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Capability Development to Generate Business Value Through Customer-centric Analytics in the Banking Industry: A Systematic Review

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Abstract. Data is growing significantly, and banks are one of the ecosystems that contribute to data growth. Data governance is a challenge in banks due to the high level of confidentiality and the involvement of regulators in data management and technology implementation. Big data requires technology to manage it, while technology investment is a challenge, namely how technology investment to manage big data can contribute to generating value in business. There are two main points in this study: the first is about building capability, and the second is generating value. Through the literature review, it is known that there are challenges to optimizing the capability of data technology implementation and analytics business cases in the banking industry to create business value. The challenges to building capabilities as a basis for data-driven business are data characteristics, data processing, data accessibility, data literacy, and data technology. The challenge is determining how to improve data accessibility and data literacy. When the capability has been built, generating value can be done on top of that, namely by increasing revenue, reducing costs, and lowering risk. To do this, it is necessary to run business use case analytics whose results can be measured, which focus on personalization and recommendations, optimizing processes with automation and integration, and optimizing credit risk. The results of the literature review are described in a conceptual model of capability development to generate value, which is the basis for developing a business strategy that can increase business value. Customer-centric analytics should be implemented by embedding an analytics engine in bank applications such as mobile banking, internet banking, or customer relationship management (CRM) applications that will improve the user experience such as personalization and recommendation as the keys to improving customer solutions. The impact is to increase customer attachment to a bank's applications and products because customers not only carry out daily banking activities but also have embedded insights that help them in their decision-making. By implementing Explore Understand Action Engage (EUAE) for customer journey, customer-centric analytics provide customers with a comprehensive view of their bank account activity and control over their money management, improve customer engagement by providing insights and recommendation.

Keywords: Data-driven, big data, capability development, customer solution, bank.

1. Introduction

The exponential growth of data forces organizations to incorporate data into their decision-making processes. As one of the industries whose ecosystem contributes to the expansion of data, banks face difficulties in generating insight. A high level of data security is typically associated with a high level of data access challenges. This presents a challenge for the implementation of data technology to create business value, where taking control of our data is one of the best ways to ensure that we not only own data but also have the capability to process and utilize data to extract business value. Accessibility will be the guiding principle toward a data-driven culture. The procedure for data access will become more complicated as data security increases. How to prioritize security without impeding the efficacy of the data-driven culture process poses the challenge of adapting to the optimal strategy. Data-driven analytics (DDA) is strategic decision making based on data analysis and interpretation. The banking industry has become one of the largest ecosystems that leverage analytics on product trends, market dynamics, and customer behavior to create data-driven analytics, with many users actively participating in their activities (Maja & Letaba, 2022). How to adapt to the best approach by prioritizing security without impeding the effectiveness of the data driven culture process is a challenge. Regarding the privacy and security of customer data and/or personal information, the Financial Services Authority published Circular Letter No. 14/SEOJK.07/2014. The Financial Services Authority's regulations must be followed in terms of governance, policy, and regulation while using information technology in a bank. The European Union (EU) has recently implemented significant regulations (often known as GDPR) covering the collection, storage, and use of personal information; they went into effect in May 2018 and superseded the EU's 1995 Data Protection Directive (DPD) (Han et al., 2020).

Traditional platforms for data analytics have difficulty storing, managing, and interpreting data due to the exponential growth of data. The new area of big data analytics (BDA) employs distributed and decentralized processing to overcome these issues. The financial industry attempts to remain competitive by becoming data-driven, as the quantity of data in the globe has exploded in recent years. By analyzing vast quantities of financial data, businesses can develop their strategic plans, such as for risk management, crisis management, and growth management (Yıldırım et al., 2021a). Organizations utilize data to gain a deeper understanding of how their operations operate, the strategy they will adopt, and how to produce value. Big 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 (Wong & Wong, 2021). Despite the appeal of big data analytics as a game-changer for modifying how firms make choices and operate, research reveals that more than 80% of organizations have failed to successfully implement their big data strategies. In addition, the difficulty is determining how significant technological investments may generate business value.

