From Fundamentals to Future: Tracing the Evolutionary Trajectory of Business Intelligence

Anunya Sharma, Ritika Kumari, Poonam Bansal

Indira Gandhi Delhi Technical University for Women, Kashmere Gate, New Delhi, India

Corresponding author: Anunya Sharma, Email: anunya086btcsai21@igdtuw.ac.in

The evolution of Business Intelligence continues to chart a transformative course, shaped by technological advancements and shifting paradigms. By meticulously analyzing prior research and identifying existing research gaps, this study presents a comprehensive taxonomy that offers an in-depth understanding of the past, present and future trends in Business Intelligence. A key focus is on Cloud-based Big Data Analytics, highlighting the symbiotic relationship between cloud computing and data analytics, and its profound impact on Business Intelligence. The study delves into the convergence of these technologies, elucidating their role in supporting storage and computing requirements, ultimately enhancing the decision-making process. As organizations grapple with the challenges posed by the influx of data, this review investigates how various platforms effectively address the limitations of traditional Business Intelligence tools. This comprehensive studyaims to serve as an indispensable guide for researchers, practitioners, and decision-makers navigating the dynamic landscape of next-generation Business Intelligence.

Keywords: Business Intelligence (BI), Decision Support Systems (DSS), Big Data, Big Data Analytics (BDA), Cloud Computing, Artificial Intelligence (AI), Machine learning (ML).

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1. Introduction

In a dynamically evolving business landscape characterized by diverse consumer demands and communication channels, Business Intelligenceemerges as a pivotal force essential for improved decision-making, performance optimization, spotlighting opportunities, and mitigating threats. This capability, highlighted by Kimble and Milolidakis [1], allows businesses to extract meaningful insights from the data generated in their day-to-day operations.They underscored that Business Intelligence spans diverse realms such as product intelligence, market intelligence, competitor intelligence, business counterintelligence, customer intelligence, competitor intelligence, strategic intelligence and technological intelligence.

Sirin and Karacan [2] describe a simple BI architecture as a framework that gathersraw data from various sources, prepares it for analysis, turns it into insightful information using data mining and machine learning methods, delivers it in a timely and expected format to relevant stakeholders, oversees information sharing, and ensures security through authentication, authorization, and access rights. Beyond its extensive use in business sectors, BI has found applications in diverse fields like Education, Law, Engineering, Security (Mobile Device Fraud Detection), and Medicine (Chronic Disease Management and HealthCare Informatics) [3], among others.

This study explores the evolving trends in BI, delving into the intricate realms of data storage dynamics, Big Data, Big Data Analytics, and Cloud Computing. Section 2exploresthe profound influence of the aforementioned realms oncontemporary technological frameworks. This sets the stage for a historical exploration of BI, offering insights into its transformative trajectory, which has been analyzed in stages in Section 3. Summarizing insights from prior research, Section 4 sheds light on unique attributes characterizing each stage. The study concludes in Section 5, offering a comprehensive synthesis of findings and paving the way for future research endeavors, identifying potential avenues to enrich our understanding of the evolving trends in Business Intelligence and Analytics.

2. Preliminaries

This section provides essential background information crucial for comprehending the overarching concepts addressed in the study.

2.1 Data Storage Dynamics

Data Type (Structured and Unstructured). Information that is easily processed, searchable and well-structured is referred to as structured data. Examples of this type of data include tosensor data, web log data, financial data, clickstream data, etc. On the other hand, unstructured data is not organized in a pre-defined manner, like satellite images, photographs, videos, radar data, social media data, mobile data, etc. It poses a challenge for traditional databases because of its diverse formats and the difficulty in extracting meaningful insights [3]. Effectively interpreting unstructured data demands the utilization of advanced technologies like natural language processing and machine learning.

