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Analysis of BRIsat Investment Success from Financial and Nonfinancial Perspectives

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ABSTRACT

Investment in information technology within the banking sector requires not only financial viability but also public acceptance, particularly for state-owned enterprises (SOEs) that carry both commercial and social mandates. This study aims to evaluate the success of PT Bank Rakyat Indonesia (Persero) Tbk.'s BRIsat satellite investment from both financial and nonfinancial perspectives. A Cost–Benefit Analysis (CBA) was employed to assess financial feasibility using BRI's publicly available financial statements from 2014 to 2024, while sentiment analysis using the Naive Bayes algorithm was conducted to examine public perception based on social media data from platform X covering the period 2016–2024. The financial analysis indicates that the BRIsat investment is financially feasible, with a Return on Investment (ROI) of 2.58%, a Payback Period of 6.2 years, a positive Net Present Value (NPV) of IDR 166,161,960, and a Benefit Cost Ratio (BCR) of 184.9, suggesting that every IDR 1 invested generates IDR 184.9 in economic benefits. From the nonfinancial perspective, sentiment analysis of 10,066 valid tweets reveals that 55.90% of public sentiment is negative (5,627 tweets), while 44.10% is positive (4,439 tweets), with the Naive Bayes model achieving an accuracy of 96.76%. Positive sentiment is primarily associated with keywords such as "successful," "fast," and "service," reflecting appreciation for BRIsat as a strategic innovation, whereas negative sentiment is dominated by terms such as "error," "failed," and "disruption," indicating persistent technical issues in digital banking services. These findings highlight a clear contradiction between the strong financial performance of the BRIsat investment and the predominantly negative public perception of service quality. The study implies that the success of large-scale technology investments in SOEs cannot be assessed solely through financial metrics, but must be accompanied by continuous improvements in operational reliability and digital service quality to ensure sustainable value creation and public trust.

I. INTRODUCTION

The rapid development of digital technology has fundamentally transformed economic activities and public service delivery, particularly within the financial sector. In Indonesia, increasing internet penetration rising from approximately 64.8% in 2018 to nearly 79.5% in 2024 reflects not only improved digital accessibility but also the expansion of national information and communication technology (ICT) infrastructure [1]. This digital transformation has significantly reshaped the banking industry, enabling electronic transactions such as payments, fund transfers, and account monitoring through internet-based platforms [2].

Despite these advancements, digital inequality remains a persistent challenge, especially in remote, frontier, and outermost (3T) regions where terrestrial communication infrastructure is limited [3]. For banks operating with nationwide mandates, such inequality poses a strategic risk to service continuity and financial inclusion. As a response to these structural constraints, PT Bank Rakyat Indonesia (Persero) Tbk. (BRI) initiated a large-scale technology investment through the development of BRIsat, a dedicated communication satellite launched in 2016. This investment, valued at approximately USD 217 million, positioned BRI as the first commercial bank globally to fully own and operate a satellite infrastructure [4].

Besides requiring substantial cost, this decision is highly strategic considering that Bank BRI, as part of a State-Owned Enterprise (BUMN), has a dual mandate: business and social responsibility [5]. Regulatory changes concerning BUMNs, particularly the enactment of Law No. 1 of 2025 on February 4, 2025, further solidify BRI's role. This law governs more transparent and accountable BUMN management while encouraging public participation in enhancing Micro, Small, Medium Enterprises and Cooperatives (UMKMK) as the backbone of the Indonesian economy. This change is an update from Law No. 19 of 2003, aiming to focus more on increasing the effectiveness and competitiveness of BUMNs, as well as fulfilling legal needs and public participation [6]. Therefore, it is essential to analyze the BRIsat investment not only from a financial perspective but also from a nonfinancial one, considering BRI's dual role as a BUMN.

From a theoretical perspective, investment success has been widely defined as the extent to which an investment achieves its intended objectives while generating value that exceeds its associated costs [7], [8]. In financial terms, investment success is commonly measured using quantitative indicators such as Return on Investment (ROI), Net Present Value (NPV), Payback Period (PP), and Benefit–Cost Ratio (BCR), which collectively assess profitability, time efficiency, and economic feasibility [9]. However, contemporary investment theory increasingly recognizes that financial performance alone is insufficient, particularly for public-sector or hybrid organizations [10]. Nonfinancial dimensions such as stakeholder satisfaction, service quality, and societal impact are now considered integral components of investment success [11].

