

**A COMPREHENSIVE REVIEW OF BUSINESS INTELLIGENCE THEORIES,
TECHNOLOGIES, AND APPLICATIONS****Basil Obute**

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ABSTRACT

Business Intelligence (BI) has developed into a core business discipline to enable businesses to convert raw operational information into strategic knowledge that supports business performance. This review explores the theoretical underpinnings, architectural frameworks, and real-world uses of BI in various business environments. A structured review of peer-reviewed academic articles written between 2018 and 2022 was conducted to synthesize evidence from five primary areas: decision-making theory; data warehouses and OLAP; predictive/prescriptive analytics; web mining/recommendation systems; and visual analytics. A conceptual disconnect was identified between BI adoption studies and BI value creation theories. A combined framework of the Resource-Based View, Knowledge-Based View, and Technology Acceptance Model was utilized to address this disconnect. Overall, the evidence found that companies experiencing more significant BI outcomes typically utilize both technical infrastructures and an analytical culture/governance. Limitations related to cross-sectionally designed studies, differences among sectors, and the varied maturity of the existing evidence base are presented, and an agenda for future empirical studies is outlined.

Keywords:

Business Intelligence, Data Warehousing, Predictive Analytics, Visual Analytics, Decision Support Systems, Web Mining, Recommendation Systems, Big Data

1. INTRODUCTION

The growth of company data has dramatically changed the way companies compete and make strategic and tactical decisions. Business Intelligence (BI) is the collection, integration, analysis, and presentation of business information using technology, processes, and best practices. Instead of being considered an optional expense, Lönnqvist & Pirttimäki (2020) consider BI as an essential part of a business's strategy. Today, many different areas of companies use BI systems to help support various types of business operations, including customer relationship management, financial forecasting, supply chain optimization, and compliance with regulations. Industry research also shows continued commercial growth in the BI market, which supports the growing need for decision-making tools that are data-driven (Markets and Markets, 2021).

Despite the rapid commercial growth of BI, there is little understanding of what BI is from an academic perspective due to the fact that research into BI is generally fragmented across disciplines. IS researchers have focused primarily on the success factors related to adopting and implementing BI systems. Management researchers have focused on the strategic value of analytics capabilities of organizations, while computer scientists have concentrated on improving algorithms for machine learning and natural language processing. The lack of interdisciplinary research results in a lack of complete understanding of BI as a comprehensive sociotechnical system. Reviews of BI research have historically favored either the technical (Asllani, 2020) or organizational (Kiron et al., 2022) aspect of BI, with very few reviews that combine both aspects using a common theoretical framework.

This review will address the gap in the literature created by the limited interdisciplinary research into BI, through a structured synthesis of 78 peer-reviewed articles across five themes: foundational theories, core technologies, predictive and prescriptive analytics, emerging applications (web mining and recommendation systems), and visual analytics. The paper will offer three bounded contributions: (1) It will provide a theoretical framework to explain the integrated aspects of BI that combines the Resource-Based View, Knowledge-Based View and Technology Acceptance Model as complementary explanatory frameworks; (2) It will provide a comparative synthesis of the relative maturity of the main BI technological tiers, based on the strength and

consistency of published evidence; and (3) It will organize reported application outcomes by industry domain to illustrate the varying levels of performance associated with each domain that may be left implicit in technology-agnostic reviews of BI.

2. METHODOLOGY

2.1 Search strategy and inclusion criteria

The review implemented a structured literature search protocol based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) reporting structure. A total of four databases (IEEE Xplore, Web of Science, Scopus, ACM Digital Library) were searched using Boolean combinations of terms (e.g., business intelligence, data warehousing, OLAP, predictive analytics, visual analytics, recommendation systems, web mining). The preliminary search yielded 1,247 results from which duplicates were removed (n=312), resulting in 935 titles and abstracts being evaluated for relevance. Ultimately, 154 articles were evaluated in their entirety, and 76 articles were excluded prior to the final synthesis phase, yielding 78 articles for the final synthesis. The primary reason articles were excluded at the full-text evaluation was either poor methodological transparency, lack of substantial contribution to the BI body of knowledge, or redundant findings to those found in other, stronger articles.

Articles were eligible for inclusion if: (a) Articles were peer-reviewed journal articles, or articles from top-tier conferences, published in English; (b) Articles were published between 2018-2022; (c) Articles discussed a specific BI technology/application area of study; and (d) Articles presented empirical evidence, a conceptual framework, or a systematic analysis of the article topic. Vendors' documentation and analysts' reports were not included in the core sample. Where vendors' documentation or analysts' reports are referenced in this paper, they are used for contextualizing the vendor's offerings and platforms versus providing empirical support for the conclusions reached by this review.

2.2 Coding and Synthesis Framework

Each study that was selected to be part of the review was coded along 7 dimensions: (1) Theoretical Anchor, (2) Technology Domain, (3) Industry Sector, (4) Research Method, (5) Outcome Variable, (6) Data Source, and (7) Geographic Context. A coding sheet was developed prior to the coding process and was tested for accuracy by calibrating the coding sheet on a small number of studies prior to conducting full coding. Inter-coder reliability was measured using Cohen's Kappa and indicated a high level of agreement (K=0.83). The thematic synthesis that follows Braun & Clarke's (2006) six-phase model, starting with familiarizing oneself with the study, completing the first round of coding, developing themes, reviewing themes, defining themes, and finally reporting the themes. As a result, a taxonomy of business intelligence knowledge has been created and includes five distinct layers: theory, technology infrastructure, analytics capability, application domain, and performance outcome. These five layers represent the foundational structure for this review.