Data Warehousing. It serves as a cornerstone for BI applications, providing a centralized repository for data collected from various sources.In the late 2000s, Automation tools, and Real-time Data Warehousing emerged, offering quicker and cost-effective data acquisition. During the mid-2010s, the synergy of data lakes, warehouses, augmented analytics, machine learning, andblockchain revolutionized data management, facilitating diverse data needs, automated insights and heightened transparency and security.By the late 2010s, serverless data warehousing emerged as a notable trend, focusing on analytics without managing the underlying infrastructure. Cloud data warehousing, exemplified by Amazon Redshift, Snowflake, and Google BigQuery, emerged as a dominant force over the last decade, offering scalable and flexible solutions.

Data Mining. It alludes to the extraction ofvaluable insights and patterns from vast historical and current data to uncover hidden trends and facilitate decision-making. Shearer [4] delineated it through the Cross Industry Standard Process for Data Mining, encapsulating a life cycle comprising stages like business understanding, data understanding, data preparation, modeling, evaluation, and deployment. It makes use of several algorithms, like association rules, clustering, classification, and regression, for knowledge discovery [5]. Established and emerging standards, likePredictive Model Markup Language (PMML), SQL-based standards, Microsoft Data Mining Extensions (DMX), and Java-based APIs, play a crucial role in streamlining data mining and statistical models, fostering their seamless integration with application software.

2.2 Big Data

Big Data is characterized through its vast size, differing from traditional data in terms of volume, structure and variety. Primarily sourced from online social media, it includes unstructured, semi-structured and structured data, often quantified in terabytes, petabytes or exabytes. According to Kimble and Milolidakis [1], big data provides extensive insights instead of easy answers, underscoring the importance of interpretation and context. While traditional data value chain consists of four phases- generation, collection, analysis, exchange [2]- the Big Data value chain expands to seven phases: generation, acquisition, pre-processing, storage, analysis, visualization and exposition [8].

Shekhar and Sharma [6] provided three definitions to characterize big data. The attributedfinition underscores the 4Vs: volume, velocity, variety and veracity, addressing the challenges posed by massive data generation, rapid processing requirements, diverse data types, and data uncertainties [7]. Architectural definitions stress horizontal scaling for effective processing, while comparative definitions pit big data against traditional data. Faroukhi et al. [8] expanded the traditional Vs by introducing three additional dimensions. Variability deals with rapid changes in data meaning. Visualization stresses presenting data comprehensibly for interpretation and decision-making. Value highlights the transformative impact of big data insights on the economy.

Wani and Jabin [9] meticulously outlined critical issues of Big Data, listed in Table 1. They also identified challenges demanding immediate attention along with their respective solutions, as summarised in Table 2. This compilation also encompasses challenges outlined by Sirin and Karacan [2]. Certain deficiencies still persist in the proposed solutions, warranting thorough examination by researchers.

Table 1. Issues of Big Data, possible solutions and drawbacks of the same.

Issue	Possible solutions	Drawbacks
Storage	Distributed File Systems, NoSQL, Cloud Computing	An exabyte requires 25000 disk spacesand transferring it to cloud is time-intensive
Management	In-memory DBMS and quotient computing	Transferring the entire business to a new platform can be costly and time-intensive
Processing	Scalable streaming systems, Advanced Indexing schemas, and MapReduce	Handling Zettabytes and Exabytes of data remains a significant concern

Table 2. Challenges to Big Data, possible solutions and drawbacks of the same.

Challenge	Possible solutions	Considerations
Professionals	Establish a skilled data force	Cost-intensive
Analytical Mechanism	Employing advanced analytical mechanisms for in-depth insights	Choose analytical tools based on the nature and goals of analysis
User Engagement	Crafting user-centric systems	User-centric system development
Cooperation	Encourage collaboration and cooperation among stakeholders	Clear communication channels and protocols for collaboration
Visualization	QlikView, Tableau, etc.	Use of tools that enhance the efficiency of processing big data
Loading and Synchronization	Hadoop and MapReduce to load various formats of data in a distributed and synchronous manner	Address data heterogeneity challenges
Data Representation	Employ effective methods	Align representations with needs
Reduce Redundancy Compress Data	Implement techniques to reduce redundancy and compress data	Balancing compression ratios with processing efficiency
Data Lifecycle Management	Develop comprehensive strategies to manage the entire data lifecycle	Consider compliance requirements and ethical considerations
Data Confidentiality	Implementrobust measures to ensure data confidentiality	Compliance with data protection rules and ethical considerations
Energy Management	Implement energy efficient solutions toprocess big data	Consider the environmental impact and long-term sustainability
Expandability and Scalability	Design expandable and scalable systems	Consider future growth and evolving technology trends