In the context of information technology investments, prior studies demonstrate that combining financial evaluation with nonfinancial assessment provides a more comprehensive understanding of investment outcomes [12]. Nevertheless, existing empirical research on BRIsat remains limited. Previous studies have primarily focused on short-term financial ratios before and after the satellite's launch, often reporting mixed or declining profitability indicators without fully accounting for investment costs, long-term benefits, or broader stakeholder impacts [13], [14]. Moreover, these studies do not incorporate public perception analysis, despite the importance of societal acceptance for SOEs operating under public scrutiny.

To address this gap, the present study conceptualizes investment success as a multidimensional construct, encompassing both financial feasibility and nonfinancial public perception. Financial success is evaluated through Cost–Benefit Analysis (CBA), which integrates ROI, NPV, PP, and BCR to assess whether the economic benefits of BRIsat outweigh its substantial investment costs [15]. Nonfinancial success is examined through sentiment analysis of social media data, capturing public responses to BRI's digital services as an indirect indicator of perceived service effectiveness and technological reliability.

Sentiment analysis can be implemented using various machine learning approaches, including Naïve Bayes, Support Vector Machines (SVM), and more recent transformer-based models such as BERT. Prior comparative studies suggest that while transformer-based models generally achieve higher accuracy in complex linguistic contexts, they require extensive computational resources and large annotated datasets, which may not always be feasible for domain-specific or longitudinal analyses [16]. SVM has demonstrated strong performance in high-dimensional text classification tasks but often involves higher computational complexity and parameter tuning [17]. In contrast, Naïve Bayes remains widely adopted due to its computational efficiency, robustness with limited training data, and competitive accuracy in sentiment classification tasks within financial and digital service domains [18]. For these reasons, Naïve Bayes is employed in this study as a baseline model, while its limitations relative to more advanced methods are explicitly acknowledged and discussed.

By integrating financial and nonfinancial perspectives, this study contributes to the literature on IT investment evaluation in SOEs by offering a more holistic framework for assessing investment success. The findings are expected to provide both theoretical insights and practical implications for policymakers and practitioners in evaluating large-scale digital infrastructure investments under dual commercial and social mandates.

II. METHOD

This study adopts a mixed-methods research design to evaluate the success of the BRIsat investment from both financial and nonfinancial perspectives. This approach is grounded in prior literature which emphasizes that large-scale information technology and infrastructure investments should not be assessed solely through financial indicators, but also through public perception and service acceptance.

Financial data were obtained from BRI Annual Reports covering the period 2014–2024 [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28]. These reports provide information related to investment costs, operational expenditures, and cash flow components associated with the BRIsat program. Nonfinancial data were collected from public tweets on the social media platform X, retrieved through web scraping using Indonesian language keywords related to BRIsat and BRI's digital banking services over the period 2016–2024.

The methodological framework of this study consists of two main components, financial evaluation using Cost–

Benefit Analysis (CBA) and nonfinancial evaluation using sentiment analysis based on machine learning techniques. This dual-perspective framework enables a comprehensive and multidimensional assessment of investment success [12].

The financial evaluation was conducted using Cost Benefit Analysis (CBA), a widely applied method in long-term investment appraisal for assessing economic feasibility and value creation [29]. The cost components considered in this study include the initial capital expenditure for the BRIsat satellite, as well as operational and maintenance costs and other investment related cost reported in BRI Annual Reports. The benefit components comprise the total of revenue of banking and digital service operations. The analysis involved calculating the following metrics:

A. Calculating Return On Investment (ROI)

Return on Investment (ROI) was employed to measure the profitability of the BRIsat investment relative to the assets [9]. ROI reflects how efficiently organizational resources are converted into net profit and is commonly used in corporate financial performance evaluation . This metric calculated as:

$$\text{ROI} = \frac{\text{Net Profit After Tax}}{\text{Total Asset}} \text{ x } 100\%$$