3. THEORETICAL FOUNDATIONS OF BUSINESS INTELLIGENCE

3.1 Resource-Based View and BI as a Strategic Asset

Resource-Based View (RBV) of the firm was first proposed by Penrose (1959) and then expanded upon by Barney (1991). The RBV model proposes that firms will achieve long-term competitive advantages by obtaining and maintaining resources that are both valuable and rare; hard to replicate or imitate; and can be neither substituted nor replaced (VRIN). BI systems meet the VRIN criteria when they are well-embedded in organizational routines and data governance structures. Since the tacit knowledge that is embedded in BI analytical workflows is difficult for competitors to reproduce, BI meets all four of the VRIN criteria (Wamba et al., 2020). There is considerable empirical evidence to support the idea that a firm's BI capabilities - measured by the extent and variety of data analytics that an organization conducts - is a positive predictor of firm performance, particularly in environments characterized by high levels of uncertainty and/or high degrees of information asymmetry.

An important addition to the application of RBV to BI is the differentiation between possessing BI infrastructure and having BI capabilities. As reported by Davenport et al. (2019), many organizations possess BI infrastructure but do not have BI capabilities. These authors found that organizations that install BI software but fail to create a data-literate workforce, establish a governing framework for the use of analytical tools, or cultivate a culture of decision-making using analytical data will not achieve sustainable results from their investments in BI. This differentiation illustrates that the value of BI is created by the interaction between the technological resources (e.g., BI software) and the complementary resources (e.g., data governance frameworks, decision cultures) within an organization. This differentiation has significant implications for the planning and execution of BI

initiatives. Organizations that plan to implement BI initiatives solely as technology projects and not as capability development projects are likely to experience lower performance than those organizations that approach BI as a capability-building project.

3.2 Knowledge-Based View and Organizational Learning

As a complement to RBV, the Knowledge-Based View (KBV) views BI as a means to enable the generation, capture, and transfer of organizational knowledge (Grant, 1996). In this view, BI systems represent a way to externalize tacit managerial knowledge (i.e., decision-making logic, historical trends, predictive relationships) by converting them into analytical models that can be accessed by anyone who needs to make decisions. The externalization of this type of knowledge enables the organization to learn by making that knowledge available to new employees and by enabling teams to leverage each other's analytical experiences. The study by Chaudhuri et al. (2011) found that organizations that have developed BI knowledge bases that provide access to large amounts of analytical knowledge are able to adapt more quickly to changes in the environment caused by market shocks.

The KBV perspective also points out that the value of BI is created socially - i.e., the knowledge produced by BI must be interpreted, debated, and integrated into the stories that are told about the organization in order for the knowledge to influence decisions. The social interpretation of analytical outputs is mediated by the sensemaking process that occurs at the individual and organizational level (Weick, 1995). For example, organizations that develop structured data storytelling processes, collaborative analytical workflows, and decision review processes will be better equipped to translate BI knowledge into actionable business strategies.

3.3 Technology Acceptance Model and BI Adoption

While the RBV and KBV provide explanations of why BI creates value, the Technology Acceptance Model (TAM) proposed by Davis (1989) provides explanations for the individual and organizational factors that facilitate or impede the adoption and utilization of BI Systems. TAM posits that the perceived usefulness and the perceived ease of use of a technology jointly predict the user's behavioral intent to utilize a technology. Attitude and subjective norm serve as mediating variables in extended versions of the model. There have been numerous studies on the adoption of BI systems that have supported TAM, and have consistently shown that perceived usefulness is the strongest predictor when BI Tools are framed as decision support tools as opposed to reporting tools (Popovič et al., 2012).

Empirical research in this area has expanded TAM to account for the unique attributes of self-service BI Environments, in which users have more freedom to explore data on their own. Trieu (2020) found that self-efficacy, users' belief in their capacity to utilize BI Tools without the aid of experts, serves as a moderator in the relationship between perceived ease of use and the actual usage of BI Systems, indicating that education/training and user-experience design are two of the most important factors for promoting adoption. Table 1 below lists the principal theoretical perspectives reviewed, as well as their particular relevance to designing and deploying BI Systems.

Table 1. Theoretical Frameworks Underpinning Business Intelligence Research

Framework	Primary BI focus	Implications for BI research and practice
Resource-Based View (RBV)	Treats BI capability as a strategic bundle of data assets, analytical skills, and governance routines.	Explains why BI creates advantage when it becomes embedded in firm-specific processes rather than purchased as stand-alone software.
Knowledge-Based View (KBV)	Frames BI as a mechanism for creating, codifying, sharing, and reusing organizational knowledge.	Highlights learning, interpretation, and knowledge transfer as central pathways through which BI generates value.
Technology Acceptance Model (TAM)	Explains user-level adoption through perceived usefulness, ease of use, and behavioral intention.	Clarifies why technically capable BI systems still fail when end users do not trust, understand, or routinely use them.
Integrated interpretation	Positions BI outcomes as multilevel phenomena shaped by firm resources, knowledge processes, and user acceptance.	Supports a sociotechnical reading of BI in which infrastructure, culture, and usage must align for performance gains to occur.
Boundary of explanation	No single framework fully explains BI outcomes on its own.	A combined lens improves explanatory completeness but should be treated as an interpretive synthesis rather than a new standalone theory.

