Harnessing Big Data and AI for Next-Generation Business Intelligence in Cloud Environments

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Abstract

As the volume and diversity of data grow at an unprecedented pace, new technologies have emerged to manage and analyze enormous data collections captured across a range of domains. In particular, big data technologies challenging existing business analytics models are increasingly implemented on cloud infrastructure with significant thrusts from AI, machine learning, and workflow management techniques. However, to exploit these techniques in practice, the necessity for scalable performance, geo-distributed storage, and disaster recovery compellingly encourages platform providers toward dynamic decentralized cloud topologies. This chapter analyzes potential pitfalls and capabilities of future cloud infrastructures and offers an optimal practice for creating next-generation business intelligence projects fully harnessing the advanced big data technologies applied in cloud environments, converging and delivering a variety of service models. Supportive projects focusing on advanced industry demands, proposed as tools-as-a-service, will be introduced and detailed, providing both benchmarking performance analysis, as well as a demonstration of best practices for non-experts.

Keywords: Big Data, Cloud Computing, AI, Machine Learning, Business Analytics, Workflow Management, Scalable Performance, Geo-Distributed Storage, Disaster Recovery, Decentralized Cloud, Cloud Infrastructure, Business Intelligence, Service Models, Tools-as-a-Service, Data Management, Benchmarking, Performance Analysis, Industry Demands, Next-Generation Computing, Advanced Technologies.

1. Introduction

The rapid advancements in information technology, coupled with the ever-growing data on the Internet, are providing unimaginable possibilities for various applications. One of the specific applications is to collect a significant amount of data, store it efficiently, and utilize advanced data analytics tools, including artificial intelligence and machine learning algorithms, to extract meaningful information and generate business intelligence for decision-making. By bringing big data and AI together, new-generation tools and techniques have emerged to facilitate business processes, enhance customer relations, optimize costs, and facilitate business intelligence in the cloud. In this chapter, we explore how AI and big data can be synergistically coupled to generate effective business intelligence tools in cloud environments. However, the presence of heterogeneous and vast datasets makes the processing of big data challenging. Furthermore, the need for real-time decision-making demands efficient and scalable systems that can generate insights from data in real time. This attracted the attention of businesses looking for the latest information on how the current market is performing, customers' latest preferences, and environmental considerations. Data analytics is the process of uncovering hidden patterns in the data. Big data analytics refers to the sophisticated technologies used to process and analyze the vast volume, variety, and velocity of big data and draw insights. Various data analytics tools, frameworks, platforms, and techniques have emerged to scale against and efficiently process big data. With the continual advancements in AI, its techniques can be leveraged to explore business intelligence and decision support systems further.

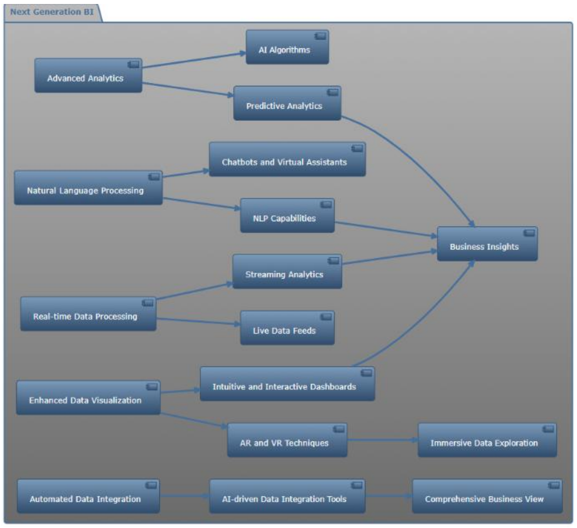

Fig 1 : Next Generation Business Intelligence (BI)

1.1. Background and Significance

Organizations face several challenges when they try to gain insights from their data. Challenges related to handling big data, integrating data sets, cleansing data, and extracting value from data make business intelligence (BI) tasks very complex and difficult. It is even harder for small and medium enterprises to cover the expenses related to the short cycles of deploying these tasks on evolving hardware, software, installations, updates, upgrade processes, and post-upgrade testing. These challenges become more difficult for non-dominion industries, which hold vast quantities of unstructured or semi-structured data. They also require solutions that offer the same functionality as existing solutions catered for more traditional scenarios but at lower costs. This work proposes a cloud-based BI reference architecture that takes advantage of the flexibility, scalability, and relatively low cost of cloud environments. By using big data technologies, applying agile data warehousing methodologies, and integrating data mining, artificial intelligence, and machine learning techniques, organizations can use the information lifecycle management framework to maximize the value of their data.

