“The state of implementing big data in banking business processes: An Indonesian perspective”

AUTHORS	Hamzah Ritchi Gina Andriani Reza Zulkarnaen Akmal Zaidaan

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Hamzah Ritchi (Indonesia), **Gina Andriani** (Indonesia), **Reza Zulkarnaen** (Indonesia), **Akmal Zaidaan** (Indonesia)

THE STATE OF IMPLEMENTING BIG DATA IN BANKING BUSINESS PROCESSES: AN INDONESIAN PERSPECTIVE

Abstract

Notwithstanding the perceived global potentiality, how big data enhances decision-making quality prompts an intriguing inquiry, especially in an increasingly competitive banking environment in developing economies. Building on an industry data-driven framework, this study strives to understand the state of implementing big data in the Indonesian banking sector. A deductively organized descriptive method employing in-depth interviews was conducted with subject matter experts representing Indonesian banking-related areas. The result and the following analysis show the modest status of big data implementation across three major banks and two complementary companies, as indicated by many elements of the framework phases that were found during the early adoption stage. This denotes a steady buy-in across banking business processes as particularly reflected in the framework's four phases – continuing push to meet the variety aspect (intelligence), structured data architecture domination (design), limited choice of performance indicator for big data value (choice), and customer–corporate vision decoupling (implementation). While Indonesian banks have evidently initiated the big data implementation, further improvement remains imperative for the decision-making process. Accordingly, big data should be tightly coupled with a strong data-driven vision that drives decision-making across intra-firm actors. Handling data omnipresence shall be viewed as the embodiment of a data-driven vision.

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Hamzah Ritchi, Dr, Associate Professor, Department of Accounting, Faculty of Economics and Business, Universitas Padjadjaran, Indonesia. (Corresponding author)

Gina Andriani, B.Sc., Graduate, Department of Accounting, Faculty of Economics and Business, Universitas Padjadjaran, Indonesia.

Reza Zulkarnaen, M.Sc., Lecturer, Department of Accounting, Faculty of Economics and Business, Universitas Padjadjaran, Indonesia.

Akmal Zaidaan, Undergraduate, Department of Management and Business, Faculty of Economics and Business, Universitas Padjadjaran, Indonesia.

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INTRODUCTION

In 2020 alone, a massive amount of data grew rapidly and reached a new record of 64.2 zettabytes. By 2025, global data growth is projected to grow to over 180 zettabytes (Holst, 2021). The growth reached a new record during the COVID-19 pandemic as workers are increasingly working, studying, and watching entertainment from home. The phenomenon brings about the notion of big data, which is typically characterized with leaps in volume, velocity, veracity, variety, and value. Coumaros et al. (2014) state that financial institutions perceive big data analysis generates significant competitive advantages and think that successful big data usage will determine who will excel in the future.

Banking business process heavily leverages technology advancements to pursue and create process innovations and product innovations (Yaw Obeng & Boachie, 2018). Many banks in Indonesia view big data implementation as a strategic imperative to enable business process innovation and data-driven decision-making. Data-driven decision-making refers to making decisions grounded by data in a comprehensive manner. On average, more data-driven decision

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making is substantially associated with an increase in productivity (Brynjolfsson & McElheran, 2017). It also improves other performance measures, such as return on assets, return on equity, asset utilization (output per total asset), and market value/market to book ratio (Patel et al., 2017).

Due to its potential, big data study in the banking industry has received much attention. Earlier research suggests that Indonesia's competitive banking sector may benefit from the big data implementation by strengthening data security, capturing customer-related data, preventing fraud, and enhancing credit risk management (Ravi & Kamaruddin, 2017; Ruzgas & Bagdonavičienė, 2017). However, during the implementation, banks are still experiencing several challenges such as infrastructure limitation, data accuracy, previous technologies incapable to integrate, and high adaptation costs (Indriasari et al., 2019). Big data capabilities are only attainable if the challenges in implementation are addressed, leading to reliable decision making. Skillsets, overstated promises, and a lack of implementation state comprehension are few hindrances seen to require serious handling (Hassani et al., 2018; Sun et al., 2020). Despite the potentials and challenges, the implementation aspect of big data initiative to support business process and strategic goals has been understudied and not comprehesively explored in Indonesian setting. A research endeavor to help banks identify obstacles and solutions implementation wise is then required. This study thus aims to fill the gap from previous studies about the current state of big data adoption and the associated challenges of Indonesia's banking sector.