2.3 Big Data Analytics

BDA serves as the process for scrutinizing large data, using statistical models,data mining and machine learning techniquesto uncover hidden patterns, market trends, and valuable business information.Recognizing its growing importance, businesses have been investing significantly in BDA, with Ram et al. [9] claiming that effective use of Big Data can enhance a business'operating profit margin by up to 60%. Prioritizing processing speed, Wani and Jabin [10] identified two key techniques for processing big data: real-time data-stream processing and batch-based stored data processing.Jayasree [11] comparedtwo popular open-source big data systems,Apache Spark and Hadoop MapReduce, withtraditional relational database management systems that struggle with big data's volume, variety, and heterogeneity. Ketu et al. [12] concluded that while both are designed to handle big data, Apache Spark offers advantages over Hadoop MapReduce, such as faster processing, support for multiple data processing tasksand ease of use with high-level APIs.

Figure 1 traces the progression of technological advancements, starting from the era of Enterprise Resource Planning (ERP) in the 1980s, transitioning to Customer Relationship Management (CRM) in the

1990s, evolving further into web and e-commerce services during the 2000s, and culminating in the dominance of BDA in the 2010s.

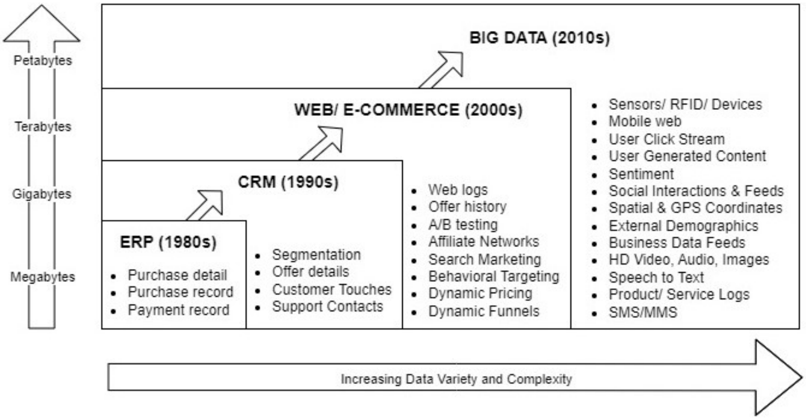

Figure 1. Technology developments in data analysis (adapted from Bloem et al. [13]).

2.4 Cloud Computing

Cloud computing, as per NIST, is a model providing omnipresent, on-demand access to a shared and configurable pool of computing resources [14]. It effectively addresses the limitations of on-premise solutions in data processing and storage, and reduces costs for hardware and software, improving overall resource utilization. In a multi-tenant environment, cloud solutions optimize resource sharing and provide isolation solutions at various levels for tenants. Balachandran and Prasad [14], alongside Al-Aqrabi et al. [15] highlightedkey features of cloud computing includingresource pooling,on-demand capabilities, extensive network access, quick elasticity and measured service. Their insights extended to deployment models coveringpublic, community, privateand hybrid clouds. They also exploredcloud framework services, encompassingSoftware as a Service (SaaS), Data as a Service (DaaS), Infrastructure as a Service (IaaS) and Platform as a Service (PaaS). Table 3 provides an overview of key issues related to cloud computing, along with potential solutions to address each challenge.

Table 3. Issues of Cloud Computing, possible solutions and drawbacks of the same.

