Artificial Intelligence-Driven Big Data Analytics for Business Intelligence in SaaS Products

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***Abstract*—The prevalence and gravity of data-related issues facing modern businesses have propelled the field of business intelligence and analytics (BI&A) to the forefront of academic and professional discourse. A paradigm change is occurring in the way businesses make decisions and prepare for the future, and this paper explores AI and data analytics are changing the face of BI. An aim of the study was to look at BI from every angle, particularly how it has changed with the addition of AI and sophisticated data analytics, and to see where these technologies are headed in the corporate world. The combined use of BI, AI, and BDA in SaaS products is the topic of this review. It describes big data analytics, lists its essential elements, and talks about how it relates to business intelligence. The review examines AI trends in BI, examines successful sector-specific applications, suggests a Big Data Analytics Service-Oriented Architecture (BASOA), and examines SaaS adoption in BI. Further research areas encompass the AI frameworks, optimising the scalability and performance of business intelligence applications built on SaaS platforms.**

Keywords—Business intelligence (BI), Big Data Analytics (BDA), artificial intelligence (AI), Machine learning, NLP, Software as a Service (SaaS), BASOA.

I. Introduction

An emerging, data-focused economy has emerged from many parts of human and corporate activity, spurred by the ubiquitous digital technology seen in industry, services, and daily life[1]. Urban studies, geography, economics, public health, physics, genetics, and the social sciences are few of the many disciplines that stand to benefit greatly from the new avenues of inquiry made possible by the abundance and quality of this data[2]. All these different, sophisticated datasets that constitute "big data" are just too much for traditional methods of data administration and processing to manage. In order to make an educated judgement or assessment, "big data" describes massive amounts of data, which might be organised or unstructured[3][4]. Data may be retrieved by a huge range of sources, like past purchases, social media accounts, geolocation data, and even medical information. Complex data sets that would be incomprehensibly processed by more conventional, simplistic database management methods are called "big data.". Big data is characterised by five primary features, including [5]:

- **Volume:** It is a measure of the massive dataset.
- **Variety:** Many different sources, both internal and external, provide businesses with data. There is inconsistency in data since these records come from different sources. Rarely is external data structured.
- **Velocity:** the pace of big data generation.
- **Veracity:** this level of confidence in huge data.
- **Value:** After all steps are completed, a product should be made, and that product improves a process.

Big data and predictive analytics have great potential to improve BI, especially when it comes to decision-making. For the purpose of making strategic decisions about the growth and improvement of a company's marketing and operations, BI refers to insights derived from company and marketing data[6][7]. Global corporate investments in information technology (IT) are disproportionately concentrated in areas connected to business intelligence (BI)[8][9]. Predictive analysis is a critical component of BI operations[10]. Analytical technologies and tools that encompass mathematical calculations, statistical modelling, result simulation, and finding visualisation are extensively developed for the purposes of business strategy simulation and expectation forecasting[11][8].

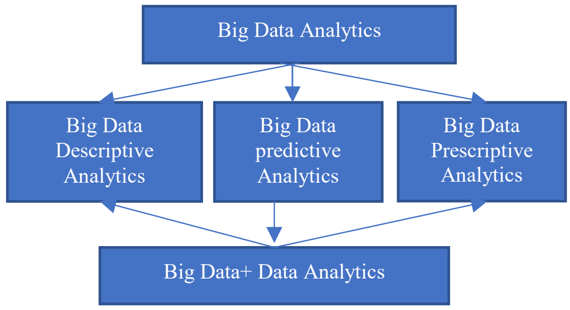

Fig. 1. An ontology of big data analytics[12]

Figure 1 defines data analytics as a process or strategy for discovering, describing, and predicting anything via the employ of data, information, and expertise. Data analytics, in a nutshell, are the findings in intelligence, communications, and knowledge that are driven by data. In a broader sense, data analytics is the study and practice of using data for the purposes of learning, describing, and predicting.

