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# A Multi-Algorithm AIoT Framework for Sustainable Performance Assessment in Rural Banks

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## ABSTRACT

Sustainability assessment in Rural Banks (RBs) remains challenging due to fragmented operational data, limited analytical capabilities, and inadequate integration of economic, social, and environmental indicators. This study aims to develop an Artificial Intelligence of Things (AIoT)-based decision support framework for comprehensive, data-driven sustainability assessment in rural banking. The proposed framework integrates Global Reporting Initiative (GRI) indicators, the Analytical Hierarchy Process (AHP), a Sustainability Index, and the Random Forest algorithm. Using a Design Science Research approach, the framework was evaluated using operational and organizational data from five Rural Banks in South Kalimantan, covering 2021–2025. The dataset comprised 100 quarterly observations and 31 sustainability indicators derived from sensor-based operational monitoring and non-sensor organizational disclosures. AHP assigned the highest weight to the environmental dimension (0.38), followed by the social (0.34) and governance (0.28) dimensions, with an acceptable consistency ratio of 0.073. The Random Forest model achieved an $R^2$ of 0.87, an RMSE of 0.18, and an MAE of 0.12, outperforming Linear Regression, Support Vector Machine, and XGBoost. Feature importance and SHAP analyses identified emissions and energy consumption as the dominant indicators, followed by workplace and customer safety. These findings demonstrate the potential of integrating AIoT monitoring, multi-criteria weighting, and machine learning to improve sustainability evaluation. Practically, the framework supports transparent performance monitoring, predictive analysis, and evidence-based strategic decision-making. Future research should expand the number of participating banks and improve automated monitoring of non-sensor indicators.

## INTRODUCTION

The banking sector plays an important role in economic development, particularly as it promotes sustainable practices. Pressure from regulators, investors, and the public demands that the bank not only focus on profitability but also on social and environmental impact. Conceptual sustainability in banking refers to the triple bottom line principle, which balances economic, social, and environmental dimensions. The implementation of sustainability practices can enhance institutional reputation, strengthen stability, and increase transparency of non-financial information in global banking (Huang, 2026).

However, the implementation of sustainability in the banking sector still faces various challenges.. Many institutions do not yet have a comprehensive, measurable evaluation mechanism to evaluate sustainability performance. Assessment generally remains descriptive, with reports on sustainability lacking support from an analytical, data-driven study.

Problems become more complex in Rural Banks (RBs), which has limited resources, infrastructure, and data analysis capacity compared to large commercial banks. RBs play a strategic role in supporting inclusive finance at the local and rural levels, but the evaluation process's sustainability within institutions remains very limited and generally focuses only on financial indicators. In fact, sustainability RB operations are also influenced by social empowerment, community financing, and environmental factors related to sustainable financing. The lack of a structured evaluation system makes it difficult for RB to monitor performance in an in an integrated manner.

To address these limitations, digital technologies offer significant opportunities to improve the effectiveness of sustainability monitoring and evaluation in the banking sector. One of the increasingly sophisticated approaches is the integration of Artificial Intelligence of Things (AIoT), which combines Internet of Things (IoT) technology with

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Artificial Intelligence (AI) that enables collection, processing, and analysis of data automatic and integrated technology AIoT enables systems to monitor various operational and sustainability indicators in a continuous manner as well as produce analysis predictive that supports the decision-making process. The integration of digital technology into sector finances has also been shown to increase transparency, operational efficiency, and the accuracy of deep data analysis in modern banking systems (Mamun,2025 )(Bouteraa, 2026).

In this context, standardized frameworks are required the international standard has been developed to help organizations measure and report sustainability performance systematically. One of the most widely used is the Global Reporting Initiative (GRI), which provides a framework and indicators for measuring the impact of organizations on economic, social, and environmental issues. The GRI standards allow organizations to report on performance and sustainability transparently and to be compared globally. In the banking sector, GRI indicators are often used to evaluate banks' contributions to sustainable development and to improve the quality of non-financial information disclosure to stakeholders' interests (Sardianou et al, 2021)(Aguado-Correa et al, 2023).

Although various studies have developed evaluation models for sustainability in the banking sector, some major studies still focus on methods such as statistical analysis or multi-criteria decision-making models without fully leveraging digital technology. In addition, research has been conducted at large commercial banks in developed countries, while studies specifically evaluating sustainability in RB remain very limited. Thus, there is a research gap in the development of a technology-based decision support systems that can integrate sustainability indicators with system data monitoring.

This study aims to develop an AIoT-based decision support system for sustainability assessment in rural banks. The framework integrates data collection, analysis, and sustainability indicators, and provides visualization to support strategic decision-making. The objectives of this study include of indicators relevant to sustainability for RB, development of an AIoT system for sustainable monitoring, design of a framework for evaluating operational, social, and environmental data, and evaluation of the potential implementation system to improve decision-making quality and sustainability. This study contributes by proposing an AIoT-based decision support framework that integrates GRI indicators, the Analytical Hierarchy Process (AHP), the Sustainability Index, and Random Forest. The proposed integration results in an AIoT-based sustainability decision support model capable of evaluating sustainability performance in a comprehensive and data-driven manner, thereby supporting strategic decision-making in Rural Banks.

This study offers novelty by integrating Artificial Intelligence of Things (AIoT) technology with Global Reporting Initiative (GRI) indicators within a decision-support system framework to evaluate the sustainability of the Rural Bank sector in a general, integrated approach. This not only focuses on reporting sustainability but also on monitoring and analyzing operational data in an integrated way. The main contributions of this study include development framework AIoT-based decision support system integrates GRI indicators, a hybrid AHP implementation method, a Sustainability Index, and Random Forest for sustainability evaluation, as well as an AIoT-based implementation-based monitoring system in the banking local sector.

## LITERATURE REVIEW

The development of Artificial Intelligence of Things (AIoT) has enhanced system monitoring through Internet of Things (IoT) sensors, artificial intelligence-based analytics, and cyber-physical systems. Conventional systems face data fragmentation, limited interoperability, and inadequate real-time analysis. AIoT addresses these limitations through perception, computation, system, and control layers, enabling automated sensing, processing, and decision-making (Liu et al., 2026). Its applications include environmental and agricultural monitoring (Liao et al., 2022; Bayar et al., 2025; Le et al., 2025; Rahman et al., 2024). Random Forest-based irrigation systems have improved water-use efficiency by up to 13% (Lu et al., 2025). In transportation and industry, AIoT supports driver detection with accuracy reaching 99% and infrastructure monitoring using convolutional neural networks (Phan et al., 2026; Zhang et al., 2021; Choo et al., 2026). Applications also extend to industrial, chemical, service, and healthcare sectors (Liu et al., 2026; Wang et al., 2025; Yaqoob et al., 2026). However, security and privacy challenges persist, encouraging hypergraph convolution networks, adversarial defense, and Privacy-by-Design approaches (He et al., 2026; Kuang et al., 2026; Ivanovska et al., 2025; Li et al., 2025). AIoT therefore provides a foundation for adaptive, intelligent, and sustainable monitoring (Iqrar et al., 2026; Braga et al., 2025).

Sustainability assessment in banking employs analytical approaches to evaluate economic, social, and environmental performance. Shi et al. (2025) integrated Data Envelopment Analysis (DEA), Random Forest, and Shapley Additive Explanations (SHAP) to assess banking activities and improve model interpretability. Ecer and Pamucar (2022) combined LOPCOW and Dombi-Bonferroni within multi-criteria decision-making (MCDM), using Global Reporting Initiative (GRI)-aligned indicators and identifying economic performance as dominant, although environmental considerations are increasing. Evidence from 46 African countries indicates that banking stability supports infrastructure and sustainable agro-environmental development through improved financing access (Ketchoua et al., 2025). In BRICS countries, conventional banking remains associated with resource exploitation and carbon emissions, whereas fintech and digital banking can reduce environmental impacts through operational efficiency (Pu et al., 2024). Green banking also promotes energy efficiency and renewable energy adoption in developing countries

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(Ding & Li, 2026; Rahman et al., 2023).

