

Analysis of the Management Decision-Making Process Based on Predictive Analytics in Projecting PT Telkom (Persero) Tbk. Ability to Meet Long-Term Financial Obligations

Raihan Fauzan Adim ¹ Agustina Septiana ² Muhamad Nur Amin ³ Fabio Alfarabi Putra ⁴ Asri Sundari ^{5*}

^{1, 2, 3, 4, 5*} Universitas Kebangsaan Republik Indonesia, Bandung, Indonesia

Email: asrisundari@fe.ukri.ac.id

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ABSTRACT

Purpose: This study analyzes the solvency of PT Telkom Indonesia (Persero) Tbk and assesses the adequacy of documentary evidence regarding the use of predictive analytics in financial decision-making.

Research Method: This study employs a descriptive case study approach with a documentary analysis of the audited consolidated financial statements for 2025 and the restated comparative figures for 2024. The analysis covers the liability structure, profitability, free cash flow, lease-adjusted leverage, net debt, and cost of capital coverage.

Results and Discussion: Long-term liabilities increased by 4.72%, while operating income decreased by 16.42% and the TIER proxy fell from 7.96 to 6.66 times. Conversely, operating cash flow increased by 3.64%, net financial debt decreased, and the debt-to-equity ratio (DER), adjusted for leases, remained relatively stable at 49.76%. The analyzed document does not provide specifications or validation of the predictive model; therefore, the effectiveness of its implementation cannot be concluded.

Implications: Solvency assessments need to use multidimensional indicators and verifiable disclosures regarding model governance.

Originality: This study identifies the empirical boundary between descriptive financial analysis and predictive analytics in assessing the solvency of telecommunications companies.

Keywords: predictive analytics; management decision-making; solvency; leverage.

1. Introduction

The acceleration of the global digital transformation has fundamentally changed the telecommunications industry landscape, shifting the business focus from conventional voice and text messaging services toward data ecosystems, cloud computing, and the Internet of Things. These changes require telecommunications companies to make significant investments in digital infrastructure, such as 5G networks and data centers, which demand long-term funding. On the other hand, competitive pressures and the commoditization of data services may limit profit margin growth. These conditions make the ability to meet long-term obligations and maintain capital structure a critical aspect of business sustainability. In this study, solvency is defined as a company's ability to meet all of its long-term obligations. At the same time, debt repayment capacity refers more specifically to the

adequacy of cash flow to pay the principal and interest on debt according to schedule. These two concepts are distinct from liquidity, which relates to the ability to meet short-term obligations.

As a state-owned enterprise and one of the largest telecommunications companies in Indonesia, PT Telkom Indonesia (Persero) Tbk plays a strategic role as a driver of national digitalization and a business entity that must maintain its financial health. To support the expansion of digital infrastructure, the company utilizes both internal and external funding sources, including loans and long-term liabilities. The use of debt-based financing entails obligations such as principal payments, interest payments, and other contractual obligations. Therefore, management must assess the company's ability to service its debt by considering not only operating cash flow but also capital expenditures, free cash flow, net debt, maturity schedules, lease liabilities, interest expenses, and other cash commitments. These considerations are crucial because a positive operating cash flow does not, by itself, guarantee that all long-term obligations can be met without financial strain.

Historically, financial decision-making has largely been supported by the analysis of financial statements and ratios derived from past data. Such analysis remains important for illustrating a company's financial position and changes in performance. However, as historical indicators, financial ratios have limitations in anticipating nonlinear changes, interactions among factors, and economic uncertainties. Relying solely on historical trends and simple extrapolation can result in inadequate projections when a company faces changes in interest rates, inflation, exchange rates, demand for services, or capital expenditure needs. The issue addressed in this study is not that traditional analysis is useless, but rather the need to supplement it with a more forward-looking approach.

This need can be explained through Simon's decision-making model, which includes the stages of intelligence, design, choice, and implementation (Simon, 1977). Under conditions of bounded rationality, managerial decisions are constrained by the availability of information, data-processing capabilities, time, and uncertainty. A data-driven decision-making approach has the potential to expand the information used in the problem identification and alternative evaluation stages. At the same time, trade-off theory explains that the use of debt can provide benefits but also increases the cost of financial distress when leverage exceeds a company's capacity (Kraus & Litzenberger, 1973). Thus, predictive analytics can conceptually be positioned as a decision-support tool that processes historical information and external factors to assist in developing projections. At the same time, solvency indicators and debt repayment capacity are used to evaluate the consequences of financing decisions.

Several studies have discussed the elements supporting this relationship. Maidiana & Harahap (2021) proposed a seven-stage decision-making framework that includes problem analysis, data collection, evaluation of alternatives, and implementation. This framework demonstrates that decision quality depends on a structured process of information collection and evaluation. Prasetya *et al.*, (2024) also identified four analytical stages—namely, data collection, processing, analysis, and interpretation—that can support strategic decision-making. Both studies provide a procedural foundation for data-driven decision-making but have not specifically addressed its application in assessing telecommunications companies' ability to repay long-term liabilities.

