources, and on decision making by creating knowledge, and finally on Business Performance management.
41	The set of techniques and tools for the transformation of raw data into meaningful and useful information for Business Analysis purposes
42	The concept has a wide range of concealment of all the processes and conducts analysis and/or evaluation of the work at the strategic level, tactical level, or operational level by providing direction for optimizing business performance.
43	Transformation of data collected from all aspects of the business into a decision making tool.

44	A term used to refer to collective technologies, infrastructure, algorithms and visualization techniques that are used in collecting, organizing, and storing data, knowledge extraction, and presentation of information for business strategic decision-making process.
45	A term coined in the late 1980s, describes the enterprise's ability to access and explores information, analyzing that information and developing insights and understanding, which leads to improved and informed decision making. BI products include decision support systems (DSS), executive information systems (EIS), and query and report writing tools.
46	A collection of data warehousing, data mining, analytics, reporting and visualization technologies, tools, and practices to collect, integrate, cleanse, and mine enterprise information for decision making
47	A set of technologies and processes that use data to understand and analyses business performance encompassing data access, reporting and analytics.
48	Is a broad spectrum of issues such as practices, methods, or tools, with data analysis. BIs transcribe data into information and knowledge. BI can be an independent system integrated with other systems or exist as a Management Information System module.
49	A technology that uses data analysis tools and applications to help business users make more informed decision.
50	Creation of collaboration and correlation between disparate systems resulting in enhanced customer service and optimized business processes
51	A broad category of applications, technologies, and processes for gathering, storing, accessing, and analyzing data to help business users make better decisions.
52	A set of processes, technologies and tools comprising data warehousing, On-Line Analytical Processing, and information delivery in order to turn data into information and information into knowledge.
53	A tool that allows the generation of reports in an automated way and in real time. This methodology is based on professional software solutions. The collection of data and their aggregation in readable documents give the management and operational functions the keys to guide the company's strategy.
54	A set of processes, technologies and tools comprising data warehousing, On-Line Analytical Processing, and information delivery in order to turn data into information and information into knowledge.
55	A general term that refers to a range of capability and tools used to analyze an organization's raw data and transform them to actionable knowledge by data mining, online analytical processing, querying, reporting and so on.
56	It is a data analysis strategy that aims to extract knowledge from large databases or big data to improve processes within the company.
57	It refers to the meaningful and useful knowledge extracted from data and information.
58	This results from information systems that combine data with analytical tools in order to provide information relevant to decision making, while seeking to improve the quality and availability of this information to decision makers.
59	A technological driven process for analyzing data and presenting information, in such a way that user can take immediate actions and unable decision making.
60	Solution offers tools for sophisticated analysis that work with stored data in various information sources. IT users evaluate intuitive user-friendly interface with support needed flexibility, agility and predictability.
61	A set of theories, methodologies, architectures, and technologies that transform raw data into meaningful and useful information and knowledge for business purposes, by handling large amounts of both structured and unstructured data.
62	A set of processes, technologies and tools comprising data warehousing, On-Line Analytical Processing, and information delivery in order to turn data into information and information into knowledge.
	Almost all that definition are a available at : https://www.igi-global.com/dictionary/business-intelligence/3043