Blockchain, regulatory technology (RegTech), and financial technology (FinTech) improve banking transparency and efficiency (Mbaidin et al., 2023; Quintiliani, 2025). Corporate social responsibility, green employee behavior, and customer perceptions influence reputation and loyalty (Han et al., 2025; Rahim et al., 2026; Sajid, 2026). Sustainability disclosure can reduce liquidity risk by improving non-financial transparency (Huang et al., 2026; Gupta, 2026). Natural disasters may increase credit risk and non-performing loans (Nguyen et al., 2025), highlighting banks' roles in low-carbon transitions through policy, finance, and technology (Chavosh Nejad et al., 2021; Fernández Fernández, 2025). Traditional and shadow banking also support development financing and the Sustainable Development Goals (SDGs) (Konstantakis et al., 2024; Isayev & Gokmenoglu, 2024). Participatory approaches and fiscal measures further strengthen policy effectiveness and sustainability (Karim et al., 2026).

The Global Reporting Initiative (GRI) promotes transparency and accountability in corporate sustainability reporting by providing standardized guidelines for disclosing environmental, social, and governance impacts. Recent research has examined organizational adherence to GRI standards and identified institutional pressures, organizational characteristics, and external auditing as factors associated with reporting compliance (Friske et al., 2024). Furthermore, a systematic literature review highlights the continuing importance of GRI in sustainability reporting while identifying persistent challenges related to disclosure quality, stakeholder interests, and greenwashing (Bais et al., 2024). Integrating GRI indicators with the Sustainable Development Goals (SDGs) can further strengthen the alignment between corporate sustainability reporting and global sustainability objectives (Lau & Wong, 2023). Nevertheless, reporting complexity and inconsistent disclosure practices may limit transparency and comparability. In the higher education sector, research indicates that sustainability reporting remains limited and that existing reporting standards may require adaptation to the specific characteristics of educational institutions (Sari & Faisal, 2022).

AI-based Decision Support Systems (DSS) facilitate sustainability decisions through predictive analytics, integrated data, and automated recommendations. An environmental governance framework integrating AI, IoT, the Technology–Organization–Environment (TOE) framework, and Analytic Hierarchy Process (AHP) reportedly improved ecological management decision-making effectiveness by up to 80% (Zhang, 2025). Agricultural AI-DSS combining multisensor data, Random Forest, and Long Short-Term Memory (LSTM) achieved crop-yield improvements of 13.1% and water-use efficiency gains of 15.5% (Emara et al., 2026). A hybrid Whale Optimization Algorithm and Support Vector Machine model achieved 98.2% classification accuracy in energy-efficient housing planning (Kavuran et al., 2026). AI-supported Delphi and statistical methods have also assessed urban sustainability indicators (Ghandehariun & Faghihi, 2025). Broader research confirms AI-based DSS applications across sustainability domains (Dhal et al., 2026; Fernández-Arroyo et al., 2026; Mills & Sætra, 2025; Xia et al., 2026).

Despite these advances, existing studies predominantly employ conventional analytical methods and focus on large financial institutions in developed economies. Integration of sustainability indicators with real-time operational data remains limited, restricting dynamic assessment. AIoT applications for sustainability evaluation in Rural Banks (RBs) are particularly underexplored. This study therefore develops an integrated AIoT-based DSS combining GRI-aligned sustainability indicators and operational data to support comprehensive, adaptive, and evidence-based sustainability assessment in rural banking.

## METHOD

### Research Design

This study employs the Design Science Research (DSR) approach to develop an AIoT-based Decision Support System (DSS) framework for evaluating sustainability in Rural Banks (RBs). DSR was selected because it produces practical artifacts integrating Internet of Things (IoT)-based data collection, Artificial Intelligence of Things (AIoT), and Global Reporting Initiative (GRI) sustainability indicators. The research follows six stages: problem identification and motivation, solution objectives, design and development, demonstration, evaluation, and communication. The primary problem is the predominantly manual and insufficiently integrated sustainability assessment process in RBs, which limits monitoring efficiency and strategic decision-making. The framework integrates AIoT architecture and decision-support models to enable automated sustainability monitoring using operational data collected directly from integrated IoT devices during banking operations. System evaluation examines its effectiveness in supporting data-driven sustainability decisions. The dataset comprises real operational data validated for consistency and alignment with banking operational standards. Consequently, the developed framework provides an empirically grounded solution to improve transparency, monitoring efficiency, and sustainability-related decision-making in RBs.

### Proposed AIoT Architecture

The proposed architecture supports automated and integrated sustainability monitoring and evaluation in Rural Banks (RBs) by combining Artificial Intelligence of Things (AIoT) technology with Global Reporting Initiative (GRI) indicators. The architecture comprises five layers: data acquisition, communication, data processing, AI analytics, and decision support. The data acquisition layer collects continuous, measurable, time-series operational data through IoT devices, including smart energy meters, digital water meters, and integrated digital records of banking operations and

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transactions, covering economic, social, and environmental indicators. The communication layer transmits data through IoT network protocols to centralized cloud storage or internal servers. The data processing layer performs data integration, validation, and cleansing to ensure data quality. Subsequently, the AI analytics layer applies the Analytical Hierarchy Process (AHP), Sustainability Index, and Random Forest algorithm to calculate sustainability scores and generate predictive insights. Finally, the decision support layer presents interactive dashboards, visual indicators, trend analyses, and recommendations, enhancing transparency, operational efficiency, and strategic decision-making in banking sustainability management.

The AIoT-based sustainability assessment framework consists of five integrated layers. The IoT Device Layer (Data Acquisition Layer) collects operational data from core banking systems, consumption sensors, energy systems, digital transactions, and social and financial services. IoT technology enables continuous, automated data collection to support the assessment of economic, social, and environmental sustainability in Rural Banks (RBs). The Data Communication Layer transmits data from IoT devices to the central computing system using protocols such as MQTT, HTTP, and REST APIs. Cloud storage supports scalable data management, integration, and secure monitoring. The Data Processing Layer integrates operational data from multiple sources, performs data cleaning, removes incomplete or inconsistent records, and stores validated information in a structured database for subsequent sustainability analysis. The AI Analytics Layer applies the Analytical Hierarchy Process (AHP) to determine sustainability indicator weights, calculates aggregated sustainability indices, and uses the Random Forest algorithm to identify patterns and predict sustainability performance. These analyses generate sustainability scores and predictive insights for identifying potential risks. Finally, the DSS Dashboard Layer presents analytical results through interactive dashboards, graphs, and GRI-based sustainability indicators. It enables management to monitor performance transparently, generate automated sustainability reports, and support evidence-based strategic decision-making. Figure 1 shows the architecture of the AIoT implemented in this study. This support system supports decision-making in evaluating the sustainability of the Rural Bank.