1. LITERATURE REVIEW

As a financial intermediary, a bank serves to facilitate the payment traffic with trust in mind (Dinesh, 2018; Law of The Republic of Indonesia, 1998). Banking has been among the heavy adopters of digital technology, allowing innovation of its business processes and rapid development in services. Constantly dealing with a vast amount of data, banks risk themselves of becoming laggards as data is still managed at a current conventional pace (Groenfeldt, 2016). Over time, data is generated through social media interaction, smartphones or sensors uses, and other myriad channels. From these technologies, it is estimated that society creates more than 2.5 trillion bytes or 2.5 billion terabytes of data every day (IBM, 2017). A large amount of research has been carried out on speed and volume, whereas complete and efficient solution for variety aspect is still not available in the market (Naeem et al., 2022).

As data grow and are captured in warp speed, banks are expected to make better decisions through bigger grasp on customer situations and offerings. As a result of the increasing variety of consumer needs, banks offer advanced features, such as integrated bill payments, credit scoring, and even personalization of banking services at the individual level. In addition, the emergence of multichannel digital finance in banking has increased the speed and variety of data received or sent (Ozili, 2018) as an anticipatory step for banks to face and compete against the onslaught of fintech, which potentially undermines the essentials of banking processes (Murinde et al., 2022). Banks thus need to respond more quickly to this exponential data growth through advancing IT infrastructure to take advantage of this data opportunity in data-driven decision-making.

In the last two decades, the banking industry has undergone radical changes due to intense competition, globalization, mobility and consumer demand, and deregulation by regulators. However, as banks relatively offer homogenous products, many leading banks are currently revising their strategy by presenting consumer-oriented products to overcome intense competition (Bedeley & Iyer, 2014). The situation could change if banks were able to effectively process large volumes of data that is created and collected to deliver better and more granular insights (Arias, 2017). Arguably, this condition entails technology scalability demands to support seemingly unstoppable data growth, and hence big data technology.

Lee (2020) and Naeem et al. (2022) characterize big data in five dimensions (variety, volume, velocity, veracity, and value) of two solid-line triangles as depicted in Figure 1. The smaller triangle represents the traditional data capabilities that

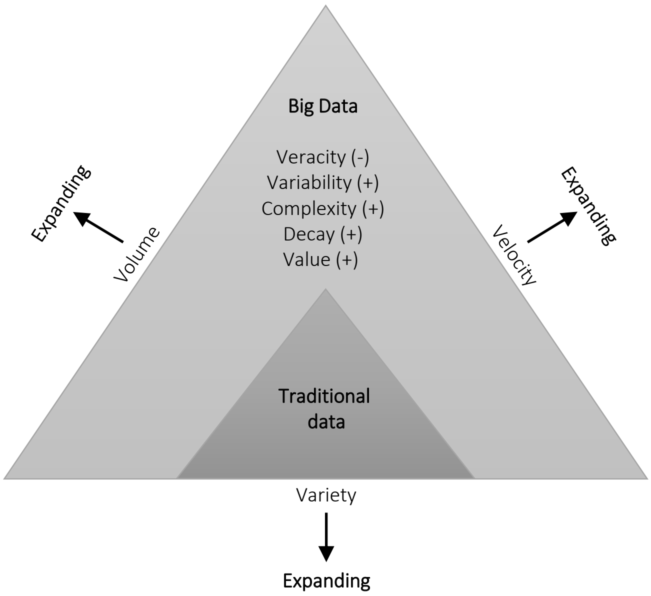

Figure 1. Big data in an integrated view

are limited in almost all dimensions in addressing increasing organization needs. The bigger triangle shows the early use of big data that scales up processing capability primarily lies in volume, variety, and velocity. It thus allows organizations to set an initial step to address veracity shortcoming (i.e., conformity to facts). Veracity generates authentic and relevant data by eliminating bad data. The unreliability and uncertainty of data arise due to incompleteness, inaccuracy, latency, inconsistency, subjectivity, and even fraud in the data sources used, causing managers and company decision-makers tend not to trust data in making decisions. As capability matures, big data enables organizations to attain the value of data for relevant decisions. A recent study suggests how business values are gained when implementing big data. These include creating data transparency, identifying patterns for performance improvement, enhancing segmentation strategies, automating native human-centered tasks, and enabling new services, models, and products introduction (Wamba et al., 2015).