Previous research proposed a data-driven technological roadmap for the future bank: Big data analysis to enable technological road mapping (Maja & Letaba, 2022). The study established nine hypotheses, each of which was tied to the proposed conceptual model, based on research and empirical evidence (Maja & Letaba, 2022). (1) The analysis of big data facilitates and directs expert knowledge; (2) the data mining process can be guided by expert knowledge; (3) big data analytics improve competitive intelligence by enhancing the precision and timeliness of data availability; and (4) competitive intelligence relies on advanced analytics to deduce proactive signals and actions suitable for sustaining competitive advantage. (5) The incorporation of big data analytic capabilities enables the production of many scenarios with diverse data to investigate, plan, and manage uncertainties and opportunities within the roadmap's tiers. (6) The larger the use of big data analytics and competitive intelligence, the greater the likelihood of visualizing interlayer dependencies and impacts. (7) Real-time data feeds lead to proactive decision-making and the development of pertinent strategy options suited to each tier's patterns and trends. (8) The technology road plan of the bank of the future will be an iterative process that largely relies on internal and external data to align strategic goals with the shifting environment. (9) The data provided by a bank of the future can be fed into competitive intelligence, so enhancing its utility. As organizations embrace machines and data-driven decision-making, it is recommended that they consistently harness expert knowledge to create judgments that are cost-effective for the firm, promote positive societal impact, and make ethical use of emerging technologies (Maja & Letaba, 2022). From this conceptual model, it is sufficient to provide a basis for how big data analytics is able to contribute to business value through competitive intelligence. Through this Literature review, the foundation that has been built will be further developed towards customer centric analytics that will increase revenue, reduce costs and lower risk. In addition to optimizing the implementation of data technology, the main driver within the bank is technology enabler, increasing accessibility and increasing data literacy, why is this important because natural banks with high levels of confidential data will be difficult to access. Understanding data is very challenging towards customer centric analytics where many business use case analytics will be built that will create value. The fundamental purpose of the bank is to acquire new customers and keep existing ones by providing differentiated products. The development of data that helps with the delivery of decision-making insights can help banks acquire new customers and maintain existing ones. This study refines the conceptual model of capability development to generate business value through customer-centric analytics in the banking industry once the research questions have been answered. The primary focus is on how data-driven organizations may become analytics-driven by selling analytics as a product via the customer solution. Analyzing the customer journey with and without an analytics-driven strategy

2. Theoretical Foundation

2.1. Technology in the Banking Industry

As an ecosystem that generates vast amounts of data, the management of big data presents challenges to banks. BDA refers to big data and analytics, 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 and manipulating diverse data to generate insight (Yıldırım et al., 2021b). Key characteristics of big data include its volume, velocity, variety, veracity, and value (Fosso Wamba et al., 2015). There are six main parts to the BDA architecture, and they are as follows: data production, data collecting, data storage, advanced data analytics, data visualization, and decision-making for value creation (Saggi & Jain, 2018). Investments in IT by themselves have not been proved to increase a company's worth, according to previous studies. Instead, businesses should focus on creating talents that are both distinctive and difficult to replicate (Mikalef et al., 2017). Immediate effects can be felt at any step in the big data deployment process, not only the acquisition of big data technologies. In actuality, there are a lot of obstacles to get beyond. The transformation into a data-driven company, where insights from data analysis are used to inform all decisions, is challenging and riddled with pitfalls. The purpose of the literature review is to identify the variables and methods that make DDA difficult, so that, once known, they may be taken into account in efforts to foresee and address any issues.

2.2. Advanced Analytics Techniques

Technological progress has increased the demand for swift, well-informed business judgments. Data-driven methods transform raw data into useful information, insights, and expertise. Knowledge of the past, the ability to predict the future, the ability to evaluate behavior, and an appreciation of context are all components of wisdom. Traditional databases can no longer keep up with the explosion of data. By generating numerous data points and opening up novel avenues for decision-making, BDA is revolutionizing the business world (Saggi & Jain, 2018). By the same token, BDA can be seen as a strategic function that, when executed effectively, can benefit a company (van Rijmenam et al., 2019a). Artificial intelligence (AI), machine learning (ML), and deep learning (DL) are just some of the methods used in BDA to sift through mountains of data in search of patterns and insights. Estimation, association, classification, and clustering are only few of the methods that can be used to carry out the analytics. Logistic regression (LR), Naive Bayes (NB), K-Nearest Neighbor (k-NN), neural network (NN), decision tree (DT), support vector machine (SVM), and random forest (RF) are all utilized for analytics (Wahono, 2015).

3. Methodology

3.1. Review Method

A method known as a systematic literature review (SLR), which is a process for locating, evaluating, and interpreting all relevant material on a particular research question, topic, or phenomenon of interest, was utilized in the execution of this study (Kitchenham, 2021). In the context of this strategy, a protocol for review must be determined. The validation procedures are outlined in detail in the protocol for review. Concerning research topics, inclusion and exclusion criteria, search methodology, study selection, data extraction, data synthesis, and dissemination strategies, choices must be made. If the procedure is selected beforehand, the possibility of bias in the validation process can be reduced. The SLR method is depicted in Figure 1, which follows.

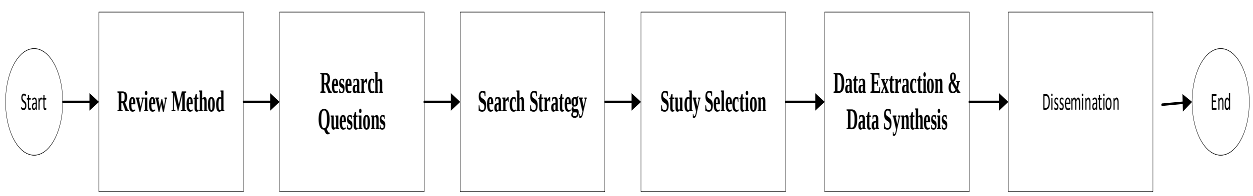

Fig. 1. The SLR Procedure

3.2. Research Questions

The Research questions (RQ) have ensured that the focus is preserved. They were constructed with population, intervention, comparison, results, and context in mind (PICOC) (Kitchenham, 2021). Population associated with certain big data analytic categories. Intervention involving a method, instrument, or procedure that solves a particular topic of big data analytics issues and approaches. In this study, the comparison is not provided. The results should relate to the significance of big data analytics capability build and value creation in the context of banking industry. This SLR addresses the research question, outlined in Table 1 below.