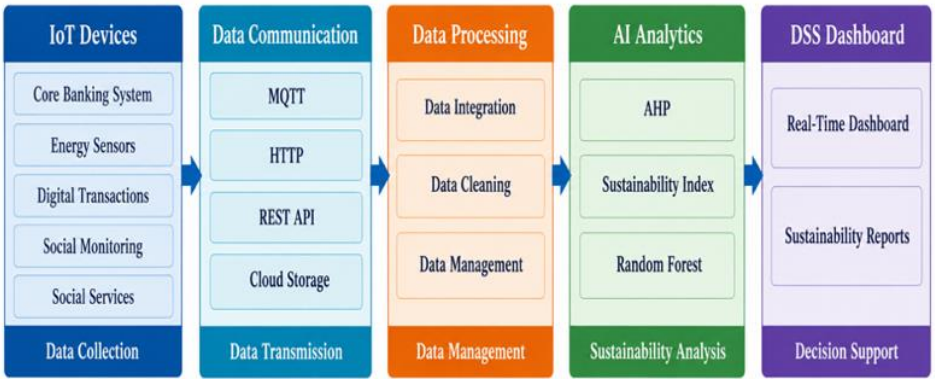


Figure 1. Proposed AIoT-Based Sustainability Architecture for Assessment in Rural Banks

Figure 1 illustrates the proposed AIoT-based sustainability assessment architecture for Rural Banks (RBs), consisting of five interconnected layers. The IoT Device Layer collects operational data from sensors and banking systems. The Data Communication Layer transmits the collected data to centralized storage. The Data Processing Layer validates, cleans, and integrates data to ensure consistency. The AI Analytics Layer applies the Analytical Hierarchy Process (AHP), Sustainability Index, and Random Forest algorithm to evaluate and predict sustainability performance based on relevant GRI indicators. Finally, the Decision Support Layer presents results through dashboards and performance visualizations to support monitoring and managerial decision-making. The integration of these layers enables systematic sustainability assessment and supports more transparent, data-driven decisions in Rural Banks.

**GRI Indicator Mapping**

Evaluation of sustainability in the banking sector, especially the Rural Bank (RB), requires standardized indicators to conduct structured evaluations. One of the internationally used standards is the Global Reporting Initiative (GRI), which covers economic, environmental, and social issues. In this study, the GRI indicators serve as the basis for developing an AIoT-based sustainability assessment. Some indicators can be monitored automatically through sensors and the Internet of Things, such as energy consumption, water use, emissions, and waste management. In contrast, other indicators still require reporting based on organizational documents. AIoT integration enables sustainable data collection, improving data accuracy and transparency. Table 1 below shows GRI indicators that can be monitored using AIoT sensor technology. Indicators. This is generally related to environmental and safety aspects, with physical parameters that can be measured quantitatively by IoT devices.

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Table 1. GRI Indicators that Can Be Used Using AIoT Sensors

| GRI Code | Topic |
|---|---|
| GRI 301 | Materials |
| GRI 302 | Energy |
| GRI 303 | Water |
| GRI 305 | Emissions |
| GRI 306 | Waste |
| GRI 403 | Occupational Health & Safety |
| GRI 416 | Customer Health & Safety |

Although AIoT-capable technology monitors various operational parameters periodically, not all Global Reporting Initiative (GRI) indicators can be measured using sensors. Many indicators related to policy organization, governance, practice, employment, human rights, and the impact of the social economy require a reporting document. The data usually originates from the sustainability report, system management source, human resources, financial reports, and organizational policy documents. In the proposed framework, indicators can still be integrated through data digitization and analysis using artificial intelligence. This integration enables a more comprehensive sustainability evaluation. A list of GRI indicators that do not use sensors is presented in Table 2.

Table 2. GRI Indicators that are not Using Sensors

| GRI Code | Topic | GRI Code | Topic | GRI Code | Topic |
|---|---|---|---|---|---|
| GRI 2 | General disclosures | GRI 203 | Indirect economic impacts | GRI 406 | Non-discrimination |
| GRI 3 | Material topics | GRI 204 | Procurement practices | GRI 407 | Freedom of association |
| GRI 201 | Economic performance | GRI 205 | Anti-corruption | GRI 408 | Child labor |
| GRI 202 | Market presence | GRI 206 | Anti-competitive behavior | GRI 409 | Forced labor |
| GRI 308 | Supplier environmental assessment | GRI 401 | Employment | GRI 412 | Human rights assessment |
| GRI 402 | Labor relations | GRI 413 | Local communities | GRI 417 | Marketing and labeling |
| GRI 404 | Training and education | GRI 414 | Supplier social assessment | GRI 418 | Customer privacy |
| GRI 405 | Diversity | GRI 415 | Public policy | GRI 419 | Socioeconomic compliance |

After the Global Reporting Initiative (GRI) indicators are mapped to data sources, the next step is to determine the mechanism evaluation level and disclosure sustainability. This study uses a disclosure scoring method to determine the extent to which the organization discloses information related to GRI indicators in its sustainability report and supporting documents. This approach provides quantitative measures of transparency and completeness in information organization. The assessment scale ranges from 0–5, with 0 indicating no disclosure and 5 indicating very complete disclosure, including narrative, quantitative data, trends, performance, sustainability targets, and evidence of policy implementation. Criteria evaluation level disclosure: GRI indicators are presented in Table 3.

Table 3. Disclosure Score Scale (0–5)

| Score | Criteria |
|---|---|
| 0 | No revealed The same very |
| 1 | It is stated very briefly (narrative) general, without data) |
| 2 | Revealed in a way descriptive, without quantitative data |
| 3 | Revealed with limited data |
| 4 | Revealed Enough complete (narrative + data + policy) |
| 5 | It is disclosed very completely (narrative, trend data, targets, evaluation, evidence) implementation) |

**Decision Support Model and Evaluation**

The decision support system model integrates the Global Reporting Initiative (GRI) sustainability with operational data collected through Artificial Intelligence of Things (AIoT) architecture. The model aims to produce a Sustainability Score for Rural Bank operations. Analysis process covering three main areas: determination of indicator weights using the Analytic Hierarchy Process (AHP), calculation of scores using the Sustainability Index, and predictive analysis using Random Forest in sustainability based on bank operational data.

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**Analytic Hierarchy Process (AHP) for Indicator Weighting**

The Analytic Hierarchy Process (AHP) method is used to determine the weights of indicators of sustainability aligned with the GRI standards, including the economic, environmental, and social dimensions. This method allows systematic determination of a priority indicator through pairwise comparison. The AHP process begins by building a hierarchical structure consisting of the objective system (sustainability assessment), dimensions of sustainability, and relevant GRI indicators. Furthermore, a pairwise comparisons were conducted for compiling, matrices were used for counts and weights, and the priority of each indicator was determined.

$$w_i = \frac{\sum_{j=1}^{n} a_{ij}}{\sum_{i=1}^{n}\sum_{j}^{n} a_{ij}} \quad (1)$$

Where:
$w_i$= weight indicator i-th
$a_{ij}$ = value comparison indicator i-th to indicator to -j
$n$ = number indicator
To ensure consistency in the assessment process, the AHP method uses the calculated Consistency Ratio (CR) using the following equation:

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (2)$$

$$CR = \frac{CI}{RI} \quad (3)$$

Where:
$CI$ = Consistency Index
$RI$ = Random Index
$\lambda_{max}$= maximum eigenvalue of the comparison matrix
If the CR value < 0.1, then the consistency level is considered acceptable.

**Sustainability Index Calculation**

After the weight indicator is obtained using the AHP method, the next step is to calculate the Sustainability Index, which represents the bank's overall sustainability. In this study, each GRI indicator is assessed using a disclosure scoring method on a scale of 0 to 5 that describes the level of completeness of disclosure information for sustainability organizations.
To ensure consistency between indicators, values are scored and then normalized to the range 0–1 using the following equation:

$$S_i = \frac{x_i}{5} \quad (4)$$

Where:
$S_i$ = normalized indicator scores
$X_i$ = score disclosure indicators (0–5)

The Sustainability Index value is then calculated using a combination of normalized score indicators, with weights obtained via the AHP method. The Sustainability Index equation can be written as follows:

$$SI = \sum_{i=1}^{n} w_i S_i \quad (5)$$

Where:
$SI$ = Organizational Sustainability Index
$w_i$ = weight indicator i-th
$S_i$ = score indicators that have been normalized
$n$ = number indicator sustainability
The resulting Sustainability Index value reflects the level of sustainability of bank operations in general and serves as a basis for decision-making by decision support system.