Many banks in Indonesia view big data implementation as instrumental for business process innovation and data-driven decision making. The more data-driven a company becomes, the better it can control various confounding factors. Additionally, the difference is very significant where one standard deviation leads to 4% higher productivity, 6% greater profitability, and 50% higher market value (Brynjolfsson & McElheran, 2017). Banks could leverage big data in their business processes to become powerful modern banks with advanced analytics (BCG, 2019). Big data differs in the variety of types generated by people, applications, and machines (Daniel, 2019). It also associates with complex and varied structures that cannot be managed by traditional data handling methods and techniques (Mazzei & Noble, 2019).

Accommodating a large amount of data from multiple sources makes big data supportive for the decision-making process. Big data could also reveal data faster and better than traditional business intelligence (Ruzgas & Bagdonavičienė, 2017). Based on data grouping, the data generated by the banking industry mostly consists of texts or numbers. More than 70% of banking executives worldwide stated that customer-centricity is very important. A deeper understanding of customer needs is required to achieve greater customer-centricity.

Ravi and Kamaruddin (2017) assert some wide possible functions of big data in the banking sector. First is the sentiment analysis as one part of computational linguistics that has a role in studying opinions, emotions, and methods designed to identify and detect emotional reactions or bank consumer attitudes/sentiments expressed in the text. The other one is customer segmentation

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analysis – a complex process that requires knowledge, skills, experience in big data regarding financial product sales, market understanding and intuition (Lutfullaeva et al., 2018). The purpose of segmentation is not to identify any group of users in a particular market, but rather to find users who have different financial service requirements (Mihova & Pavlov, 2018). Fraud analytics also exemplifies another big data function achieved by detecting fraud quickly with analytics on big data immediately after detecting suspicious transactions with low nominal and vast transaction volumes. Difficulties in tracking transactions virtually, managing and controlling e-banking risks effectively, especially customer transaction risks, are important issues that needs to be of serious concern for the bank (Guo et al., 2018).

Other uses may include risk analytics, social analytics, analysis of customer interaction, sensor data from IoT devices, online footprints, spend pattern analysis, analyzing the offline transactions, online and offline interaction with the bank, and security analytics. From organizational sense, four impacts could be derived from which big data is adopted to banking activities: i.e., improvement of current practices, core banking process transformation, boost in IT performance, and new revenue streams (Baltassis et al., 2015).

However, big data implementation also poses barriers. Out of 85% of companies embracing big data, only 37% are successful and effective in big data-based insights (Vaghela, 2018). A study by Wirdiyanti (2018) asserts that, of digital banking technology adoption in Indonesia, there is a trade-off between bank performance efficiency and bank market outreach. The bank's market outreach and efficiency are increasing significantly by adopting digital technology, and this can be seen from the increased transaction volume of its funding and liquidity activities. However, on the other hand, the adoption of digital technology that is too aggressive might cause banks to have lower performance efficiency.

Like many other technological strategic moves, challenges exist to devise the value of big data to draw the attention of executives and project managers. A framework is thus needed to help provide the cascading explanation from the top holistic view down into a more granular implementation translation. Several frameworks typically aim to provide certain abstractions or dimensions of an enterprise information system and capabilities, such as Zachman Framework by Zachman (1987), GERAM by IFIP-IFAC (1999), and TOGAF by Desfray and Raymond (2014). To the best of the author's knowledge, little has been observed on the Framework that governs the pattern on how to deliver solutions in a big data environment specifically.