Massive data analysis has emerged as the most promising approach for extracting business intelligence insights, as organisations accumulate an increasing volume of data by both internal and external platforms[13][14][15][16]. Particularly, there has been a dramatic increase in the depth of BI forecast analysis, thanks to AI technology[17] revolutions that have shown great advantages in terms of efficiency, accuracy, time savings and resource conservation. A large number of open-source analytics tools that use DL and ML have been utilized in commercial decision-making processes [18], like a tools of Microsoft Power BI [19], Google Analytics [20], SETLBI [21] and accessible models of GitHub Repositories[22]. AI and BDA provide a potent instrument for well-informed decision-making and user experience improvement within the dynamic SaaS-providing market. Let us look at an intersection of AI-driven BDA and SaaS-BI. Thus, can customise their products, make processes more effective, and remain as a frontrunner in a very competitive market.

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A. Motivation and contribution of this paper

This article is driven by the emerging convergence of AI, Big Data Analytics, and BI in SaaS solutions. Its key contribution is to explain this intricate interplay and its implications for the present decision-making processes. It increases understanding by providing an in-depth review of fundamental frameworks, sectoral illustrations, architectural ideas, and insights into SaaS utilisation, as well as helpful suggestions for efficiently exploiting AI-driven big data analytics in varied business scenarios. This comprehensive strategy intends to enable organisations to leverage the transformative effects of AI and big data in BI, fostering data-driven insights and informed decision-making in an increasingly digital environment. To illustrate the potential research contributions of integrating AI, Big Data Analytics (BDA), and BI in the SaaS industry, consider the following:

- To enhance predictive analytics: Investigating how advanced ML algorithms can improve the accuracy of demand forecasting and customer behaviour predictions, enabling SaaS companies to better anticipate market trends and optimise resource allocation.
- To automate data processing: Exploring the development of AI-driven data preprocessing techniques that streamline the extraction, transformation, and loading (ETL) processes, reducing the time and effort required to prepare large datasets for analysis.
- To personalise user experiences: Exploring AI and BDA can be integrated to enhance the customisation of services using real-time user data, thus, improving customer experience with SaaS applications.
- To optimise decision-making: Investigating the integration of BI tools with AI to create intelligent decision-support systems that provide actionable insights and recommendations, helping business leaders make more informed and strategic decisions.

B. Organization of paper

The rest of a paper is organised as follows: Section II provides the fundamentals of big data analytics, definition of BI also BI and BDA that discussed in Sections III, and IV, Next section V provide the AI in business intelligence, and Section VI describes BASOA, Then Section VII discuss the SaaS- A response to business intelligence, last Section VIII discuss a literature review of this topic, finally offers a conclusion and future work of this review.

II. Business Intelligence And Big Data Analytics

A term "BI" describes the method by which a company may get useful insights and information for making strategic decisions by gathering, analysing, and interpreting massive volumes of data. The process entails using variety of techniques, tools, and technologies to collect information from internal and external sources, convert it into useful insights, and display it in way that facilitates decision-making.

While this word was mentioned in 1958 by an IBM researcher, but BI is now being applied more practically in both academia and the industry over the last 20 years [23]. There are numerous distinct definitions of BI. For example,

- Process of converting diverse data sources, structured and unstructured, into actionable insights for decision-makers is what is referred to as BI.
- In the realm of operational control, BI encompasses a collection of tools and software that furnish valuable insights to managers via data extraction, encompassing both internal and external operations.
- BI is a compilation of multiple principles which are aimed at improving data-based systems of decision-making in businesses.

The primary focus of the first BI definition is on providing decision-makers with knowledge and information. The second definition places more emphasis on "a collection of ISs and technologies," while naming "managerial decision makers of operational control" and describing "information on internal and external operations" as a decision makers and information source, respectively. As a final definition, "a combination of ideas, theories, and methodologies to enhance corporate decision-making" is highlighted. In light of the above, business intelligence (BI) may be described as an assemblage of theories, methodologies, architectures, and tools that provide useful data, information, and knowledge to aid in company decision-making. This description shows how BI and related technologies have developed over time, beginning with DSS and how they link to data warehouses and executive information systems [24].