A BI reference architecture was described to help solution architects, analysts, consultants, and developers who are planning or developing BI solutions in public, private, or hybrid cloud environments. Modifying ongoing research efforts and aligning them with the interests of potential stakeholders interested in cloud-based BI, we also aim to address open research issues, particularly (a) how to design a cloud-based reference architecture that better leverages the technologies of data warehousing, business intelligence, big data, agile methods, data mining, and business analytics; and (b) how to develop BI platforms using a data-centric approach. Due to time and space restrictions, ongoing research that targets domain expertise sketches architectural styles, defines components, and refines a BI reference architecture was not included in this work and shall be reported elsewhere.

Equation 1 : Scalability Performance Model

$$P_s = \frac{W}{T_p \times N}$$

where:

P_s = Scalable system performance

W = Workload size

T_p = Processing time per unit workload

N = Number of distributed computing nodes

1.2. Research Objectives

A desirable feature of any BI system is to provide its users with insights regarding their organization's business processes. With the emergence of more comprehensive open data, large internal and external data sources, and advanced analytics, this analysis can now be much more in-depth. Business analytics is the statistical and quantitative analysis and examination of data or business models to gain new insights, understandings, characteristics, and elements of a business domain, to make business decisions, and to guide business processes such as organizational and operational changes. Insights can also be gained from more advanced machine learning and artificial intelligence and their ability to perform more advanced analytics; for these analyses to address and solve more complex business problems; and for the results of these analyses to drive business process improvements. A further desirable feature of BI is how business users can employ the BI system's human-computer interfaces to interact with and consume its presented insights. These HCIs need to be user-friendly and intuitive and should preferably not require users to have a high degree of analytical or technical skills to operate them. Moreover, the HCIs should adapt to how BI is used within the enterprise. This way, the BI system can properly tailor its presentation of those particular insights that matter most to the user so that the user does not have to look for them.

1.3. Structure of the Paper

In this article, the driving forces behind the business interest in big data and AI in cloud data analytics are summarized. Key technologies and theories underlying this phenomenon are examined and critically reviewed, and a holistic view of the hybrid offerings of big data and AI in cloud environments is covered. On top of the state of the art, some challenges and future directions are discussed and emphasized. This work aims to make the underlying drivers and technology clear to a wide audience including business managers, commercial decision-makers, and technical researchers who have an interest or a stake in accessing and utilizing data and tools that could generate pervasive and breakthrough impacts on society and the economy. The rest of this paper is organized as follows. Section 2 gives a general introduction to cloud-based business intelligence. Section 3 reviews the ecosystem of business intelligence. Section 4 analyzes the significance and pattern of big data for business intelligence. This is followed by a brief overview of big data in cloud environments and AI in cloud environments in Section 5 and Section 6. Next, synergies of big data and AI in cloud environments are illustrated in Section 7. A thorough discussion is given in Section 8. Finally, conclusions are drawn in Section 9.

2. Big Data and AI Fundamentals

The term big data refers to digital data assets characterized by velocity, volume, variety, and veracity in their generation. The use of AI includes machine learning, natural language processing, and deep learning to emulate or augment human-like intelligent behavior such as reasoning, learning, knowledge representation, understanding, and perception. Cloud computing is an enabling technology that provides scalable and elastic IT capabilities, both hardware and software, delivered through the Internet using various service models.

The three main properties of cloud computing—elasticity, scalability, and rapid provisioning—allow organizations to deploy large-scale and high-performance big data applications and facilities. Business intelligence (BI) is a technology-driven process for analyzing data and presenting actionable information to help executives, managers, and other corporate end users make informed business decisions. BI encompasses a variety of tools, applications, and methodologies to enable an organization to quickly understand, evaluate, and act on information. The new approach to management reporting through BI should overcome the limitations of conventional management reporting systems and provide a comprehensive and accurate view of the data that drives the organization. With the advent of the big data era, BI is evolving, with a new generation of BI able to build on advanced big data analytics and AI to harness massive and diverse big data sources, making BI more predictive, prescriptive, and programmatic, which are referred to as big data business intelligence, or the next-generation BI.

