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Optimizing Big Data Implementation to Create Business Value and Architecture Proposed in the Banking Industry : A Systematic Review

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***Abstract* - The exponential growth of data is compelling organizations to employ data in decision-making. As one of the businesses with an ecosystem that contributes to data growth, banks have challenges in generating insight. A high level of data security is frequently linked to a high level of data access difficulties. This poses a challenge to the implementation of data-driven business, where taking control of our data is one of the best ways to ensure that we not only own data but also have the ability to process and use data to extract business value. Through literature review, a number of challenges to optimizing the implementation of big data analytics in the banking industry were discovered. Data governance refers to the methods and procedures that assist banks in managing and securing data. A big data architecture is presented to address the highlighted issues, particularly with a multi-tiered approach to big data structures. With the adoption of this architecture, it will be simpler to generate business-value-generating insights for the banking industry using big data with accessibility and protection of data.**

Keywords : data-driven, big data, data governance, big data architecture, business value, bank

I. INTRODUCTION

The financial industry is becoming more data-driven to stay competitive. In recent years, the amount of data in the world has increased dramatically. By analyzing vast quantities of financial data, organizations can develop their strategic plans, such as for risk management, crisis management, and growth management [1]. Traditional data analytics tools have difficulty storing, managing, and evaluating data as the volume of data grows exponentially. The new area of big data analytics (BDA) employs distributed and decentralized processing to overcome these issues. Organizations utilize data to gain a deeper understanding of how their operations operate, the strategy they will adopt, and how to produce value. Data has been converted into knowledge in order to add value; nevertheless, the value depends on the quality of the data, which must be confirmed prior to its usage [2]. The banking industry has become one of the major ecosystems that employ analytics on product trends, market dynamics, and consumer behavior to generate data-driven analytics, with many users actively participating in their operations [3]. Data-driven analytics (DDA) is strategic decision-making based on the interpretation and analysis of data.

Data governance sets up high-level policies to protect data from being lost, changed, stolen, or used in the wrong way. Stewardship is a set of practices that make sure an organization's data is easy to find, useful, safe, and trustworthy. It means keeping an eye on every part of the data lifecycle, such as creating, preparing, using, storing, archiving, and deleting data, in accordance with an organization's established data governance principles for promoting data quality and integrity. Data stewardship makes sure that these policies are actually followed. The bank will attempt to safeguard information with a high level of security. The general data protection regulation (GDPR) is a data protection regulation that prohibits the use of consumers' personal data without their consent. This general data protection legislation must be adhered to by everyone in the world who processes, stores, or transmits the personal data of European Union (EU) inhabitants. Driving toward a data-driven culture, accessibility will be the keyword. The higher the level of data security, the more challenging the procedure for data access will be. The challenge is how to adapt to the best approach by prioritizing security without impeding the effectiveness of the data-driven culture process.

II. THEORETICAL FOUNDATION

A. Technology and Data Governance

As an ecosystem that generates vast amounts of data, the management of big data offers challenges to a bank. Big data and analytics (BDA) refers to the processing and analysis of large datasets computationally to reveal patterns, trends, and insights from the data, which refers to the techniques, technologies, systems, methods, and tools that enable accessing diverse data, manipulating and transforming it to generate insight [4]. The qualities of big data are volume, velocity, diversity, validity, and value [5]. The BDA architecture consists of six components: data generation, data collection, data storage, advanced data analytics, data visualization, and value-creating decision-making [6]. Previous study on the business value of information technology has demonstrated that investments by themselves do not provide value to a company. Instead, organizations must develop competencies that are distinct and difficult to replicate [7]. The implementation of big data is not restricted to the acquisition of big data technology, but its effects are noticed instantly. In actuality, there are many obstacles to overcome. The move to a data-driven organization, in which all decisions are affected by data-generated insights, is challenging and riddled with difficulties. Data governance comprises the following: organization, policies, data catalogs, data and analytics definitions, data sourcing, data quality, master data, data operations, and data security. Data management entails acquiring the data, storing it, and doing data cleansing and transformation in order to prepare it for integration and visualization [8]. Data lineage is the lifecycle of a piece of data, including its origin, transformation, and movement over time. With visibility into data lineage, including the underlying business context, data stewards can identify the core causes of any errors or issues that arise while using data for analytics. Analytics entails utilizing strategies and tools to model data and prepare it for BDA insight. Optimal data storage, maintenance, classification, and accessibility are prerequisites for the monetization of data.