Table 1. Research Questions

No	Research Question
RQ1	What are the challenges to building the capability of data technology implementation in the banking industry?
RQ2	What are the business cases for analytics in the banking industry to create business value?

3.3. Search Strategy

The search process consists of selecting a digital library, defining a search string, executing the search string, refining the search string, and retrieving the initial list of primary studies matching the search string from the digital library. The listing of electronic databases:

- ScienceDirect (sciencedirect.com)
- Scopus (scopus.com)
- ACM Digital Library (dl.acm.org)
- IEEE Explore (ieeexplore.ieee.org)
- Springer Link (springerlink.com)

This is how the search string was constructed: The first step is to determine the PICOC search terms to use. The second stage is generating search terms by combining research questions with relevant titles, abstracts, keywords, and synonyms. A complex search string can be created by combining search words with Boolean ANDs and ORs, which brings us to our third point. When a search term was entered into either of the databases, corresponding articles were returned from the respective libraries. Next, you'll want to read the titles of the articles; if these don't give you a good idea of what the articles are about, then you can go on to the abstracts. Downloading an article for additional research is only done if the title and abstract are a good match for the research topics. Candidate studies are the total number of paper downloads. Each candidate's study results are studied carefully in order to find solutions to research issues. The purpose of these articles is to act as "selected studies" in the field of study (Kitchenham, 2021). The search criteria:

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

3.4. Study Selection

Using the criteria for inclusion and exclusion, the primary studies were chosen. Table 2 illustrates these circumstances.

Table 2. Inclusion and Exclusion Criteria

Inclusion Criteria	• Only works published in 2018 or later are eligible for consideration. • Only research papers. • When multiple publications of the same study exist, only the most recent and thorough will be included.
Exclusion Criteria	• Research not written in English

On the final list of chosen primary studies, there were 31 publications. Extracted from the selected primary study are the data, information, and insights that contribute to answering the research questions. Figure 2 illustrates the outcomes of the literature review.

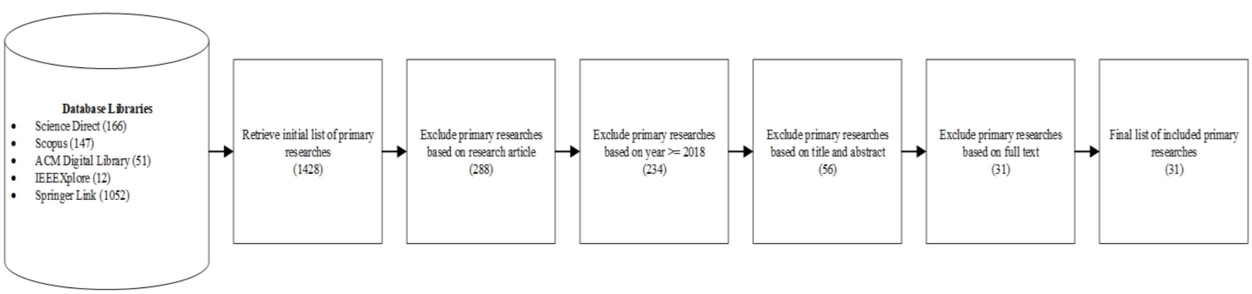

Fig. 2. Literature Review Outcomes

3.5. Data Extraction and Data Synthesis

Data are extracted from the primary studies that contribute to answering the research questions addressed by this review. The goal of data synthesis is to compile evidence from selected studies to address research questions. A single piece of evidence may have limited persuasion, but multiple pieces can strengthen an argument.

4. Results

4.1. The Challenges to Building the Capability of Data Technology Implementation in the Banking Industry

Without technology, analytics centered on the customer would be impossible. The foundation of analytics is data. In the introduction, we discussed the significance of data-driven because it will affect the way in which organizations utilize analytics. This is because data management and information extraction are required in order to gain insight. A combination of well-maintained data and a sophisticated analytics method can provide insight. It is not as simple as purchasing technology and installing it; a lot of considerations must be taken into account in order to maximize everything. Through a review of the literature guided by the research question "What are the Challenges to Developing the Capability of Data Technology Implementation in the Banking Industry?" since the capability of a platform or technology is the cornerstone upon which a commercial use case is constructed, capability development is essential. The literature review yielded the following correlational analysis shown in Table 3.