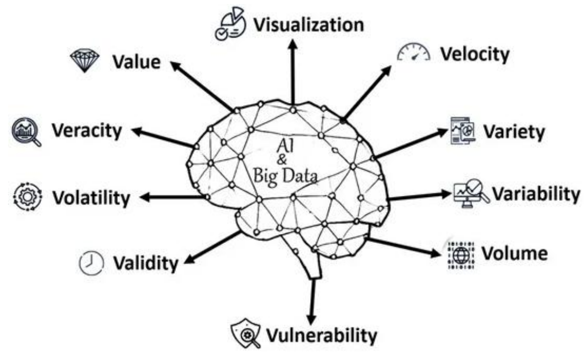

Fig 2 : AI and Big Data

2.1. Definitions and Concepts

Big Data, Business Intelligence (BI), Advanced Analytics, and Data Science—these terms are often confused and sometimes used interchangeably. As with others, a consensus or a standard related to the meaning and scope is needed. Big Data is a term given to data that has characteristics in terms of volume, variety, veracity, and velocity. Big Data is data that is so large that it tries to exceed the capacity of current computing environments. This characteristic changed with the evolution of data processing models that are traditionally executed by referring to the large volume of data processed in the first stages of a business intelligence outreach process, such as the sample calculation phase that generates a massive volume of statistical samples. Before 2007, data management was primarily focused on structured data storage and processing. After that year, the broadening of this data perspective to include four patterns defined as the 4 V's: volume, variety, veracity, and velocity.

The evolution of processing and extracting value from Big Data has given a spin to the concept of Business Intelligence itself, transforming it into a more robust one, acquiring advanced analytical concepts, data visualization, and user-facing techniques. In a previously focused BI system from a technological perspective, Big Data, therefore, brought in the need for maturity to consider aspects of data governance, data privacy, the emergence of a hybrid data lake, the choice of a blend of technologies, particularly about cloud, governance techniques, and aspects of continuous processing and continuous ETL, among others. With Big Data, Advanced Analytics (AA) emerges, dealing specifically with these issues using modern approaches such as Machine Learning and anticipating Data Science standards and techniques. Data Science is an evolution of previously named categories. In addressing the term Advanced Analytics related to the Business Intelligence process, the distinction is made into three larger categories in terms of the analytical treatment of the data. Broadly speaking, descriptive analytics addresses the past and diagnoses what happened. Predictive analytics addresses the future and projects what will happen based on past and current data. Prescriptive analytics decides what to do about the future, makes recommendations, and tells whether it is the best or worst decision. With that in mind, we developed a generic concept of Business Intelligence applied to the meaning of this article.

2.2. Technologies and Tools

Huge volumes of data that are flowing at an incredible rate are showing variety as they are available in many different forms. Their fast flow has them arrive promptly and increasingly contain valuable information. This enormous data comes from all sorts of sources, including social media, mobile applications, click streams from web browsers, telemetry from appliances, gameplay from games, and video recorders. All this big data has the potential to sharpen insights for organizations that harness it in shorter analysis life cycles, thereby driving new business opportunities or improving existing competitive advantages. Yet, to tap these many treasures efficiently demands a new generation of business intelligence technologies that can harness and rapidly make sense of all this big data.

Big data and artificial intelligence tools work together to empower next-generation business intelligence in cloud environments. Harnessing big data and AI together enables lowering acquisition and analysis life cycles by transforming and fusing the results of large numbers of federated AI processes associated with various context templates, property/relationship/association templates, and top-k templates. The result combination process can additionally correct or transform the results for multiple federated knowledge bases, for example, by constructing new models of a specific form or fusing multiple existing results. Since these changes are propagated widely, everyone can use them, even those without access to the original data federations.

3. Business Intelligence in Cloud Environments

Business intelligence (BI) represents a set of technologies, applications, and practices for the collection, integration, analysis, and presentation of business information, which can assist organizations in the decision-making process. Effective and efficient BI applications can help companies identify new business opportunities, promote expansion, improve efficiency, or gain significant advantages over their competitors. Traditional BI technologies and practices have reached their limits in terms of decreasing costs, increasing return on investment, and improving the decision-making capabilities of an organization. Even though some businesses have internal functional-domain cloud applications for Human Resource Management, Customer Relationship Management, etc., the leveraging of cloud architectures for BI applications is still in the infancy stage.