B. *Advanced Analytics Techniques*

Because of technological advancements, businesses must act decisively and quickly. Data is transformed into information, knowledge, and wisdom via data-driven processes. Knowing the past, predicting the future, evaluating behavior, and comprehending context are all examples of wisdom. Growing amounts of data exceed conventional databases. BDA generates vast quantities of data and offers new decision-making opportunities [6]. BDA can be considered as a strategic function that can provide value to an organization if implemented well [9]. BDA use a number of methods, such as artificial intelligence (AI), machine learning (ML), and deep learning (DL), to analyze massive amounts of data and generate insights. Several methods exist for conducting analytics, including estimate, association, classification, and clustering. Logical regression (LR), Nave Bayes (NB), K-Nearest Neighbor (k-NN), neural network (NN), decision tree (DT), support vector machine (SVM), and random forest are utilized for analytics (RF) [10].

II. METHODOLOGY

A. *Review Method*

This study was conducted utilizing a systematic literature review (SLR), a method for discovering, assessing, and interpreting all relevant research on a specific research question, topic, or phenomenon of interest. [11]. In this strategy, a review protocol must be identified. The review protocol specifies the validation procedures. Decisions must be made concerning research topics, inclusion and exclusion criteria, search strategy, study selection, data extraction, data synthesis, and dissemination plans. By selecting the procedure beforehand, the possibility of validation bias will be reduced. Figure 1 illustrates the SLR procedure.

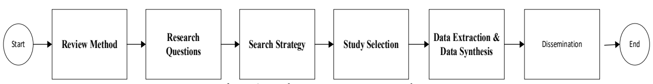

Fig. 1. The SLR Procedure

B. *Research Questions*

The Research questions (RQ) have ensured that the emphasis is maintained. They were designed with consideration for population, intervention, comparison, outcomes, and context (PICOC) [11]. Population associated with certain big data implementation demographic categories. Intervention involving a method, instrument, or procedure that solves a particular topic of big data implementation issues and approaches. In this study, the comparison is not provided. The results should relate to the significance of big data implementation challenges in the context of baking sectors. This SLR addresses the research question, outlined in Table 1 below.

Table 1. Research Questions

No	Research Question
RQ1	What are the data governance challenges to optimizing big data implementation to create business value in the banking industry?
RQ2	What are the other challenges outside of data governance to optimizing big data implementation to create business value in the banking industry?

C. *Search Strategy*

Selecting a digital library, defining a search string, executing the search string, refining the search string, and retrieving the initial list of main studies from the digital library that match the search string comprise the search process. The list of digital databases: ScienceDirect (sciencedirect.com), Scopus (scopus.com), ACM Digital Library (dl.acm.org), IEEE Explore (ieeexplore.ieee.org), and Springer Link (springerlink.com).

The search string was created using the following procedures: First, identify the PICOC search phrases. Second, the identification of search phrases derived from research questions and associated titles, abstracts, keywords, and synonyms. Third, identification of search phrases utilizing Boolean ANDs and ORs to generate advanced search strings. After entering a keyword, each database's library provided a list of articles relating to that term. The next step is to read each article's title, however if the title does not reflect research topics, the abstract should be reviewed. If the article's title and abstract correspond to the research questions, the article will be downloaded for further study. The number of papers downloaded is referred to as "candidate studies." All candidate research results are thoroughly read in order to identify responses to research inquiries. These papers will serve as "'selected studies" for research purposes [11]. The search criteria:

("advanced analytics" AND "data driven" AND challenges AND bank)

D. *Study Selection*

Using the inclusion and exclusion criteria, the primary studies were selected. Table 2 demonstrates these conditions.