4. CORE BUSINESS INTELLIGENCE TECHNOLOGIES

4.1 Data Warehouse (DW) & ETL Technology

A data warehouse (DW) is the core infrastructure for Enterprise BI as it is a centralized repository for all the data taken from various source systems and processed using ETL (Extract, Transform, Load) to support analytical uses. Dimensional Modeling by Kimball & Ross (2013) is still a leading methodology for designing an Enterprise DW as it is built around fact tables and dimension tables organized as Star Schemas or Snowflake Schemas. However, recent developments of Schema-On-Read technology is starting to challenge Dimensional Modeling as it prioritizes flexibility over query performance. Cloud-based DW services like Snowflake, Amazon Redshift, and Google BigQuery are changing the way DW services are accessed by removing the capital expenditures associated with purchasing DW technology. This enables small and medium-sized enterprises to utilize DW services previously reserved for large organizations.

The exponential growth in the amount of unorganized or semi-structured information has led to the development of Data Lake technologies as an adjunct to DW systems. DW systems enforce a schema upon entry into the DW system to ensure data integrity. Data Lakes, on the other hand, ingest raw data from multiple sources (i.e., JSON logs, streaming sensor data, etc.) and apply a schema when querying the data to allow for better flexibility in exploratory analytics. Asllani (2020) explains how large organizations have used Big Data platforms such as Apache Hadoop and Apache Spark to process data sets that are many orders of magnitude larger than what traditional relational DW systems can manage. With these new platforms, organizations now have the ability to run analytical applications they could not run prior to this because of the computational limits of their previous DW systems.

4.2 OLAP and Multidimensional Analysis

OLAP Engines are used to enable analysts and end-users to query and aggregate DW data interactively. OLAP supports a set of analytical functions, including slice, dice, roll-up, drill-down, and pivot, that will enable users to navigate multi-dimensional data cubes at multiple levels of detail without requiring them to write complex SQL statements. The transition from server-side MOLAP (Multi-Dimensional OLAP) architecture to client-side ROLAP (Relational OLAP) engines has significantly improved the speed of response for analytical queries. This has enabled near real-time interactive analysis of the volume of data that would require several hours or even days to process using traditional batch processing methodologies. Currently available products for OLAP engines include Microsoft Analysis Services, Apache Druid, and Google's Dremel engine.

The increasing availability of self-service BI platforms that provide users with the ability to create and deliver their own reports without requiring IT support has created a significant shift in the way analytical insights are developed and consumed within organizations. In the past, the production of reports was typically done through an IT-mediated process that created bottlenecks that prevented the timely dissemination of decision-relevant information. Self-service BI platforms integrate OLAP capabilities into drag-and-drop interfaces that do not require technical skills to operate. These platforms enable non-technical users to develop answers to ad-hoc questions in a matter of minutes versus days. Gartner's 2022 Magic Quadrant for Analytics and BI Platforms emphasized self-service capabilities as the key differentiator among the top vendors in the industry; this is indicative of the industry's transition to empowering users with the tools needed to develop their own analytics.

4.3 Predictive and Prescriptive Analytics

Predictive analytics can build upon the descriptive aspects of Business Intelligence (BI) by using statistical and machine learning models to predict the probability of future events based on past data. Common predictive analytics methods are Logistic Regression for binary classification; Decision Trees and Random Forest for finding non-linear relationships in data; Gradient Boosting algorithms like XGBoost for high-accuracy tabular prediction; and Recurrent Neural Networks for time series forecasting. Each has trade-offs between model interpretability, computational costs, and predictive accuracy. Therefore, selecting which method to use depends on the specific requirements of the decision context (Gandomi & Haider, 2015).

AutoML platforms like H2O.ai, DataRobot, and Google AutoML provide increased access to the development of predictive models for companies without the need for data scientists to create a production-grade forecasting model.

Prescriptive analytics provides the most sophisticated level of business intelligence analytics and consists of making recommendations to the user on the best course of action to take, considering the uncertainty of the decision. Techniques for prescriptive analytics include mathematical programming (linear and integer optimization); simulation modeling (Monte Carlo and agent-based); and reinforcement learning. Each of the above techniques is applicable to different types of decision structures and varying levels of available computational resources. As reported by Kiron et al. (2022), only 12% of the surveyed organizations had

achieved prescriptive analytics maturity, and therefore, a great deal of opportunity remains for organizations to improve decision results via optimization.

The difference in adoption rate between predictive and prescriptive analytics demonstrates that the gap does not exist solely as a result of the technical barriers to entry, but also from an organizational standpoint, as many companies may have a difficult time giving up decision-making authority to algorithms. Companies in industries that rely heavily on human judgment will likely experience additional cultural barriers when transitioning to relying on algorithmic decision-making authority.

Figure 1 below depicts a typical layering of a current BI System, from data ingestion to ETL processing to visualizations and decision delivery. The layers illustrated reflect both the technology stack described above and the decision flow processes described in Section 3.