The core objective of a framework on big data is to provide a structure for enterprises that aim to benefit from the potential of big data initiatives, both in the short and long-run competitive advantage. Elgendy and Elragal (2016) propose the "Big – Data, Analytics, and Decision" (B-DAD) Framework to signify the tools, architectures, and analytics of big data that are involved during the decision-making process (see Figure 2). Four phases of the framework include intelligence, design, choice, and implementation.

1) In phase *intelligence*, the contents used in decision making are collected from various data sources in public and private organizations (identify big data box). This relates to the collection, conservation, and integration of relevant information that is useful in producing the content. Different types of sources include XML, text, audio, video, post, image, time forecast, etc. This phase also considers technologies needed to acquire data like the distributed Hadoop Distributed File System (HDFS), as shown in the Acquire/Store box. During the intelligence phase, data stored is then retrieved and organized using range of a data organization method such as Extract Transform Load (ETL) approach, SQL, and more.

2) Phase *design* involves a range of technologies to analyze data such that several alternatives could be defined and selected. The design phase requires a big data team to determine any of the available mode of data analysis to run the readily available data. This could range from choosing classification-based analysis, clustering analysis, graph analysis, or other necessary analysis. To do this, big data analysis should be configured using different options of

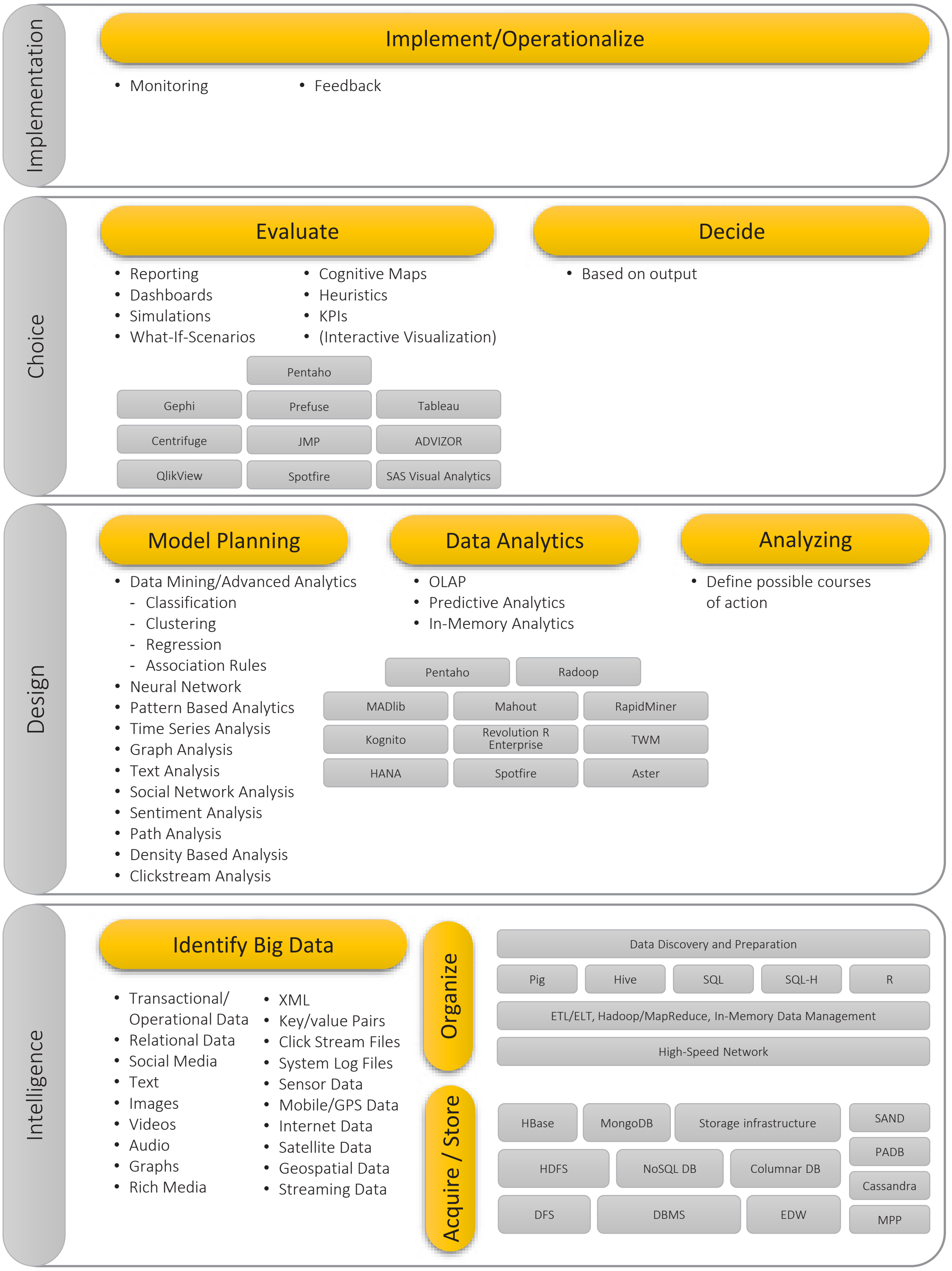

Figure 2. B-DAD framework

a data analysis scheme, such as online analytical processing (OLAP), or other data mining tools like rapid miner. The result will give data analysts a number of possible solutions.

3) Following analyzing the data, possible solution will be executed in the *choice* phase. At this point, decision-makers evaluate the best candidates of data analysis results from dif-

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ferent set of visualization technologies. These technologies help analysts build evaluation using reporting, dashboards, simulation, cognitive maps and more choices. The evaluation step is then followed by deciding the best possible combination of output.

4) Lastly, the *implementation* phase is where data being used into operational activity. Organizations need to actively solve any identified problems. This phase provides information about the result of the decision. All information can be captured, registered, and stored in a repository to provide organizational memory about domain issues and will always be available for use. This information will then become new data for both public and private data sources.

2. METHODS

The goal should not be here. In particular, this study looks at different circumstances in which big data currently supports the banking business processes in existing bank use cases.