In the field of analytics, Husein *et al.*, (2021) demonstrated the application of the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology using the XGBoost and ARIMA algorithms for forecasting activities. The results of this study highlight the usefulness of analytical methods in identifying patterns and generating estimates. However, the measures of predictive performance must be interpreted in accordance with the definitions of the metrics used in the original study. Asrul *et al.*, (2024) also demonstrated that predictive analytics can improve forecasting quality. Meanwhile,

Magfiroh & Komarudin (2025) found that Big Data Analytics supports the accuracy of risk analysis and credit decisions in a banking context. These studies demonstrate the potential of data analytics in forecasting and risk assessment. However, the context, units of analysis, and outputs differ from those used to assess the debt repayment capacity of telecommunications companies.

Other research examines payment capacity and financial risk from a more specific perspective. Erjha *et al.*, (2023) identified solvency ratios as indicators for assessing the ability to meet long-term obligations. Marlina & Bakri (2021) demonstrated that data mining can be used to classify payment behavior into delinquent and current categories. Dewi & Wessiani (2021) integrated risk management and NPV-at-Risk simulation to evaluate investment feasibility under conditions of uncertainty. Meanwhile, Arifin *et al.*, (2024) used the Debt Service Coverage Ratio (DSCR) to analyze long-term payment capacity. They reported a 2022 DSCR value of $-76,980$, indicating that the research subjects were unable to pay principal and interest. However, the study by Arifin *et al.*, (2024) still relied on a financial ratio approach and did not develop a predictive analytics model.

These previous studies provide complementary support but remain fragmented. Decision-making research offers a process framework, analytical research provides forecasting and classification techniques, while financial research uses ratios to evaluate solvency and debt repayment capacity. No sufficient evidence has been found in these sources regarding the application of validated predictive analytics models to project PT Telkom's capacity to pay its long-term liabilities. This paper also does not have access to internal algorithms, data architecture, model parameters, forecasting results, measures of prediction error, or evidence of the company's internal decision-making. Therefore, this study does not claim that predictive analytics has been implemented or proven effective at PT Telkom.

Given these gaps, the research questions are: (1) what is the state of PT Telkom's solvency and capacity to pay its long-term liabilities based on available financial data; and (2) how can predictive analytics conceptually be used as a framework to support financial decision-making based on these indicators? This study aims to conduct a descriptive analysis of PT Telkom's solvency and debt repayment capacity and to formulate the conceptual relevance of predictive analytics as a decision-support tool. The novelty of this research lies in integrating Simon's decision-making model, bounded rationality, data-driven decision-making, trade-off theory, and debt repayment capacity indicators in a documentary study of a capital-intensive telecommunications company. The contribution of this study is not in the form of algorithm testing or proving the effectiveness of predictive analytics, but rather in establishing a conceptual foundation and financial indicators that can be used in developing models for future research.

The remainder of this paper is organized as follows. Section 2 provides a literature review and hypothesis development. Section 3 presents the research method and design. Section 4 provides the results and discussion. Section 5 presents Concluding Remarks and Recommendations.

2. Literature Review and Hypothesis Development

2.1 Management Decision-Making Theory

Management decision-making theory explains the process by which managers identify problems, gather and interpret information, evaluate alternatives, select courses of action, and assess the consequences of decisions. In practice, managers are not always able to make decisions based on perfect rationality because they face limitations in information, time, cognitive capacity, and environmental uncertainty.



Therefore, managerial decisions result from the interaction between rational considerations, experience, intuition, emotions, and organizational conditions. Kanzola *et al.*, (2024) demonstrate that emotions, cultural values, risk propensity, and fast- and slow-thinking mechanisms all contribute to strategic planning and crisis management. Advances in data analytics have subsequently expanded managers' capacity to process information and evaluate alternatives. Elgendy *et al.*, (2023) refer to this development as "collaborative rationality"—the collaboration between humans and technology to produce better-informed decisions. However, this collaboration still requires evaluation, as analytical outputs are not immune to limitations in data, model design, and user interpretation.

In data-driven decision-making, the quality of decisions is determined not only by the availability of technology but also by data literacy, information quality, an analytical culture, and managers' ability to interpret analytical results. (Steinhardt, 2024) emphasizes that data literacy helps managers transform data into information and knowledge relevant to selecting alternatives. Szukits & Móricz (2024) found that top management support and perceptions of data quality foster an analytical decision-making culture. However, data centralization does not automatically increase its use in decision-making. Szukits (2022) also demonstrated that advanced analytics can strengthen the role of information in supporting decision-making but do not necessarily replace intuition and professional judgment. At the organizational level, big data analytics capabilities can support operational and strategic agility in responding to environmental changes (Turi *et al.*, 2023). Meanwhile, artificial intelligence can mitigate some limitations in information processing but also has the potential to create new biases stemming from data and algorithms (Lindner *et al.*, 2025). Thus, predictive analytics in this study is positioned as a conceptual tool to support financial decision-making, not as a substitute for management responsibilities or the technology that has been proven effective at PT Telkom.

