An Overview of the Rise of Business Analytics Adoption in Banking and its Impact on Performance

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Abstract
Banking is now interacting with customers over many Internet channels or touchpoints. This progression into the digital realm is leading to a proliferation of big data, warranting advanced analytic methods to manage service systems effectively for banks. One of the highlighted technological innovations is Business Analytics (BA). These techniques harness insights from data to improve customer experience and risk management in the banking industry. Thus, due to the rapidly increasing popularity of BA, its adoption and subsequent impact on banks' performance have become important research topics. Therefore, drawing on the BA literature, this paper presents an overview of BA as well as its adoption and impact on performance within the banking industry.

Keywords: Business Analytics, Adoption, Performance, Banking

1. Introduction

In the past few years, the number of available information technology (IT) applications and their usage in organizations has grown exponentially. Several factors contribute to this trend, such as the lower acquisition and storage costs for structured and unstructured data, but most notably, the transformation of business models through IT. As a result, data acquisition is increasing across a wide range of IT domains, such as enterprise systems, web applications, databases, and various social media platforms. The forms of this data can be numeric, text, audio, or video (Raghupathi & Raghupathi, 2021).

As data storage and collection technologies continue to improve over time, stakeholders from various industries recognize the opportunity and potential to utilize advanced analytics to gain insights from data and make fact-based decisions (Kristoffersen et al., 2021). Hence, this is where Business Analytics (BA) emerges as one of the leading techniques for deriving decisive insights from data, attracting significant interest from academicians and practitioners alike due to its potential advantages to its adopters across operational, tactical, and strategic levels in various industries, including finance, financial services, insurance, manufacturing, and retail (Yalcin et al., 2022; Horani et al., 2023).

BA can be conceptualized as a systematic and iterative process that involves collecting, analyzing, and interpreting data to acquire insightful information. This information can significantly improve the quality of business decisions and overall performance (Chatterjee et al., 2022). The primary objective of

BA is to enhance an organization's ability to extract, load, and process current and historical data from diverse sources. This process necessitates clear visualization of the information flow within a suitable framework, thereby aiding in interpreting and understanding the data. In doing so, BA employs statistical and mathematical models, as well as advanced technologies like Artificial Intelligence (AI) algorithms. These tools facilitate optimal decision-making, trend prediction, and effective handling of other related tasks (Liu et al., 2023).

Typically, the BA process involves a sequential range of analytical techniques: descriptive, predictive, and prescriptive (Schmitt, 2023). Each technique serves different purposes and has distinct tools and functions. For instance, descriptive analytics is concerned with employing common statistical techniques and advanced data analysis to identify hidden patterns and trends in data. On the other hand, predictive analytics harnesses the power of machine learning and artificial intelligence techniques, utilizing vast amounts of data to forecast future outcomes. At the same time, prescriptive analytics takes the process further by utilizing optimization algorithms to enhance predictions and recommend better decision options (Chen et al., 2020).

BA has recently experienced a surge in popularity, garnering significant interest from industry analysts and resulting in widespread adoption (Bawack & Ahmad, 2021). This increasing popularity can be attributed to several factors, including the explosion of Big Data (BD), technological advancements, and the growing need for organizations to optimize their operations and embrace data-driven decision-making practices (Rana et al., 2022).

Meanwhile, global investments in BA tools have been consistently increasing, experiencing substantial growth in market expenditures (Aydiner et al., 2019). A market report (Business Analytics Software Market) projects a remarkable expansion of the global BA solutions market, with an estimated value of $120.27 billion by 2027 and a compound annual growth rate (CAGR) of 10.5% between 2019 and 2027 (Gaikwad & Rake, 2020). These statistics underscore the significance of BA adoption and its potential impact on diverse industries and sectors. Similarly, the literature further highlights the crucial role of its adoption in enhancing business performance through evidence-based decision support (Bayraktar et al., 2023).

