

Emergence and Evolution of Business Intelligence

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EMERGENCE AND EVOLUTION OF BUSINESS INTELLIGENCE

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ABSTRACT

For the last few decades, data has become increasingly available and valuable. As technology advances, organizations are looking into ways to harness the value of hidden patterns and insights within data. Capturing this value can enhance organizational success and give companies a competitive advantage in the market. Furthermore, data analysis can help organizations better understand their position and which direction they want to advance. Overall, the ultimate purpose of extracting value from data in business is to enhance the decision-making process. Data-driven decision-making results from business intelligence (BI), transforming data into information for making and acting upon those decisions. BI integrates business analytics and databases into analytical tools, applications, and methodologies. Today, the capabilities of BI are advancing at an astonishing rate, giving organizations opportunities to utilize and view data like never before. This paper aims to provide an overview of BI, its history, and its capabilities while examining existing literature to rationalize the integration and adoption of emerging BI trends.

HISTORY OF BUSINESS INTELLIGENCE

Business Intelligence can be traced back to the 1960s after IBM released its hard disk drive (HDD) for commercial use. This recognition of the need for data storage led to the creation of Decision Support Systems (DSS). DSS was developed to aid organizations in making decisions by analyzing large data sets. These database management systems were created as more data became available, and organizations required more reports on different levels of granularity. It is commonly accepted that the modern version of BI emerged from DSS.

During the 1970s and 1980s, various tools and techniques were developed to give users more access to data. Two such innovations were data warehouses (DW) and online analytical processing (OLAP), which became increasingly popular as data volume increased. Traditionally data would be stored in departmental silos or disparate repositories. Data warehouses acted as a central data repository that combined data from disparate sources, cutting the time needed to access data and create reports. In addition to storing and organizing large amounts of data, users needed to analyze data from many perspectives or dimensions. OLAP provided multidimensional capabilities by extracting data from multiple relational data sets, serving as a solution to query performance and multifaceted analysis.

Into the 1990s, as data and technology advanced, so did the need for more versatile reporting. Executives needed reports on demand, which led to the development of executive information systems (EIS). EIS was created to provide top-level management with summarized and graphical information through dashboards and scorecards, enabling executives to monitor key performance indicators (KPIs) and track their organization's performance. The architecture of EIS utilized a middle data tier or data warehouse to generate reports while maintaining the integrity of transactional data in Online Transactional Processing Systems (OLTP).

In the late 1990s and early 2000s, with the emergence of the World Wide Web (WWW) and complimentary technological advancements comprising hardware and software, business intelligence gained prominence, replacing the legacy label of DW-driven DSS. As dozens of BI vendors became more prevalent in the data market, organizations began investing in online initiatives and adopting many BI practices as a core asset of their success. Self-sufficient data tools became more widely available, allowing decision-makers more flexibility. With the release of cloud-based BI software, smaller companies could use BI without paying for expensive data infrastructure. Furthermore, real-time processing became possible through frameworks like Hadoop. These innovations helped organizations advance their BI capabilities.

In 2010, BI had evolved to handle larger sets of data, known as Big Data. The most accepted definition of Big Data is data sets that are so massive that conventional data management and traditional data-processing application software are no longer viable. Organizations began to equip the necessary Big Data analytical tools (advanced analytics) and integrate sufficient storage

capacity. It is important to note that global storage capacity still needs to catch up to the velocity at which data is generated in real-time.



Figure 1. Volume of Data Created and Replicated Worldwide (IDC, n.d., as cited in Reinsel et al., 2018)

Today, BI serves many organizational needs, from real-time data analysis to on-demand reporting. BI tools are continuously evolving to enhance decision-making in the 21st century. Organizations constantly search for and update their BI capabilities to match emerging trends and developments. Developing from basic decision support systems to sophisticated technologies, BI has yet to show any signs of slowing down.