Issue	Possible solutions	Drawbacks
Scalability	Horizontal scaling through load balancing, auto-scaling	Complexity in configuring and managing auto-scaling systems
Security	Encryption, Multi-factor authentication, Regular audits	Dependency on third-party security measures, Potential for data breaches
Downtime	Redundant servers, High Availability configurations	Costly infrastructure setups
Data Privacy	Data encryption and privacy regulations	Limited data control in cloud, Compliance overhead
Resource Allocation	Virtualization, Resource monitoring and allocation tools	Overhead in managing virtualized environments, Resource contention

2.5 History of Business Intelligence

The phrase "Business Intelligence" was coined by Richard Millar Devensin "Cyclopædia of Commercial and Business Anecdotes", in 1865 toelucidate how banker Sir Henry Furnesegained a competitive advantage through information gathering and swift decision-making. The concept evolved with Hans Peter Luhn's 1958 article [16], "A Business Intelligence System", describing the potential of BI for optimal decision-making. Luhn is considered as the father of BI because of his contributions in BI's development, laying foundations for IBM's analytical systems [17]. The advent of computers, particularly IBM's hard disk invention in 1956 marked a revolutionary moment in data storage. Subsequent advancements expanded storage capacities, leading to the creation of the first data management systems, known as Decision Support Systems (DSS), considered as the precursor to contemporary BI by many historians [18].

Reintroduced by Howard Dresner of the Gartner Group in 1989, the phrase "business intelligence" has evolved over the years, embracing concepts like business analytics and BDA. Vendors introduced tools like data warehouses, EIS and OLAP, for simplified data access and organization [18]. This era, termed as BI 1.0, spanning the 1990's and early 2000's, focused on data production, reporting, and presenting data in a visually organized manner. However, challenges persisted in terms of time and complexity during this evolutionary phase of technology. The dawn of 21st century marked a pivotal moment, addressing both speed and complexity challenges with the introduction BI 2.0 [19]. Obeidat et al. [3] succinctly encapsulated key facets of this era, like balanced efficiency, real-time analytics, data integration,collaboration and teamwork, while also highlighting challenges, particularly the exclusive focus on organized internal data, ignoring essential insights in unorganized and external data, resulting in biased decisions and an incomplete understanding of reality.

2.6 Big Data Analytics and Business Intelligence

The boundaries between BI, Big Data and BDA are often unclear for businesses, as these concepts coexist organically in an integrated DSS. Researchers like Fan et al. [20] emphasize the integration of Big Data and BDA into BI, viewing them as disruptive technologies that reorganize BI processes for better decision-making.

Challenges in implementing BDA for BI, as highlighted by Ram et al. [9], include concerns about intelligent data sources, real-time analytics capabilities, network resources, and the high cost of software and computational infrastructure. Security and privacy issues are particularly prominent, given the riskof hacking resulting from the storing of largeamounts of mixed heterogeneous data. Hardware-technology supporting BDA also poses challenges, such as the inability to offer a unified computing configuration for scalable andreal-time analysis, growing voids in networking bandwidth, and the lack of established rules for predicting the storage capacity growth. Despite these challenges, BDA holds significant potential for businesses, provided the associated issues are effectively addressed.

2.7 Cloud-based Business Intelligence

The adoption of cloud-based services in the BIlandscape, as illustrated in Figure 2, is seen as a significant advancement, offering scalability and flexibility [21].Chaudhuri et al. [22] and Muriithi et al. [23], rightly anticipated cloud computing to be a catalyst for the next leap forward in BI. The conceptual framework by Muriithi et al. [23], combining aspects of conventional BI, decision theory, information technology outsourcing and cloud computing, suggested that cloud BI could provide a cost-effective solution, particularly beneficial for smaller companies facing resource constraints. Cloud Analytics as a Service (CLAaaS), integrates BDA into cloud computing,for enhanced predictability and cost advantages, offering predictive insights from massive data through subscription-based or utility pricing.