As a result, the adoption of BA has particularly impacted various sectors, notably the banking industry (Pillay & van der Merwe, 2021). The banking industry continuously evolves in response to dynamic market conditions and customer demands. With the proliferation of BD and the advent of advanced analytics techniques, banks can leverage their vast datasets to gain insights that otherwise remain hidden. Through BA adoption, banks have a unique opportunity to improve various aspects of their operations, including customer information, risk measurement, products, and market expectations (Nobanee et al., 2021). In light of this, traditional banks may face challenges in competing with emerging players in the industry, such as FinTech companies (Kikan et al., 2019). These new entrants possess a notable competitive advantage because they can provide more accurate projections, especially in a volatile business environment.

While a growing corpus of literature on the BA domain underscores the significance of BA as a field of study, this body of literature has many perspectives on BA, covering its adoption, techniques, impact, and applications across various domains. Therefore, this review paper endeavors to present an overview of BA, specifically focusing on its adoption and impact on performance within the banking industry.

2. An Overview of BA

BA is a relatively new term in the business lexicon (Delen & Ram, 2018), representing an inherently forward-looking concept that has evolved from business intelligence (BI) (Janiesch et al., 2022). However, the term BA is often interchangeable with similar concepts, such as Big Data Analytics (BDA) and Business Intelligence and Analytics (Horani et al., 2023). The scope of BA covers a broad spectrum of approaches (Bowers et al., 2018). These approaches range from conventional BI, which involves visualization and reporting, to predictive modelling like data mining and forecasting, operations research which includes optimization and simulation, and even specific applications of analytics such as marketing and web analytics.

The core of BA lies in its ability to leverage data to develop analytical models that aid in making well-informed business decisions, mainly when the future is uncertain or unknown (Pinder, 2022). This process involves synthesizing and integrating statistical analysis, information technology, and management science aiming to assist managers in arriving at the most optimal solutions for addressing business challenges

BA plays a critical role in enhancing the management of substantial data and information pertinent to the organization. This process involves classifying, processing, and interpreting data into meaningful intelligence information. The tasks encapsulated by BA address historical and current executive issues, making it an indispensable administrative tool for analyzing the business environment and facilitating decision-making processes (Zheng & Khalid, 2022). By leveraging BA, organizations acquire a valuable means to better understand their operations, identify patterns and trends, and ultimately make well-informed and strategic decisions to drive business growth and success.

2.1 Definitions of BA

BA has emerged as an attractive term in academia, but there is currently no universally established definition for BA (Liu et al., 2023). In the early literature on BA, as seen in Davenport and Harris (2007), it was defined as a sequential process that involves collecting, storing, cleaning, analyzing, visualizing, and interpreting data to enhance decision-making and improve business performance (P. Paulino, 2022). However, as organizations have grown more aware of the essence of BA, definitions of it have evolved. Table 1 presents various prevalent definitions of BA found in the literature.

Table 1: Prevalent Definitions of BA

Definition	Reference
BA is a broad class of technologies, methodologies, practices, applications, and systems that analyze critical business data to aid firms in better understanding their business and market, supporting faster and more timely decision-making.	Chen et al. (2012)
BA involves the generation of data-driven insights for value creation, which necessitates actionable insights, business relevancy, performance and value measurement.	Stubbs (2013)
BA is a set of technological solutions that provides powerful mechanisms for obtaining, generating, integrating, selecting, and disseminating knowledge relevant to the decision making process.	Holsapple et al. (2014)

BA is an interdisciplinary field that combines knowledge of information systems, management science, operations research, statistics, and machine learning.	Delen & Ram (2018)
BA "is a systematic way of thinking that uses qualitative, quantitative, and statistical computational tools and methodologies to analyze data, acquire insights, inform, and assist decision-making."	Power et al. (2018, p. 52)
BA may be conceptualized as a technique and expertise as well as a practice for analyzing an organization's performance in order to obtain inputs that may aid in effective business planning.	Chaudhuri et al. (2021)
BA involves the extensive use of diverse analytical tools complemented by a query and reporting mechanism to aid decision and policymakers in making well-informed and thoughtful decisions within a closed-loop framework, aiming for continuous process improvement through monitoring and learning from big data.	Min et al. (2021)
BA is a sensitizing device, given its inherent ability to augment business processes and functions that predict outcomes and assess their impact on the organization.	Zamani et al. (2022)
BA is "the process of developing actionable decisions or recommendations based on insights from historical data, as well as frequent monitoring of the performance of business processes through accurate presentation, multidimensional data analysis, and report creation."	Akel et al. (2023, p. 201)

Regardless of the perspective from which BA is defined, this paper concludes that BA refers to a set of techniques, applications, methodologies, and practices employed to derive insights from data through continuous and iterative analysis of past and current business performance. The primary objective is to enable organizations to understand their operations and the market they operate in, facilitating timely decision-making and driving effective business planning.