The research follows a qualitative and descriptive approach. In particular, the work of Elgendy and Elragal (2016) was adopted building on design science methodology. In general, the qualitative method is used to obtain a deductive analysis which is aimed at explaining the extent of big data implementation base on a reliable framework using qualitative observation. Azungah (2018) stated that a deductive approach is based on the existing literature on the topic of inquiry or what is known about the phenomenon of inquiry as supported by research objectives, questions, and interview questions. Therefore, the qualitatively oriented deductive approach is viewed to be the preferred approach for the current study. It brings forth the deductive reasoning and data operationalization using B-DAD Framework as the working reference, such that emerging and relevant concepts from the interview cases are carefully mapped to the elements composing the framework.

Qualitative research arguably can generate potential and complementary benefit to the body of knowledge on big data study. It does not take more from a single study of big data but benefits from collecting data from several cases with deep and information-rich topics (Davidson et al., 2018). Moreover, a descriptive method was employed to describe the phenomena that occur under observation. Descriptive research can describe the state of its development as it depicts a condition as it is without any manipulation (Hamdi, 2014).

People involved in data or business development analysis in banking processes and implementing big data constitute the inclusion criteria. Purposive sampling was used as a nonprobability sampling technique that did not provide the same opportunity for each member of the population to be selected as the sample of this study. Table 1 presents the list of informants along with its codification. Aside from selecting three banks as the informants, the researchers also asked companies from adjacent sectors to provide comprehensive cognizance on big data implementation.

While the number of respondents was fairly low, the authors argue that the number would not markedly diminish the whole process of analysis and conclusion for two reasons. First, a stringent selection policy was set toward available candidates. All informants were chosen as they were considered qualified subject matter experts whose big data knowledge and experience were obtained through the enculturation process. This process allows more complete profiling of a respondent with natural experience and subtler cognitive processing on his/her big data experience. Second, because people with complex perspectives towards big data implementation projects were sought, limiting only a few persons with rich experience in both successful and poor big data implementation serves a relevant early milestone for the next broader research scale and validation. With average experience of ten years in big data implementation projects, these qualities exhibit internally rich experience, which supports the achievement of informational redundancy or theoretical saturation without sacrificing the deep, case-oriented analysis, which is crucial to qualitative inquiry (Boddy, 2016; Sandelowski, 1995). To that end, it is viewed that the choice of cases has addressed the scope of the study, the nature of the topic, the quality of data, and the study design.