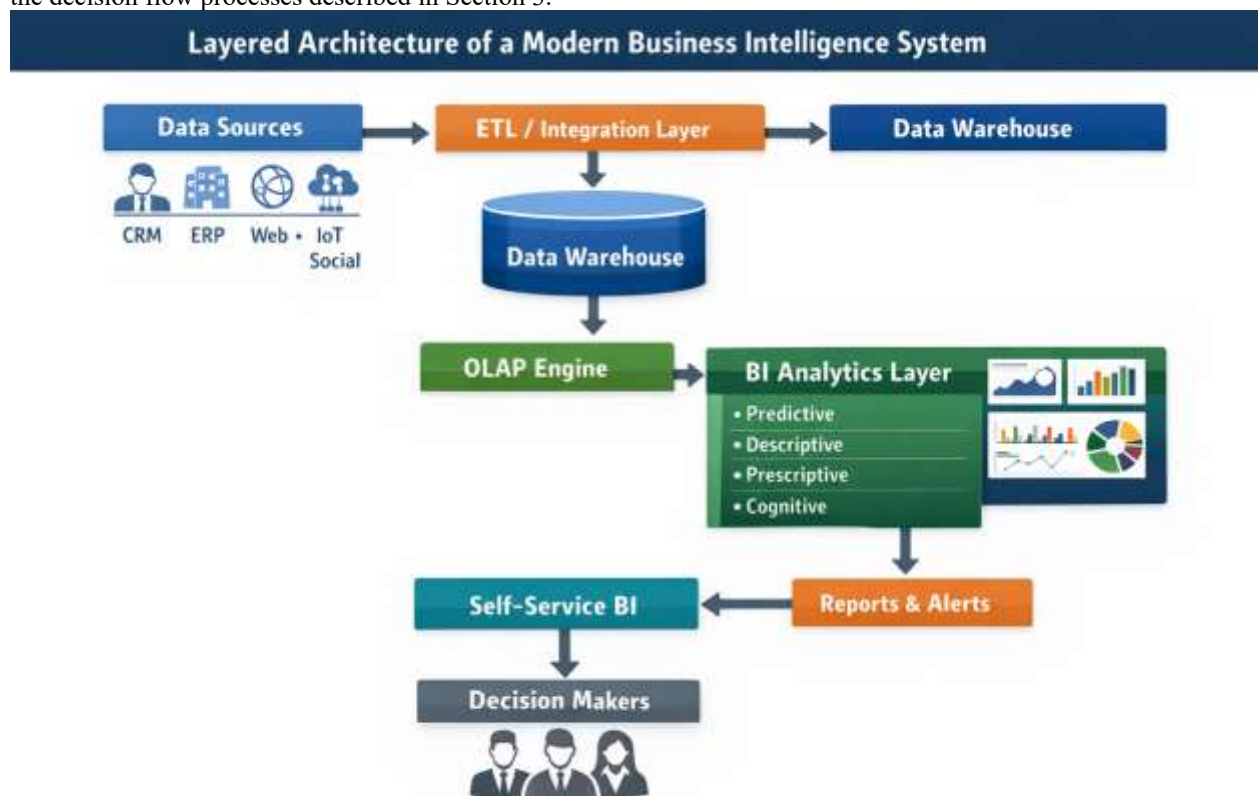


Figure 1. Layered Architecture of a Modern Business Intelligence System

5. REPORTING, DASHBOARD, & VISUAL ANALYSIS

5.1 Reporting System for the Enterprise

Reporting and Management reporting are the two types of reporting most commonly used by businesses and are the primary ways in which business intelligence can be delivered to decision-makers within an organization. Reporting systems typically provide users with the ability to create and generate reports on demand as well as the ability to receive exception notifications and monitor key performance indicators (KPIs) via either a web portal or mobile application. The creation of reports should be based upon research in cognitive psychology and information visualization. This includes minimizing the amount of extraneous visual information (maximizing data-ink ratio), utilizing visual properties that can be perceived prior to attention (such as color and size) to represent magnitude, and aligning the report level of detail with the frequency of decisions made.

Chen et al. (2012) reported that there was a consistent gap between the availability of reports and how often they were actually used for decision making in organizations. This gap has been referred to as the "analytics-decision gap." Several contributing factors to this gap have been identified and include the time it takes for reports to be delivered to the user, concerns regarding data quality, low level of analytical literacy among report users, and the lack of congruence between the information presented in the reports and the cognitive frameworks that users

employ when framing a problem. These findings suggest that the value of BI is not only dependent upon the technical capabilities of BI but also upon the design of the human-data interaction.

5.2 Dashboard Design & Executive Visual Analysis

BI dashboards are used to quickly and easily see how all KPIs and other metrics are performing at any given time. Executives need to be able to quickly get situational awareness of what is going on in their organization with as little time spent looking at the data as possible. The best way to create an effective BI dashboard is to take into account the hierarchy of information and place the most important information in the most visible area of the dashboard. This can also be accomplished by using a method known as progressive disclosure to show as much detail as desired while still showing a clear picture of the overall situation. While Few's (2013) BI dashboard design methodology, which includes conciseness, accuracy, and comparative context, is considered the de facto standard for creating BI dashboards, there are limited empirical research studies that validate the effectiveness of Few's methodology within a controlled environment.