Table 2. Inclusion and Exclusion Criteria

Inclusion Criteria	Only works published in 2018 or later will be considered, research paper only, when there are multiple publications of the same study, only the most recent and comprehensive will be included.
Exclusion Criteria	Research not written in English

There were 25 publications in the final list of selected primary studies. The chosen primary study is extracted in order to gather the data, information, and insights that contribute to addressing the research questions. Figure 2 depicts the results of the literature search.

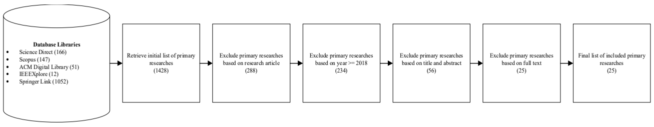

Fig. 2. Literature Search Results

III. RESULTS

A. *Data Governance Challenges to Optimizing Big Data Implementation to Create Business Value in the Banking Industry*

As shown in Table 3, to address the question RQ1 "What are the data governance difficulties associated with maximizing the adoption of big data to produce business value in the banking sector?"

Table 3. Data Governance Challenges

Challenges Category	Challenges	References
Data Characteristics	5Vs of Big Data Data Quality Challenges	[12][2][13][14][15][16][17][18][19][2][20][21][22]
Data Processing	Data Extraction, Collection & Cleansing Data Aggregation & Integration Insight Generation & Interpretation	[12] [13][14][15][16][18] [19]
Data Governance	Organization Policies Data Catalogs Data & Analytics Definitions Data Sourcing Data Quality & Master Data Data Operations Data Security	[12][13][14][15][18] [19][20]

B. *Other Challenges Outside of Data Governance to Optimizing Big Data Implementation to Create Business Value in the Banking Industry*

In addition to the data governance aspect, Table 4 represents another recognized challenge in optimizing big data implementation to provide business value in the banking sector. (RQ2).

Table 4. Data Governance Challenges

Challenges Category	Challenges	References
Data Knowledge	Technical Skill Managerial Skill Data-driven Culture Data Literacy	[12][13][14][15][23][18][19]
Data Architecture & Technology	Technical Data Infrastructure & Capability	[12][13][17][3][23][19][24]
Analytics Business Case Techniques	Imbalanced Dataset Feature Selection Data enrichment Accuracy & Performance	[13][9][25][16][26] [27][2][4] [28][29] [30] [31][25][16][1][2][32][33][34] [34][20][35][36]

IV. DISCUSSION

A. *Data Governance Challenges to Optimizing Big Data Implementation to Create Business Value in the Banking Industry*

A data-driven organization is one whose strategic decisions are based on data. The significance of a process's link to other processes, as well as the obstacles that affect the success of data-driven procedures, will be investigated in this study. Integrating BDA into the decision-making process remains challenging despite the fact that the use of big data tends to deliver value across the value chain for organizations [37]. The discussion is as follows:

Data characteristic challenges: Characteristics as structured, semi-structured, unstructured data with volume, velocity, variety, velocity and value [12]. Log files and data coming from all software applications, hardware, and network devices represent data sources, which are characterized by high variety, high volume, and high velocity due to the fact that they are continuously generated in various formats and in large quantities by all the systems involved [38]. Data manipulation challenges include high-dimensional, high-order, sparse, incomplete, hierarchical, cross-sectional, longrange, asymmetric, skewed, evolving, largescale, imbalanced, streaming, noise, missing values, feature extraction and engineering, dimension reduction, sampling and resampling methods, and visualization [36]. Businesses can use new technologies to automate the process of gathering structured and unstructured data from social media, e-commerce, sensors, devices, video/audio, networks, log files, transactional applications, websites, etc., cleaning the data, identifying patterns to identify useful and applicable data, and integrating the various databases [21]. Big data has been converted to knowledge for the benefit of organizations. However, the value depends on the quality of the data [2]. Data quality (DQ) is an organization's data's dependability, quantity, and timeliness. High-quality data is essential for data-intensive applications like machine learning. According to prior research, high-quality data should be naturally precise and contextually relevant to the action at hand. Poor data quality can have serious ramifications for companies [17].