B. Calculating Payback Period (PP)

The Payback Period (PP) was calculated to determine the length of time required to recover the initial investment based on annual cash flows on investment activity [29]. PP serves as an indicator of investment risk by highlighting the speed of capital recovery. This metric calculated as:

$$\text{PP} = \frac{\text{Initial Investment}}{\text{Cash Flow}} \text{ x 1 Year}$$

C. Calculating Net Present Value (NPV)

Net Present Value (NPV) was applied to evaluate the present value of future net cash flows discounted over the investment horizon [30]. NPV incorporates the time value of money and using discount rate to calculate it. This metric calculated as:

$$\text{NPV} = \frac{C_1}{(1+r)^1} + \frac{C_2}{(1+r)^2} + \frac{C_3}{(1+r)^3} + \frac{C_n}{(1+r)^n} - C_0$$

Where C_1 represents net cash flow in period 1, r denotes the discount rate, and C_0 is the initial investment charged.

D. Calculating Benefit Cost Ratio (BCR)

The Benefit–Cost Ratio (BCR) compares the present value of benefits to the present value of costs and is used to assess economic efficiency. A BCR value greater than one indicates that the benefits outweigh the costs [29]. This metric calculated as:

$$\text{BCR} = \frac{\text{PV Benefit}}{\text{PV Cost}}$$

Meanwhile, To capture public perception as a nonfinancial dimension of investment success, this study applies sentiment analysis to social media data. sentiment data processing will follow these adapted stages [31]:

A. Data Cleansing

Data cleansing was performed using RapidMiner to remove irrelevant and noisy content, including duplicate entries, spam, punctuation marks, numerical characters, URLs, and other non-linguistic symbols. This step aims to improve data quality prior to further analysis and reduce noise that could negatively affect sentiment classification performance [32]. The data cleansing process is shown in Figures 1 and 2 below:

B. Data Labeling

Sentiment labeling was conducted manually using Microsoft Excel, where each social media comment was classified into positive or negative sentiment categories. Manual labeling was selected to ensure higher contextual accuracy in Indonesian-language text, particularly for informal expressions, abbreviations, and domain-specific terminology that may not be accurately captured through

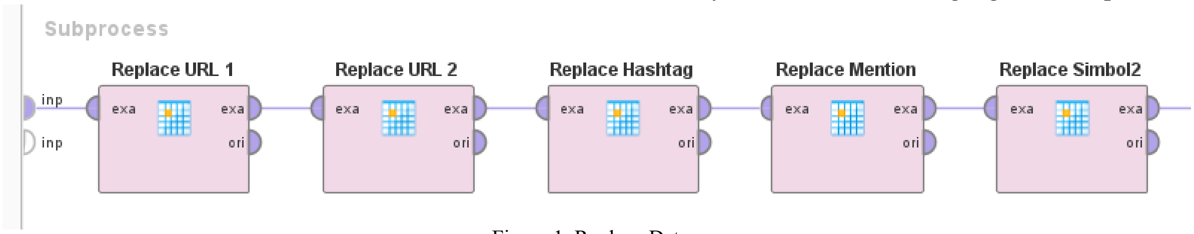

Figure 1. Replace Data

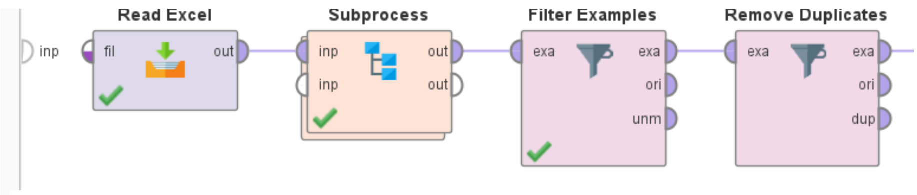

Figure 2. Filter Examples & Remove Duplicates

automated labeling techniques [33]. This labeled dataset was used to train the Naïve Bayes algorithm.

C. Dataset Division

The dataset was divided into training and testing subsets to evaluate model generalization and reduce overfitting. This dataset division was performed using Microsoft Excel prior to model implementation.