Table 3. Category of Capability Development

No	Selected Studies	Category of Capability Development
1	AI in operations management: applications, challenges and opportunities (Dogru & Keskin, 2020)	Data Processing
2	Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis (Goodell et al., 2021)	Data Characteristics, Data Processing, Data Literacy
3	Artificial intelligence for anti-money laundering: a review and extension (Han et al., 2020)	Data Characteristics, Data Processing, Data Literacy
4	Avoid being the Turkey: How big data analytics changes the game of strategy in times of ambiguity and uncertainty (van Rijmenam et al., 2019b)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
5	Big data analytics for default prediction using graph theory (Yıldırım et al., 2021b)	Data Characteristics, Data Processing, Data Literacy
6	Big data analytics for supply chain relationship in banking (Hung et al., 2020)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
7	Big data and firm marketing performance: Findings from knowledge-based view (Gupta et al., 2021a)	Data Technology
8	Big data quality prediction informed by banking regulation (Wong & Wong, 2021)	Data Characteristics, Data Processing, Data Literacy
9	Big-data driven approaches in materials science for real-time detection and prevention of fraud (Sirisha Madhuri et al., 2021)	Data Characteristics, Data Processing, Data Literacy
10	Building dynamic service analytics capabilities for the digital marketplace (Akter et al., 2020)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology

No	Selected Studies	Category of Capability Development
11	Combating emerging financial risks in the big data era: A perspective review (Cheng et al., 2021)	Data Processing
12	Credit Scoring Model based on Weighted Voting and Cluster based Feature Selection (Tripathi et al., 2018)	Data Characteristics, Data Processing, Data Literacy
13	Data science and AI in FinTech: an overview (Cao et al., 2021)	Data Characteristics, Data Processing, Data Literacy
14	Data science: a game changer for science and innovation (Grossi et al., 2021)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
15	DGHNL: A new deep genetic hierarchical network of learners for prediction of credit scoring (Pławiak et al., 2020)	Data Characteristics, Data Processing, Data Literacy
16	Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities (Mikalef & Krogstie, 2020)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
17	Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities (Mikalef et al., 2020b)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
18	History, Evolution and Future of Big Data and Analytics: A Bibliometric Analysis of Its Relationship to Performance in Organizations (Batistič & van der Laken, 2019)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
19	How do data scientists and managers influence machine learning value creation? (Ferreira et al., 2021)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
20	Implementing big data strategies: A managerial perspective (Tabesh et al., 2019)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
21	Influence of new-age technologies on marketing: A research agenda (Kumar et al., 2021)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
22	Innovating through digital revolution: The role of soft skills and Big Data in increasing firm performance (Caputo et al., 2019)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
23	Operational research and artificial intelligence methods in banking (Doumpos et al., 2022)	Data Characteristics, Data Processing, Data Literacy
24	Opportunities and Risks for Data Science in Organizations: Banking, Finance, and Policy - Special Session Overview (Azzini et al., 2018)	Data Characteristics, Data Processing, Data Literacy
25	Security Evaluation of a Banking Fraud Analysis System (Carminati et al., 2018)	Data Processing, Data Accessibility, Data Literacy, Data Technology

No	Selected Studies	Category of Capability Development
26	The future of data-driven relationship innovation in the microfinance industry (Hani et al., 2022)	Data Characteristics, Data Processing, Data Literacy
27	The role of compatibility in predicting business intelligence and analytics use intentions (Jakli & Grublje, 2018)	Data Technology
28	Towards a data-driven technology roadmap for the bank of the future: Exploring big data analytics to support technology roadmapping (Maja & Letaba, 2022)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
29	Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics (Akter et al., 2022)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
30	Unlocking the drivers of big data analytics value in firms (Côrte-Real et al., 2019)	Data Characteristics, Data Processing, Data Accessibility, Data Literacy, Data Technology
31	Zhima Credit Score in Default Prediction for Personal Loans (Wang et al., 2022)	Data Characteristics, Data Processing, Data Literacy

Figure 3 is the distribution of selected studies, most studies discuss data characteristics, data processing, data accessibility, data literacy and data technology as the keys that underlie the development of capability development that will support running analytics business cases.

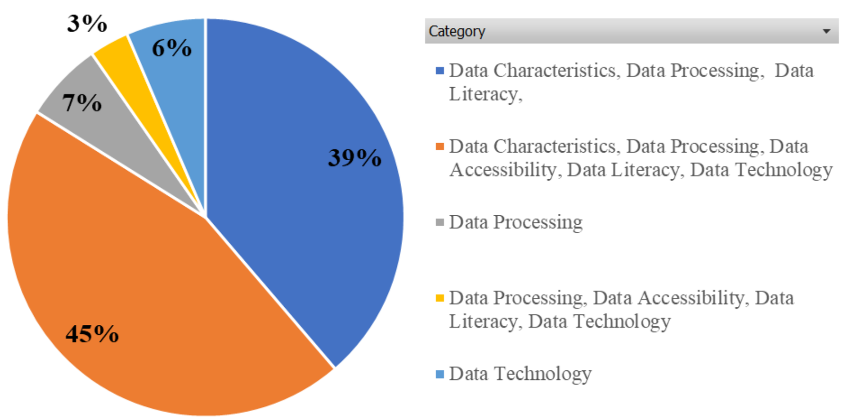

Fig. 3. Total Distribution by Category of Capability Development

4.2. The Business Cases for Analytics in the Banking Industry to Create Business Value

Several advantages and possibilities will become available to businesses and individuals as a result of the advent of advanced analytics technology (Dogru & Keskin, 2020). Advanced analytics is a broad term that describes the use of a variety of analytical techniques to build a model that can be used to evaluate how well it works. Analytics business cases in the banking industry to provide business value is shown in Table 4. The banking industry uses analytics business cases as a use case to produce insights that have the potential to produce business value.