**Random Forest for Sustainability Prediction**

Besides producing the Sustainability Index, the system supports decision-making by using machine learning to analyze sustainability patterns based on bank operational data. The algorithm used is Random Forest, namely an ensemble method that combines several decision trees to increase predictive accuracy. In this study, the calculated

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indicator from the Sustainability Index is used as an input variable to predict bank sustainability based on historical data from the AIoT system. Random Forest predictions can be stated in a mathematical way as an average result prediction from all the tree decisions in the model:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \quad (6)$$

Where:
$\hat{y}$ = value sustainability score prediction
$T$ = number of decision trees
$h_t(x)$ = function prediction tree decision to -t
$x$ = vector indicator sustainability

This Approach allows the system not only to assess current sustainability performance, but also to identify trend changes in performance and bank sustainability based on collected operational data, in a sustainable way through AIoT system. In this study, the Random Forest model is configured with key parameters to balance model complexity and generalization performance. The model uses 200 decision trees (n_estimators = 200) with a maximum depth of 10 (max_depth = 10) to prevent overfitting, and a minimum of 5 samples per leaf node (min_samples_leaf = 5) to ensure consistent learning across varying data. The Gini impurity criterion is used for node splitting, enabling the model to achieve stable and accurate predictions.

Random Forest was selected in this study because of its ability to handle multidimensional data, reduce overfitting, and provide stable classification performance compared to methods such as Logistic Regression and Support Vector Machine (SVM) in complex data cases.

**Comparative Model Evaluation**

To evaluate the robustness and performance of the proposed Random Forest model, this study compares it with several baseline machine learning models, including Linear Regression (LR), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). All models were trained on the same dataset and feature set, with a consistent 80% training and 20% test split to ensure a fair comparison. Model performance was evaluated using three standard regression metrics: Coefficient of Determination ($R^2$), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

Linear Regression was used as a baseline statistical model to represent linear relationships among variables. SVM was selected for its ability to handle non-linear patterns via kernel functions. XGBoost was included as a state-of-the-art ensemble learning method known for its high predictive performance. This comparative evaluation aims to demonstrate the effectiveness of the proposed Random Forest model in capturing complex relationships among sustainability indicators.

## RESULT

This study implements an AIoT-based decision support system for Sustainability Assessment at 5 RBs in South Kalimantan, integrating AI and IoT to monitor and analyze sustainability performance. The data were obtained from AIoT-based operational systems and organizational reports. The analysis was conducted using a hybrid model that combines the Analytic Hierarchy Process (AHP), Sustainability Index, and Random Forest. The research results cover AIoT System Implementation and Sustainability Scoring Model in 5 RBs in South Kalimantan.

**AIoT System Implementation**

The implementation of the Artificial Intelligence of Things (AIoT) system in this study focuses on integrating sensor and non-sensor data to measure sustainability performance of five Rural Banks (RBs) during the 2021–2025 period. The dataset used consists of quarterly data on sustainability indicators based on the Global Reporting Initiative (GRI), sourced from AIoT sensors and non-sensor-based disclosures.

AIoT-based indicators measure operational aspects such as energy consumption, water use, emissions, waste, and safety for workers and customers. Meanwhile, non-AIoT indicators cover governance, economic, social, and compliance aspects obtained from report management and institutional documents. The implementation of the AIoT system is done in two main stages, namely the data acquisition and data integration processes, which serve as the foundation for the formation of a comprehensive sustainability dataset.

**Data Acquisition**

The data acquisition stage is the process of collecting data from various sources, including AIoT sensor-based and non-sensor sources. Data for the study were obtained through a system-integrated AIoT sensor-based data collection system integrated with Rural Bank operations. This Approach reflects the implementation of the AIoT system in a direct, operational environment in the banking sector.

- **Data based AIoT (Sensor Data)**

AIoT-based data in this study were obtained directly through an integrated Internet of Things (IoT) sensor device

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in Rural Bank (RB) operations. This system serves as a data-acquisition layer, enabling continuous and measurable collection of operational parameters, with indicators aligned with the Global Reporting Initiative (GRI). Energy consumption (GRI 302) is measured using a smart energy meter that records electricity use in real time. Water use (GRI 303) is measured using a digital water meter sensor that records water consumption periodically. Carbon emissions (GRI 305) is calculated automatically based on energy consumption data obtained from the sensor, with the use factor emission integrated into the system. Operational waste indicators (GRI 306) is collected through a sensor-based monitoring system and digital recording of activities integrated into operations. In contrast, indicators of safety work and customer satisfaction (GRI 403 and GRI 416) are obtained through incident reporting systems, digitized, and connected to the internal network information system. All data is transmitted via IoT protocols to a centralized system for integration and analysis. The data are obtained in real-time or near real-time with time-series characteristics, allowing for sustainable monitoring performance. To ensure data quality, validation and synchronization processes are performed across data sources before they are used in analysis. Next, all data with different units were normalized to a scale of 0 to 5 based on performance and disclosure levels. The normalization process aims to ensure consistency across indicators and support data integration in system models, supporting AIoT-based decision-making.

- **Non- AIoT Data (Non-Sensor Data)**

Non-sensor data were obtained from secondary sources in the form of annual reports, financial reports, and documents on operational and policy aspects of Rural Banks (RBs). The indicators used cover economic, social, and governance aspects based on GRI standards, such as GRI 201–206 for the economic aspect and GRI 401–419 for the social and compliance aspects. Data that is converted into a 0–5 disclosure score reflecting completeness of the information presented in organizational documents. This approach aims to standardize data so it can be integrated with AIoT-based indicators within a single analysis framework.

- **Dataset Characteristics**

The dataset used in this study has a panel data structure, consisting of five Rural Banks (RBs) as units of analysis, with observations over a five-year period (2021–2025) and a quarterly frequency. A total of 100 observations were obtained, reflecting the combination of entities and time. The dataset includes 31 sustainability indicators, comprising AIoT-based indicators and non-AIoT indicators, representing environmental, social, and governance dimensions. This generates empirical datasets based on operational data that have been transformed into GRI framework indicators, allowing for more comprehensive and measurable sustainability analysis, with conditions for implementation in the field.

**Data Integration**

The data integration stage combines all data into a single dataset, ready for sustainability analysis. This process begins with data standardization, in which all indicators, including those derived from AIoT sensors and non-sensor data, are transformed to a uniform scale of 0 to 5 to eliminate differences in measurement units across indicators, such as kWh for energy, liters for water, and tons for emissions, thereby enabling consistent comparisons between variables. Besides that, using a uniform scale also makes it easier to implement advanced methods, such as AHP weighting and machine learning algorithms.

Next, data from various sources were combined into a single-panel dataset, where each row corresponds to a combination of RB, year, and quarter, and each column corresponds to the GRI indicators used in the research. This structure allows analysis that not only considers variation over time but also variation between entities. In the integration process, an inspection is also carried out to ensure data consistency, identify any values that are not logical, and ensure data completeness throughout the observation period. Final results from this stage include a comprehensive, ready-to-use, structured dataset used for sustainability index calculation, weighting indicators using the Analytical Hierarchy Process (AHP), and predictive model development using Random Forest.

**Dataset Construction**

The dataset construction stage is the stage that supports AIoT implementation, aiming to produce a structured dataset ready for analysis and sustainability. This dataset was built based on the results of the data acquisition and integration process, obtained directly through IoT sensor devices and systems operationalized and integrated into the Rural Bank (RB). All data used is operational data collected automatically through the AIoT system.

The dataset is compiled from a combined indicator derived from IoT sensors and operational data, integrated into a single data framework. Each observation unit in the dataset represents a combination of an RB entity, a time period (year), and quarterly intervals, producing a panel data structure capable of capturing variation over time and between entities in a systematic way. The data collected have time-series characteristics, obtained from the sensor-based monitoring process and the continuously running digital system in an operational environment.

During dataset construction, all indicators were normalized to a uniform scale of 0 to 5 based on performance and disclosure levels. The normalization process is performed to ensure consistency and support analysis in analysis, including sustainability index calculation and the implementation of machine learning methods.