D. Preprocessing Data

Text preprocessing was conducted using Rapid Miner to prepare the sentiment data for machine learning classification. Rapid Miner was selected for this stage due to its capability to manage complex text preprocessing workflows in a transparent and reproducible manner. First, two initial operations are performed: "nominal to text" and "data set meta data information" to configure the sentiment attribute as the label. Subsequently, preprocessing is executed using the "process documents from data" operator, which includes a series of sub-operations. The data is first tokenized to break text into individual words. It then undergoes case transformation to convert all characters to lowercase. Finally, a stopword to filtering out common words that carry little meaningful information for sentiment analysis. The data processing process is shown in Figures 3, 4, and 5 below:

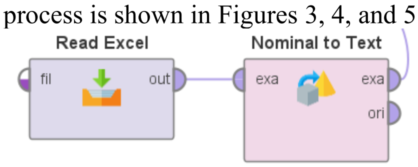

Figure 3. Nominal to Text

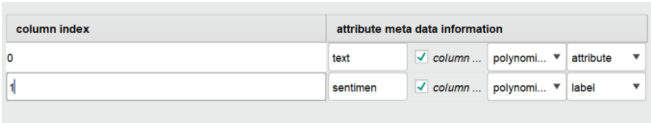

Figure 4. Data Set Meta Data Information

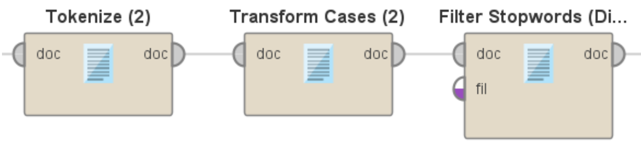

Figure 5. Preprocessing Data

E. TF-IDF

At this stage, measure the importance of words in the document and weight words based on the relative frequency of occurrence. This calculation is carried out automatically by the system after running the "process document from data" operator using Rapid Miner.

F. Naïve Bayes Classification

Sentiment classification was conducted using the Naïve Bayes algorithm implemented in RapidMiner. Naïve Bayes assumes conditional independence among features and has been widely applied in text classification tasks due to its computational efficiency and stable performance on moderate sized datasets [18]. The classification process consists of two stages: model training using the training dataset and model testing using the testing dataset. The model training and testing process is shown in Figures 6 and 7 below:

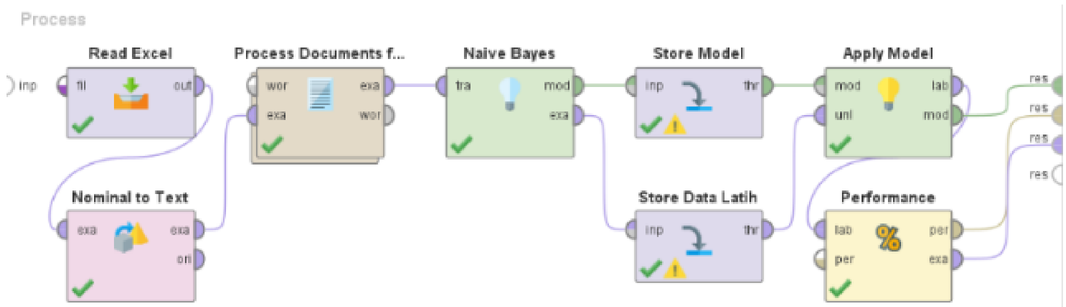

Figure 6. Training Data

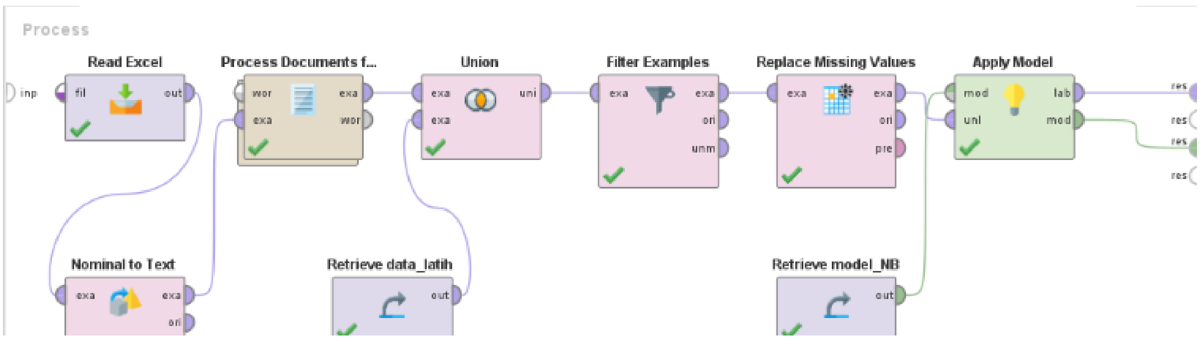

Figure 7. Testing Data

G. Wordcloud

To support descriptive analysis of sentiment related textual patterns, a wordcloud visualization was generated using Rapid Miner. The wordcloud highlights frequently occurring terms within the sentiment corpus and serves as a complementary visualization tool to illustrate dominant themes in public discourse related to. The wordcloud process is shown in Figure 8 below:

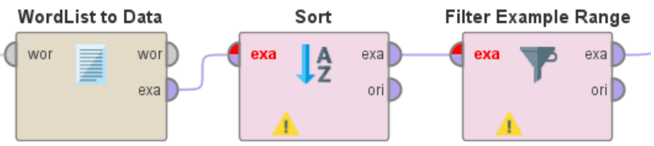

Figure 8. Wordloud

The methodological framework integrates financial evaluation through CBA and nonfinancial evaluation through sentiment analysis to reflect the multidimensional nature of investment success. This integration enables a structured assessment of economic feasibility alongside public perception, in line with contemporary investment evaluation literature [10].

III. Result and Discussion

A. Feasibility Analysis Using Cost Benefit Analysis (CBA)

The financial feasibility of the BRIsat investment was evaluated using the Cost–Benefit Analysis (CBA) framework over a ten-year observation period, based on the availability of financial data from BRI Annual Reports covering 2014–2024. This period encompasses the initial investment planning phase, the recognition of the BRIsat investment in the financial statements, and subsequent operational years.

The CBA incorporates four key indicators—Return on Investment (ROI), Payback Period (PP), Net Present Value (NPV), and Benefit Cost Ratio (BCR) each derived from different subsets of the financial data and serving distinct analytical purposes.

1) Return on Investment (ROI)

$$ROI = \frac{29.044.334}{1.126.248.442} \times 100\%$$

$$ROI = 2{,}58\%$$

Return on Investment (ROI) was calculated using financial data from the 2017, which represents the first year in which the BRIsat investment was formally recognized and expensed in BRI's financial statements. The calculation utilizes net profit after tax and total assets reported for that year. The resulting ROI value of 2.58% indicates that, in the year following investment recognition, the assets associated with the BRIsat program contributed positively to the company's profitability. As the analysis relies on a single-year snapshot, ROI is interpreted as an indicator of short-term asset efficiency rather than a comprehensive measure of long-term investment performance.

2) Payback Period (PP)

$$PP = \frac{831.895}{49.213.146} \text{ x 1 Year}$$

$$PP = 6{,}2 \text{ Years}$$

The Payback Period (PP) analysis was based on initial investment data reported in 2014, corresponding to the early planning and capital allocation phase of the BRIsat project, and annual cash flow data from subsequent operational years. The calculated Payback Period of approximately 6.2 years reflects the time required for cumulative cash inflows to recover the initial capital outlay. Given that the BRIsat satellite is designed for an estimated operational lifespan of approximately 15 years, the PP result suggests that capital recovery occurs within the first half of the asset's useful life. Accordingly, the PP metric indicates a moderate risk profile, which is generally considered acceptable for capital-intensive infrastructure investments with long-term strategic value.

3) Net Present Value (NPV)

TABLE 1
NET PRESENT VALUE
(In millions of rupiah)

Year	Cash Flow	Discount Rate
0	127.737	
1	30.995.996	10%
2	26.999.124	
3	5.188.442	
4	116.007.831	
5	73.095.605	
6	-27.227.960	
7	4.989.092	
8	188.189	