Table 4. Value Creation Categories

No	Selected Studies	Value Creation Categories
1	AI in operations management: applications, challenges and opportunities	Insight Generator
2	Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis	Optimize Credit Risk
3	Artificial intelligence for anti-money laundering: a review and extension	Optimize Credit Risk
4	Avoid being the Turkey: How big data analytics changes the game of strategy in times of ambiguity and uncertainty	Insight Generator
5	Big data analytics for default prediction using graph theory	Insight Generator
6	Big data analytics for supply chain relationship in banking	Insight Generator
7	Big data and firm marketing performance: Findings from knowledge-based view	Personalization & Recommendation
8	Big data quality prediction informed by banking regulation	Insight Generator
9	Big-data driven approaches in materials science for real-time detection and prevention of fraud	Optimize Credit Risk
10	Building dynamic service analytics capabilities for the digital marketplace	Personalization & Recommendation
11	Combating emerging financial risks in the big data era: A perspective review	Optimize Credit Risk
12	Credit Scoring Model based on Weighted Voting and Cluster based Feature Selection	Optimize Credit Risk
13	Data science and AI in FinTech: an overview	Insight Generator
14	Data science: a game changer for science and innovation	Insight Generator
15	DGHNL: A new deep genetic hierarchical network of learners for prediction of credit scoring	Optimize Credit Risk
16	Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities	Insight Generator
17	Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities	Insight Generator
18	History, Evolution and Future of Big Data and Analytics: A Bibliometric Analysis of	Insight Generator

No	Selected Studies	Value Creation Categories
	Its Relationship to Performance in Organizations	
19	How do data scientists and managers influence machine learning value creation?	Insight Generator
20	Implementing big data strategies: A managerial perspective	Insight Generator
21	Influence of new-age technologies on marketing: A research agenda	Personalization & Recommendation
22	Innovating through digital revolution: The role of soft skills and Big Data in increasing firm performance	Insight Generator
23	Operational research and artificial intelligence methods in banking	Optimize Credit Risk
24	Opportunities and Risks for Data Science in Organizations: Banking, Finance, and Policy - Special Session Overview	Insight Generator
25	Security Evaluation of a Banking Fraud Analysis System	Optimize Credit Risk
26	The future of data-driven relationship innovation in the microfinance industry	Insight Generator
27	The role of compatibility in predicting business intelligence and analytics use intentions	Insight Generator
28	Towards a data-driven technology roadmap for the bank of the future: Exploring big data analytics to support technology roadmapping	Insight Generator
29	Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics	Insight Generator
30	Unlocking the drivers of big data analytics value in firms	Insight Generator
31	Zhima Credit Score in Default Prediction for Personal Loans	Optimize Credit Risk

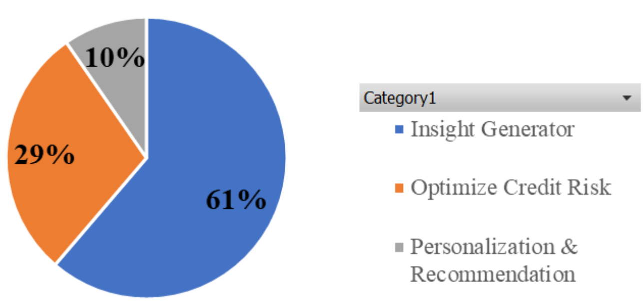

Fig. 4: Total Distribution of Value Creation Categories

Most business use case analytics in specific banks are for insight generators, optimize credit risk, and personalization and recommendations. Figure 4 shows the distribution of the value creation categories.

5. Discussion

5.1. The Challenges to Building the Capability of Data Technology Implementation in the Banking Industry

A data-driven business is one that bases strategic decisions on data. The importance of a process's connection to other processes will be examined in this study, along with the challenges that influence the success of data-driven procedures. Integrating BDA into the decision-making process remains a difficulty despite the fact that the use of big data tends to provide value to organizations across the value chain. (Akter et al., 2019). The discussion is as follows:

Data accessibility : Organizations acquire a vast quantity of data from the minute they are founded, and some of it even precedes their foundation. This data is kept in thousands of folders, formats, and data kinds on physical or cloud-based servers. Although the data is available, it may not necessarily be usable within the organization. Data accessibility comes into play here. It is the extent to which your personnel are able to utilize data. It is a procedure that transforms the provided data into a usable format, regardless of the employee's experience or knowledge. However, due to the fact that data exists in various forms and data types, it can be extremely difficult to make it completely accessible, as it is of little use in its current state. The degree to which individuals within a company base their choices on data-driven insights (Mikalef et al., 2020a). Data-to-insight, decision-to-insight, and decision-to-execution cycles are successful when a data-driven culture with an emphasis on selecting actions based on evidence is developed and maintained (Mikalef et al., 2020a). In addition, it is the responsibility of managers to guarantee that all organizational levels make data-driven decisions and that data ownership, usage, protection, privacy, security, accountability, cybercrime, and intellectual property rights are managed (Grossi et al., 2021). When it comes to protecting the privacy of consumer information, the bank has its own issues. Moreover, the Indonesian regulator oversees the procedures for governance and banking transactions. If a bank decides to establish a cloud-based application, customer data cannot be stored in the cloud, let alone in a place outside of Indonesia. Governance is required to assure the completeness, correctness, timeliness, and adaptability of data aggregation administration.