The resulting dataset covers indicators that represent the dimensions of environmental, social, and governance,

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providing a comprehensive overview of the performance and sustainability of each RB, based on data obtained directly from the system monitoring AIoT.

To gain a better understanding of the dataset's structure and characteristics, the following section presents the dataset structure, data examples, and descriptive statistics for the indicators used. The complete dataset consists of 100 observations collected via an IoT-based data collection process at five RBs during the observation period. As part of the results presentation, some data (sample) and descriptive statistics to describe the distribution and characteristics of the data in general. The dataset structure, samples, and descriptive statistics for selected indicators are presented in Tables 4, and 5.

Table 4. Structure of the Dataset

| Variable | Description | Type | Scale |
|---|---|---|---|
| BPR | Credit Bank identifier | Categorical | - |
| Year | Observation year (2021–2025) | Numeric | - |
| Quarter | Observation period (Q1–Q4) | Categorical | - |
| GRI 301 | Materials usage | AIoT -based | 0–5 |
| GRI 302 | Energy consumption | AIoT -based | 0–5 |
| GRI 303 | Water usage | AIoT -based | 0–5 |
| GRI 305 | Emissions | AIoT -based | 0–5 |
| GRI 306 | Waste management | AIoT -based | 0–5 |
| GRI 403 | Occupational health & safety | AIoT -based | 0–5 |
| GRI 416 | Customer health & safety | AIoT -based | 0–5 |
| GRI 2 | General disclosures | Non- AIoT | 0–5 |
| GRI 3 | Material topics | Non- AIoT | 0–5 |
| GRI 201–419 | Economic, social, governance indicators | Non- AIoT | 0–5 |

Table 5. Descriptive Statistics of Selected Indicators

| Indicator | Mean | Min | Max | Std. Dev |
|---|---|---|---|---|
| GRI301 | 3.10 | 1 | 5 | 1.02 |
| GRI302 | 3.25 | 1 | 5 | 1.10 |
| GRI303 | 2.95 | 0 | 5 | 1.20 |
| GRI305 | 3.05 | 1 | 5 | 1.08 |
| GRI306 | 2.85 | 0 | 5 | 1.15 |
| GRI403 | 3.40 | 2 | 5 | 0.95 |
| GRI416 | 3.20 | 1 | 5 | 1.00 |
| GRI201 | 3.00 | 1 | 5 | 1.12 |
| GRI401 | 3.15 | 1 | 5 | 1.05 |
| GRI405 | 2.90 | 0 | 5 | 1.25 |

**Sustainability Scoring Model**

This study develops an assessment model for sustainability based on multi-criteria decision-making and machine learning methods. This model consists of three main stages: determination of indicator weights using the Analytical Hierarchy Process (AHP), calculation of the sustainability index based on aggregated weights, and predictive modeling using Random Forest. This approach not only allows static evaluation of sustainability performance but also enables prediction of key influencing factors for RB sustainability based on data variation.

**AHP Weighting of Sustainability Indicators**

The determination of indicator weights is done using the Analytical Hierarchy Process (AHP) method, with a hierarchical structure consisting of three levels: objectives (sustainability performance), main criteria (environmental, social, economic/governance), and GRI indicators as sub-criteria. The comparison process in pairs was conducted using Saaty's scale (1–9), which reflects the relative importance of indicators.

The resulting comparison matrix is then used to compute eigenvector values to get the weight priority. To ensure consistency assessment, use the Consistency Index (CI) and Consistency Ratio (CR). Test results show that the CR value is below the threshold limit of 0.1, indicating that the matrix comparison's own-level the consistency is considered acceptable. AHP Weights and Consistency Results are presented in Table 6.

Table 6. AHP Weights and Consistency Results

| Dimensions | Weight |
|---|---|
| Environmental | 0.38 |
| Social | 0.34 |
| Governance | 0.28 |

| Metric | Value |
|---|---|
| CI | 0.042 |
| CR | 0.073 |

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The AHP results show that the environmental dimension has the highest weight, indicating that operational-based AIoT factors, such as AIoT like energy and emissions, are the determinants in the main evaluation of sustainability. This is consistent with global trends that prioritize environmental aspects in sustainability practices.

**Sustainability Index Calculation**

The Sustainability Index calculation measures an organization's sustainability level based on previously assessed Global Reporting Initiative (GRI) indicators. The sustainability index is calculated using an AHP-based approach, with the obtained weights and presented in Table 7.

Table 7. Sustainability Index (Normalized Results)

| BPR | Year | Quarter | Raw SI | Normalized SI |
|---|---|---|---|---|
| BPR_A | 2021 | Q1 | 3.25 | 0.65 |
| BPR_A | 2021 | Q2 | 3.45 | 0.72 |
| BPR_B | 2021 | Q1 | 2.95 | 0.55 |
| BPR_C | 2022 | Q1 | 3.10 | 0.60 |
| BPR_D | 2023 | Q3 | 3.60 | 0.78 |

Normalization allows comparison across time and between entities in a more objective way. The results show variation in performance sustainability between RBs, which reflects differences in operational strategy and the level of implementation of sustainability practices.

**Random Forest Sustainability**

To evaluate the non-linear relationship between indicators and improve predictive ability, the Random Forest algorithm is used. This model is trained using all GRI indicators as independent variables, with the sustainability index as the dependent variable. The dataset is split into training (80%) and test (20%). Model evaluation was carried out using several metrics, namely: Coefficient of Determination ($R^2$), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The performance evaluation model and the importance indicators are presented in Tables 8 and 9, respectively.

Table 8. Performance Evaluation Model

| Metric | Value |
|---|---|
| $R^2$ | 0.87 |
| RMSE | 0.18 |
| MAE | 0.12 |

Table 9. Importance Indicators

| Indicator | Importance |
|---|---|
| GRI305 (Emissions) | 0.16 |
| GRI302 (Energy) | 0.14 |
| GRI403 (OHS) | 0.13 |
| GRI416 (Customer Safety) | 0.12 |
| GRI201 (Economic) | 0.11 |

The results show that the Random Forest model has high accuracy ($R^2 = 0.87$), indicating that the combination of indicators is capable of explaining significant variations in the sustainability index. AIoT-based indicators, such as emissions and energy, appear to be the most dominant factors, confirming the importance of integrating technology into sustainability management. In addition, significant contributions from indicators such as safety at work and safety for customers show that sustainability is not only determined by operational efficiency, but also by quality management, sources of power, human rights, and stakeholder protection. These findings strengthen the argument that an effective sustainability approach must be multidimensional and integrated.

The distribution of sustainability index values shows that a large number of RBs have a index value in the medium to high range, indicating that performance sustainability is relatively stable, with moderate variation between entities and time periods. The distribution pattern is normal, indicating no extreme outliers, so the dataset can be considered representative for continued analysis. The results of the feature importance analysis show that AIoT-based indicators, such as emissions (GRI 305) and energy consumption (GRI 302), make the greatest contribution to determining the sustainability index. In addition to that, indicators such as safety at work (GRI 403) and customer safety (GRI 416) also show significant influence. These findings confirm that RB sustainability is influenced by a combination of operational and social factors, underscoring the importance of a multidimensional approach in Sustainability evaluation. The distribution of the sustainability index is presented in Figure 2. And Feature importance is presented in Figure 3.