Source: BRI Annual Report 2017-2024

$$NPV = \frac{30.995.996}{(1+0{,}1)^1} + \frac{26.999.124}{(1+0{,}1)^2} + \frac{5.188.442}{(1+0{,}1)^3} + \frac{116.007.831}{(1+0{,}1)^4} + \frac{73.095.605}{(1+0{,}1)^5} + \frac{-27.227.960}{(1+0{,}1)^6} + \frac{4.989.092}{(1+0{,}1)^7} + \frac{188.189}{(1+0{,}1)^8} - 127.737$$

$$NPV = 28.178.178 + 22.313.326 + 3.898.153 + 79.234.910 + 45.386.620 + (15.369.474) + 2.560.193 + 87.792 - 127.737$$

$$NPV = 166.161.960$$

The Net Present Value (NPV) was calculated using annual net cash flow data from 2017 to 2024, representing the operational phase of the BRIsat investment as reported in BRI Annual Reports. A discount rate of 10% was applied consistently across all years to account for the time value of money and investment risk. The resulting positive NPV of Rp166,161,960 million indicates that, when discounted to present value terms, the cumulative benefits generated during the 2017–2024 period exceed the initial and ongoing investment costs. This confirms that the BRIsat investment creates net economic value over the observed time horizon. The NPV analysis is constrained by data availability and therefore reflects a partial lifecycle evaluation, rather than the full operational lifespan of the satellite.

4) Benefit Cost Ratio (BCR)

TABLE 2
BENEFIT COST RATIO
(In millions of rupiah)

Year	Revenue	Cost	DF	PV Benefit	PV Cost
2017	29.044.334	127.737	0,9091	26.403.940	116.125
2018	32.418.486	218.978	0,8264	26.792.137	180.974
2019	34.413.825	218.978	0,7513	25.855.616	164.521
2020	18.660.393	218.978	0,6830	12.745.300	149.565
2021	30.755.766	202.328	0,6209	19.096.911	125.630
2022	51.408.207	220.584	0,5645	29.018.593	124.514
2023	60.425.048	220.786	0,5132	31.007.604	113.298
2024	60.643.808	220.858	0,4665	28.290.784	103.032
				199.210.884	**1.077.658**

Source: BRI Annual Report 2017-2024

$$BCR = \frac{199.210.884}{1.077.658}$$

BCR= 184,9>1 Feasible

The Benefit Cost Ratio (BCR) was calculated using discounted benefit and cost data from 2017 to 2024, aligned with the same period applied in the NPV analysis. Benefit values were derived from annual revenue figures associated with BRIsat supported banking and digital services, while cost values consist of investment and operational expenditures related to the BRIsat. The resulting BCR value of 184.9 reflects the ratio between the present value of aggregated benefits and the present value of relatively concentrated infrastructure costs over the analysis period. The exceptionally high BCR arises from the fact that BRIsat functions as an enabling infrastructure, where a limited cost base supports large-scale revenue generating activities across the banking network. Therefore, the BCR is interpreted as an indicator of economic leverage and efficiency, rather than as a direct profitability multiplier.

Each financial indicator in this study is derived from different but complementary timeframes, as ROI reflects short-term asset efficiency using 2017 data; PP captures capital recovery dynamics beginning from the 2014 investment phase; and NPV and BCR assess long-term value creation using discounted cash flows from 2017–2024. When interpreted collectively, these indicators provide a coherent and multidimensional assessment of financial feasibility, demonstrating that the BRIsat investment generates value over time while supporting large-scale operational benefits.

B. Sentiment Analysis

1) Data Collection

This study analyzes public sentiment toward Bank Rakyat Indonesia (BRI) based on user-generated content from social media platform X (formerly Twitter). Data were collected through a web scraping process conducted in Google Colab, resulting in an initial dataset of 54,313 tweets posted between June 2016 and December 2024. This period was selected to capture long-term public perception after the operational deployment of the BRISat satellite.

2) Cleansing Data

The cleansing data in RapidMiner involved several sequential steps. First, the "Replace" operator was used to cleanse the text by removing meaningless characters; this was executed five times in sequence to eliminate URLs, hashtags, mentions, and punctuation. Following this, the "Filter Examples" operator was applied using the "is not missing" condition to select only relevant text data, which resulted in the removal of 3,090 missing values and left 51,223 data points. Finally, the "Remove Duplicates" operation was performed, identifying and eliminating 41,157 duplicate entries, which further refined the dataset to a final total of 10,066 instances. The substantial reduction in data size indicates a high level of redundancy and noise in raw social media data.