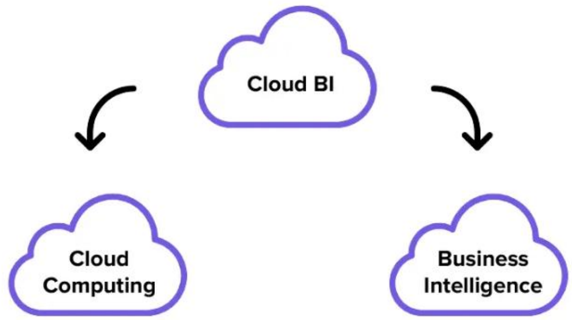

Fig 3 : Cloud Business Intelligence

As big data solutions are rapidly evolving, the need for updated BI solutions is also increasing. New data sources such as internet searches, clickstreams, blogs, sensor data, chat and email archives, social media, and call center notes, as well as the novel data management technologies that handle this data, are creating an opportunity for firms to mesh insights with information extracted from big data and BI tools. The collection of large and diverse sets of informational assets, often such as the data a firm generates from various sources, as well as novel technologies capable of analyzing diverse and voluminous informational sources, allows firms to extract value from the data deluge as well as to derive insights effectively. Finally, to turn these insights and data into actions that support the corporate mission and to do so at the strategic level, big data investments should focus on generating business value.

3.1. Overview of Business Intelligence

There is no widely accepted definition of BI to date. In the IT literature, BI is typically defined as the process of using technology to enhance business decision-making. An associated concept that has been used interchangeably with BI is data analytics. There is, however, academic literature that has attempted to define BI. BI is defined as the use of many data sources, which may be stored according to various design models, to provide information, insight, and understanding to support improved decision-making and to generate a better bottom line through improved business performance. In this research, we consider BI to be the application of business intelligence capabilities, including a range of techniques concerning data warehousing, online analytical processing, reporting, and data mining for business data analysis, querying, and reporting to support business decision-making.

BI consists of several tools and methods that, when applied to enterprise systems data, can generate useful insights and assist in achieving operational, tactical, and strategic business goals. BI tools and methods are applied to the entire range of data created by or managed by the enterprise systems, including both the transactional systems and data warehouses. Business intelligence systems are used to assist several business activities, including capabilities related to query, reporting, online analytical processing, data visualizations, data mining, analytics, enterprise performance management, and business event management. BI capabilities enable business users to access and analyze collective intelligence for enhanced decision-making. Many of these capabilities have both descriptive and predictive analytics purposes. Extant BI literature both models and empirically tests BI integration outcomes, often employed as upgraded or broader functionality to enterprise systems.

3.2. Cloud Computing in Business Intelligence

Cloud computing, from the standpoint of business intelligence, is the perfect enabler of the real-time data-is-the-new-software paradigm. In cloud-based BI, analyzed information gathering and analysis are performed on cloud software. This puts all the advanced BI capacities of smaller to medium-sized companies, where traditionally business intelligence has lagged due to unawareness, costs, and lack of capacities, on an equal footing with BI giants. Flexibility, scalability, significant cost advantages, and no CAPEX risk are some of the compelling reasons this scenario is seen as the future of BI architecture, irrespective of company size.

Business Intelligence (BI) is an integrated set of tools utilized to help decision-making personnel in organizations make more rapid, informed, and high-quality business decisions. Since it entered into the IT glossary at the beginning of this century, Business Intelligence has been evolving through various steps and has almost reached perfection in predicting business trends, observing market changes, analyzing customer values, understanding customer attitudes, and identifying new business opportunities. With numerous connections to all kinds of data sources possible, not only in classical form but also in the so-called big data feeds from social media, it is much more successful. It transcends and is about to substitute enterprise resource planning, completing the spinning of this important category of business software into a new advance in this millennium, reflecting extreme changes in the business environment regarding how business is conducted and how technology enables it.