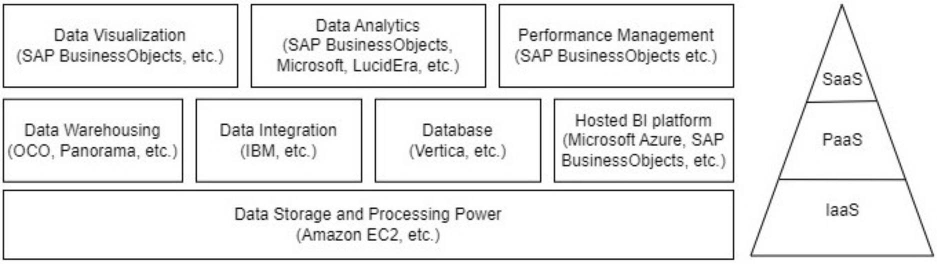

Figure 2. Cloud in BI (adapted from Deloitte report [24]).

While Cloud BI offers substantial advantages, challenges, as highlighted by Bousty et al. [25], include security concerns, data exchange over the internet, and the looming threat of potential attacks. Adopting a hybrid cloud BI model can address security risks by segregating sensitive and low-sensitive data. Encryption is a potential solution, but key management and performance drops are additional concerns. Availability and latency issues, especially in critical services like Forex BI, can discourage Cloud BI adoption, emphasizing the need for suitable solutions maintaining required service quality.

3. Stages of Evolution of BI&A

This section discusses the evolving landscape of Business Intelligence and Analytics.

3.1 Early Decision Support Systems (DSS)

The origins of BI can be traced back to the development of early Decision Support Systems (DSS) in 1950s-1960s, depicted in Figure 3, which aimed to assist managers with decision-making processes using computer technologies.They processed large amounts of data from internal and external sources, offering graphical and textual tools for analysis, and supported strategies like satisfying, optimization, and heuristics [26]. The retail industry employed various categories of DSS, such as Data-Driven DSS and Knowledge-Driven DSS, each contributing to improved business processes. However, this technology was considered cumbersome, and challenging to use.

Figure 3. A classical DSS (adapted from Wren et al. [26]).

3.2 Introduction of Traditional BI systemsfocusing on Historical Data Analysis

The formal recognition of BI,in the late 1980s, as a collection of concepts and techniques to enhance fact-based decision-making, marked a significant milestone in the decision-making process.In the 1990s, the advent of BI systems, exemplified bycompanies like Proctor & Gamble and Walmart, was primarily centered on analyzing historical data, offering organizations valuable insights into past performance. Thetraditional BI systems, exemplified by a three-tier architecture (presentation, application, database) depicted in Figure 4, relied onreporting mechanisms to access transaction data in data warehouses. Figure 5 provides a detailed illustration of the components of a traditional BI architecture. Criticized for being slow and rigid, these systems required expert knowledge for maintenance.

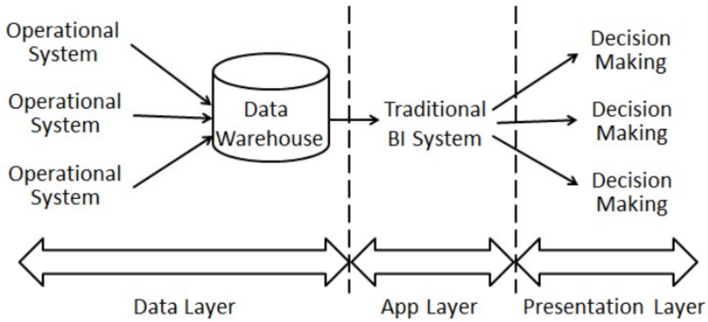

Figure 4. A traditional BI system (adapted from Vo et al. [27]).