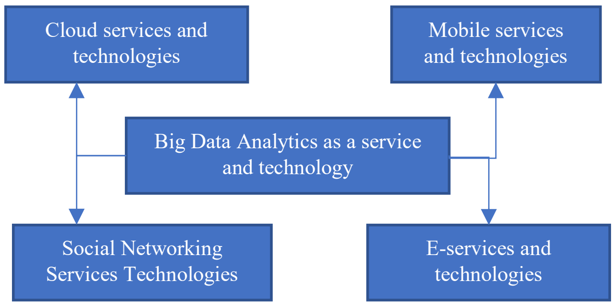

Fig. 2. Interrelationship between BDA and web services[25] [12]

Presently, BI is constructed upon four paradigm-shifting technological pillars: Social technologies, cloud, mobile, and big data [26]. Every of these pillars represents a distinct category of web services: Social networking, mobile, cloud, and big data services; collectively, they comprise contemporary web services. Technologies and services for analytics have provided support for each of these services. In addition, as shown in Figure 2, are aided efficiently by the technology and service of big data analytics.

III. Artificial Intelligence (AI) In Business Intelligence With Data Analysis

AI encompasses the more extensive notion of developing intelligent systems capable of simulating intelligence akin to that of humans. Using NLP and computer vision, two AI methods relevant to BI, information is retrieved by unstructured data sources, like written documents, pictures, and videos. This opens the door for businesses to acquire insights from more types of data coming from more places. There are several benefits to BI that makes use of ML and AI. Companies may save a lot of time and effort by using these technologies to automate integration, data cleansing, and report generation, for example. As a consequence, critical resources may become available, allowing personnel to concentrate on more organizationally significant and strategic pursuits.

A. *Trends in AI in Business Intelligence*[27]

1) *Predictive analytics and forecasting*

ML techniques are used in predictive analytics to sift through mountains of historical data in search of trends and valuable insights. Complex connections and linkages may go undetected by more conventional forms of analysis when these algorithms are used. Businesses are able to generate accurate projections about the future by using predictive analytics[28][29]. Their operations may be optimised, demand variations can be anticipated, and resource allocation can be improved. Additionally, it is useful for seeing dangers coming and getting a head start on mitigating them.

2) *AI-powered chatbots and virtual assistants*

Chatbots and virtual assistants driven by AI understand and respond to customer questions using NLP. They may learn from client interactions and gradually enhance their replies with the help of ML[30][31][32]. Automated chatbots and virtual assistants streamline mundane consumer interactions, including answering FAQs, making product suggestions, and helping with basic problems. This improves the efficiency of customer support while freeing up human resources[33][34].

3) *Explainable AI and ethical considerations*

A comprehension and interpretation of AI models' decision-making processes are becoming increasingly crucial as their complexity increases. The goal of explainable AI is to make AI models more transparent and interpretable so that people can understand the logic behind certain forecasts or judgements. Constructing trust and mitigating risks through transparent and ethical AI models: Developing and deploying AI with increasing attention to ethical concerns. The main characteristics of the issues that the organisations should address are fairness, accountability, and openness, while the bad effects are prevented altogether. Such AI and ML advances in business intelligence are redefining companies' approaches towards consumers, data analysis, and ethical and transparent AI policies.

IV. BASOA: Big Data Analytics Services Oriented Architecture

This section describes a BASOA and then takes a look at each of the key components of that architecture. The suggested BASOA differs from the conventional SOA [35], in that it maps general services to services that analyse large data, as shown in Figure 3. By using BA as a stand-in for BDA in this BASOA architecture, BA may be used interchangeably with BDA. In turn, this is made feasible by the rise of big data and massive analytics, which are both based on data and analytics.

The BASOA primarily involves three parties: the supplier of big data analytics services, the requestor of such services, and the broker of such services. Subsequently, they shall examine each of these in considerable depth, with BI as our consideration.

Organisations, governments, and executives at all levels (including the CEO, CIO, and CFO), in addition to managers, apply to request BDA services. Further users of BDA services include e-commerce platforms and ERP systems. Customers looking for BDA services often inquire about a range of options, including business analytics, information analytics, and knowledge analytics. Many of these services use visualisation methods to provide data about knowledge patterns and decisions in an aesthetically pleasing way, such a table, figure, or report. BDA service requestors are the people that often seek out analytical reports from bda service providers to use as a foundation for their decisions or data acquisitions [25]. Hence, everyone requesting analytics services on their smartphone is also requesting BDA services.