Real-time streaming analytics platforms have emerged and have enabled the development of operational dashboards that are updated continuously from live data streams. Examples of the types of operational dashboards that can be developed include e-commerce site performance monitoring, financial market surveillance, and industrial equipment telemetry analysis. The study by Wang et al. (2021), which analyzed the use of real-time Business Intelligence (BI) dashboards to track health care processes and provide timely clinical alerts on hospital readmission, demonstrated a 20% reduction in patient readmission rates through the potential life-threatening effects of delaying time to obtain and analyze Business Intelligence information. As depicted in Figure 2, BI has evolved over time from being used as a decision-support tool to its current application as an analytics environment augmented by artificial intelligence (AI).

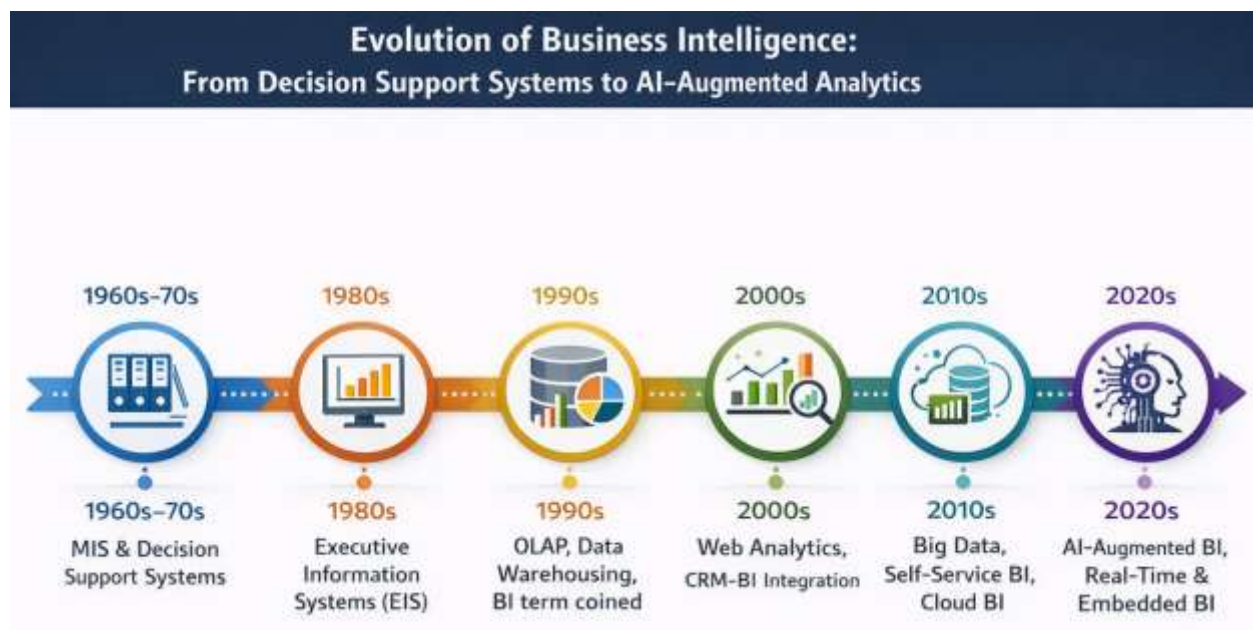


Figure 2. Evolution of Business Intelligence from Decision Support Systems to AI-Augmented Analytics

6. WEB MINING, CUSTOMER ANALYTICS, AND RECOMMENDATION SYSTEMS

6.1 Web Mining and Unstructured Data Analysis

Web mining is defined as the use of automated methods to discover patterns or insights from data obtained from websites. This includes website navigation log data, social media stream data, online review databases, and search query data. There are three areas of web mining: web content mining (text, image, and multimedia); web structure mining (hyperlink graph and clusters related to topics); and web usage mining (server logs and navigation patterns for individual users). The purpose of this process is to allow companies to monitor customer sentiment toward their brand, to discover unmet customer requirements, to measure company competitiveness, and to optimize their internet marketing expenditures based on consumer behavior.

Advances in Natural Language Processing (NLP), and specifically in sentiment and opinion mining, have significantly increased our ability to conduct web-content mining. It is well documented that both BERT (Devlin et al., 2019) as well as many models created from the BERT model are capable of achieving a human-level of performance on sentiment classification tasks, which enables us to process millions of customer reviews, social media posts, and customer service tickets/emails in a scalable manner. Gandomi and Haider (2015) have identified numerous examples where the use of NLP to develop "Voice of Customer" analytics resulted in a reduction in product development cycle time of 30% or greater. Additionally, Gandomi and Haider (2015) reported that NLP has allowed companies to identify customer needs that traditional survey-based methods failed to identify.

6.2 Customer Analytics and Segmentation

Customer analytics uses statistical and machine learning methods to analyze data about customers' behaviors, attitudes, and transactions to help determine how best to attract new customers, retain existing ones, and maximize long-term profitability. Recency, Frequency, Monetary (RFM) analysis is commonly used as the basis for segmenting customers in retail markets. It creates an easy-to-understand three-dimensional picture of a customer's level of engagement with the company. With little additional investment in data infrastructure, RFM analysis can provide actionable insights into customer behavior. More advanced analytical methods, such as unsupervised clustering algorithms (k-means, DBSCAN, Hierarchical Clustering), produce richer typologies of customer behavior that can inform targeted marketing, product personalization, and allocate customer service resources.