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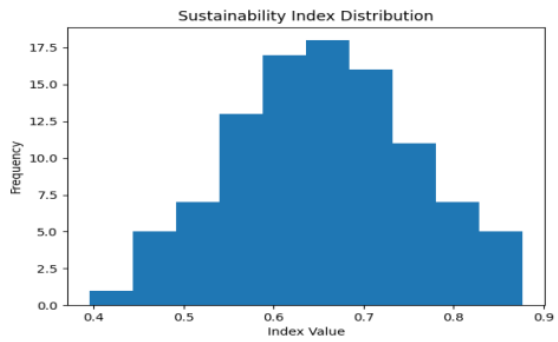



Figure 2. Distribution of sustainability index

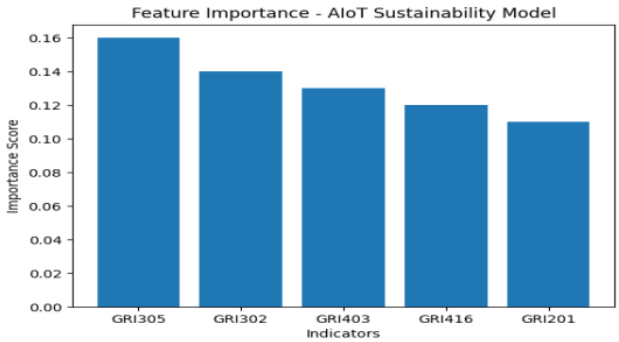



Figure 3. Feature importance

The boxplot shows the distribution of the sustainability index for each RB, indicating variation in sustainability performance across entities. It is visible that some RBs have more distribution stability (variance low), while others show more fluctuations. This indicates differences in the consistency, implementation, practice, and sustainability of each RB. The time-series trend shows an increase in the sustainability index from 2021 to 2025. This pattern indicates the gradual restoration of performance sustainability in RB, likely influenced by the adoption of AIoT technology and increased awareness of sustainability practices. The relatively stable trend also shows that the model used can consistently capture longitudinal dynamics. The boxplot of the sustainability index distribution is presented in Figure 4. and the trend in the sustainability index is presented in Figure 5.

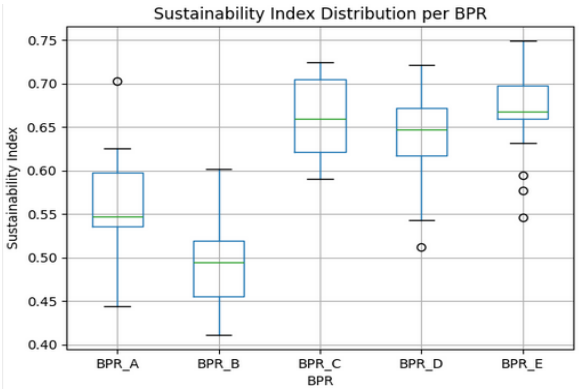



Figure 4. Boxplot of sustainability index distribution

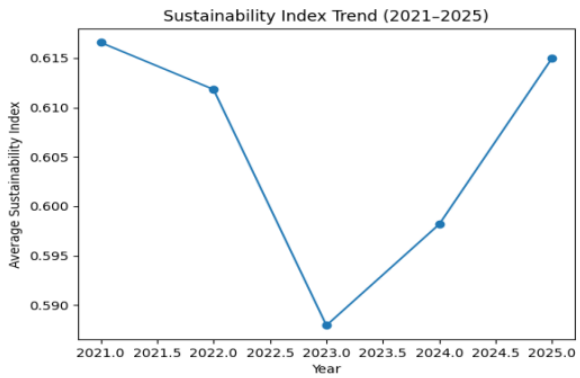



Figure 5. Sustainability index trend

SHAP (Shapley Additive exPlanations) analysis is used to interpret the contribution of each indicator to the Random Forest model's output. The results show that emission indicators (GRI 305) and energy (GRI 302) have the greatest influence on sustainability index prediction, followed by indicators social, such as safety at work (GRI 403) and safety of customers (GRI 416). This approach provides transparency into the machine learning model used, increasing interpretability and trustworthiness of the results. SHAP Feature importance analysis is presented in Figure 6.

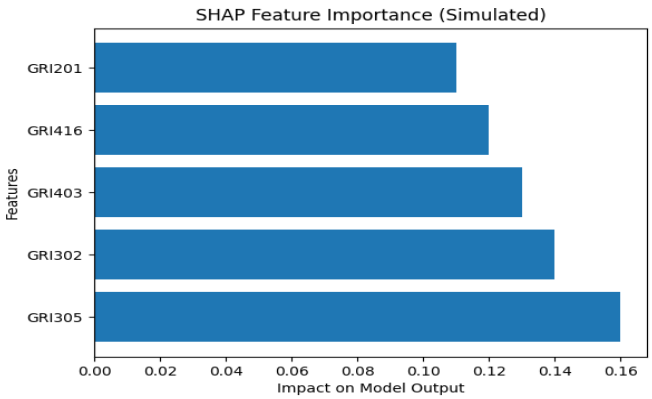



Figure 6. SHAP Feature importance

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The comparative results demonstrate that the Random Forest model outperforms the baselines across all evaluation metrics. While Linear Regression performs relatively poorly due to its limitations in capturing linear relationships, SVM and XGBoost achieve better results.

The performance gap between Random Forest and Linear Regression also indicates the presence of non-linear relationships in sustainability data, suggesting that sustainability indicators interact in complex ways. This finding highlights the importance of using non-linear and ensemble-based models in sustainability analytics.

However, Random Forest achieves the highest $R^2$ (0.87) and the lowest error values (RMSE = 0.18, MAE = 0.12), indicating its superior ability to model complex interactions among sustainability indicators. This result confirms that ensemble-based approaches are more effective in sustainability assessment scenarios involving multidimensional and heterogeneous data. Comparative model performance is presented in Table 10.

Table 10. Comparative Model Performance

| Model | $R^2$ | RMSE | MAE |
|---|---|---|---|
| Linear Regression | 0.71 | 0.29 | 0.21 |
| SVM | 0.79 | 0.24 | 0.18 |
| XGBoost | 0.85 | 0.20 | 0.14 |
| Random Forest | 0.87 | 0.18 | 0.12 |

**Sustainability Index Output**

The sustainability index output in this study represents the results of an AIoT system, AHP weighting, and machine learning modeling using Random Forests to evaluate the sustainability of Rural Banks (RB). The resulting index value is an a weighted aggregation of all sustainability indicators, including the environmental, social, and governance dimensions, all normalized to a uniform scale. This allows for objective comparison between entities and time periods.

The process of forming the Sustainability Index has begun with data acquisition based on AIoT that reflects operational conditions in a periodic, integrated manner, including energy consumption, emissions, and power use. It is combined with non-AIoT data that reflect governance, social, and compliance aspects. Furthermore, the indicators are assigned weights using the Analytical Hierarchy Process (AHP) to reflect their relative importance. Then the index value is aggregated and normalized to produce a score within a standardized range.

The results of the Sustainability Index show varying sustainability performance between RB and across time periods, which reflects differences in the level of implementation of sustainability practices and in the effectiveness of operational and governance management. In addition, the Random Forest model, equipped with feature importance and SHAP analysis, shows that AIoT-based indicators, particularly emissions and energy consumption, makes a dominant contribution to determining the sustainability index, followed by social indicators such as workplace and customer safety. This confirms that RB sustainability is greatly influenced by the integration of operational efficiency and quality management.

The Sustainability Index serves not only as a quantitative measurement tool but also as an analytical instrument, providing strategic insight for decision-making and integrating operational data in a systematic weighting, as well as predictive models that can support explainable AI. This gives a more comprehensive and adaptive approach to evaluating and improving RB sustainability performance. The results of the sustainability index are presented in Figure 7.