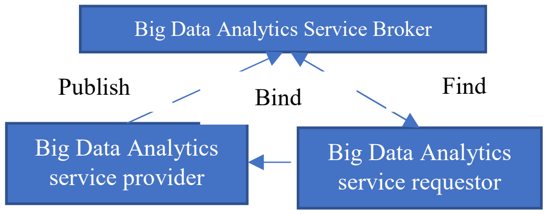

Fig. 3. BASOA: A big data analytics SOA

The growth of BDA services is facilitated by a wide variety of organisations, such as academic institutions, consulting companies, popular presses, social media, conventional media, and university students, among many more. Several of these resources have recently found their way into computer science and business courses taught at universities. All of these courses use various approaches to help students learn more about web analytics, data analytics, business analytics, and big data analytics services. A role of brokers such as IDC, Boston Consulting Group (BCG), and McKinsey Consulting (http://www.mckinsey.com/) in pushing "big data" and big data analytics inside organisations and businesses has been crucial. Globally renowned BDA service brokers include Forrester and Gartner as well[36].

V. SaaS – A Response To Business Intelligence

The case for SaaS BI applications becomes more attractive and deserving of consideration when the demand for business intelligence applications to be delivered at a reduced cost and in a shorter timeframe increases. Business executives, who are irritated by the sluggish pace of BI solution development, are particularly concerned with applications. SaaS application software is rented rather than licensed and possessed by a company; rather, it is provided as a service. The cost of the service may fluctuate based on factors such as the quantity of users, data usage, package alternatives, or additional determinants. Payment is established via subscription. The demand for these solutions is increasing, according to market research, especially among small and medium-sized businesses that lack the financial resources to implement BI initiatives. Thus, Aberdeen's study into SaaS BI indicated that the total customer base for this model continues to be dominated by smaller enterprises, who are drawn to the lower prices. Business units in bigger organisations that have SaaS BI solutions in their portfolio are more worried about the time it takes to build and deploy a BI solution.

The market for business analytics platforms is anticipated to maintain its position as one of the most rapidly expanding software markets by 2016, expanding at a 7% annual rate, according to Gartner. BI tools are utilised for the purpose of consolidating data from diverse origins, executing calculation algorithms, examining data for discernible patterns and trends, traversing through data, and generating reports that are commonly prescriptive or diagnostic in nature. Implementing the SaaS model necessitates modifications to their architecture and operation, which affects the performance of the services provided, the facilities provided, and the business models of the organisations that utilise them.

When discussing the SaaS model, adoption necessitates a number of adjustments. It produces altering the Business Model first. This may entail one or more of the subsequent:

- The software is not owned by the corporation, but by an outside vendor;
- The external vendor is accountable for the administration, maintenance, and development of the SaaS application's technical infrastructure;
- Software service expenses are diminished via the implementation of economies of scale and specialisation;
- Modifications to software and business processes are required from both the supplier and the customer.

SaaS was first used extensively for CRM and sales automated processes. There are a lot of corporate processes that now use it, such as accounting, ERP, computerised billing, invoicing, human resource management, finances, content management, collaboration, document management, and service desk management. Scalability, multi-tenant efficiency, and configurability are essential attributes of a well-designed SaaS application[37]. The most notable difference from more conventional apps is multi-tenancy.

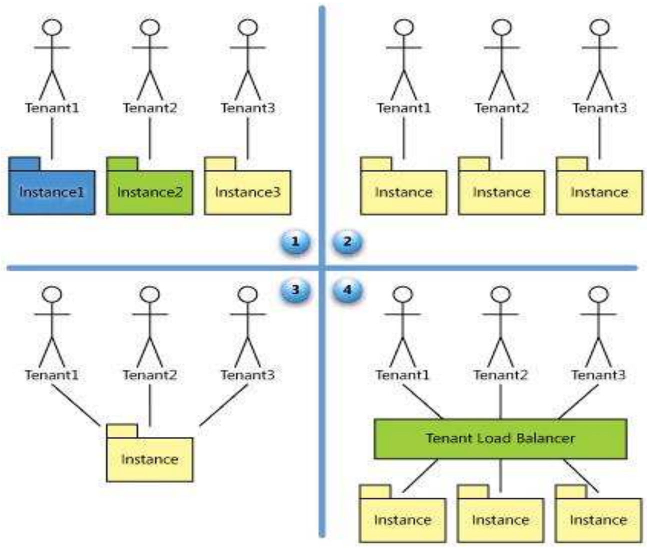

Fig. 4. SaaS application maturity model [38].