2.2 The Concept of Predictive Analytics and Digital Financial Transformation

Predictive analytics is an approach that uses historical data, statistical techniques, and machine learning algorithms to identify patterns and estimate future conditions. This approach differs from descriptive analytics, which explains past events, because it focuses on generating projections to support decision-making. In finance, predictive analytics can be used to forecast cash flows, corporate performance, default risk, funding needs, and potential financial stress. Hoang & Wiegatz (2023) explain that machine learning in finance encompasses supervised and unsupervised learning methods that can be used for measurement, classification, and prediction. Hezam *et al.*, (2025) note that various algorithms have been used to predict corporate performance, but model suitability depends on data characteristics and analysis objectives. Therefore, the application of predictive analytics must specify the target variable, predictors, data sources and time periods, algorithms, prediction horizon, validation procedures, and error metrics. Without these elements, a discussion of predictive analytics merely highlights conceptual potential and does not demonstrate the applicability or accuracy of a predictive model.

Digital financial transformation encompasses changes in technology, work processes, human resource competencies, and data governance within the finance function. Bedford *et al.*, (2025) distinguish between automation for process efficiency and analytics that support the finance function as a strategic partner to management. Thus, digital transformation should not be evaluated solely based on technology adoption but must also consider its alignment with strategy, data quality, organizational capacity, and decision-making objectives. Cui & Wang (2023) found that digital transformation is associated with reduced financial distress through reduced operational risks and financing constraints.

Chen *et al.*, (2024) also demonstrated that digital transformation is linked to lower debt default risks through increased productivity and reduced funding constraints. However, these benefits are not always linear, as an excessively rapid pace of transformation can increase adjustment costs and resource pressures (Sun *et al.*, 2024). The financial impact also depends on the company's internal characteristics and capabilities (Yavuz *et al.*, 2025). Therefore, this study positions predictive analytics as a conceptual component of digital financial transformation that has the potential to support the analysis of long-term liabilities, rather than as a technology that has been proven to be implemented or effective in improving PT Telkom's solvency.

2.3 Projected Long-Term Solvency (Solvency)

Solvency reflects a company's ability to meet all of its obligations—particularly long-term obligations—supported by its assets, equity, operating income, and cash flow. This concept differs from liquidity, which focuses on short-term liabilities. Assessing solvency requires more than just operating cash flow or a single financial ratio; it must also consider debt structure, maturity schedules, interest expenses, lease liabilities, capital expenditures, and other cash commitments. Arhinful & Radmehr (2023) point out that leverage must be analyzed alongside interest coverage and fixed-cost ratios because the use of debt creates payment obligations that must be supported by sustainable revenue and cash flow. Therefore, indicators such as the Debt-to-Equity Ratio, Debt-to-Asset Ratio, Times Interest Earned Ratio, Debt Service Coverage Ratio, net debt-to-EBITDA, and free cash flow provide complementary perspectives. Kebede *et al.*, (2024) also emphasize that financial distress is influenced by a combination of a company's internal conditions; thus, an assessment of debt-repayment capacity must encompass profitability, operational efficiency, leverage, and the adequacy of financial resources. In line with this approach, Rusma *et al.*, (2026) integrate profitability, liquidity, and solvency into a single analytical framework to explain firm value through dividend policy. This reinforces the view that solvency must be evaluated alongside the ability to generate profits and meet short-term obligations to ensure a more comprehensive understanding of a company's financial condition.

Projections of a company's ability to pay long-term obligations constitute a forward-looking assessment of its capacity to pay principal, interest, and contractual obligations on schedule. Such projections require assumptions regarding revenue growth, operating margins, capital expenditures, working capital, interest rates, exchange rates, and refinancing needs. Dainelli *et al.*, (2024) emphasize that financial health and the probability of default depend on the credibility and uncertainty of a company's projections. Zhao *et al.*, (2024) demonstrate that financial difficulties can recur, so assessments must account for changing conditions and time. Abdelkader & Wahba (2024) further recommend integrating financial ratios, market indicators, governance factors, and macroeconomic variables into financial distress predictions. Risk disclosures in annual reports can also complement numerical indicators (Hajek & Munk, 2024). Although predictive models have evolved from ratio analysis toward machine learning, every model still requires a clear definition of the target, selection of predictors, validation, and transparent performance metrics (Zhou *et al.*, 2022). Since this study does not include a model or validation results, the analysis of PT Telkom is limited to historical solvency conditions as a conceptual basis for developing projections, rather than as proof of future payment capacity.

2.4 Financial Risk Management in the Age of Digital Transparency

Financial risk management is a system of policies, oversight, controls, and the allocation of responsibilities designed to identify, measure, monitor, and respond to risks that may affect a company's financial condition. These risks include liquidity, credit, interest rate, foreign exchange, refinancing, investment failure, and the inability to meet obligations. Purwanti (2023) emphasizes that treasury and financial risk management must be integrated into a proactive organizational framework so that companies can respond to market volatility, maintain financial stability, and strengthen long-term resilience. In a digital environment, the scope of governance has expanded as financial decisions are supported by big data, automated systems, and analytical algorithms. These developments increase the speed of information processing but also give rise to risks related to data quality, algorithmic bias, cybersecurity, and unclear accountability. Hu & Yang (2024) demonstrate that digital governance is associated with improved disclosure quality through reduced managerial transaction costs and enhanced human capital structure. However, the relationship between digital transformation and risk is not always linear. Huang *et al.*, (2023) found a U-shaped relationship between digital transformation and idiosyncratic risk, meaning that expanding technology without adequate governance readiness can increase complexity and risk exposure. The economic value of digitalization is also influenced by organizational capital, governance quality, and the quality of corporate information (Zareie *et al.*, 2024).