BUSINESS INTELLIGENCE CAPABILITIES

Business intelligence (BI) has many capabilities comprised of both services and tools. These tools are designed to collect, analyze, and visualize data for decision-making, giving organizations the ability to gain a competitive advantage. BI capabilities range from data integration and warehouse, data visualization and reporting, to data mining, machine learning, and cloud computing. It is important to cover certain services and tools to understand their emergence and how they revolutionize BI.



Figure 2. Business Intelligence Services

Data integration combines various sources to give organizations a holistic view of their processes. Data integration is crucial, considering data is generated in many formats and can contain inconsistencies. Data integration involves:

- Extracting data from disparate sources.
- Transforming it to the desired state.
- Loading it into a centralized repository for analysis and reporting.

The extraction phase consists of extracting data from multiple sources. These sources range from databases and spreadsheets to web services and external applications. Once data is extracted, it must be transformed to ensure compatibility. Data is cleansed, normalized, enriched, and validated during transformation. Data validation verifies that the data conforms to rules or constraints, such as data type, format, and range (Seenivasan, 2023). Data transformation ensures that the data is consistent and usable. After transforming data, it is loaded into a centralized repository or data warehouse. Data warehouses offer users a structured environment for housing integrated data, allowing for efficient querying, analysis, and reporting.

Data integration can be accomplished through various techniques and tools. Extract, Transform, and Load (ETL) tools automate data integration. These tools act as pipelines to connect executives with the data needed for decision-making. Without ETL, data would remain in silos, scattered

across different systems and formats, making it difficult to gain insights and make data-driven decisions (Seenivasan, 2023).



Figure 2.1 *Extraction, Transformation, & Loading* (Data Integration Techniques (ETL and Data Federation), n.d.)

In conjunction with the ETL process, data warehousing refers to developing a centralized repository for storing and manipulating large volumes of data from numerous sources. Data warehousing is a critical service enabling BI. Data warehouses allow organizations to see data from multiple sources in a consolidated view for decision-support purposes. The framework for data warehouses integrates data from transactional databases, operational systems, and external sources. The three-tier approach is the most widely used data warehouse architecture, consisting of a bottom, middle, and top tier. The bottom level is the database, where data is loaded. The middle tier arranges the data for analysis using an OLAP server, while the top tier displays the results and provides users with tools for data mining. Data warehouses provide a historical view of business operations and enable analysts to excavate the data for patterns and insights for making better-informed decisions.



Figure 2.2 Data Warehouse Architecture (Data Warehouse Architecture - Detailed Explanation, 2022)

Another compelling BI capability involves data visualization. Data visualization compiles data into interactive visual formats like charts, graphs, maps, and dashboards. Consolidating information gathered from data into a visually appealing manner aids organizations in understanding complex problems in a way that is easy to understand. Data visualization gives organizations the ability to transform data into actions. Leading data visualization software includes Microsoft's Power BI, Tableau, Qlik Sense, Klipfolio, Looker, Zoho Analytics, and Domo.

In addition to visualization, reporting and analytics services in BI refer to the tools, technologies, and processes used to generate reports and analyze data. These services play a vital role in data visualization and drive organizational performance. Reporting services involve creating and distributing reports summarizing data for specific needs and inquiries. Information and reports like Tableau Software can be static or interactive. On the other hand, analytical services focus on advanced data analysis to uncover valuable insights within the data. These services allow organizations to analyze data, from performing ad-hoc queries to applying analytical techniques such as data mining or machine learning.

Both reporting and analytics are embedded into developing fruitful dashboards and scorecards. Dashboards and scorecards visually represent key performance indicators (KPIs), which monitor company metrics. Both dashboards and scorecards offer a centralized visualization of every level of the organization to ensure the company is headed in the right direction. Dashboards provide a visual display of consolidated data from multiple sources and departments. At the same time, scorecards are a performance measurement tool that tracks a company's progress toward its goals and objectives. Often scorecards are displayed and included in dashboards and establish metrics for different processes or departments. Dashboards are typically represented through charts, graphs, gauges, tables, and other visual elements, giving organizations a holistic data view.