2.2 Levels of BA

Since BA involves utilizing analytical tools, methods, and techniques to make decisions based on factual evidence, its value is determined by the nature of the business question posed and the level of analytics applied to address it (Nacarelli & Gefen, 2021). The maturity of the BA concept is closely tied to the depth of analytics employed to answer the business question. These levels of analytics are commonly categorized as descriptive, predictive, and prescriptive (see Figure 1).

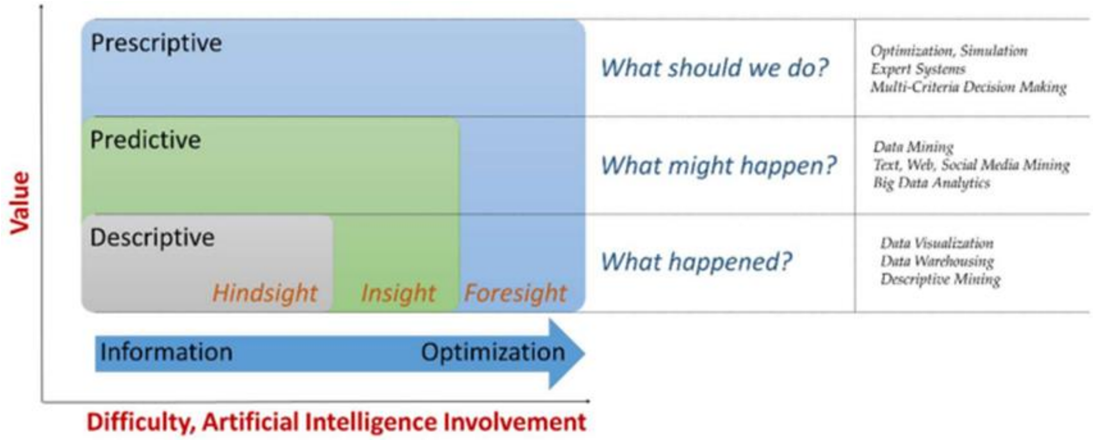

Figure 1: Levels of BA. Adopted from Çelebi (2021)

In the past, organizations predominantly relied on descriptive analytics, using query and reporting tools to gather historical performance data and categorize structured data to address their issues. With the evolution of data warehouse technologies, disparate data can be merged into a comprehensive database and prepared for analysis. Consequently, organizations progressed from descriptive to predictive analytics, enabling them to forecast future events. Concurrently, organizations also adopted prescriptive analytics to support forecasting and proactive decision-making (Raghupathi & Raghupathi, 2021). In essence, the focus shifted from merely answering questions like 'what happened' and 'how often it happened' to explaining the reasons behind events ('why something is happening'), exploring potential trends ('what if this trend continues'), predicting future outcomes ('what will happen next'), and identifying the optimal scenarios for the future (Omar et al., 2019).
The gradual adoption of more sophisticated analytics levels, such as predictive and prescriptive analytics, allows organizations to gain deeper insights into their operations and market dynamics. As a result, they can make informed decisions and take proactive measures to stay competitive and achieve their strategic objectives. The transition from descriptive to prescriptive analytics represents a progressive and dynamic approach in the field of BA, facilitating better decision-making and enhanced performance across various industries and sectors (Min et al., 2021).

2.2.1 Descriptive Analytics

Descriptive analytics is the most common and comprehended type, also known as reporting. Most organizations use descriptive analytics techniques to analyze data to understand past and current business performance and make fact-based decisions. These techniques are utilized to categorize, characterize, consolidate, and classify data to turn it into useful information to comprehend and analyze business outcomes (Raghupathi & Raghupathi, 2021).
Descriptive analytics provides summarized information that can be effectively displayed through charts or reports. Visualization has emerged as a powerful technique within this type of analytics, enabling managers to access standard and custom reports, delve into data, and perform queries to understand trends and patterns effectively (Raghupathi & Raghupathi, 2021). Various data visualization tools have been developed to create visual representations of large data sets, including popular ones such as Tableau, Microsoft Power BI, Excel, FusionCharts, Sisense, and more. Meanwhile, numerous online visualization tools, such as Sovit, RAWGraphs, and Infogram, are also available (Liu et al., 2023).