Data literacy: Everyone must possess the ability to iterate over data in order to process information. The importance of data to the success of a business, however, has led to an increase in the number of firms requiring employees to possess this expertise. Here is a list of data literacy abilities that workers in the digital age are believed to need to possess: determine the type of data that is appropriate for various specific purposes, interpret data visually using media such as graphs and charts, pattern of critical thinking about the information generated by the data, capacity to analyze data, understanding of the methods and tools that can facilitate the process of data analysis, and data storytelling. Define a structured team with a facilitator position to facilitate good IT-business collaboration (Côrte-Real et al., 2019). Understand business requirements for big data functionality. Personnel having BDA-related expertise or capabilities, The ability of expertise to make business decisions based on insights enabled by BDA. Globally, organizations are attempting to organize, process, and harness the value of the huge volumes of data they generate and transform them into insightful 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 unearth new insights in data. It has become vitally important to recruit highly skilled data scientists.

Data characteristic: Structured, semi-structured, and unstructured data with volume, velocity, diversity, velocity, and value (Mikalef et al., 2019). Log files and data originating from all software programs, hardware, and network devices provide data sources that are characterized by great diversity, high volume, and high velocity because they are continuously generated in diverse formats and in enormous numbers by all the systems involved (Elia et al., 2020). Handling data complexities such as high-dimensional, high-order, sparse, incomplete, hierarchical, cross-sectional, longrange, asymmetric, skewed, evolving, largescale, imbalanced, and streaming data, noise, missing values, feature extraction and engineering, dimension reduction, sampling and resampling methods, and visualization are just a few of the numerous challenges encountered in data manipulation (Cao et al., 2021). Using modern technologies, firms may automate the process of obtaining structured and unstructured data from many sources, cleaning the data, recognizing patterns to identify meaningful and applicable data, and connecting the numerous databases (Kumar et al., 2021). Knowledge has been derived from big data for the benefit of enterprises. However, the value is contingent upon the accuracy of the data (Wong & Wong, 2021). Data quality (DQ) refers to an organization's data's dependability, quantity, and timeliness. When dealing with data-intensive applications, such as machine learning, it is essential to have high-quality data, hence increasing the likelihood that ML projects will be beneficial. In addition, prior research indicates that high-quality data should be naturally precise and contextually relevant to the task at hand, whereas poor data quality can have significant repercussions for businesses (Ferreira et al., 2021).

Data processing: Before reaching a final decision, managers collect data, design many alternative tactics, and assess these methods and their ramifications with great care (Mikalef et al., 2019). Acquiring the data, storing it, and doing data cleansing and transformation in order to prepare it for integration and display are components of data management. Utilizing strategies and tools to model data and prepare it for BDA insight constitutes analytics (Maja & Letaba, 2022). BDA is thus a subtype of the process of gaining insights from big data. This huge amount of data and information is processed and evaluated by predictive algorithms based on time series that are capable of learning and forecasting any possible problems, bottlenecks, or network outages (Elia et al., 2020). Data extraction and collecting, data cleansing, data aggregation, data integration, data analysis, insight development, and insight interpretation are among its activities. Data analytics is a process that employs a variety of strategies, which will be examined in data-driven analytics techniques.

Data technology: Integration of data from several sources is made feasible by technologies such as data integration and analytics platforms that facilitate access to data from multiple sources, give load capabilities, data mining, and visualization (Maja & Letaba, 2022). If the information technology infrastructure and data architecture are incompatible, it may be difficult to store, analyze, and derive relevant information from structured, semi-structured, and unstructured data collections (Akter et al., 2022). Data visualization offers stakeholders effective methods for visualising, interpreting, and analyzing data patterns, anomalies, and trends. Visualization tools are crucial because they enable data visualization capabilities like as maps, dashboards, interactive drill-down for further analysis, no-code data searches, and meta-data management (Maja & Letaba, 2022). According to this report, there is a considerable association between investments in big data and revenue growth (Caputo et al., 2019). The installed big data application allows for the storage, administration, and real-time analysis of all network and information system-related data and information (Elia et al., 2020).

5.2. The Business Cases for Analytics in the Banking Industry to Create Business Value

Personalization & Recommendation: It is comprised of several technologies and summaries of inferred facts that illustrate the current and historical state of affairs. Standard reports, ad hoc reports, dashboards, querying, and drill-downs are a few examples of descriptive analytics. It involves examining the past to determine what is occurring in the present. "What is happening?" Descriptive analytics technologies facilitate the discovery of hidden and potentially important business process data (Tabesh et al., 2019).