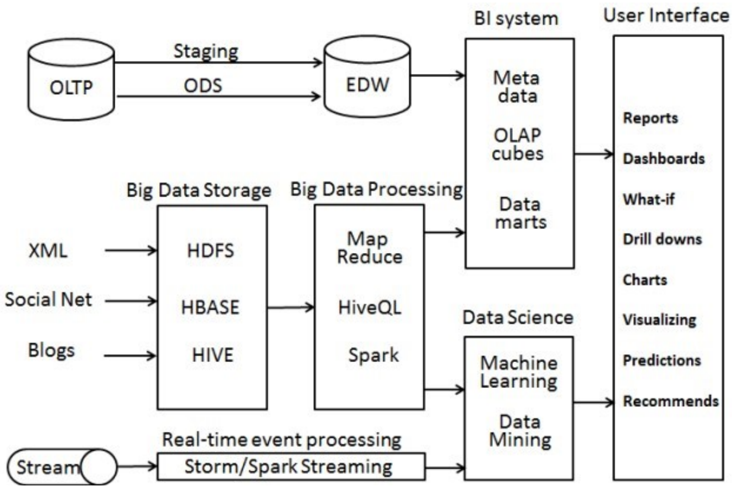

Figure 5. Components of a traditional BI system (adapted from Vo et al. [27]).

3.3 Shift Towards Modern BI (Self-Service and Real-Time)

The early 2000s witnessed a pivotal shift towards modern and operational BI platforms,characterized by self-service analytics, real-time data access and improved user interfaces.The modern BI platforms marked a departure from merely answering the question "What happened?" to addressing the more nuanced queries of "What is happening, what will happen, and why?" by incorporating fast analytics and predictive capabilities, as elucidated by Ahmed A. A. and Gad-Elrab [28].

3.4 Integration of Advanced Analytics and Big Data

The 2010s witnessed a paradigm shift towards the integration of BI systems with advanced analytics, ML, and big data technologies, depicted in Figure 6. This era was characterized by organizations recognizing the imperative of extracting insights from expansivedata, extending beyond the confines of conventional structured data.However, the implementation of BDA for BI brought forth a spectrum of challenges, as discussed in section 2.4, which underscored the necessity in-depth research in the field.

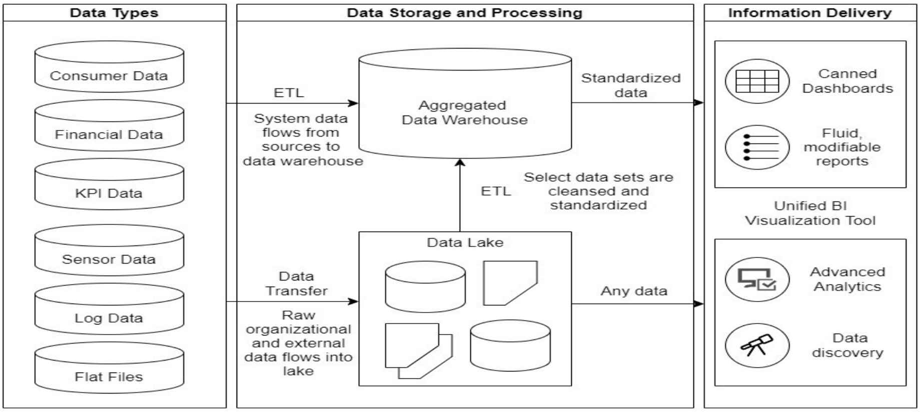

Figure 6. A modern BI system functioning over Big Data (adapted from Deloitte report [25]).

3.5 Cloud-Based BI and Mobile Analytics

During the 2010s, cloud-based BI systems and mobile analytics, depicted in Figure 7, gained significant traction. This shift allowed individuals to effortlessly access and analyse data from any location, enhancing flexibility and scalability. This not only simplified data access for users but also laid the groundwork for a more adaptable and user-friendly approach to information interpretation.