Equation 2 : AI-Driven Predictive Analytics

$$Y = f(X) + \epsilon$$

where:

Y = Predicted business outcome

X = Feature set from big data inputs

$f(X)$ = AI/ML model mapping input to output

ϵ = Error term accounting for uncertainties

4. Integration of Big Data and AI in Business Intelligence

Before embarking on detailed discussions, further background remarks are necessary. At one extreme, big data refers to the massive volume of traditional numeric data generated by various large organizations worldwide. It is only relatively recently that non-traditional data such as text, video, and audio have become included in the definition. Big data can come from anywhere, such as sensors and smart devices connecting to the Internet of Things, social media activity, transaction records of online shopping, and so on.

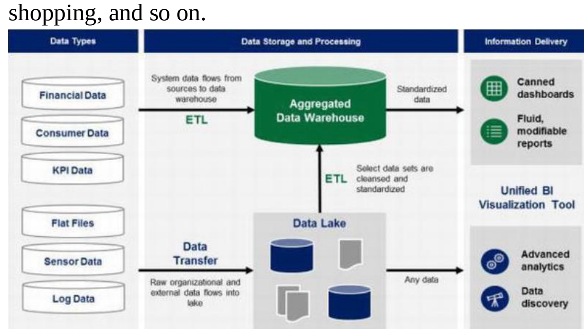

Fig 4 : Modern Business Intelligence

Indeed, nearly 90 percent of the world's data was created in the last decade. At the other extreme, while the concept of AI has been around for nearly seven decades and is perceived quite correctly by some as capable of replacing rather than transforming humans, AI faces widespread implementation challenges. It is easy primarily due to the lack of desired or appropriate leaders, professionals, units, systems, and processes. It must also be remembered that the genius of AI is entirely dependent on the volume, variety, and most especially quality of the available data.

4.1. Data Collection and Storage

Physically, big data challenges a traditional data lifecycle that encompasses five main stages: data creation, analysis, distribution, preservation, and consumption. To maintain and support the lifecycle, the data must be stored and accessible for any further manipulation and exploitation in the future. The increasing data volume needs distributed data storage and flexible access. These include three dimensions requiring acquired support: space for diverse collections, time for rapid data queries, and further extension for new data types without bogging the system down. Meanwhile, advanced cloud database management systems have been developed and deployed to handle cloud dataset storage and access. These also present an option for developers to easily build more complex big data applications that can rapidly and effectively consume and act upon the complexities of big data.

Data storage is done across the five cloud layers, from close to the user device at the edge, near the user at the access point, regional data centers offering computing resources, and centralized big data storage centers. These are connected by presenting a comprehensive and programmable data storage system to tens of thousands of servers. These cloud storage systems are often built using distributed and replicated algorithmic frameworks aimed at large-scale storage in globally distributed settings. At a higher level, distributed cloud database management systems are designed to provide relational databases in distributed cloud settings. Large distributed cloud systems have extended to include twelve dimensions. These include extra benchmarks, indexing, elasticity, and exabyte support. At present, cloud databases also try to leverage specialized devices and data center installations to accomplish the best trade-off among volume, response time, distributed storage management, and price, and choose different frameworks based on a specific cloud application under consideration.

4.2. Data Processing and Analysis

In the cloud, large data volumes are stored through storage services, particularly those of cloud-based storage providers. These providers also have explicit support for the data sharing feature, which permits the data owner to define access rights such as read, write, and perform these access options with other clients and entities. However, to analyze the enormous industrial, business, and scientific data that need to be transferred from remote storage (organized as massive parallel data pipelines) such as computing clusters or data streaming engines, which permit real-time flow visualization and rapid shared decision-making processes. Governmental data, on the other hand, are generally sourced and transferred through more secure means to ensure the protection of sensitive and confidential data. To execute AI and cloud computing on the fly, capabilities are embedded directly in cloud storage. Owing to their geographical coverage and capacities, cloud service providers are well-positioned to enable fast data processing on the fly with big data and machine learning capabilities.

After the data has successfully been transferred to the virtual computing environment within the actual cloud service, a vast quantity of tools developed to manage and analyze the data at various lifecycle stages are used. On-demand created virtual computing environment connection points as well as API in the cloud are among the mechanisms to build/manage these clusters. To support the data inquiries, a large amount of data management and technology selection procedures and strategies also forward the user or self-service interfaces. The vast quantity of such implemented tooling can either be used through query interfaces or it can be run automatically via workflow orchestrators or serverless computing services. If the business data is relocated from on-premises to cloud-based software services, querying this data for gathering information on industrial application use or specific business process flows and outcomes will generally utilize database solutions run within the big data clusters, impacting the interest expressed by large managers and decision-makers.