Descriptive analyses rely on methods that attempt to convert unstructured customer data into meaningful information and facilitate decision-making processes (Gupta et al., 2021b). Included in customer profiling are the customers' demographics, behaviors, geographies, and interests. Existing customers are segmented in order for the bank to gain a deeper understanding of the consumer. For instance, the recommendation algorithm will instantly recognize that a bank customer is traveling abroad and recommend that they acquire travel insurance based on the transaction data. Even financial institutions can cross-sell and up-sell their products.

Optimize Credit Risk: Predictive models enable decision makers to predict estimates of variables of interest using existing data (Tabesh et al., 2019). By optimizing procedures and enhancing decision-making, predictive analytics enables firms to capture opportunities (van Rijmenam et al., 2019a). Customer acquisition and retention are fundamental to the success of the bank. Banks are willing to invest heavily in client acquisition via channel advertising, and they are also eager to develop novel customer retention programs. If the loan rate is high, banks will be thrilled, but nonperforming loans should not be exorbitant. Risk management involves approaches for predicting credit default and financial fraud.

In this literature study, what is novel is a conceptual model of capability development to generate business value through customer-centric analytics in the banking industry depicted in Figure 5. The higher the value that can be generated, as illustrated by the downward arrow, the stronger the built capability. Capability is built through technological enablers, increasing accessibility, and increasing data literacy by solving challenges such as data characteristics, data processing, data accessibility, data literacy, and data technology. Data on the value creation analytics use case side is a generator that is used to increase revenue, reduce costs, and lower risk.

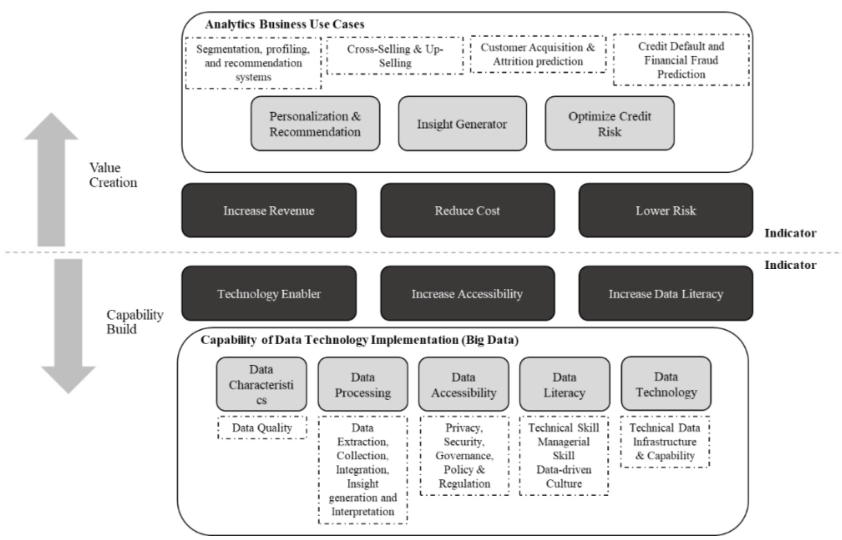

Fig. 5: A Conceptual Model of Capability Development to Generate Value

In relation to customer-centric analytics, banks need to make updates in their customer journey. Traditional banks have developed digital channels to enable customers to conduct banking activities from anywhere and at any time, including via mobile applications. Banks also develop digital products, which are bank products that may be accessed via digital channels. In general, Table 5 depicts the traditional customer journey.

Table 5. Traditional Customer Journey

Step	Journey	Descriptions
1	Acquire	The salesperson gave the customer the option of opening an account or starting it themselves.
2	Onboard	Customer signed up, and the journey can begin.
3	Active	What customers do with their banks.
4	Retain & Growth	Customers get information about new products from tele sales, banners, or emails (whether its relevant or not)

In implementing customer-centric analytics, it would be especially advantageous for banks to be optimized through digital channels because they have digital product. The journey process is shown in Table 6 for analytics as a product for customer solutions.

Table 6. Customer-centric Analytics for Customer Solution Journey

Step	Journey	Descriptions	Analytics Support
1	Explore	Customers learn what they may get by providing their personal information and indicating their preferences.	Customer segmentation & profiling
2	Understand	Customer service is enhanced by obtaining a personalized offer and insight based on their present activities and requirements.	Personalized insight and recommendation
3	Action	Customer Act to broaden their activities across their whole journey, including everyday transactions, loans, and investments.	Cross-Selling, Up-Selling
4	Engage	Customer engages as primary operating bank account	Digital engagement

Impact of customer-centric analytics for customer solution journey, providing individualized insight to assist banks in enhancing customer engagement, digital activity, active transaction, and product holding. Provide customers with a unique and analytical view of their bank account activity, ultimately granting them greater control over their money management. Enhance customer engagement by delivering relevant insights and recommendations. Provide products and services that anticipate and meet the demands of customers. By combining big data analytics capability development to create value with customer-centric analytics for customer solution journeys, a conceptual model of capability development to generate business value through customer-centric analytics in the banking industry is created, as shown in Figure 6. With support from the analytics engine, customer touchpoints such as mobile apps can provide insight so that customers don't just make transfers, payments, or purchases; they can even explore their profile to be able to understand themselves, and then they can make decisions that will provide value for them. The final impact is that customer engagement with products or applications owned by banks will be higher because there is more value when they use them. The stronger the customer's impression of utility, the greater their satisfaction and loyalty (Shin, 2022).