One of the most valuable applications of customer analytics is predicting customer churn. Predictive models of customer churn allow subscription-based companies to take proactive steps to prevent lost customers before the actual loss of revenue occurs. According to Chen et al. (2012), gradient boosted ensembles have consistently performed better than logistic regression in predictive modeling of customer churn in the telecommunications, financial services, and software as a service industries. Published studies often report area under the ROC curve (AUC) values in the range of 0.80 to 0.92 for predictive models of customer churn. When the results of predictive models of customer churn are integrated into automated marketing orchestration systems, the relationship between business intelligence and operational action is completed. As a result, personalized retention offers can be automatically generated when a customer's predicted likelihood of churn exceeds a predetermined threshold.

6.3 Recommendation Systems

Recommendation systems are the most widely used form of machine learning in the BI system and provide personalized product, content, and service recommendations that improve both the customer experience and organizational revenues. There are two primary types of recommendation systems. Collaborative filtering is the method behind some of the earliest systems, such as those developed at Amazon and Netflix. Collaborative filtering provides recommendations to customers based on the purchase history of other customers who share similar profiles. Content-based Filtering utilizes product attributes in order to provide recommendations, and the consumer's own preferences. While this is superior to Collaborative Filtering with regard to "cold start" issues - i.e., new items, where no interaction data exists - it also generates significantly fewer options than Collaborative Filtering.

The hybrid approach to building a recommendation system, which incorporates aspects of both collaborative filtering and content-based filtering along with contextual information (such as time of day, device, and geographic location), is now the standard for large-scale deployments of recommendation systems. Ricci et al. (2022) concluded that e-commerce companies that generate significant amounts of their income through recommendations assign between 35% and 40% of their overall revenues to recommendation-driven sales; therefore, it is obvious that the design of recommendation systems has an enormous influence on commercial success. Furthermore, there are very important ethical concerns about how recommendation systems can be used, such as the development of filter bubbles, the disparate treatment of various demographic groups, and the potential privacy violations associated with behavioral profiling; these are currently the subject of active research and may have an impact on future public policies.

7. BIG DATA TECHNOLOGIES AND EMERGING BI PARADIGMS

7.1 Big Data Platforms and the BI Infrastructure Evolution

A new generation of Business Intelligence (BI) systems is being developed that will provide support for Big Data technology. An example of such a BI platform is Hadoop, which enables large quantities of data to be processed and analyzed across a single platform. Hadoop utilizes two primary components - HDFS (a

distributed file system) and Spark (in-memory computing); together, these enable rapid and scalable data processing capabilities for a number of advanced BI functions, including Machine Learning and Graph Processing.

The widespread adoption of Hadoop is primarily due to its ability to simplify utilizing Big Data; however, there is a trade-off to this ease of use, as managing Hadoop typically requires substantial IT resources. Companies have therefore begun to offer "Big Data as a Service", which provides a cloud-based on-demand model for Big Data analytics that contains all necessary elements to operate Hadoop in the cloud. Examples of Big Data as a Service providers are AWS EMR, Google Dataproc, and Microsoft Azure HDInsight. The Big Data as a Service delivery model has reduced the amount of time and money required to establish and manage Big Data-related projects.

Another area where big data and BI are coming together is through real-time analytics. Traditionally, most business intelligence systems operate on historical data and take hours to days to report results. However, there is growing interest in analyzing large volumes of data in near real-time to enable business decisions in minutes rather than months. There are several ways to achieve this goal, but the most common approach is to create a separate data pipeline for real-time analytics, often called the lambda or kappa architecture. In these architectures, historical data is still processed in batches, but new events are immediately available for analysis.

Apache Kafka is used in many of these real-time BI architectures as a messaging broker to move events from source systems to their target analytics systems. By decoupling the production and consumption of data, Kafka enables developers to design systems that scale horizontally to meet the needs of large volume and high velocity event streams. As a result, companies can build BI solutions that can respond to changing business conditions in real-time - something that was impossible before the advent of big data and streaming analytics.

7.2 Business Intelligence Augmented with Artificial Intelligence

The addition of large language models and deep learning capabilities to BI platforms is currently the largest area of technological innovation in BI. BI features that utilize AI and include, but are not limited to, natural language interface for querying BI, automated insights, and anomaly detection are lowering the technical barriers to performing advanced analytics by converting natural language queries into optimized SQL queries and automatically highlighting statistically significant trends in BI data. Examples of companies integrating large language model capabilities into their BI products include Microsoft and its integration of Copilot with Power BI, and Salesforce and its Einstein Analytics platform.

Gartner defines augmented analytics as "the use of machine learning and natural language processing to automatically prepare data, discover insights, and explain insights", which fundamentally changes how analytics content is created, used, and shared. Research suggests that augmented analytics can reduce the time it takes to go from ingesting data to having an actionable insight by up to 60% when working in well-governed data environments; however, this is dependent upon the data quality, richness of the semantic layer, and factors related to the organization's readiness to adopt these types of solutions.