Descriptive analytics focuses mainly on historical events, employing a variety of tools. Apart from conventional statistical methods like frequency distribution analysis, concentration trend analysis, and dispersion analysis, more advanced data mining techniques are utilized to explore the intrinsic features of the data. Association and cluster analysis are two common data analysis methods frequently used in descriptive analytics (Liu et al., 2023).
The outcomes of descriptive analytics can assist managers in gaining a better understanding of past and present events. However, it also introduces uncertainty when making future decisions. Decisions based solely on historical and current events may not directly apply to future events. As a result, managers may face challenges in determining which decisions will significantly impact the business's future performance (Nacarelli & Gefen, 2021).

2.2.2 Predictive Analytics

Predictive analytics is the second level of analytics, typically reached by organizations after they have matured in their usage of descriptive analytics. This type of analytics focuses on forecasting future events by analyzing historical business data, uncovering hidden patterns or relationships within this data, and then projecting these patterns or relationships into the future (Raghupathi & Raghupathi, 2021).
Through advanced techniques such as statistical modelling (regression and time series) and machine learning, predictive analytics can reveal hidden relationships or patterns in large datasets. It groups or segments data into coherent sets to predict events and behaviour or detect trends (Raghupathi & Raghupathi, 2021).
Predictive analytics employs various techniques to forecast future outcomes, including statistical analysis, text mining, forecasting models, Natural Language Processing (NLP), and neural networks (Ashrafi & Zareravasan, 2022). In addition, AI technologies such as deep learning and artificial neural network have revolutionized the field of BA by enabling more predictions, particularly with the advent of the BD era (Liu et al., 2023).
While descriptive analytics helps managers better understand past and current events, it does not guide specific actions or solutions. Likewise, though predictive analytics is powerful, it may still leave managers uncertain about which decisions will significantly impact future performance (Nacarelli & Gefen, 2021).

2.2.3 Prescriptive Analytics

Prescriptive analytics represents the highest level of analytics, employing operations research methods like optimization and simulation to identify the optimal alternatives and choices for achieving the best possible performance. Often referred to as normative analytics, it focuses on determining what "should" be the optimal outcome and provides recommendations for courses of action once the outcome is predicted (Ashrafi & Zareravasan, 2022).
Compared to traditional decision-making methods that heavily rely on human knowledge or experience, perspective analytics offers more reliable and rational decision-making by applying scientific approaches, including traditional optimization and heuristic algorithms (Liu et al., 2023).
In the analytics hierarchy, prescriptive analytics builds upon the insights derived from descriptive and predictive analytics. By using optimization approaches, it recommends solutions and assesses their potential impact on the business (Ashrafi & Zareravasan, 2022). As a result, this level of analytics adoption

empowers managers to effectively harness the power of analytics, leading to the highest level of decision satisfaction possible (Nacarelli & Gefen, 2021).

2.3 Evolution of BA

The utilization of analytics in decision-making is not a recent development, as BA has existed since the mid-1950s (Analytic 1.0) and is now embarking on a new era (Analytics 4.0). Figure 2 illustrates the various era of analytics and their key distinguishing features.