Digital transparency requires that risk information be communicated in a manner that is relevant, timely, traceable, and understandable to management and stakeholders. Algorithmic transparency does not mean disclosing all source code or confidential data, but rather explaining the data sources, model objectives, assumptions, limitations, and the consequences of its use. Sætra (2023) emphasizes the importance of evaluating and disclosing the impacts of artificial intelligence capabilities, assets, and activities as part of technological accountability. In risk management, disclosures based on the ISO 31000 framework can enhance transparency regarding risk sources and mitigation mechanisms (Al-Khazaleh *et al.*, 2024). Chouaibi *et al.*, (2023) also demonstrate that the quality of governance is linked to the disclosure of financial risks. Furthermore, digital transformation can support fraud prevention when accompanied by adequate control mechanisms (Shang *et al.*, 2024). Therefore, the use of predictive analytics in financial decision-making must be subject to risk management oversight, internal audit, access controls, model validation, and professional judgment. However, this study does not assert that these mechanisms have been implemented or are effective at PT Telkom, as there is no internal evidence regarding the company's data governance, analytical models, and actual decisions.

3. Research Method

This study employs a descriptive documentary case study design with embedded quantitative financial analysis at PT Telkom Indonesia (Persero) Tbk during the 2024–2025 period. This design is used to: (1) describe the company's solvency and capacity to pay long-term liabilities based on available financial information; and (2) explain the conceptual relevance of predictive analytics as a tool to support financial decision-making. This study does not examine the application or effectiveness of predictive models at PT Telkom because internal algorithms, dataset architecture, model parameters, forecasting outputs, error metrics, or evidence of the use of predictive results in the company's actual decisions are not available. Thus, the units of analysis in this study are PT Telkom's financial documents and indicators, not company officials or employees. Techniques such as purposive sampling, key informants, interviews,

and triangulation were excluded because the study did not use primary data or involve human participants.

All research data consists of secondary data sourced from PT Telkom's 2024 and 2025 Annual Reports, the Audited Consolidated Financial Statements and their notes, transcripts of public presentations, and disclosures published on the company's official website and the Indonesia Stock Exchange. Documents were selected if they met four criteria: they were published by an official source; covered the study period; provided comparable financial information; and contained data on liabilities, equity, operating income, financial expenses, cash flow, capital expenditures, lease liabilities, or debt maturities. The data collection instrument consists of a document extraction sheet that records the document name, year, source page, financial line item, unit of presentation, value, formula, and comparability notes. The collection procedure involves document identification, completeness checks, data recording, reconciliation of figures between financial statements and notes to the financial statements, and cross-verification with official disclosures. Differences in classification or presentation between periods are noted and are not reconciled without an explained basis.

The analysis is conducted at two levels. First, descriptive financial analysis calculates nominal and percentage changes as well as indicators: Debt-to-Equity Ratio (total liabilities divided by total equity), Debt-to-Asset Ratio (total liabilities divided by total assets), Times Interest Earned Ratio (earnings before interest and taxes divided by interest expense), Debt Service Coverage Ratio (cash flow available for debt service divided by the sum of principal and interest due), net debt (interest-bearing debt minus cash and cash equivalents), net debt to EBITDA, and free cash flow (operating cash flow minus capital expenditures). The analysis also covers the composition of long-term debt, maturity schedules, lease liabilities, and other identifiable cash commitments. The formula, units, year, source page, and notes regarding data availability accompany each result. Ratios for which components are not available separately are not calculated and are marked as limitations, rather than estimated without a basis. Second, focused content analysis is used to group documentary information into four stages of decision-making: problem identification, formulation of alternatives, selection of actions, and evaluation. The process involves data condensation, coding, presentation in matrices, cross-source comparison, and concluding. Statements regarding predictive analytics were classified as: (1) evidence of actual implementation if supported by company documents; or (2) conceptual potential if derived solely from theoretical and literature synthesis. Historical financial results were presented separately from discussions of conceptual scenarios to ensure that the potential use of analytics was not treated as evidence of implementation. Data validity is ensured through source page traceability, formula consistency, cross-document reconciliation, and documentation of the analysis trail. Because the study is non-experimental, covers two years, and does not employ predictive models or inferential statistical testing, the results are not used to conclude cause-and-effect relationships, forecasting accuracy, or the effectiveness of predictive analytics.

4. Results and Discussion

4.1 Analysis Results

4.1.1 Changes in the Structure of Long-Term Liabilities

The analysis was conducted on the 2025 Consolidated Financial Statements of PT Telkom Indonesia (Persero) Tbk using restated comparative figures for 2024. Restated 2024 figures were used to maintain



consistency in the measurement basis and comparability across years. The analysis results show that total long-term liabilities increased from Rp60,418 billion in 2024 to Rp63,274 billion in 2025, or by 4.72%. This change does not in itself indicate a decline in solvency, as it must be analyzed in conjunction with the company's liability structure, equity, cash-generating capacity, financing costs, and cash commitments.