Figure 2.3 KPI Dashboard from Power BI

An additional BI capability, and one of the most notable, is cloud-based BI. Cloud-based BI services offer organizations the option to store and manage data off-site. This ability can be cost-effective and save time and effort in integrating a data infrastructure framework. Cloud computing platforms offer the ability to store, process, analyze, and visualize data, providing scalability and flexibility, which allows organizations to adjust their resource allocation as needed. Cloud-based BI offers several options, from full cloud integration to hybrid delivery solutions, such as IaaS (Infrastructure-as-a-Service), PaaS (Platform-as-a-Service), and SaaS (Software-as-a-Service). Cloud-based BI has many benefits, such as scalability, accessibility, cost savings, and collaboration capabilities, among many others. It is essential to note the inherited risks of performing BI on the cloud. These risks include data security, lack of control, vendor selection, performance, and lack of standardized pricing models.



Figure 2.4 IaaS, PaaS, SaaS – Cloud Computing Services (GmbH, n.d.)

Finally, data mining and machine learning are two crucial components of BI that encompass advanced analytical techniques to extract valuable insights and patterns from large datasets. Organizations can use the value captured from data to make impactful business decisions. Data mining and machine learning have revolutionized many industries, from healthcare and finance to manufacturing and energy optimization. Typical applications of these tools include customer segmentation, predictive analytics, fraud detection, and sentiment analysis.

Data mining can be defined as the process of discovering patterns, relationships, and trends within a dataset and involves algorithms and statistical techniques. A data analyst can use data mining for classification, regression, clustering, and association rules. On the other hand, machine learning is a subset of artificial intelligence that utilizes algorithms and models that enable computers to make predictions or decisions without explicit programming (Mahesh, 2020). The algorithms involved

with machine learning can be categorized into supervised, unsupervised, and reinforcement learning. **Figure 2.5** *Machine Learning Algorithms*

Each service attributed to BI contributes to a valuable resource readily available for organizations. However, organizations only select specific services and tools based on their needs. Nonetheless, the evolving landscape of BI continues to incentivize organizations to harness the power of



data to drive success. As technology advances, so do the services and tools utilized by many organizations.

EMERGING TRENDS IN BUSINESS INTELLIGENCE

One of the most significant trends is the integration of artificial intelligence (AI) and machine learning (ML) technologies within BI. The advanced algorithms used in ML have the potential to automate data analysis, identify patterns, and provide valuable insights. Standard ML algorithms include supervised learning techniques such as Decision Trees, Naive Bayes, and Support Vector machines (SVM) to unsupervised learning techniques such as K-Means Clustering and Principal Component Analysis. While supervised learning is efficient when using a smaller labeled dataset, unsupervised learning generally gives better results for large datasets (Mahesh, 2020).



Figure 3. Common Machine Learning Algorithms (Liu et al., 2020)

AI and ML algorithms allow organizations to extract more profound information from data, improve forecasting and prediction, and automate tasks related to business intelligence. Organizations can utilize ML to drive organizational success in all industries. Considering the significant impact of using business intelligence in today's businesses, it is suggested that machine learning algorithms be used to improve sales performance and product supply to enhance marketing and profit (Hamzehi & Hosseini, 2022).

In addition to AI and ML, natural language processing (NLP) is an emerging and promising branch of AI that can be used for BI. NLP focuses on enabling computers to understand and interpret human language. This branch of AI can perform sentiment analysis and opinion mining to crucial phrase extraction and document categorization. Furthermore, Organizations can use NLP to uncover insights from customer reviews or social media posts, allowing companies to modify, adjust, and improve customer experience. Considering the increasing shift towards Big Data, NLP could hold tremendous potential, as most Big Data is textual. Big Data platforms such as Spark utilize NLP to excavate unstructured textual data and discover interesting and useful patterns for business intelligence (Gutfreund, 2017).