4.3. Machine Learning and AI Algorithms

Machine learning and AI refer to advanced algorithms that continually learn from the customer's data in the cloud and on-premises, thus requiring minimal effort in terms of initial and ongoing rule and model creation and management. In contrast, traditional business intelligence platforms, dimensional filters, models, queries, and calculations are created by developers explicitly and manually. Data and analytics leaders are looking for ways to act faster and pursue new opportunities while learning about new advanced information systems and analyzing data. Artificial intelligence can help in these tasks. Machine learning is a type of algorithm that learns itself without explicit programming when processing data. AI is a set of versatile techniques and process types that analyze and learn from data and produce business insights.

Unlike traditional business intelligence platforms and cloud-based products, machine learning and AI require minimal initial and ongoing rule and model creation and management. Instead, data is synthesized with information systems, benchmarks, and integrated AI assistants, which use continuous intelligence to navigate relations and narrow down opportunities. As a result, with these dynamic compounds and high-level data science capabilities, the opportunities for traditional machine learning features used within playing systems are increased, leading to faster responses and shorter processing request queues. These systems utilize their grasp and understanding of the customer to help decision-making more than those of a data science engineer.

5. Challenges and Opportunities

While the cloud is viewed as a major move towards creating the necessary infrastructure for big data and AI, models built on the full exploitation of cloud and data paradigms are lacking. The transition of big data and AI to the cloud is indeed challenging, and complicating further is that the cloud world evolves fast, offering more products than ever. Business intelligence expectations are high with cloud-based solutions, and recent innovations in cloud brokering, cloud analytics, and MLaaS make it clear that cloud infrastructure is the future of business software. It provides an environment where big data and AI can synergistically thrive and be made available to non-ICT experts. In this chapter, a wide range of digital repositories where models and data live is presented, and we notice that many systems explicitly ask for filling out a form before downloading a dataset, while a few block user access because the server is congested or a subscription is needed. With our workload models, we find that exposing resources within the business intelligence platforms associated with the cloud services, when needed for collecting big data or analyzing them, can be beneficial. We make use of a straightforward, flexible, and ready solution to serve during large-scale cloud experimentation and recognize that we need to rely more on machine facilities to avoid any business implications from the large scales of our demanded resources for promoting orchestration, optimization, and allocation among various cloud providers.

5.1. Privacy and Security Concerns

Privacy and security are the main concerns in any related area. While the idea of big data intelligence can bring many potential benefits to communicating and processing data collected from various sources, including clients, it also creates some privacy concerns for individual privacy. Big data can invade personal lives and uncover details about personal data that are normally invisible to others. When an individual put their data online, it is largely out of their control, and others could use this big data technology to collect the data for business analysis. In today's globally competitive market, extracted data can be a valuable informational asset that drives business intelligence in terms of capitalizing on this data and how it can harm clients' mental and physical well-being. Clients' interests, opinions, attitudes, and emotions may appear as information in big data analysis. There is a standard idea to use voluntary consent as a tool against breaches of client privacy.

However, this is often relevant to both the data's value and the ambiguity of privacy breaches. To develop business intelligence, it may be possible to promote consent in general based on informed choice, personal autonomy, and respect for individuals' ability to control their personal lives. There are several models to classify privacy-preserving methods in data mining. Based on our concerns here, cell suppression, noise addition, data perturbation, and output perturbation can be used as these kinds of privacy-preserving methods. Various groups of client information should be classified as data storage systems and data access models, and also different types of clouds without their way of working. As we discussed, to build large-scale and robust big data mining processing systems, different cloud systems have their powerful access models that can work within the distributed parallel data mining processing pipeline.