Table 1. Structure of Long-Term Liabilities of PT Telkom Indonesia (Persero) Tbk

Long-term liability components	2025 (billion rupiah)	2024 (billions rupiah)	Changes
Long-term loans	26.099	25.518	2.28%
Long-term lease liabilities	18.547	18.468	0.43%
Pension and post-employment benefit liabilities	12.996	11.540	12.62%
Long-term contract liabilities	2.851	2.484	14.77%
Deferred tax liabilities	1.233	992	24.29%
Estimated long-service awards	1.308	1.192	9.73%
Other non-current liabilities	240	224	7.14%
Total long-term liabilities	63.274	60.418	4.72%

Note: The change is calculated using the formula. The figure for 2024 is restated.

Source: Audited Consolidated Financial Statements of PT Telkom Indonesia (Persero) Tbk for the Year 2025, p. 1, processed by the researcher.

Long-term loans constitute the largest component, amounting to Rp26,099 billion, or 41.25% of total long-term liabilities in 2025. Lease liabilities rank second at Rp18,547 billion, or 29.31%. Thus, long-term loans and lease liabilities together account for 70.56% of total long-term liabilities. This composition indicates that an assessment of the company's ability to pay its obligations must include lease liabilities and not merely consider bank loans or bonds.

The largest nominal increase occurred in pension and post-employment benefit liabilities, amounting to Rp1,456 billion, followed by long-term loans at Rp581 billion and long-term contract liabilities at Rp367 billion. In percentage terms, the highest increase was in deferred tax liabilities at 24.29%, but their nominal value was smaller than that of loans, lease liabilities, and post-employment benefits. These findings indicate that the company's long-term obligations are not entirely in the form of interest-bearing debt. Therefore, a solvency assessment must distinguish between interest-bearing debt, lease obligations, obligations to employees, and other operating liabilities.

Although long-term liabilities increased by Rp2,856 billion, the company's total liabilities remained relatively stable, standing at Rp137,185 billion in 2024 and Rp137,222 billion in 2025. This occurred because short-term liabilities decreased from Rp76,767 billion to Rp73,948 billion. This change indicates a shift in the composition of liabilities from short-term to long-term. However, this aggregate data does not yet reveal whether the shift resulted from refinancing, changes in maturity schedules, or other transactions.

4.1.2 Operating Performance and Cash Generation Capacity

Table 2 presents changes in operating performance and cash flow that are relevant for assessing the company's ability to meet its long-term obligations. Revenue declined by 2.15%, while operating income and net income fell by 16.42% and 17.08%, respectively. The greater decline in profit than revenue indicates pressure on operating margins during 2025.

Table 2. Operating Performance and Cash Flow of PT Telkom Indonesia (Persero) Tbk

Indicator	2025 (billion rupiah)	2024 (billions rupiah)	Changes
Consolidated revenue	146.742	149.967	-2.15%
Depreciation and amortization expense	37.649	34.181	10.15%
Operating income	34.648	41.453	-16.42%
Financing costs	5.206	5.208	-0.04%
Net income	24.458	29.497	-17.08%
Net cash flow from operating activities	63.842	61.600	3.64%
Purchases of property, plant, and equipment	22.871	26.005	-12.05%
Purchases of intangible assets	2.897	3.658	-20.80%
Dividends to parent company shareholders	21.047	17.683	19.02%
Loan payments	72.037	47.607	51.32%
Lease liability payments	7.356	7.387	-0.42%

Note: Expenditure figures are presented as positive numbers to facilitate comparison. Source: [Audited Consolidated Financial Statements of PT Telkom Indonesia \(Persero\) Tbk for the Year 2025](#), pp. 2 and 5, compiled by the researcher.

The operating profit margin fell from 27.64% in 2024 to 23.61% in 2025. This decline coincided with a 10.15% increase in depreciation and amortization expenses. Meanwhile, financing costs remained relatively unchanged at around Rp5,206 billion. Thus, the decline in operating profit cannot be directly attributed to the increase in financing costs but rather reflects a combination of declining revenue and rising operating expenses, including depreciation and amortization.

In contrast to the profit trend, net cash flow from operating activities increased by 3.64% to Rp63,842 billion. The divergent trends between profit and operating cash flow indicate that the two provide different types of information. Profit reflects accounting performance after incorporating non-cash expenses and accruals, while operating cash flow shows the net cash generated by operating activities during a given period. However, operating cash flow cannot be treated as sole evidence of the ability to pay obligations because a portion of that cash must still be used for capital expenditures, intangible assets, dividends, lease payments, and other commitments.

After deducting purchases of fixed assets and intangible assets, simple free cash flow increased from Rp31,937 billion in 2024 to Rp38,074 billion in 2025. If dividend payments to shareholders of the parent company are also taken into account, the remaining cash flow amounts to Rp17,027 billion in 2025 and Rp14,254 billion in 2024. These calculations do not yet include all investment needs, dividends to non-controlling interests, principal loan payments, and other contractual obligations. Therefore, these figures serve as a descriptive indicator of cash availability and are not a definitive measure of funds available to repay debt.