Not only is the SaaS software maturity model a standard that is acknowledged by the industry, but it is also a guideline that SaaS developers adhere to. The fundamental cloud computing model not only enhances the convenience and intelligence of information resources and services, but also organises and analyses data in a manner that identifies and extracts information piecemeal based on user requirements in order to provide personalised development services to users. After employing data mining, search engines, autoscanning, keywords, and other pertinent resources, information products that cater to customer requirements are extracted via induction restructuring, which is accomplished through extensive information resource filtering. This process ensures that SaaS users receive timely and effective predictive information [39].

It is essential that the architecture shown in Figure 4 can do this by allowing tenants to share resources while maintaining the privacy of their respective data. To customise the appearance and behavior of the programme for every client, metadata will be used. A SaaS application is considered to have reached one of Microsoft's four maturity levels based on these three factors in:

- **Level I**

  Ad Hoc/Custom - Each client operates a unique application on the server of the host and is provided with a customised version of the hosted application at this tier. Analogous in nature to the pattern presented by ASP. With minimal effort, an application can be transformed from a traditional model to a level 1 SaaS model.

- **Level II**

  Configurable - In this particular scenario, every vendor operates an individual application instance for every client; however, these instances all utilise identical code. The vendors furnish comprehensive configuration options that enable them to customise the appearance and functionality of the application for each client. Transitioning to this level necessitates greater architectural modification effort if the application was originally developed to support individual customisation and does not employ configuration metadata.

- **Level III**

  Configurable, Multi-Tenant-Efficient - At this stage of development, the vendor operates a single instance application that utilises configurable data to provide distinct visual and functional experiences for individual clients. A security policy and authorisation ensure that all client information is kept private and secure, distinct from that of other tenants. Despite the increased efficiency in utilising computing resources, this model exhibits limited scalability.

- **Level IV**

  Scalable, Configurable, Multi-Tenant-Efficient - Every client's data is kept independently, and the vendor uses adjustable metadata to provide each tenant their own unique application, all on a farm of identical machines. Adding more users doesn't need reworking the app's framework since the system is extensible.

The determination of an appropriate level of maturity for the intended application is contingent upon a number of considerations: the economic viability of an isolated approach, the compatibility of the application's architecture with single-instance operation, the assurance of contract-mandated services to clients, and even the client's explicit desire to isolate the application due to a lack of trust.

VI. SCOPE OF THIS PAPER

The scope of this paper on integrating AI, Big Data Analytics (BDA), and Business Intelligence (BI) in the SaaS industry includes:

- **Literature Review:** Conducting a comprehensive review of existing research and case studies that highlight the current state of AI, BDA, and BI in the SaaS industry, identifying gaps and opportunities for further exploration.

- **Technological Frameworks:** Describing the technological frameworks and tools used in AI, BDA, and BI, and their applicability to SaaS platforms, including an overview of the latest advancements and best practices.
- **Implementation Strategies:** Outlining practical strategies for implementing AI, BDA, and BI in SaaS companies, focusing on system integration, data management, and deployment challenges.
- **Case Studies and Applications:** Presenting real-world case studies and applications of AI, BDA, and BI in the SaaS industry, showcasing the benefits, challenges, and outcomes of these integrations.
- **Future Trends and Research Directions:** Identifying emerging trends and future research directions in the field, including potential innovations, ethical considerations, and the impact of evolving technologies on the SaaS industry.

VII. LITERATURE REVIEW

The literature review for this study on artificial intelligence-driven big data analytics for BI in saas products in was meticulously designed to ensure a comprehensive and relevant collection of sources like IEEE Xplore, ScienceDirect, and Google Scholar, to ensure a comprehensive coverage of academic and industry literature.