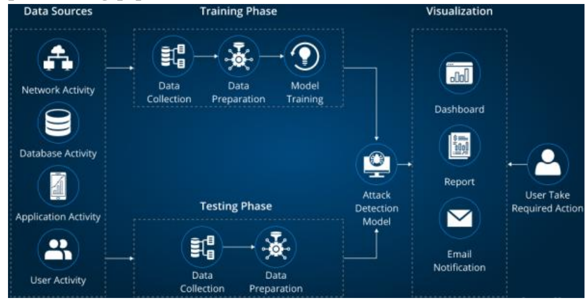

Fig 5 : Data security in AI systems

5.2. Scalability and Performance Issues

Several companies have built a lot of data centers and, in the process, have learned a lot of things and have implemented many of them in the open-source domain. Companies that provide cloud services host services over a large number of powerful computers called data centers. The large number of customers provides a level of redundancy to ensure high levels of reliability of these resources. Many factors impact the performance of these cloud-based services, such as the server's CPU, memory size, and external network characteristics like round-trip time and client network capacity. An alternative method of workload involves renting computing power for a short period to handle peak computationally intensive tasks in the cloud, which has potentially significant performance implications. Cloud-based systems provide a cost-effective platform for auto-scaling to manage the variability inherent to the cloud. Providers can offer a hardware and software stack that automatically provisions extra resources when demand increases, while concurrently identifying unused resources that are idle and can be provisioned off. Software-implemented auto-scaling systems offer a platform that ensures performance and instantiates resources as needed.

5.3.Future Trends and Opportunities

There are immense opportunities for the BI market for the use of BDAI in cloud environments. In practice, BDAI technologies enable businesses to discover new insights or to discover new business models based on these new insights when using structured data despite complexities or a lack of preparation of the data. However, a complex, unpredictable, and unreliable environment created by the dynamic contribution of various contexts increases the level of difficulty for xICT functionality configuration. Therefore, we think that one future direction of the implementation of BDAI lies in BI based on DBI under

ICT environments. In this respect, the traditional BI domain would be deeply divided into several directions such as business data management, business data analytics, business intelligence processing, and management of BDAI operation infrastructure.

To improve the DBI functions, one of the most potentially valuable asset sources in BDAI is the inclusion of an edge character. The data in the xICT functionality space in harvested edge environments would lead users to the advantages of added xICT business data value such as near-time business data decision-making opportunities, the support of derived data formats that reduce the original data format volume, lower ICT loading, and costs incurred by edge-generated information needing to be transmitted to a cloud environment, and the support of the backup and recovery of merged data. In practice, edge ICT networks or systems would be constructed with computers, equipment, ICT networks, wireless technology, sensors, or devices.

6. Case Studies

In this chapter, we provide case studies of big data handling using big data frameworks over both local clusters and cloud environments. We describe each case study from obtaining data to analysis and visualization. Finally, we compare the results of the locally built cluster with the results obtained on our cloud framework. We provide detailed results with discussions in Section 6.10.

We provide several concise case studies, encompassing both an R and Scala environment, sparklyr and the sparklyr companion, respectively. The sparklyr interface is especially useful, since all the different actions on the data, including summarization, transformation, and visualization that we perform over sparklyr, can be directly handled within the R environment. For the reproducibility of any case study, readers can copy and paste the relevant code lines into the cloud environment of their choice.

6.1. A. Real-World Implementations

This book section provides an overview of some of the real-world implementations of cloud enterprise BI platforms as follows. Amazon QuickSight, Microsoft Power BI, and SAP Analytics Cloud are cloud enterprise BI platform offerings that are based on serverless cloud analytics architectures. These platforms are not machine learning platforms per se, and ML models developed and tested using these platforms can only be consumed via external application integration.

Google has assembled its cloud AI, BigQuery, Data Studio, and Looker platforms to create a new collaborative BI action experience in addition to its existing BigQuery BI Engine that supports visualization analysis at interactive speed. IBM and Oracle have added serverless machine learning and AI platforms to their existing cloud enterprise BI platforms as new service offerings to simplify ML model build and test processes and enable discovery, operationalization, and governance in self-service BI panels for both citizen data scientists and advanced data engineers. In the field of resource and service optimization, the resource usage, allocation, and performance of business services and systems can be intelligently planned and managed in real-time and at a cloud scale via AI models developed and operationalized within these cloud enterprise BI platforms. Finally, the implementations and their serverless AI/BI integration identify areas for innovation and implementation, and the potential value that can be enhanced in the cloud responder organizations with well-defined business strategies and execution plans in the machine learning ecosystem.