Table 1. List of informants

No.	Informant	Role	Institution
1.	Informant 1	Senior Quality Assurance Analyst	Bank A
2.	Informant 2	Team Leader Data Scientist, Advance Analytics Department	Bank B
3.	Informant 3	IT Management Strategic Information Technology Group	Bank C
4.	Informant 4	Business Development Manager	Company A
5.	Informant 5	Chief Marketing Officer	Company B

The primary data obtained in this research were primary data. Primary data is data collected directly by researchers regarding certain research problems encountered by using procedures that are most appropriate to the objectives and research problems (Ajayi, 2017). Primary data is collected to address the problem at hand in this study. The primary data were obtained from a semi-structured in-depth interview with an average of 45 minutes each. The interview was conducted between two people at a time in order to gain a comprehensive understanding of a particular topic (Esterberg, 2002).

3. RESULTS

The data of this study were analyzed based on Miles and Huberman's (1984) model. Data analysis is the process of collecting and arranging the data obtained systematically by classifying data into several categories, describing them in units, synthesizing and organizing them according to the pattern, and then selecting the important data to create an understandable conclusion.

The authors are cognizant of the constant possibility for diverging interpretation among researchers. Data sources triangulation was initially employed to preclude inconsistent coding results. One researcher independently collated response from two informants and subsequently any discrepancies are recorded. She went comparing the data with another response from other pair of informants. Another member of the research team also independently performed method triangulation analyzed coded responses with existing literature, that is according to the B-DAD framework and other supporting literature. It was expected that the complementary checking could reinforce the categorization of big data implementation dimensions.

The determination of big data implementation maturity in the banking sector was based on the big data analytic roadmap proposed by Coumaros et al. (2014). The roadmap essentially decomposes the extent and measurement of big data implementation capacity spanning four criteria: culture, capabilities and operating model, data, and technology. Assertion ranges from the entity's beginning point of its big data initiative (Beginner) until the entity has established a fully strategic and integrative model of its big data deployment (Expert).

Most sample banks (Bank B and Bank C) already have sufficient competency in analyzing big data as they are in the second phase of maturity. This indicates that most organizations have achieved the Proficient level. In terms of culture, these banks are seen to gain popular buy-in from diverse business processes. Analytics are used to comprehend issues, and options across the business are grounded on data. From the angle of capabilities and business model, the organization shows a well-defined talent sourcing process for analytics needs, supported by a planned budget for analytics training. In light of data, organizations have established a workable architecture and more defined pipeline from data upstream infrastructure (e.g., the extract, transform and load mechanics and data lake) towards the data

Table 2. Implementation of big data

No.	Institution	Maturity			Infrastructure
		1st Phase	2nd Phase	3rd Phase	
1.	Bank A	v	–	–	Hadoop
2.	Bank B	–	v	–	Hadoop
3.	Bank C	–	v	–	Hadoop

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downstream, encompassing data mart, analytics, business intelligence, and dashboarding facilities. From technology-wise, the use of some statistical and forecasting tools can also be observed easily under this proficient state.

While obtaining more pictures of Indonesia banks are warranted, the current observation is arguably able to resonate the common preliminary portrayal of business processes at the nation's banking operation. Putting it more concise, Bank B and Bank C are able to conduct analytics on their business process. Meanwhile, Bank A is only in the first phase of maturity. It indicates that Bank A is not capable yet of conducting analytics on its business process as it just initiated some training and workshops to improve the employee's knowledge and skills about big data analysis.

Furthermore, Table 2 denotes that all banks have already established their own infrastructure, and Hadoop appears to be the technology of choice. Actually, there are five kinds of big data infrastructures: Hadoop, NoSQL, In-Memory Database (IMDB), Massively Parallel Processing, and Cloud Computing (Venkatraman & Venkatraman, 2019). Despite the variety, all banks under study appear to select Hadoop due to its advantages. Hadoop is an open-source software framework with massive storage that can store data and run virtually limitless concurrent tasks through its applications. The bank intends to upgrade its banking services could adopt *Hadoop on Premise*. Informant 2 confirmed this, asserting that the bank has conducted a proof of concept with Cloudera.