Figure 3.1 Applications of AI (Patel et al., 2020)

Augmented analytics or intelligence combines AI, ML, and NLP to prepare data, generate insights and explanations, and automate tasks. Augmented analytics features include automatic data identification, statistical techniques, intelligent data prep, recommendations, and natural language interactions. Automatic data identification can detect and convert data housed in formatted files, not normally accessible, such as a table of data in a PDF. Data prep features can minimize the data cleansing process by giving recommendations and automating steps. Augmented recommendations can aid a user in building a query and deciding which chart type to use. Natural language interactions allow users to type code in plain rather than code. The system then translates the test into a query while feeding back suggestions and recommendations to the user. Augmented analytics streamlines the process by assisting users in exploring data, detecting patterns, and providing intelligent recommendations. It reduces reliance on data scientists, allowing organizations to gain insights quickly and efficiently. In a study conducted, researchers identified the perceptions of Romanian companies about the advantages and limitations of augmented BI solutions and the impacts of these tools on managerial decisions and business evolution (Alghamdi & Al-Baity, 2022, as cited by Grigorescu & Baiasu & Chitescu, 2020). The findings demonstrated that augmented BI helped respondents to obtain faster and more accurate reporting, save time, improve strategies and plans, improve tactical decisions, implement more efficient processes, enhance customer service, save costs, improve decision-making, and increase revenue (Alghamdi & Al-Baity, 2022).



Figure 3.2 Augmented Analytics Workflow Characteristics

Augmented analytics holds great promise for the future as more organizations shift from relying on humans to relying on augmented analytics to perform data preparation, integration, and modeling. According to a study on analytical trends, between 2022 and 2028, 50% of the workflow related to data analysis will be performed by augmented analytics (Abas et al., 2023). Although implementing augmented analytics poses many challenges, it is entirely possible. Again, the need for expert data analysts will remain as they can validate the insights and discoveries produced through augmented analytics.



Figure 3.3 How Augmented Analytics Changes the Analytics and BI Workflow

In addition to augmented analytics, real-time analytics is gaining prominence as organizations seek immediate answers. With ever-increasing competition and rapidly changing customer needs and technologies, enterprise decision-makers are no longer satisfied with scheduled analytical reports, pre-configured key performance indicators, or fixed dashboards (Azvine et al., 2005). Real-time analytics allows organizations to draw instant results from data immediately after it is collected using in-memory databases and real-time visualization tools. Real-time analytics is becoming widely adopted by many industries, whether on-demand or continuous. On-demand analytics delivers results at a user's or system's request, while continuous (streaming) real-time analytics monitors real-time events. One such use case involves implementing Microsoft's Azure framework, which offers a solution for the media and entertainment industry by building analytics from live streaming data (Martinekuan, n.d.). This framework allows users to pull data from any IoT device from the event hub to produce real-time results.



Figure 3.4 Real-Time Analytics on Big Data Architecture (Microsoft Azure, n.d)

As data becomes more relevant and easier to manipulate, there is a demand for more data democratization. Data democratization removes the barriers that create bottlenecks in the data

pipeline, allowing data and insights to be accessible to a broader range of users and departments within an organization. In the past, data would be confined to a select department or group of people, limiting a company's decision-making power. Organizations must foster a data-driven culture to gain a competitive advantage in the digital age. To facilitate data democratization, organizations can integrate a data federation platform. Federated data platforms are emerging as key resources to enable secure data sharing without physically moving the data from outside its organizational or jurisdictional boundaries (Alvarellos et al., 2023).



Figure 3.5 Data Federation (Data Integration Techniques (ETL and Data Federation), n.d.)