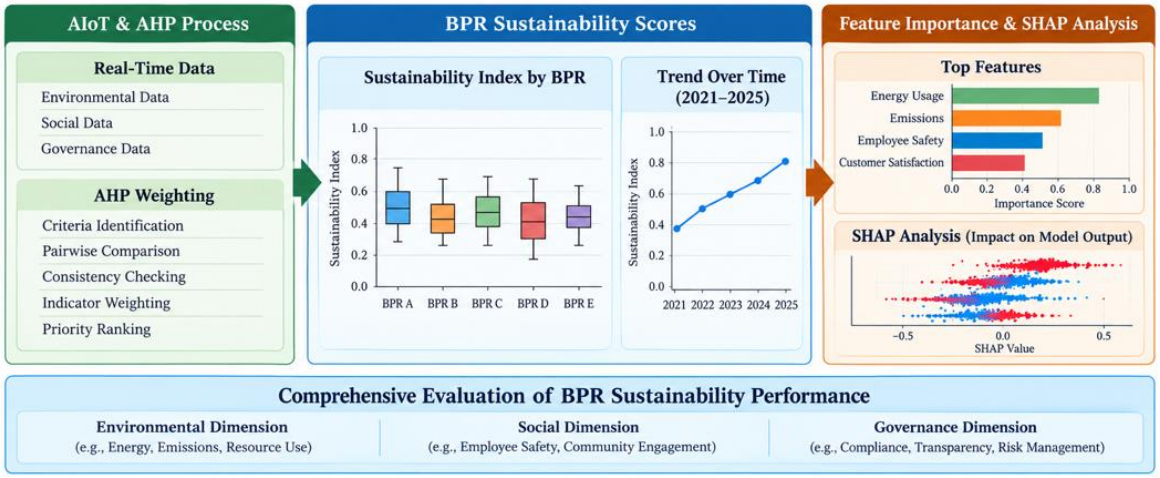



Figure 7. Sustainability Index Results

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## DISCUSSION

This study demonstrates that integrating Artificial Intelligence of Things (AIoT) into decision support systems improves sustainability assessment in Rural Banks (RBs) through automated, continuous, and time-series data collection. Combining Analytical Hierarchy Process (AHP), Sustainability Index, and Random Forest enables standardized performance evaluation, with environmental indicators receiving the highest weighting. Random Forest achieves strong predictive performance ($R^2 = 0.87$), while feature importance and SHAP analyses identify emissions (GRI 305) and energy consumption (GRI 302) as dominant sustainability determinants. Workplace safety and customer safety also contribute significantly, confirming sustainability's multidimensional nature across environmental, social, and governance aspects. The increasing sustainability index indicates improving RB performance. However, findings are limited by the five-bank sample, incomplete automated monitoring of GRI indicators, and machine-learning interpretability challenges, partially addressed through SHAP. Theoretically, this study advances AIoT-based sustainability assessment research; practically, its framework supports transparent, data-driven monitoring, strategic decision-making, and sustainable digital transformation in rural banking.

## CONCLUSION

This study develops an AIoT-based Decision Support System (DSS) for sustainability assessment in Rural Banks (RBs), integrating AIoT technology, Global Reporting Initiative (GRI) indicators, Analytical Hierarchy Process (AHP), Sustainability Index, and Random Forest. The framework enables comprehensive, data-driven evaluation through real-time operational data collection. The model achieves a coefficient of determination ($R^2$) of 0.87, indicating strong explanatory performance. Emissions and energy consumption emerge as dominant sustainability indicators, consistent with AHP results prioritizing the environmental dimension. These findings confirm that sustainability encompasses environmental, social, and governance aspects. Integrating the Sustainability Index and Random Forest enables standardized performance assessment and predictive analysis using historical data. Theoretically, this study advances research on AIoT-based sustainability assessment, particularly in rural banking. Practically, the framework supports adaptive monitoring, strategic decision-making, and digital transformation. Future research should expand sample sizes, integrate non-sensor indicators, and explore alternative machine learning algorithms to improve predictive accuracy and model interpretability.

## REFERENCES

Aguado-Correa, F., et al. (2023). Evaluation of non-financial information and its contribution to advancing the sustainable development goals within the Spanish banking sector. European Research on Management and Business Economics, 29(2), 100211. https://doi.org/10.1016/j.iedeen.2022.100211

Bais, B., Nassimbeni, G., & Orzes, G. (2024). Global Reporting Initiative: Literature review and research directions. Journal of Cleaner Production, 471, Article 143428. https://doi.org/10.1016/j.jclepro.2024.143428

Bayar, J., et al. (2025). Artificial intelligence of things (AIoT) for precision agriculture: Applications in smart irrigation, nutrient and disease management. Smart Agricultural Technology, 12, 101629. https://doi.org/10.1016/j.atech.2025.101629

Bouteraa, M., Al-Daihani, M., Chekima, B., & Baddou, A. (2026). Empirical analysis of blockchain integration and ESG moderation in sustainable digital transformation: Evidence from the banking sector. Journal of Strategy & Innovation, 37, 200564. https://doi.org/10.1016/j.jsinno.2026.200564

Braga, C. M., Suarez-Bárcena, A., Serrano, M. A., & Fernández-Medina, E. (2025). TrustAIoT: A framework for building trustworthy AIoT platforms. Internet of Things, 34, 101751. https://doi.org/10.1016/j.iot.2025.101751

Chavosh Nejad, M., Mansour, S., & Karamipour, A. (2021). An AHP-based multi-criteria model for assessment of the social sustainability of technology management processes: A case study in banking industry. Technology in Society, 65, 101602. https://doi.org/10.1016/j.techsoc.2021.101602

Choo, Y., et al. (2026). AIoT image analysis for real-time dispatching of shipyard transport devices: A focus on trailers. Expert Systems with Applications, 296, 128947. https://doi.org/10.1016/j.eswa.2025.128947

Dhal, S. B., Kar, D., & Capareda, S. (2026). Intelligent valorization: Integrating AI, imaging, and sustainability for next-generation biofuel systems. Global Energy Interconnection. https://doi.org/10.1016/j.gloei.2025.10.009

Ding, M., & Li, C. (2026). Green banking and sustainable development: Exploring energy efficiency, environmental policy, and financial resilience in emerging economies. International Review of Economics & Finance. https://doi.org/10.1016/j.iref.2026.104988

Ecer, F., & Pamucar, D. (2022). A novel LOPCOW-DOBI multi-criteria sustainability performance assessment methodology: An application in developing country banking sector. Omega, 112, 102690. https://doi.org/10.1016/j.omega.2022.102690

Emara, E. I. R., Al-Saeed, A. M., & Hamed, L. M. M. (2026). AI-driven decision support system enhances productivity, water use efficiency, and soil sustainability of strategic crops in sandy soils. Agricultural Water Management, 325, 110198. https://doi.org/10.1016/j.agwat.2026.110198

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**E-ISSN : 2807-9035**
**Volume** 6, **Number** 4, November 2026
https://doi.org/10.47709/brilliance.v6i4.9802

Fernández-Arroyo, E. R., Area, A. C., & Peña, D. Q. (2026). Maximizing profits and sustainability in RoR hydropower: An AI-driven hydrogen decision support model (H2-DSM). Energy Conversion and Management: X, 30, 101660. https://doi.org/10.1016/j.ecmx.2026.101660

Fernández Fernández, J. A. (2025). The architecture of sustainable banking: Financial, institutional and technical pillars for the transition to a low-carbon economy. Borsa Istanbul Review, 25, 1558–1571. https://doi.org/10.1016/j.bir.2025.10.010

Friske, W., Nikolov, A. N., & Morgan, T. (2024). Making the grade: An analysis of sustainability reporting standards and Global Reporting Initiative adherence ratings. Corporate Social Responsibility and Environmental Management, 31(3), 2098–2108. https://doi.org/10.1002/csr.2686

Ghandehariun, S., & Faghihi, S. V. (2025). Dynamic decision-support for heritage-sensitive urban regeneration: An AI-driven framework integrating socio-cultural sustainability. Results in Engineering, 28, 108189. https://doi.org/10.1016/j.rineng.2025.108189

Gupta, M. (2026). Unveiling the impact of sustainability reporting on banking performance: Role of country-specific determinants. Journal of Economics and Business, 138, 106246. https://doi.org/10.1016/j.jeconbus.2025.106246

Han, X., Samad, S., Kim, W., & Wei, F. (2025). From corporate responsibility to green loyalty: How CSR initiatives shape customer identification and pro-environmental identity in banking. Acta Psychologica, 255, 104944. https://doi.org/10.1016/j.actpsy.2025.104944