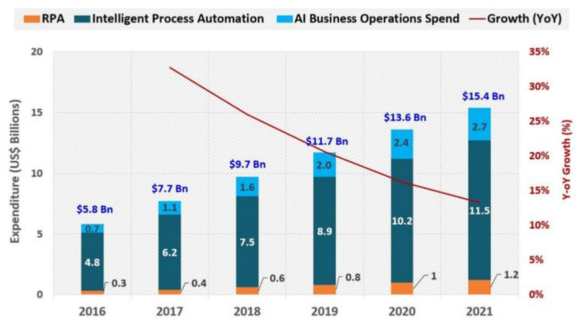

Fig 6 : Big Data and AI Are Driving Business Innovation

7. Conclusion and Future Directions

The objective was to understand the recent advancements of big data and AI technologies for the realization of business intelligence in cloud environments. We began by understanding the relevance of these technological trends for contemporary business decision-making. Next, we laid down key theoretical concepts such as business intelligence, big data, cloud computing, and other technologies of relevance. We also identified the challenges that are currently being faced in realizing BI in cloud environments. Thereafter, we understood the role of big data technology in paving the way for cognitive business systems. Then, we presented five critical BI functionalities supported by big data and AI technologies. Consecutively, we elaborated on the role of cloud computing in facilitating intelligence in enterprises. In the marketing discipline, we explored the application of the cloud for intelligence applications within the direct response markets. Next, we presented selected tools and techniques in the form of cloud services for supporting business intelligence in the cloud. Then, we combined those services to demonstrate a framework for achieving BI within cloud environments. After that, we understood the driving forces behind the need for Big AI in cloud environments and also the challenges of integration. Thereafter, we showed how big AI can be used for achieving BI within cloud environments. Next, we demonstrated the real-world case of Seoul for the realization of big AI in the cloud. We then elucidated the proposed framework. After that, we reviewed one practical situation in the real world using the proposed framework. Finally, we synthesized the study and presented future research directions.

Equation 3 : Cloud Resource Optimization

$$C_{opt} = \min \sum_{i=1}^{n} (R_i \times U_i)$$

where:

C_{opt} = Optimized cloud resource cost

R_i = Resource unit cost for service i

U_i = Usage level of service i

n = Total number of cloud services

7.1.Summary of Key Findings

The failure to leverage the wealth of information that datasets provide has thwarted business leaders from making informed decisions to avoid market risks, operational irregularities, and unavoidable liabilities. This chapter has demonstrated the potential of harnessing big data and the power of AI in developing next-generation business intelligence platforms in cloud-based environments. We have divided the proposed framework into three layers. The bottom layer is the infrastructure that lays the groundwork for the collection, storage, and processing to carry out the data searches required by the upper layers. The middle layer is the Software as a Service and Data as a Service that provides enterprise access- and government-wide data. The top layer is the enterprise business intelligence that enables business functions.

Although the current business intelligence infrastructure complicates important trends and the disparate evolution of big data sources, we have proposed a future architecture that simplifies the trends and facilitates research. The alignment between business intelligence priorities and business intelligence implementation strategy might affect the use, impact, and values of business intelligence and its different components. Business intelligence systems address this challenge by aggregating different aspects of organizational activity and producing key performance indicators that can help in articulating the strategic outcomes that result from published principles. We have successfully applied recipient-oriented optimization models for developing next-generation business intelligence systems in cloud repositories. The design of the overall architecture described in this chapter is also feasible with existing platforms today. We have also based the value framework on building and flexibility. Overall, it demonstrates how the proposed architecture addresses data sources, data aggregation, assessment methods, and value models for the specific modeling requirements and the nature of business intelligence activities that need to be performed.

7.2. Recommendations for Future Research

There is still some open-ended future work to carry out after the orientation provided by this research. For example, as this study involves cloud BI and strategies for flourishing in AI and big data, there are more factors to investigate within a specific cloud BI context. It is also fascinating to look at responses from different geographic locations and cultures, different types of enterprises, and various levels of knowledge and BI maturity. When matured further, the OverBFRIS influence model could be used as an allegorical tool within a BI system, a cloud using a private or hybrid cloud BI system, or to improve a specific big data decision support service. This research could be carried forward to more complex application areas, i.e., environments or services aimed at increasing a firm’s productivity, profit, faster development lead time, and so on. The OverBFRIS is suitable for guiding the implementation and use of intelligent decision support services in big data environments too. There is an opportunity to learn what makes firms adopt and take up the innovations the cloud has to offer using these strategies, to learn how business intelligence can be tailored towards the vulnerable and emergent cloud business scenarios observed, and to evaluate how it can best be economically exploited.

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