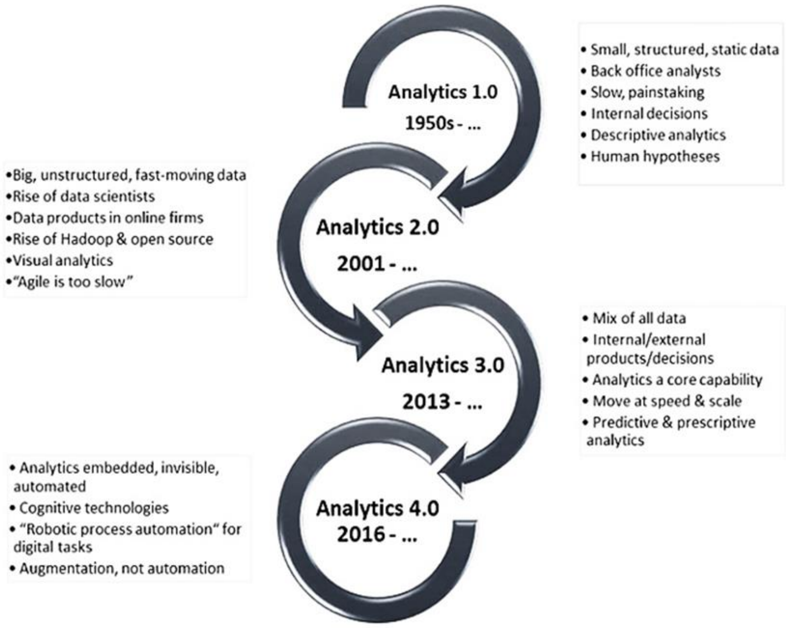

Figure 2: Evolution of BA. Adopted from Vassakis et al. (2018)

With the emergence of analytics 4.0, a prominent characteristic is integrating AI methods and the more efficient utilization of autonomy, mainly through machine learning automation. This integration entails a collaborative environment where intelligent humans work alongside automated intelligent machines to make decisions and take action. Consequently, modern analytics environments must be equipped with the necessary tools and technologies, and individuals must possess the required analytical skills. Therefore, it becomes imperative for organizations to continuously assess and enhance their data and analytics practices to maximize value and maintain competitiveness (Davenport, 2018).

2.4 Data Sources for BA

Data collection is the initial step in the BA process. The data collected during this process can be categorized as structured or unstructured. Structured data typically takes the form of numbers and letters, adheres to a predefined data model, and is usually stored in tabular formats like spreadsheets and relational databases. On the contrary, unstructured data, whether textual or non-textual, lacks a predefined data model and logical schema, making it more challenging to process using conventional programming techniques. Thus, the unstructured data collected by the organization from its surroundings undergoes a structuring process, rendering it readable and comprehensible, thereby transforming it into valuable information (Bayrak, 2021).

Organizations can mine both structured and unstructured data in various ways, both internal and external. "internal sources" refers to data collected by transactional or operational systems within organizations and accessible to employees. On the other hand, "external sources" refers to data published by government agencies, third parties, or social media sites that organizations wish to utilize.

Organizations typically store the data collected from internal and external sources in a centralized database or data warehouse. While some organizations choose to store their data on cloud computing platforms, providing decision-makers with convenient access from any location and at any time (Bayrak, 2021).

Overall, it becomes crucial for organizations to prioritize the mining and analysis by utilization of internal data sources before turning to external sources. While external data can offer advantages and valuable insights, internal data sources are typically easier accessible and hold more significant potential for serving the organization's objectives and needs (Hariharan, 2018).

3. BA Adoption in Banking

The banking industry is renowned for being one of the early adopters of IT for data-driven decision-making (Hung et al., 2020; Al-Dmour et al., 2023). Banks have access to vast amounts of data generated through their business operations conducted on electronic platforms (Rao & Provodnikova, 2021). With various financial services such as SME funding, online peer-to-peer lending, cryptocurrencies, trade management, money transfer, and mobile payment platforms, banks now possess a wealth of diverse and ever-expanding consumer data (Hasan et al., 2020). The effective management and analysis of this data are deemed essential by financial practitioners and experts.

The adoption of BA plays a pivotal role in enabling banks to adapt their operations and processes to meet client expectations, tackle sophisticated fraud schemes, and comply with complicated legislation. Currently, banks are storing vast volumes of customer data incorporating demographics, financial situations, and transaction behaviours from various channels, including over-the-counter transactions, ATMs, mobile apps, and social media plattforms (Hung et al., 2020).