Data processing challenges: When making significant decisions, managers collect data, design many alternative tactics, and assess these methods and their repercussions before making a final determination [12]. Data management involves gathering, storing, clearing, and transforming data for integration and visualization. Analytics involves modeling data for BDA insight using methodologies and tools [3]. BDA is a subtype of big data analysis. Predictive algorithms based on time series evaluate this vast amount of data and information to learn and predict prospective faults, blockages, or network issues [38]. Data extraction, gathering, cleaning, aggregation, integration, analysis, insight development, and interpretation are its procedures. Data-driven analytics will examine several data analytics methods.

Data governance challenges: The amount to which individuals (including senior management, middle management, and lower-level staff) in an organization make decisions based on data-driven insights. [19] . A data-driven culture is built and kept up with a focus on making decisions based on evidence, this leads to success with data-to-insight, decision-to-insight, and decision-to-execution [19]. Managers are also accountable for ensuring that choices at all organizational levels are based on data, data ownership and use, data protection and privacy, security, responsibility, cybercrime, and intellectual property rights [20]. When it comes to preserving customer data with a high level of confidentiality, the bank faces its own challenges. In addition, banking transaction policies and governance processes in Indonesia are governed by the regulator. For example, if a bank seeks to build a cloud-based application, customer data cannot be stored in the cloud, much less outside of Indonesia. Data aggregation management requires governance to guarantee correctness and integrity, completeness, timeliness, and adaptability.

The literature review discovered several challenges to big data analytics implementation in banking. Data stewardship ensures compliance with data governance standards, which protect data from loss, corruption, theft, and misuse. Stewardship involves maintaining data accessibility, usefulness, security, and dependability. Monitoring data production, preparation, utilization, storage, archiving, and deletion according to an organization's data governance standards to improve data quality and integrity. Data governance and how incoming and outgoing data affect risk and security. Figure 3 shows big data architectural recommendations for optimizing business value.

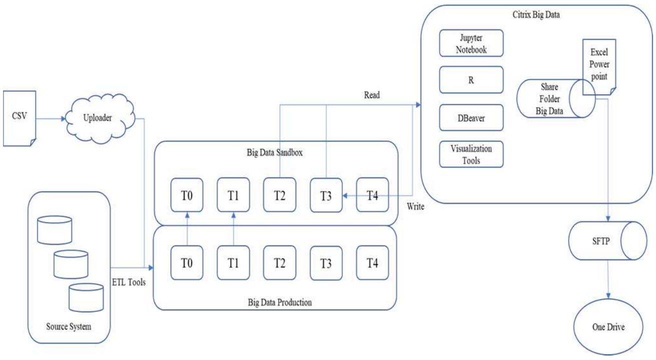

Fig. 3. Big Data Architecture Proposed

Tier 0 (T0) is the staging area where data from sources is fed into big data following the ETL procedure. From Tier 0 (T0), data is loaded into Tier 1 (T1) as a "data lake," which is a storage system capable of storing massive amounts of structured, semi-structured, and unstructured data. In Tier 1, the data is clean and segregated by application and data source. Tier 2 facilitates governance since the bank protects highly confidential data and personalizes it so that different divisions can have different access segments, or there is an access matrix (T2). T2 is also offered in the form of a virtual table (view) so that there is no need for physical table replication, which would require a significant amount of storage and add to the work schedule, hence requiring more effort from the IT side for data maintenance. Tier 3 (T3) is a workspace where business analytics users can consume and analyze data to develop insights. Figure 4 demonstrates the separation of processing into a structure with numerous tiers and a specific purpose. Tier 4 (T4) is a sandbox used for cross-division table sharing.

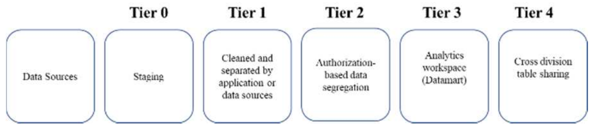

Fig. 4. Big Data multiple-tier structure approach

This architecture is a solution to the implementation of data governance to overcome the problems of accessibility and protection of data. Another advantage is the ease of maintaining data because in T2, data is presented in the form of a virtual table (view), so there is no need for table replication, which will add storage. Besides that, it is not needed to manage job schedules from T1 to T2. The drawback is that because the data is presented in the form of a virtual table (view), the query run time takes more time than the physical table.