TABLE 3
DATA CLEANSING

No	Sebelum	Sesudah
1	@santika4572 @BANKBRI_ID BRI the best punya fitur yg selalu mempermudah pengguna	BRI the best punya fitur yg selalu mempermudah pengguna
2	Kesel banget sama BRI @BANKBRI_ID gw transaksi pake internet banking tapi kode OTPnya kaga dikirim² lewat sms. Udah coba nanya call centernya lewat twitter jawabannya ga memuaskan.	Kesel banget sama BRI gw transaksi pake internet banking tapi kode OTPnya kaga dikirim lewat sms Udah coba nanya call centernya lewat twitter jawabannya ga memuaskan
…		
54.313	@kontakBRI Sudah hampir 2 jam ga ada respon dari admin @kontakBRI Beginikah layanan BRI @KemenBUMN	Sudah hampir jam ga ada respon dari admin Beginikah layanan BRI

3) Data Labelling

To ensure interpretability and methodological transparency, sentiment labels were assigned manually using

Microsoft Excel, classifying each tweet as either “positif” or “negatif”.

TABLE 4
DATA LABELLING

No	Tweet	Sentimen
1	BRI the best punya fitur yg selalu mempermudah pengguna	Positif
2	Kesel banget sama BRI gw transaksi pake internet banking tapi kode OTPnya kaga dikirim lewat sms Udah coba nanya call centernya lewat twitter jawabannya ga memuaskan.	Negatif
…		
10.066	Sudah hampir jam ga ada respon dari admin Beginikah layanan BRI	Negatif

4) Naïve Bayes Classification

Based on the results of the sentiment analysis model testing using RapidMiner software, as shown in Figure 9, an accuracy rate of 96.76% was obtained, indicating that the model has excellent classification capabilities.

5) Wordcloud

In this study, 10,066 data sets yielded a total of 15,549 words. From this total, the 20 most common words were identified, as shown in Figure 10 and 11 below, for each sentiment data set.

1) *Sentiment Positive:* Based on the results of labeling and classification using the Naive Bayes algorithm, 4,439 data points were classified as positive. The wordcloud visualization of this data can be seen in Figure 10:

Figure 10. Sentiment Positive

The image above shows the 20 most frequently occurring words in positive sentiment. The number of occurrences of the words in Figure 10 above can be seen in TABLE 5:

TABLE 5
SENTIMENT POSITIVE FREQUENCY

No	Kata	Word	No	Word	Freq
1	sukses	882	**11**	proses	138
2	cepat	761	**12**	mesin	104
3	layanan	662	**13**	tabungan	101
4	atm	543	**14**	jaringan	87
5	transaksi	487	**15**	susah	66
6	brimo	386	**16**	top	65
7	internet	373	**17**	gangguan	46
8	mudah	245	**18**	login	36
9	lancar	206	**19**	error	14
10	transfer	190	**20**	gagal	4

accuracy: 96.76%

	true Negatif	true Positif	class precision
pred. Negatif	4926	275	94.71%
pred. Positif	18	3816	99.53%
class recall	99.64%	93.28%	

Figure 9. Classification Performance

2) *Sentiment Negative:* Based on the results of labeling and classification using the Naive Bayes algorithm, 5,627 data points were classified as negative. A wordcloud visualization of this data can be seen in Figure 11:

Figure 11. Sentiment Negative

The image above shows the 20 most frequently occurring words in positive sentiment. The number of occurrences of the words in Figure 11 above can be seen in table 6:

TABLE 6
SENTIMENT NEGATIVE FREQUENCY

No	Word	Freq	No	Word	Freq
1	*error*	1630	**11**	mesin	206
2	atm	1577	**12**	susah	193
3	gagal	904	**13**	*login*	193
4	transaksi	740	**14**	*top*	144
5	gangguan	634	**15**	proses	138
6	transfer	548	**16**	tabungan	120
7	internet	525	**17**	lancar	87
8	layanan	389	**18**	mudah	18
9	brimo	367	**19**	sukses	14
10	jaringan	223	**20**	cepat	12

Based on data analysis and research results, public opinion regarding Bank BRI is divided into two, namely positive and negative opinions, with equally strong reasons. On the one hand, positive opinions (4,439 data) are mainly driven by BRI's BRISat satellite innovation. Words such as "success" (882 times), "fast" (761 times), and "service" (662 times) show public appreciation. This is evident in several tweets on X, such as "BRI becomes the first bank in the world to have its own satellite" and "With satellites, BRI services are faster and have wider reach." This innovation is seen as a smart move to expand services to remote areas and strengthen BRI's image as a progressive and superior bank globally.