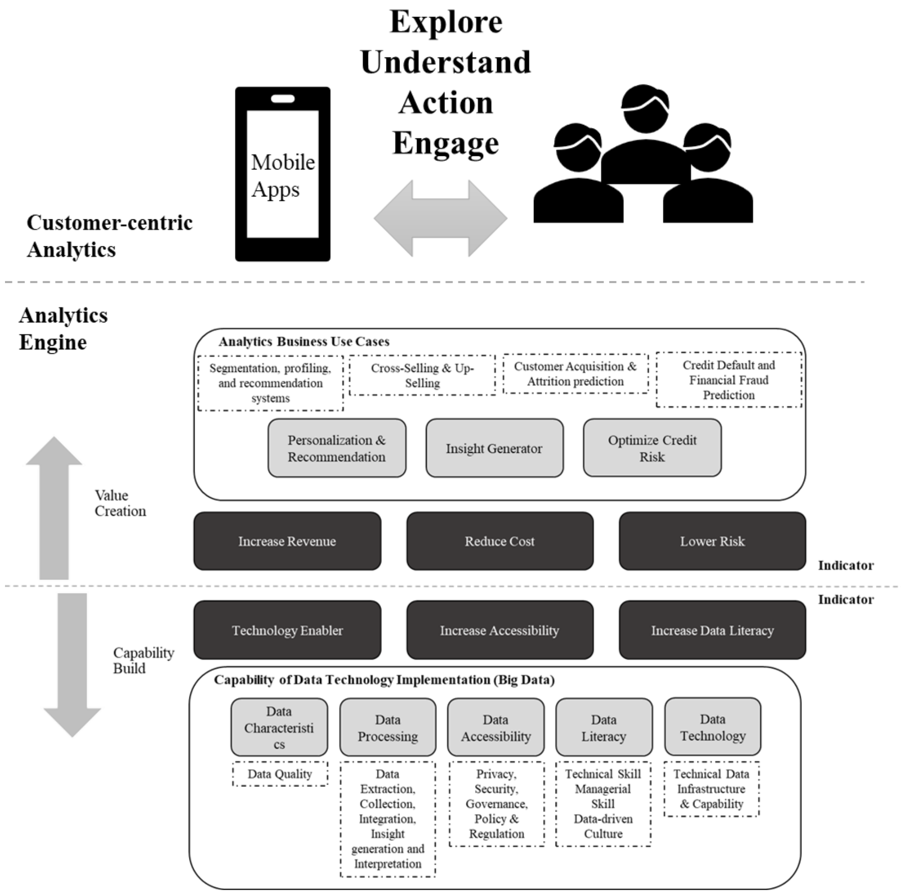

Fig. 6: A Conceptual Model of Capability Development to Generate Value through Customer-centric Analytics

6. Conclusion and Limitation

Significant data growth is occurring, and banks are one of the ecosystems that contribute to this expansion. Due to the high level of confidentiality and the engagement of regulators in data management and technology deployment, data governance is a difficulty for banks. Big data requires technology to manage it, but technology investment is a challenge in and of itself, namely how technology investment to manage big data may help to generating business value. According to the literature review, there are challenges to enhancing the potential of data technology implementation and analytics business cases to provide business value in the banking industry. Data characteristics, data processing, data accessibility, data literacy, and data technology are challenges to creating capabilities as a foundation for data-driven company. In addition, indicators that are very important to have in increasing the usability of capabilities that have been built are increasing data accessibility, increasing data literacy and technology enablers.

Once the capability has been established, value can be generated through increasing income, reducing expenses, and decreasing risk, the way to do this is to build a customer-centric analytics business case. What is common in banks are segmentation, profiling, and recommendation systems; cross-selling and up-selling techniques; customer acquisition and attrition prediction techniques; and credit default and financial fraud prediction techniques. To achieve this, it is required to conduct business use case analytics with measurable outcomes, focusing on personalization and suggestions, insight generating, and credit risk optimization. The results of the literature research are summarized in a conceptual model of capability development to generate value, which serves as the foundation for the development of a business strategy that can enhance corporate value. Customer-centric analytics should be implemented by embedding an analytics engine in bank applications such as mobile banking, internet banking, or customer relationship management (CRM) applications that enhance the user experience through personalization and recommendation as the keys to enhancing customer solutions. The result is an increase in customer attachment to a bank's applications and products, since clients are not only able to do everyday banking transactions, but also have embedded insights that aid in their decision-making. By implementing Explore Understand Action Engage (EUAE) for the customer journey, customer-centric analytics provide customers with a comprehensive view of their bank account activity and control over their money management, thereby enhancing customer engagement through the provision of insights and recommendations.

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.

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