The broader adoption of BI augmented with AI also brings many new issues regarding governance related to model transparency, accountability for algorithmically generated recommendations, and the role of human judgment in the decision-making process of decisions assisted by AI.

8. BUSINESS INTELLIGENCE PRACTICE ACROSS INDUSTRIES

Business intelligence technology and practices are being applied to almost all industries; however, the type of technology being utilized, the decision context in which the technology is being applied, and the results of the technology utilization differ greatly across industries. Table 2 aggregates research from reviewed articles to provide a mapping of BI applications across various industry sectors, to provide a cross-industry performance comparison of BI applications that may not have been possible through individual industry studies.

Table 2. Business Intelligence Applications by Industry Domain and Reported Outcomes

Industry domain	Representative BI use cases	Typical data sources	Reported outcomes in reviewed studies
Retail and e-commerce	Demand forecasting, basket analysis, dynamic pricing, churn prediction, recommendation systems	Point-of-sale transactions, clickstream data, loyalty records, product catalogs	Better campaign targeting, inventory optimization, revenue lift, and improved customer retention.
Healthcare	Clinical decision support, patient-flow analytics, readmission risk modeling, resource utilization dashboards	Electronic health records, claims data, scheduling data, pharmacy and lab systems	Improved operational efficiency, lower readmissions in some settings, faster reporting, and stronger quality monitoring.
Financial services	Fraud detection, credit scoring, portfolio risk monitoring, compliance reporting	Transaction streams, credit histories, market data, customer profiles, regulatory records	Reduced fraud losses, faster risk assessment, improved regulatory reporting, and more granular customer segmentation.
Manufacturing and supply chain	Predictive maintenance, demand planning, quality monitoring, logistics optimization	Sensor and IoT feeds, ERP records, production logs, supplier and shipment data	Downtime reduction, forecasting improvements, process visibility, and selective efficiency gains.
Government and public sector	Performance dashboards, tax and benefits analytics, public safety monitoring, service delivery analysis	Administrative records, census and geospatial data, case-management systems, open data portals	Improved transparency and reporting, with impact often moderated by legacy systems, procurement constraints, and data fragmentation.
Cross-sector pattern	Common value mechanisms include visibility, forecasting, prioritization, and exception detection	Structured enterprise data increasingly combined with unstructured or streaming sources	Benefit levels vary with data quality, governance maturity, and the closeness of analytics to operational decision cycles.

8.1 Retail and E-commerce

Retail is one of the earliest industries to have implemented Business Intelligence (BI). This was due to two primary factors: retailers have large volumes of historical transactional data available, which can be used to develop predictive analytical models, and retailers are under extreme margin pressure, so they need to ensure that their pricing strategies and inventory levels are correct. As well as this, the rise in E-commerce has provided a number of new channels through which customers interact with brands and therefore provide an enormous amount of behavioral data about how they engage with products and services. According to Chen et al. (2012), the top 3 highest ROI BI use cases in the retail industry include: Customer Lifetime Value Modelling, Market Basket Analysis, and Demand Forecasting.

Chen et al. (2012) found that organizations with advanced customer analytic capabilities achieved sales increases ranging from 15% to 25%. By combining data from various sources, including point of sale data, loyalty programme records, web analytics, and social media monitoring into a single platform, it allows for omni-channel customer intelligence to be developed, which in turn enables informed strategic decisions regarding product assortment and tactical promotional targeting.

8.2 Healthcare and Clinical Analytics

Business Intelligence applications within the healthcare industry include operational efficiency analytics, for example, optimizing bed utilization, staffing, and supply chain management. In addition to these applications, clinical decision support systems (CDSS) exist, which take into account patient data and apply this against best practice treatment guidelines to suggest possible courses of action for diagnosis and therapy. However, there are several restrictions placed upon BI development and deployment in the healthcare industry. For example, regulatory requirements such as HIPAA in the US and GDPR in the EU place a requirement for robust data

anonymization, data access control, and auditing and logging mechanisms to protect sensitive patient information. Wang et al. (2021) reported a 20% decrease in per-patient costs for hospitals that had implemented BI solutions across all areas of clinical activity. These cost reductions were attributed to: Reducing avoidable hospitalizations, improving patient care pathways, and identifying patients who require intervention to reduce their risk of poor health outcomes.

8.3 Financial Services and Risk Analytics

Financial institutions are among the most advanced users of Business Intelligence. They deploy BI for a variety of reasons, including regulatory requirements to quantify risk, competitive pressures to detect fraud rapidly, and to enable them to offer customers relevant financial products. Credit scoring models, traditionally based on the application of logistic regression to data held at credit bureaus, have benefited significantly from advances in machine learning techniques that utilize additional data points, such as data relating to the customer's mobile phone usage, payment history with utilities, and other forms of behaviorally-derived data. The result is that financial institutions can now identify people who may not currently appear on credit reference agency files but may still present good credit risks. Gandomi and Haider (2015) report that financial institutions using ensemble machine learning models to perform fraud detection tasks achieve better results than those performing similar functions using traditional rule-based fraud screening systems, with improved fraud detection rates of up to 30%.