According to the World Economic Forum, lack of data sharing is the case for the healthcare industry, where it is estimated that more than 97% of hospital data is unused. Currently, there are strict privacy regulations surrounding data sharing vs. patient privacy. In a case study involving

healthcare data, three federation methods are considered. The most compelling federation method involves privacy-preserving distributed learning technology, allowing sites to only share a statistical model and its parameters instead of sensitive data (Hulsen, 2020). Each site uses a local data store to run computations that generate aggregated statistics. This method allows organizations to collaborate by exchanging aggregated data while keeping the underlying data safely on-site and undisclosed. An example of open-source infrastructure for privacy-preserving analysis is VANTAGE6, a federated data system that has recently become available to share data while preserving the patient's privacy rights (Hulsen, 2020). Although strict regulations will remain, data federation brings enormous potential for advancing medical research (Alverellos et al., 2023).



Figure 3.6 Infrastructure of vantage6 – An open-source infrastructure for privacy preserving analysis (Notice that the nodes can only communicate through the VPN network and are still isolated from the (public) internet to minimize the risk of data breaches.) (Smits et al., 2022)

The most notable of these emerging BI capabilities is cloud-based BI. Cloud-based BI platforms have revolutionized how organizations access and utilize BI services. Organizations that opt to leverage cloud infrastructure attain a fierce competitive advantage. As mentioned, cloud computing offers vast benefits ranging from scalability, accessibility, collaboration capabilities, and cost efficiency. The cloud lets users avoid upgrading the computing power of their on-premises

systems to use BI (Olszak, 2014). Although Cloud computing has vulnerabilities, future advancements hold great promise in BI. The total addressable market for cloud computing is estimated to reach 1412.39 billion by 2031, growing at a CAGR of 17.23% from 2023 to 2031 (Research, 2023).



Global Cloud Computing Market

Figure 3.7 Global Forecast for Cloud Computing, 2017 – 2027 (Research, n.d.)

These emerging advancements in BI technologies are transforming the competitive landscape and how organizations leverage data to achieve their business objectives. By embracing trends such as AI and ML, NLP, real-time analytics, data democratization, cloud-based BI, and augmented analytics, businesses can unlock new opportunities, enhance operational efficiency, and gain a deeper understanding of consumers and markets.

CONCLUSION

In conclusion, BI has rapidly evolved from rudimentary Decision Support Systems to today's umbrella term encompassing technological advancements that lead to organizational success. As BI revolutionizes the business world, organizations strive to adopt, maintain, and advance their BI capabilities. Organizations see the value in data and BI's emerging capabilities, allowing for datadriven decision-making. The emergence and integration of artificial intelligence, machine learning, and natural language processing, along with the focus on real-time analytics, data federation, and cloud-based solutions, are shaping the future of BI and enabling organizations to gain a competitive advantage. As businesses navigate an increasingly competitive landscape driven by data, they must utilize BI to its fullest potential. By embracing BI's emerging and continuously advancing aspects, organizations can stay ahead and pave the way for a more data-driven future.

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APPENDIX



Figure 1. Volume of Data Created and Replicated Worldwide (IDC, n.d., as cited in Reinsel et al., 2018)



Figure 2. Business Intelligence Services



Figure 2.1 *Extraction, Transformation, & Loading* (Data Integration Techniques (ETL and Data Federation), n.d.)



Figure 2.2 Data Warehouse Architecture (Data Warehouse Architecture - Detailed Explanation, 2022)



Figure 2.3 KPI Dashboard from Power BI



Figure 2.4 IaaS, PaaS, SaaS – Cloud Computing Services (GmbH, n.d.)



Figure 2.5 Machine Learning Algorithms



Figure 3. Common Machine Learning Algorithms (Liu et al., 2020)



Figure 3.1 Applications of AI (Patel et al., 2020)



Figure 3.2 Augmented Analytics Workflow Characteristics



Figure 3.3 How Augmented Analytics Changes the Analytics and BI Workflow



Figure 3.4 Real-Time Analytics on Big Data Architecture (Microsoft Azure, n.d)



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