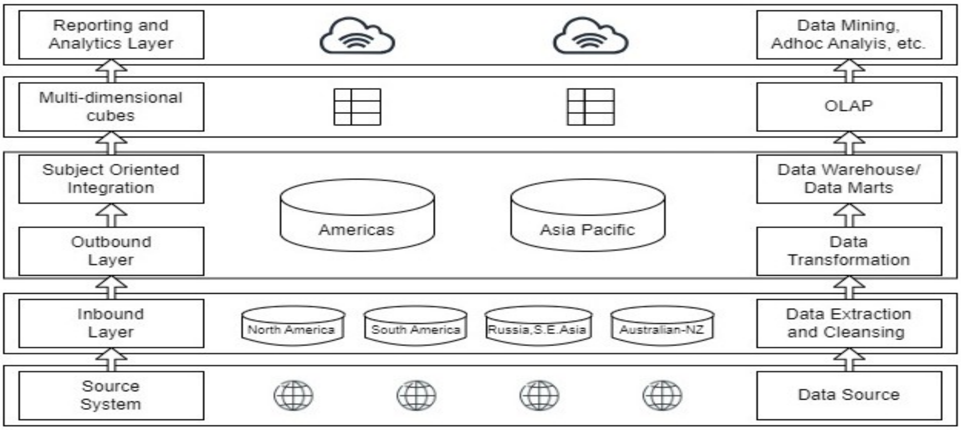

Figure 7. A modern BI system functioning over Cloud (adapted from Chandra et al. [29]).

3.6 BI&A 4.0: Possible Future Trend

There is ongoing industry discourse about an imminent phase, often tied to AI-driven analytics and augmented analytics. This envisions an even smoother integration of BI into day-to-day workflows, suggesting a future where data insights seamlessly enhance routine decision-making processes.

4. Discussion

Chen et al. [7] proposed a three-phase evolution of BI&A.Table 4 enlists the resources and methodologies employed across all the three stages.

Table 4. Attributes of BI&A evolution (adapted from Chen et al. [7])

BI&A 1.0(DBMS-based, Structured data)	BI&A 2.0 (Web-based, Unstructured data)	BI&A 3.0 (Mobile & sensor data)
RDBMS	Information retrieval	Person-centered analysis
ETL and OLAP	Question answering	Location-aware analysis
Dashboards and scorecards	Opinion mining	Context-relevant analysis
Data mining and analysis	Spatial-temporal analysis	Mobile visualization
	Social network and media analysis	Human Computer Interaction
	Web intelligence and analytics	

Adapted from the work of Watson and Marjanovic [30],Table 5 depicts the evolving landscape of decision support management or BI.The characterization done in [30] spans four generations. This study introduces a fifth generation, embodying the fifth stage of BI & A evolution, which spotlights cloud-based BI and mobile analytics.

Table 5. The attributes of five generations of business intelligence.

Attributes	1st Generation	2nd Generation	3rd Generation	4th Generation	5th Generation
Scope	Departmental	Enterprise	Enterprise	Extended enterprise	Global integration
Focus	Application	Data	Application/ Data	Application/ Data	Application/ Data
Decision supported	Strategic/ Tactical	Strategic/ Tactical	Operational/ Strategic/ Tactical	Operational/ Strategic/ Tactical	Adaptive/ Operational/ Strategic/ Tactical
Data sources	Single internal	Multiple internal	Multiple internal	Multiple internal/ external	Multiple internal/ external
Users	Single	Multiple	Enterprise	Enterprise	Enterprise
Volume	Low	High	Very High	Extreme	Extreme
Velocity	Batch	Batch/ ODS	Real time	Real time	Real time
Variety	Structured	Structured	Structured	Structured/ Unstructured	Structured/ Unstructured
Value	Low	Medium	High	Very High	Extreme
Architecture complexity	Low	Medium	High	Very High	Extreme

5. Conclusion and Future Work

In conclusion, this study provided a comprehensive exploration of the dynamic landscape of BI, covering pivotal aspects likeBDA, Cloud Computing, and an introductory discussion on the advanced integration of AI with BI. It is also essential to acknowledge the study's limitations, such as the absence of performance comparison across all evolutionary stages of BI systems. Expanding the scope to include literature from related fields like economics and psychology could have offered additional perspectives.

Future research could involve the integration of emerging and advanced technologies like AI and ML with BI systems. Exploring the evolution of BI amid dynamic industry demands and the implications of decentralized data storage presents promising avenues for future research. This study lays the groundwork for future endeavors, aiming to propel BI innovation in alignment with the evolving technological landscapes.

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