4.1.3 Solvency and Fixed-Cost Coverage Ratios

To avoid reliance on a single indicator, this study calculates several ratios covering capital structure, cost-of-funding coverage, liquidity support, net debt, and free cash flow. All ratios are calculated from figures in the audited consolidated financial statements and are intended for descriptive analysis, not for causal testing or as the results of a predictive model. The debt-to-assets ratio increased from 47.08% to 47.69%, while the debt-to-equity ratio increased from 88.96% to 91.15%. This increase was primarily due to a decrease in total assets from Rp291,389 billion to Rp287,759 billion and a decrease in total equity from Rp154,204 billion to Rp150,537 billion, while total liabilities remained relatively unchanged.

These results indicate a slight increase in the proportion of liability-based financing, but total liabilities remain below total assets and equity.

Table 3. Capital Structure and Solvency Indicators

Indicators	Formula	2025	2024 Revisited
Liabilities to Assets	Total liabilities ÷ total assets	47.69%	47.08%
Liabilities to Equity	Total liabilities ÷ total equity	91.15%	88.96%
Interest-Bearing Debt-to-Equity Ratio	Interest-bearing loans ÷ total equity	33.73%	34.31%
DER is adjusted based on rent	(Interest-bearing loans + lease liabilities) ÷ total equity	49.76%	49.85%
Operating profit margin	Operating profit ÷ revenue	23.61%	27.64%
Cost coverage or TIER proxy	Operating profit ÷ financing costs	6.66 times	7.96 kali
Cash-based interest coverage	Operating cash flow ÷ interest paid	12.21 times	11.63 times
Current Ratio	Current assets ÷ current liabilities	0.84 times	0.82 times
Operating Cash Flows vs. Long-Term Liabilities	Operating cash flow ÷ long-term liabilities	1.01 times	1.02 times
Net financial debt, excluding rent	Interest-bearing loans — cash and cash equivalents	Rp16.546 billion	Rp19.004 billion
Net debt adjusted for leases.	Interest-bearing loans + lease liabilities – cash and cash equivalents	Rp40.683 billion	Rp42.963 billion
Simple free cash flow	Cash flows from operating activities – fixed assets – intangible assets	Rp38.074 billion	Rp31.937 billion

Note: Interest-bearing debt includes short-term bank loans, the current portion of long-term debt, and long-term debt. The TIER proxy uses operating income because the publicly available financial statements do not present adjusted EBIT separately. The researchers' calculations are based on the Audited Consolidated Financial Statements of PT Telkom Indonesia (Persero) Tbk for 2025, pp. 1–5.

The Debt-to-Equity Ratio (DER) based on interest-bearing loans decreased from 34.31% to 33.73%. After including lease liabilities, the lease-adjusted DER remained relatively stable at 49.85% in 2024 and 49.76% in 2025. Additionally, net financial debt excluding lease obligations decreased by 12.93% to Rp16,546 billion, while net debt adjusted for lease obligations decreased by 5.31% to Rp40,683 billion. These findings indicate that the increase in total long-term liabilities was not accompanied by a rise in net debt in 2025.

The TIER proxy decreased from 7.96 times to 6.66 times as operating profit declined while funding costs remained relatively stable. This ratio indicates that 2025 operating profit is still several times greater than financing costs, but the profit-based coverage buffer has narrowed. Conversely, cash-based interest coverage increased from 11.63 times to 12.21 times due to an increase in operating cash flow. The differing trends of these two ratios demonstrate

4.1.4 Results of the Review of Predictive Analytics Evidence

A review of the evidence used in this study did not identify sufficient information regarding the predictive analytics model specifically applied to project the ability to pay long-term costs. The documents analyzed did not provide definitions of target variables, database structure, training periods, algorithms, model parameters, projection horizons, probability outputs, measures of prediction error, model validation, or replicable sensitivity test results. The available data provide a basis for explaining the conditions and changes in PT Telkom's financial indicators. However, they cannot yet prove that

these changes resulted from the implementation of predictive analytics. Therefore, this study does not attribute the increase in operating cash flow, changes in liability structure, the reduction in net debt, or changes in the cost of capital to the use of specific algorithms. The study's results also do not demonstrate a causal relationship between predictive analytics and refinancing decisions, covenant compliance, credit ratings, dividend policies, or the company's financial resilience. Information regarding the assets and ownership of subsidiaries such as Telkomsel, Mitratel, and Telin was not used as direct evidence of the ability to repay debt. The value of subsidiary assets reflects the scope and materiality of the entities in the consolidation but does not automatically indicate cash that can be transferred to the parent company. Assessment

4.2 Discussion

4.2.1 Liability Structure and Multidimensional Solvency Assessment

The research findings show that PT Telkom's total long-term liabilities increased by 4.72%, from Rp60,418 billion in 2024 to Rp63,274 billion in 2025. This increase stemmed primarily from pension and post-employment benefit liabilities, long-term loans, and long-term contract liabilities. Nevertheless, an increase in long-term liabilities cannot be directly interpreted as a decline in the company's ability to meet its obligations. A solvency assessment must consider the relationship between debt levels, maturity structure, equity, cost of capital, profitability, free cash flow, lease liabilities, and other cash commitments. This multidimensional approach aligns with Abdelkader and Wahba (2024), who demonstrate that predicting financial distress requires a combination of financial indicators and cannot be based solely on a single ratio. Kebede *et al.*, (2024) also emphasize that financial distress is jointly influenced by leverage, profitability, operational efficiency, and the adequacy of a company's financial resources.