B. *Other Challenges Outside of Data Governance to Optimizing Big Data Implementation to Create Business Value in the Banking Industry*

Data knowledge challenges: Define a formal team with a facilitator role to enable effective communication between IT and the business[14]. Understand the business requirements associated with big data functionality. Ability to make business decisions based on BDA-enabled insights. Globally, organizations are attempting to organize, process, and harness the value of the huge volumes of data they generate in order to transform them into relevant and high-value business insights. A data scientist is a skilled business analyst or engineer who uses statistical or scientific data discovery techniques and procedures to uncover new insights in data. It has become vitally important to recruit exceptionally qualified data science workers.

Data architecture and technology challenges: Technologies such as data integration and analytics platforms designed to ease access to data from numerous sources, offering load capabilities, data mining, and visualization make it possible to integrate data from multiple sources [3]. If the information technology infrastructure and data architecture are incompatible, it may be difficult to store, analyze, and derive usable information from data sets consisting of structured, semi-structured, and unstructured data [24]. Data visualization provides stakeholders with efficient techniques for visualizing, comprehending, and analyzing data patterns, anomalies, and trends. Visualization tools are essential because they provide data visualization capabilities such as maps, dashboards, interactive drill-down for further analysis, executing no-code data searches, and managing meta-data [3]. There is a significant correlation between big data investments and revenue growth, according to this study [23]. The installed big data application enables the storing, management, and real-time analysis of all network and information system-related data and information [38].

Analytics Business Cases Techniques: Descriptive analytics tools help uncover hidden and potentially useful information about business processes[13]. Descriptive analyses are based on approaches that try to transform unstructured customer data into useful information and facilitate decision-making processes [16]. Predictive models allow decision makers to use existing data to predict estimates of variables of interest [13]. Predictive analytics empowers organizations to seize opportunities by streamlining processes and improving decision-making [9]. Several literatures describe problems in analytical business case techniques, including imbalanced dataset, feature selection, data enrichment and accuracy & performance where one is related to one another. Many AI, ML or DL models are created with high accuracy, but when running it turns out the conversion is low. Why this happens because the data used needs to be enriched, third party data is needed to do the enrichment. Currently there are many data aggregators where organizations can do data enrichment. Feature selection refers to the reduction of inputs for processing and analysis, or the identification of the most significant inputs. Dimensionality reduction is distinct from feature selection. Both methods aim to reduce the number of characteristics in a dataset, but dimensionality reduction methods do so by producing new combinations of existing attributes. Unnecessary columns can damage the quality of the model in numerous ways, so it is necessary to do feature selection and find the best columns. Noisy or duplicated data makes discovering meaningful patterns more difficult.

V. Limitation

The database restrictions for this SLR are ScienceDirect (sciencedirect.com), Scopus (scopus.com), ACM Digital Library (dl.acm.org), IEEE Explore (ieeeexplore.ieee.org), and Springer Link (springerlink.com). In addition, the keywords utilized are extremely general, particularly ("advanced analytics" AND "data-driven" AND "challenges" AND "bank"). It would be beneficial to provide databases and keyword variants.

VI. Conclusion

The bank is extremely concerned with risk and security, making data accessibility difficult. The literature review revealed a number of challenges to maximizing the implementation of big data analytics in the banking industry. Monitoring each phase of the data lifecycle, including production, preparation, usage, storage, archiving, and deletion, in accordance with an organization's declared data governance rules is necessary to enhance data quality and integrity. A big data architecture with a multi-tiered structure approach is proposed to address the highlighted challenges. In the pursuit of a data-driven culture, accessibility will come to dominate. As data security increases, techniques for obtaining data will become increasingly challenging. With the deployment of this architecture, it will be easier to provide business-value-generating insights for the banking industry using big data with accessibility and protection of data.

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