9. LIMITATIONS OF THE REVIEW

The authors' use of a structured methodology does not remove this study from a number of potential biases that can be taken into account when reviewing the results of the study. First, the authors' literature search was systematic but limited to four electronic databases and only English-language documents. This could exclude documents published by authors who are non-English speaking, and therefore limit the amount of information obtained from researchers working within East Asian and European research communities that actively contribute to the field of Business Intelligence (BI). Additionally, excluding gray literature (practitioner reports, vendor white papers, conference workshop proceedings) will create a selection bias toward the views of academics over practitioners concerning the values and implementations of BI.

Second, the majority of studies reviewed were cross-sectional in design, thus limiting the ability to draw cause-and-effect conclusions between BI capability and organizational performance. The typical BI research is focused on capturing a snapshot of how well technology has been implemented and what level of performance outcome has been achieved at one given time; however, it does not allow for the analysis of how BI capabilities are accumulated over time, how BI technology is adopted, or the long-term learning effects expected by the KBV model. Studies using longitudinal panel designs or quasi-experimental designs based on an exogenous event, such as the adoption of cloud BI technologies as a technological shock, would provide much better causal identification.

Lastly, the thematic synthesis used by the authors was influenced by explicit coding rules, and the authors used an inter-coder reliability check, but will always include some degree of interpretation as to the importance and applicability of each study finding. As there was a wide variety of industries, organizations, and countries represented in the studies reviewed, the ability to apply findings from these studies to a particular implementation setting will vary greatly depending upon the context and additional validation. Future reviews might want to consider utilizing meta-analysis to quantify the effect size of various study designs that are similar to estimate the performance benefits of different BI capabilities.

10. DISCUSSION & ORIGINAL CONTRIBUTION

The synthesis developed in this review provides several new perspectives to enhance understanding of the Business Intelligence (BI) literature above previous one-dimensional reviews. The papers' central theoretical contributions include demonstrating that the Resource-Based View (RBV), the Knowledge-Based View (KBV), and the Technology Acceptance Model (TAM) provide more appropriate descriptions of BI as complementary rather than competing views for understanding BI. Specifically, RBV helps explain at the firm-level why BI capability can result in competitive advantage; KBV explains at the organizational-level how that capability is created and distributed throughout an organization by means of knowledge-based processes; and TAM explains at the individual-level how perception of usefulness and ease-of-use influence the activation of capability as a function of BI utilization.

Another contribution of the paper includes providing a structured comparison of the results of the studies examined relative to the various BI application domains. While it would be unwise to interpret these findings

too broadly since there was considerable variation among the studies in terms of design, metrics used to measure outcomes, and scope of implementations, they do indicate that BI is generally associated with greater visibility and measurability of benefits in the health care and financial service industries compared to the manufacturing and public sectors. The authors also believe that the degree to which data is rich, the degree of regulatory pressures, and the degree of decision-making criticality will all impact where BI value is most visible.

Finally, the authors have developed a comparative synthesis of technology maturity across the BI literature. As defined here, the authors believe that well-established BI components, such as data warehousing, OLAP, standard reporting, etc., have a higher degree of implementation consensus and have been demonstrated to be adopted more widely than newer capabilities, such as AI-augmented analytics, embedded recommendations, and real-time streaming BI. That said, the authors have observed that some commercially successful BI tools have limited to no coverage in the peer-reviewed literature and therefore represent a significant "translation" gap between academically validated explanations of BI tool functionality and the practical implementation of those tools by practitioners. This view should be regarded as a review-based interpretation rather than a formally defined maturity model.

11. CONCLUSION

In this article, we used 78 peer-reviewed articles, which were published during the years 2018-2022, to show how Business Intelligence is an overall sociotechnical discipline with theory, technology, and practice. The results of our review of the literature on BI demonstrated that value creation for BI is not dependent upon technology alone, but rather when all components of the BI system (e.g., data infrastructure, analytical capability, organizational culture, and decision governance) function together to create value. Furthermore, the overall conceptual model developed in this study using the Resource-Based View (RBV), Knowledge-Based View (KBV), and Technology Acceptance Model (TAM) provides a more complete conceptual model for understanding BI outcomes than could possibly be produced using a singular theoretical perspective.

The review of technology shows that the BI environment is changing rapidly due to the increasing prevalence of cloud-based computing, self-service capabilities, real-time streaming of data, and increased automation of analysis via artificial intelligence. While these technologies may lower some barriers to BI usage, they increase the scope of tractable analytical problems. The application evidence, drawn from six different industries (retail, healthcare, financial services, manufacturing, and government), demonstrates that BI can lead to meaningful performance improvement across all of these industry types; however, the magnitude and form of the performance improvements that result from BI can depend upon several factors including the amount of available data, the level of analytical sophistication of the organization, the presence of institutional constraints to BI adoption, and the overall quality of the BI implementation.

We recommend that future research focus on three areas: (1) conducting longitudinal studies of how organizations accumulate BI capability, (2) designing experimental studies that allow researchers to determine whether specific BI investments affect performance, and (3) comparing BI adoption rates across cultures. Finally, we believe that the growing trend toward using artificial intelligence to augment BI represents an emerging area of research ethics that holds both academic and policy implications. Maintaining a strong theoretical foundation in BI will become increasingly important as BI converges with artificial intelligence and data science in order to distinguish between sustainable mechanisms of creating value and transitory technological fads.

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