By leveraging the power of BA, banks can analyze these extensive datasets to enhance customer satisfaction and foster loyalty by creating personalized experiences tailored to individual preferences. Moreover, banks can utilize data-driven predictions to anticipate customer needs and trends, thus empowering them to proactively offer relevant products and services that cater to their client's evolving demands. For instance, banks can enhance their market targeting by categorizing and segmenting customer data based on frequently accessed services, credit card expenditures, and other characteristics. Statistical models and computational algorithms can then be applied to match customer characteristics with the most suitable product offerings (Power et al., 2018). Moreover, predictive analytics enables bank managers to identify the most profitable customers, assess the likelihood of loan applicants defaulting, and promptly alert credit card customers about potential fraudulent activities (Raghupathi & Raghupathi, 2021).

Furthermore, the adoption of BA in banks has been propelled by the imperative to reduce costs and enhance efficiency. BA can pinpoint areas that require streamlining and optimization, leading to significant cost savings and overall improvements in efficiency (Rahman, 2023). For example, banks use prescriptive analytics to determine the ideal amount of cash to keep in ATMs for maximum efficiency.

Overall, the adoption of BA in the banking industry has been motivated by several key factors: the growing abundance of data, a heightened emphasis on enhancing customer experience, and the imperative to curtail expenses while bolstering operational efficiency. This data-driven approach exemplifies how BA can empower banks to make informed decisions, enhance risk management practices, and improve operational efficiency. Thus, BA adoption enables banks to operate more effectively, allocate resources judiciously, and stay competitive in an ever-evolving financial landscape.

4. Impact of BA on Banking Performance

The banking industry is increasingly recognizing the transformative potential of BA in enhancing its overall performance and competitiveness (Zhu & Yang, 2021). According to Hung et al. (2020) and Nobanee et al. (2021), BA has become an essential tool for commercial banking to improve marketing and risk management performance.

Some of the typical BA applications in marketing strategies include customer lifetime value prediction, where the monetary value representing a customer's lifetime revenue contribution is forecasted. Another important application is customer clustering, a model used in customer relationship management to classify customers based on attribute similarity. Additionally, BA is used for product affinity prediction, which forecasts a customer's preferred products or services by analyzing their historical transactions and profiles (Hung et al., 2020). BA application is also evident in combatting fraudulent activities. Implementing BA within banks aids in identifying patterns and anomalies indicative of fraudulent behaviour in monetary transactions. This proactive approach not only helps in the early detection of fraud but also allows banks to take immediate action to prevent any potential negative consequences (Nobanee et al., 2021).

However, the existing literature highlights that organizations can achieve significant performance gains by adopting BA aligned with their business processes and objectives (Aydiner et al., 2019). Chatterjee et al. (2022) assert that modern business processes are closely intertwined with advanced technologies, with BA being a prominent example. Such innovative technologies are strategically deployed to connect multiple processes and acquire valuable, rare, inimitable, and non-substitutable (VRIN) resources, ultimately leading to improved business performance according to the concept of resource-based view (RBV) theory (Barney, 2001). According to Someh and Shanks (2015), valuable resources allow an organization to seize opportunities and defend against threats. Rare resources are unique and not easily accessible to current or potential competitors. Inimitable resources are difficult for rivals to replicate or imitate. Non-substitutable resources have no strategic equivalents, making them indispensable for the firm's competitive advantage. As such, VIRN resources are crucial to explain the variance in business performance.

Furthermore, RBV is widely recognized in the literature as one of the most common and effective theories for studying the impact of IT innovation on performance. Recent studies on the impact of BA on bank performance have also utilized the RBV theory. For example, Rahman (2023) and Aziz et al. (2023) highlight the significance of BA as a strategic resource for banks. They suggest that the application of BA can contribute to the development of bank capabilities, ultimately leading to superior performance over time. By integrating BA into their operations and aligning it with their objectives, banks can sustain success and compete in evolving business environments. To that end, the RBV theory offers a robust theoretical framework for researchers to understand how BA can impact the overall performance of the banking industry.

5. Conclusion

In the contemporary business environment, globalization of services and rapid technological advancements have significantly increased the competitive nature of banks in their offerings of new products and services. BA has emerged as a crucial set of techniques that effectively harness insights from data, leading to notable improvements in customer experience and risk management within the banking industry. The rapid rise in the popularity of BA has made its adoption in the banking sector and its subsequent impact on banks' performance essential subjects of research. Through a review of the BA literature, this paper presented an overview of BA, shedding light on its adoption and its influence on performance within the banking sector.

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