According to Adrian et al. (2017), the readiness factors of big data implementation are considered successful in an organizational context if they could capitalize all five characteristics of big data encompassing of 5V. Also, the entity should be able to convert the data obtained into valuable information. However, the fact that Bank A and Bank B only have three out of five characteristics of big data showed that the implementation of big data in Indonesia has not been complete yet. Even when Bank C already features all the characteristics, the bank still struggles to generate the value previously expected from the data. It happens because big data implementation began recently on the three banks. Informant 5 underlined the importance of analyzing the data to eventually generate value from a wide variety of data repositories and dimensions such that it composes the baseline for competitive advent.

4. DISCUSSION

Having discussed the implementation progress of the sample big data projects, this section discusses how the implementation thereof is analyzed according to the four phases of the B-DAD framework. The Framework is potentially useful to provide a coherent and cohesive view of how data,

Table 3. Summary of big data implementation

No.	Implementation Plan	Decision-Making Plan	Source
1	Sentiment Analysis	• Monitor customer opinions • Identify customers to improve word of mouth • Discover customer feedbacks	Informant 1 Informant 2 Informant 4 Informant 5
2	Customer 360	• Conduct customer profiling • Observe how the customer reacts to a product • Detects turnover	Informant 2 Informant 4 Informant 1
3	Customer Segmentation	• Create a target marketing program • Create a loyalty program based on the usage of credit card • Optimize pricing strategy • Build a relationship with the customer	Informant 2 Informant 3 Informant 4 Informant 5
4	Next Best Offer	• Improve customer loyalty with the next best offer • Measure the tendency of a product • Combine products to increase revenue	Informant 2 Informant 5
5	Fraud Analytics	• Detect suspicious transactions	Informant 2 Informant 3 Informant 4 Informant 5

data architecture, analysis, and decisions are interconnected to support an entity's decision-making process.

Table 3 is based on a triangulation technique between semi-structured interviews and documentation. This table points out how big data implementation could support the decision-making process. Furthermore, the implementation of the B-DAD Framework is described on the following

4.1. Phase 1: Intelligence

Elgendy and Elragal (2016) state that intelligence is the first phase of the B-DAD Framework. It is crucial for banks to determine what kinds of data are needed and collected. To succeed, the banks should be able to identify and improve their competitive advantages. The key to a successful business is finding out how to outrank its competitors. This explains the reason why innovative and creative strategies are very important. However, being innovative and creative is not a trivial undertaking. The role of big data is in the digitization of business models and how big data initiatives affect functional decisions in organizations as a reference for formulating new strategies unique to organizations to existing industries (Mazzei & Noble, 2019).

Cappa et al. (2021) specify that to achieve variety, the number of types of information retrieved each application from multiple sources should be measured by moderating the negative effects of big data volumes. Variety is very important because it could improve the decision-making process. Nevertheless, Table 4 shows that Bank A and Bank C only collect data from an internal source. Moreover, the three banks only stored structured data instead of combining structured and unstructured data. Thus, it can be concluded that the banks are still trying to satisfy the third characteristic of big data, variety.

Banks should be mindful of customer's privacy, data policy, and data security in collecting the data. The risk of data leakage is one of the biggest concerns in implementing big data. As a result, banks should create a certain procedure and policy to assure the confidentiality of data.

4.2. Phase 2: Design

In the second phase, banks should determine the model that will be used in conducting big data analysis. Theoretically, as mentioned before, big data analysis can be done with customer analytics, risk analytics, social analysis, etc. (Ravi & Kamaruddin, 2017). However, the data stored by Bank A, Bank B, and Bank C are only structured data. It means that the models that can be utilized are also limited. Among all the three banks, Bank B is the only bank that has reached this phase. Bank B selected classification, clustering, and regression to analyze its big data. Meanwhile, Bank A and Bank C are still preparing themselves to begin this phase.

With respect to design, Informant 4 explained that analysis performed by the banking could be combined to generate a new type of information applicable for decision-makers. However, several aspects need to be standardized to realize the combination as each data has its own format and attributes.