However, on the other hand, negative sentiment was more dominant (5,627 data points). This finding aligns with research from Umair & Susanto (2024) on the BRImo application, which concluded that sentiment analysis of BRImo user reviews yielded unfavorable user sentiment [34]. This dominance is reflected in the most frequently appearing keywords, such as "error" (1,630 times), "fail" (904 times), and "disruption" (634 times). These technical complaints are supported by the study from Azarya & Budi (2025), which indicates that “errors” are a frequent topic of discussion in user reviews, with details of issues such as “failure to activate BRImo account” and “application frequently exits unexpectedly” [35]. Furthermore, this negative keyword pattern was also observed by Sari & Irhamah (2019), who found that words like "balance cut", "transaction failed", and "balance failed" appeared frequently and indicated that there were many tweets with negative sentiment in them [36].

Therefore, it can be concluded that although satellite innovation has successfully built a positive and strategic image, BRI still faces significant challenges in improving the quality of its basic services. Without comprehensive improvements to operational services, customer trust risks declining, which could impact BRI's long-term competitiveness.

IV. Conclusion

This study evaluates the success of the BRIsat investment by integrating financial feasibility analysis and nonfinancial public perception assessment, thereby providing a multidimensional evaluation of large-scale digital infrastructure investment. The financial analysis demonstrates that the BRIsat project is economically viable over the observed period. Specifically, the investment generates a positive Return on Investment (ROI) of 2.58%, indicating that the utilization of total assets contributes positively to corporate profitability. The Payback Period of approximately 6.2 years suggests that the initial investment cost can be recovered within a reasonable timeframe relative to the satellite’s expected operational life. Furthermore, the Net Present Value (NPV) of Rp166,161,960 million, calculated using a 10 percent discount rate, confirms that the present value of future cash flows substantially exceeds the initial investment cost, thereby creating net economic value for the company. The Benefit Cost Ratio (BCR) of 184.9 reflects the structural characteristics of satellite-based infrastructure investments, where substantial upfront ratio enable long-term operational efficiency and broad service coverage.

Complementing these financial outcomes, the nonfinancial analysis reveals that public sentiment toward BRI’s digital services remains predominantly negative despite the strong economic performance of the investment. Negative sentiment is primarily driven by recurring issues related to transaction failures, system errors, and service disruptions, while positive sentiment emphasizes improved accessibility, technological advancement, and extended service reach to remote areas. This divergence highlights that investment success cannot be adequately assessed through financial indicators alone. Instead, public perception functions as a critical nonfinancial dimension that reflects service reliability, user experience, and institutional legitimacy. Within this context, sentiment analysis serves as an early warning mechanism, signaling potential reputational and sustainability risks that may undermine long-term value creation if operational issues persist.

From a managerial perspective, these findings imply that while BRIsat has successfully delivered economic value, sustaining its strategic benefits requires continuous improvement in service quality and system stability. Management should therefore align infrastructure investment decisions with customer experience management, ensuring that technological advancement is matched by reliable service delivery. Failure to address persistent service-related complaints may erode customer trust and compromise the long-term sustainability of digital banking initiatives, despite favorable financial performance.

Despite its contributions, this study is subject to several limitations. The nonfinancial evaluation relies exclusively on social media data from the X platform, which may not fully represent the broader population of BRI customers. Sentiment labeling was conducted manually to preserve contextual accuracy in Indonesian-language text, introducing subjectivity and limiting scalability. The Naïve Bayes classifier, while effective as a baseline model, is constrained by its assumption of feature independence and limited ability to capture contextual nuance, such as sarcasm or implicit sentiment. Additionally, the financial analysis is bounded by the availability of published annual reports and does not encompass the satellite's entire operational lifecycle or indirect strategic benefits that are difficult to quantify.

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