The composition of PT Telkom's liabilities shows that long-term loans and lease liabilities account for 70.56% of total long-term liabilities. The significant amount of lease liabilities means that measuring leverage without adjusting for leases may provide an incomplete picture. This is evident from the difference between the DER based on interest-bearing debt of 33.73% and the DER adjusted for lease liabilities of 49.76% in 2025. Thus, a leverage measurement that includes lease obligations provides a more comprehensive representation of long-term financing costs. This finding supports the view of Arhinful and Radmehr (2023) that leverage must be analyzed in conjunction with a company's ability to generate revenue and meet fixed costs, as the benefits of using debt must be weighed against the consequences of interest and principal payments.

From the perspective of trade-off theory, the use of debt can provide financing benefits and tax advantages. However, an increase in debt also increases the costs of financial distress and the risk of default (Myers, 1984). The research results show that total liabilities to equity increased from 88.96% to 91.15%, while total liabilities to assets increased from 47.08% to 47.69%. This increase was not primarily driven by growth in total liabilities—which rose by only about 0.03%—but rather by a decline in assets and equity. Therefore, the rise in both ratios is more accurately interpreted as a relative shift in the capital structure rather than evidence of a massive increase in debt.

Net financial debt excluding leases decreased from Rp19,004 billion to Rp16,546 billion. Net debt adjusted for leases also decreased from Rp42,963 billion to Rp40,683 billion. This decrease indicates that the increase in long-term liabilities occurred alongside an improvement in the net debt position. This situation presents a more balanced picture: the ratio of liabilities to equity increased, but

net debt after accounting for cash did not rise. These findings support the argument put forth by Dainelli *et al.*, (2024) that financial health and default risk should be analyzed through a combination of balance sheet, income statement, and cash flow indicators, rather than based solely on changes in the nominal value of liabilities.

4.2.2 Liability Structure and Multidimensional Solvency Assessment

The study found a divergence in trends between profit and cash flow performance. Revenue declined by 2.15%, operating profit fell by 16.42%, and net income decreased by 17.08%. The operating profit margin also shrank from 27.64% to 23.61%. The larger decline in profit than in revenue indicates cost pressures, primarily because depreciation and amortization expenses increased by 10.15%. In capital-intensive telecommunications companies, high depreciation and amortization are associated with significant investments in networks, equipment, and digital assets. These expenses reduce accounting profit even though they do not entirely represent cash outflows during the current period.

At the same time, net cash flow from operating activities increased by 3.64% to Rp63,842 billion. This divergence explains why profit and cash flow must be analyzed together. The decline in profit indicates a weakening of accrual-based performance. At the same time, the increase in operating cash flow suggests that the company's core activities are still generating higher cash flows compared to the previous year. However, the increase in operating cash flow cannot be treated as sole evidence of the company's ability to pay all its long-term liabilities. Operating cash flow must still be allocated toward the purchase of fixed assets, intangible assets, dividends, rent payments, interest, and loan repayments.

After deducting purchases of fixed and intangible assets, simple free cash flow increased from Rp31,937 billion to Rp38,074 billion. After accounting for dividend payments to the parent company's shareholders, the remaining cash decreased to Rp17,027 billion in 2025. This calculation indicates that the company's cash-generating capacity must be assessed after considering investment requirements and distributions to shareholders. The 19.02% increase in dividend payments also indicates competition for cash usage among meeting shareholder interests, infrastructure investment, and liability management. Therefore, the operating cash flow of Rp63,842 billion cannot be directly compared with long-term liabilities of Rp63,274 billion to conclude that all liabilities can be paid off within a single period. These two figures have different characteristics because cash flow is a measure over the course of a year, whereas liabilities represent the status of obligations as of a specific date.

The earnings-based funding cost coverage ratio, or TIER proxy, decreased from 7.96 times to 6.66 times. This decline was caused by weaker operating income, while financing costs remained relatively stable. Conversely, the cash-based interest coverage ratio increased from 11.63 times to 12.21 times due to growth in operating cash flow. This discrepancy indicates that cash-based repayment capacity has improved, but the profit-based repayment buffer has narrowed. These findings are consistent with Arhinful and Radmehr (2023), who emphasize the need to link leverage to interest coverage and fixed-charge coverage ratios. Thus, PT Telkom's condition in 2025 cannot be categorized as entirely improving or deteriorating, but rather reflects a combination of profitability pressures and strengthening cash generation.

The DSCR was not calculated because publicly available data does not distinguish between scheduled principal payments and repayments of revolving facilities, voluntary payments, and refinancing transactions. Additionally, cash flows specifically available for debt service are not presented separately. The decision not to calculate the DSCR based on aggregate loan payments represents

methodological caution, as using a non-comparable denominator could lead to misleading interpretations. Consequently, this study cannot state whether the DSCR is above or below a specific threshold, nor can it assess compliance with covenants whose terms are not available in the research documents.