4.3. Phase 3: Choice

In this phase, banks should select the most suitable solution based on the alternatives that have been made in the first phase. It is advised that the banks create visualization so that decision making can be done easily. Leo et al. (2019) stated that ideally, a bank could benefit from the model's most relevant ability. However, this step cannot be done in Bank A, Bank B, and Bank C because only a handful of comparable indicators can be used, as the implementation of big data has not been conducted thoroughly yet.

Big data will be a success factor if it is meaningful, relevant, and used to achieve organi-

Table 4. Source and type of data

No.	Institution	Source		Type	
		Internal	External	Structure	Unstructured
1	Bank A	v	X	v	X
2	Bank B	v	v	v	X
3	Bank C	v	X	v	X

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zational performance KPIs (Walls & Barnard, 2020). Accordingly, it is also necessary for the banks to measure the result of their activities with KPI. A good result of KPI might contribute to value creation. On the other hand, raw data only has little or even no influence on value creation. Thus, the raw data should be processed and analyzed so that it could be useful information that will improve the performance of a business.

4.4. Phase 4: Implementation

The last phase is to implement a selected solution and monitor the result. Based on previous research, it can be seen that research on big data implementation in the banking industry is very limited. Even if there is some research about this topic, the analysis is only conducted on the surface, and the data that were used are very limited.

Throughout the time, the companies in Indonesia only used technology to follow the trends without understanding the desire of their customers and the rationale behind it. For example, most banks in Indonesia give all of their customers the same credit card promotion, while only some of them are interested. This happens because the banks do not really understand their customer value.

To improve the content of their big data, banks could cooperate with the merchants that transacted with their customers. This cooperation will be beneficial for both parties because each of them could obtain some data that they do not have before. Also, both could utilize the big data for each of their purposes.

CONCLUSION

Big data infrastructure has been steadily introduced and integrated within the banking sector, the commonly regarded data-intensive operation, to enhance business processes and decision making. Big data exists as the volume of data generated surpasses the traditional database system's ability to process it. The study aims to provide a structural overview of big data implementation in the Indonesian banking industry using a unified view of the B-DAD Framework. Analysis from interviewing selected participants reveals that sentiment analysis, customer 360, and customer segmentation support rank the most used case of how big data is implemented and visioned, with the next best offer and fraud analytics receiving the lesser highlight. As the technology adoption maturity constantly develops, big data is expected to increasingly improve business processes by providing a variety of alternatives that can be used to solve the issues on banking services.

While many potentials offered by big data technology are clear and accessible, much work is to be done to integrate the technology into the core of Indonesia's banking strategic planning. Currently, two out of three studied banks are evidently still preparing their infrastructure and resources. Also, instead of meeting the overall characteristics of big data, banks are currently able to satisfy part of them. Thus, it can be concluded that the implementation of big data in the banking industry in Indonesia is still in the modest proficiency phase. Recognizing this state entails much more active experimental decisions on the part of banking chief information officers and other executives. Having a clear vision and support from top management is considered to be one of the ex-ante factors for the benefit of big data implementation.

In the future, big data is expected to play a bigger role in business due to the fact that the volume of data generated is becoming more and more massive. To prepare for the future, human resources should be equipped with the knowledge and skills to conduct big data analytics. Since the Indonesian banking industry has already started the implementation of big data, it means they are on the right track.

AUTHOR CONTRIBUTIONS

Conceptualization: Hamzah Ritchi.
Data curation: Gina Andriani, Reza Zulkarnaen.
Formal analysis: Hamzah Ritchi, Gina Andriani, Akmal Zaidaan.
Funding acquisition: Hamzah Ritchi, Reza Zulkarnaen.
Project Administration: Akmal Zaidaan.
Investigation: Hamzah Ritchi, Gina Andriani, Reza Zulkarnaen.
Methodology: Hamzah Ritchi, Gina Andriani.
Resources: Gina Andriani, Akmal Zaidaan.
Supervision: Hamzah Ritchi. Reza Zulkarnaen.
Validation: Hamzah Ritchi.
Visualization: Gina Andriani.
Writing – original draft: Gina Andriani.
Writing – reviewing & editing: Hamzah Ritchi, Akmal Zaidaan.

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