This table 1 offers a structured overview of an objectives, methods, key findings, advantages, and limitations of the referenced works, along with potential areas for future research and improvement. This comparison provides a comprehensive view of the various perspectives on an integration of AI and Data Analytics in BI with SaaS.

TABLE I. RELATED WORK SUMMARY

Reference	Objective	Methods	Key Findings	Advantages	Limitations & Future Work
G. Žigienė et al. [40]	Explore the impact of AI and Data Analytics on BI.	Literature review, analysis of integration in organisations.	Emergence of intelligent business analytics combining traditional BI with AI. Impact on decision-making and strategic planning.	Enhanced decision-making, deeper insights.	Challenges in implementation: specialised skills, data privacy concerns, managing large data sets. Further research on addressing these challenges.
A. A.A. Gad-Elrab [41]	Discuss the evolution of BI with big data and AI.	Literature review, analysis of modern BI trends.	Shift from historical data analysis to predicting future trends.	Improved decision-making, predictive capabilities.	Need for advanced analytics skills, data quality issues in predictive modeling. Future research on data quality management.
D. Edge et al. [42]	Explore AI applications in enhancing BI platforms.	Case studies, demonstration of AI in visual analytics.	AI enables analysis of unstructured data for deeper insights.	Enhanced scope and depth of BI insights.	Challenges in processing unstructured data at scale, need for robust AI algorithms. Future work on scalability and algorithm refinement.
C. Hahn et al. [43]	Investigate AI's role in B2B marketing.	Bibliometric analysis, review of AI applications in marketing.	AI enables data-driven insights for enhancing marketing efforts.	Improved marketing strategies, enhanced customer relationships.	Challenges in integrating AI with existing marketing systems, ethical considerations in AI-driven marketing. Future research on ethical AI and integration strategies.
N. A. Alghamdi and H. H. Al-Baity [44]	Explore Augmented Analytics (AA) in BI.	Case studies, analysis of AA features.	AA accelerates analysis and insight generation, emphasising human decision-making.	Enhanced automation and insight generation in BI.	Dependency on data quality and availability, need for human interpretation. Future work on improving AI interpretability and data governance.
M. John et al.[45]	Investigate ML/DL model development in business processes.	Multi-case study, analysis of ML/DL integration.	Importance of structured methods in integrating ML/DL models into business processes.	Improved model deployment and optimisation.	Challenges in model scalability and interpretability. Future research on scalable ML/DL architectures and explainable AI.
P. Helo and Y. Hao [46]	Study AI's role in operations and supply chain management.	Case study analysis, evaluation of AI applications.	AI applications create value in supply chain operations, from planning to optimisation.	Enhanced operational efficiency and value creation.	Challenges in AI implementation in complex supply chain environments, need for robust data integration. Future research on AI-driven supply chain optimisation algorithms.
C. Han, and J. Tang [39] [47]	Design AI-based E-commerce platform (SaaS) architecture.	Architectural design, analysis of SaaS models.	Novel perspectives in E-commerce platform design leveraging SaaS and neural networks.	Scalability and flexibility of SaaS architecture.	Challenges in SaaS software description and standardisation. Future work on addressing these challenges and optimising SaaS platform performance.

VIII. CONCLUSION AND FUTURE WORK

In conclusion, this review paper emphasises AI-driven BDA has an ability to completely change business intelligence in SaaS products. Businesses may extract important insights from massive amounts of data by employing advanced AI approaches, allowing for more agile decision-making, improved consumer experiences, and increased operational efficiency. Several instances of successful implementations in different fields show the flexibility and usefulness of the AI-powered BI solutions. In addition, the proposed BASOA architecture proposes a standardised solution for service providers, requestors, and brokers, which facilitates the process of collaboration. SaaS models are advantageous as they help in the SaaS model, which provides economical solutions that are highly scalable and configurable. Nevertheless, areas of concern like data security, privacy, and ethics also remain the case for the use of AI-assisted BI systems. The effect of these issues on AI approaches could be resolved in future research by designing

AI for better predictive analytics, explainable AI and customer experiences that are customised by SaaS-based BI paradigm.

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