4.2.3 Management Decision-Making and the Limits of Rationality

In Simon's decision-making theory, the decision-making process includes the stages of problem identification, formulation of alternatives, selection of actions, and implementation of decisions (Simon, 1977). Data regarding the growth of long-term liabilities, the decline in profit margins, the increase in operating cash flow, changes in the debt-to-equity ratio (DER), and the decrease in net debt can be categorized under the problem identification stage because they provide information about the company's financial position and changes in its financial condition. However, this data does not directly reveal the alternatives considered by management, the basis for selecting alternatives, the parties involved, or the implementation of specific decisions. Therefore, the research results only support an analysis of the financial information available for the decision-making process, not the entire internal decision-making process at PT Telkom.

Elgendy *et al.*, (2023) explain that the rationality of organizational decisions depends not only on the availability of data but also on collaborative processes, knowledge exchange, evaluation of alternatives, and decision justification. The findings of this study show that public financial statements can provide a structured information base but cannot demonstrate how that data is debated and used in management meetings. Similarly, there is no evidence that the use of data has eliminated cognitive limitations or bounded rationality. Kanzola *et al.*, (2024) demonstrate that emotions and human considerations also influence managerial decisions; thus, the presence of quantitative information does not automatically eliminate subjectivity, risk preferences, and limitations in managerial judgment.

5. Concluding Remarks and Recommendation

This study aims to analyze the solvency of PT Telkom Indonesia (Persero) Tbk and to assess the extent to which the company's documentary evidence can explain the use of predictive analytics in financial decision-making. The study employs a qualitative approach using a descriptive case study design based on secondary data, primarily the audited 2025 Consolidated Financial Statements and restated comparative figures for 2024. The analysis examined the structure of liabilities, profitability, cash flow, leverage adjusted for lease liabilities, net debt, coverage of financing costs, and cash usage commitments. The results show that long-term liabilities increased by 4.72%, from Rp60,418 billion in 2024 to Rp63,274 billion in 2025. During the same period, revenue, operating income, and net income decreased by 2.15%, 16.42%, and 17.08%, respectively. The Times Interest Earned Ratio proxy also decreased from 7.96 times to 6.66 times, indicating a narrowing of profit-based coverage of financing costs. However, operating cash flow increased by 3.64% to Rp63,842 billion, simple free cash flow reached Rp38,074 billion, and net financial debt excluding lease obligations decreased to Rp16,546 billion. The Debt-to-Equity Ratio (DER), adjusted for lease liabilities, remained relatively stable at 49.76%. This combination indicates ongoing profitability pressures occurring alongside strengthened cash generation and a reduction in net debt. Therefore, the company's solvency cannot be assessed solely based on increases in liabilities or operating cash flow but must be evaluated through several

complementary indicators. The DSCR was not calculated because public documents did not distinguish between scheduled principal payments, repayments of revolving facilities, refinancing transactions, and cash flows specifically available for debt repayment.

The documentary review did not find sufficient information regarding target variables, data structure, algorithms, training periods, projection horizons, model parameters, prediction outputs, error measures, or validation of predictive analytics. Thus, this study does not demonstrate that predictive analytics have been effectively implemented or have led to improvements in solvency, the timing of refinancing, covenant compliance, credit rating protection, or a reduction in bounded rationality in PT Telkom's management decisions. The theoretical contribution of this study lies in clarifying the boundaries between descriptive financial analysis and predictive analytics, as well as in integrating capital structure, debt-servicing capacity, management decision-making, and digital governance into a single assessment framework. Practically, companies can use the analyzed indicators as a starting point to develop a solvency monitoring system that is transparent, auditable, and accompanied by human oversight. For regulators and investors, these findings underscore the importance of disclosing methodology and model governance when companies state that they use predictive analytics in strategic financial decisions.

This study is limited to public documents and a two-year comparison; therefore, it cannot test causal relationships, long-term financial patterns, internal decision-making processes, or the accuracy of a predictive model. Data limitations also preclude calculating contractual DSCR, conducting maturity concentration analysis, covenant testing, and evaluating each subsidiary's cash flow contribution. Future research is recommended to use a longer data series and include maturity schedules, contractual interest rates, cash flows available for debt service, capital expenditures, dividends, lease liabilities, and macroeconomic variables. If future research aims to test predictive analytics empirically, it must define target and predictor variables, algorithms, training and test data, the projection horizon, error measures, out-of-sample validation, and sensitivity analysis. Interviews with finance and analytics officials may also be conducted, following procedures for informant selection, ethical approval, interview documentation, and transparent reporting of primary data analysis.

Statement of Use of Generative AI

During the preparation of this work, the author used generative artificial intelligence tools to support the scientific writing process. Grammarly was used to check grammar, refine writing style, and improve clarity in scientific writing. All interpretations, analyses, and conclusions presented in this study are the sole responsibility of the author.

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Corresponding author

Asri Sundari can be contacted at: asrisundari@fe.ukri.ac.id