He, J., Song, C., Hu, R., & Ren, Z. (2026). LogHGAD: A hypergraph-based log anomaly detection method for AIoT systems. Journal of Systems Architecture, 170, 103630. https://doi.org/10.1016/j.sysarc.2025.103630

Huang, J., Hsieh, S.-L., & Wang, J. (2026). Sustainability disclosure and bank liquidity risk: Evidence from global banking sector. North American Journal of Economics and Finance, 83, 102582. https://doi.org/10.1016/j.najef.2026.102582

Iqrar, W., Khurshid, K., Khan, S., & Saeed, N. (2026). The AIoT ecosystem for next-generation satellite systems. Physical Communication, 74, 102967. https://doi.org/10.1016/j.phycom.2025.102967

Isayev, M., & Gokmenoglu, K. (2024). The role of shadow banking towards a sustainable growth path. Renewable Energy, 228, 120640. https://doi.org/10.1016/j.renene.2024.120640

Karim, R., et al. (2026). Unveiling the roles of green tax, financial development, banking development, fintech adoption, and economic growth on sustainable development in Bangladesh. World Development Sustainability, 8, 100277. https://doi.org/10.1016/j.wds.2026.100277

Kavuran, G., et al. (2026). AI-supported decision framework for sustainable reconstruction: Case study on TOKİ housing after the 2023 Kahramanmaraş earthquake. Energy, 344, 139891. https://doi.org/10.1016/j.energy.2025.139891

Ketchoua, G. S., Wirajing, M. A. K., & Ketu, I. (2025). Advancing agro-environmental sustainability in Africa: The critical role of infrastructure development and banking sector stability. Sustainable Futures, 9, 100800. https://doi.org/10.1016/j.sftr.2025.100800

Konstantakis, K. N., et al. (2024). The interconnectedness of European banking and shadow banking for sustainable development goals: Insights from a network GVAR model. Research in International Business and Finance, 69, 102232. https://doi.org/10.1016/j.ribaf.2024.102232

Kuang, W., Tang, F., Liu, J., Hu, Y., & Li, K. (2026). FGAA: Enhancing adversarial robustness in AIoT-enabled smart systems via fine-grained activation alignment. Journal of Systems Architecture, 170, 103602. https://doi.org/10.1016/j.sysarc.2025.103602

Lau, C. K., & Wong, J. C. (2023). The integration of Sustainable Development Goals into businesses sustainability management: A reporting perspective. International Journal of Disclosure and Governance, 20, 490–505. https://doi.org/10.1057/s41310-022-00164-2

Le, T. D., et al. (2025). Exploring new frontiers: Current status and future research directions for AIoT application in shrimp farming in the Vietnamese Mekong Delta. Aquacultural Engineering, 111, 102559. https://doi.org/10.1016/j.aquaeng.2025.102559

Li, Y., et al. (2025). SDR: Stackelberg-based deep reinforcement learning for multi-skill spatiotemporal task allocation in AIoT systems. Computer Communications, 242, 108283. https://doi.org/10.1016/j.comcom.2025.108283

Liao, Y., Yu, N., Zhou, G., Wu, Y., & Wang, C. (2022). A wireless multi-channel low-cost lab-on-chip algae culture platform. Computers and Electronics in Agriculture, 193, 106647. https://doi.org/10.1016/j.compag.2022.106647

Liu, H. T., et al. (2026). An AIoT-based operations guidance system for constrained industrial processes. Journal of Industrial and Engineering Chemistry. https://doi.org/10.1016/j.jiec.2026.02.003

Liu, Q., Li, X., Tan, K. H., & Ah, K. H. (2026). A review of AIoT-enabled cyber-physical systems in building energy management: Towards intelligent operation. Applied Energy, 409, 127482. https://doi.org/10.1016/j.apenergy.2026.127482

Lu, H. L., et al. (2025). AIoT-based smart greywater reuse for urban irrigation: Energy saving, carbon reduction, and biodiversity enhancement. Smart Agricultural Technology, 12, 101288. https://doi.org/10.1016/j.atech.2025.101288

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**E-ISSN : 2807-9035**
**Volume** 6, **Number** 4, November 2026
https://doi.org/10.47709/brilliance.v6i4.9802

Mamun, M. A. A., et al. (2025). Enhancing banking performance through regulatory technology: Analyzing cost reduction, sustainability, and profitability in Bangladesh's banking sector. Sustainable Futures, 10, 101234. https://doi.org/10.1016/j.sftr.2025.101234

Mbaidin, H. O., Alsmairat, M. A. K., & Al-Adaileh, R. (2023). Blockchain adoption for sustainable development in developing countries: Challenges and opportunities in the banking sector. International Journal of Information Management Data Insights, 3(2), 100199. https://doi.org/10.1016/j.jjimei.2023.100199

Mills, S., & Sætra, H. S. (2025). Algorithms in the room: AI, representation, and decisions about sustainable futures. Technovation, 147, 103304. https://doi.org/10.1016/j.technovation.2025.103304

Nguyen, H. H., et al. (2025). Banking in the storm: How natural disasters influence non-performing loans. Journal of Climate Finance, 13, 100076. https://doi.org/10.1016/j.jclimf.2025.100076

Phan, A. C., Nguyen, N. H. Q., & Phan, T. C. (2026). AIoT-based drowsiness level detection system using a hybrid F-LSNN network. Egyptian Informatics Journal, 33, 100910. https://doi.org/10.1016/j.eij.2026.100910

Pu, G., et al. (2024). Asymmetric impact of natural resources, fintech, and digital banking on climate change and environmental sustainability in BRICS countries. Resources Policy, 91, 104872. https://doi.org/10.1016/j.resourpol.2024.104872

Quintiliani, A. (2025). Small and medium-sized enterprises and sustainable transition: Can FinTech increase the banks' ability to support the development of SMEs? Research in International Business and Finance, 73, 102625. https://doi.org/10.1016/j.ribaf.2024.102625

Rahim, A., Islam, M. F., & Rosid, M. H. O. (2026). From employee green behavior to sustainable competitive advantage: The role of fintech adoption and sustainable performance within banking institutions. Acta Psychologica, 264, 106449. https://doi.org/10.1016/j.actpsy.2026.106449

Rahman, M. A., et al. (2024). An AIoT-based hydroponic system for crop recommendation and nutrient parameter monitoring. Smart Agricultural Technology, 8, 100472. https://doi.org/10.1016/j.atech.2024.100472

Rahman, M. H., Rahman, J., Tanchangya, T., & Esquivias, M. A. (2023). Green banking initiatives and sustainability: A comparative analysis between Bangladesh and India. Research in Globalization, 7, 100184. https://doi.org/10.1016/j.resglo.2023.100184

Sajid, M. (2026). Measuring perceived sustainable banking: Scale development and its role in customer loyalty and brand advocacy. Strategic Business Research, 2, 100041. https://doi.org/10.1016/j.sbr.2025.100041

Sardianou, E., Stauropoulou, A., Evangelinos, K., & Nikolaou, I. (2021). A materiality analysis framework to assess sustainable development goals of the banking sector through sustainability reports. Sustainable Production and Consumption, 27, 1775–1793. https://doi.org/10.1016/j.spc.2021.04.020

Sari, M. P., & Faisal, F. (2022). The diffusion of sustainability reporting for higher education institution worldwide. IOP Conference Series: Earth and Environmental Science, 1048(1), Article 012010. https://doi.org/10.1088/1755-1315/1048/1/012010

Shi, Y., Charles, V., & Zhu, J. (2025). Bank financial sustainability evaluation: Data envelopment analysis with random forest and Shapley additive explanations. European Journal of Operational Research, 321(3), 614–630. https://doi.org/10.1016/j.ejor.2024.09.030

Wang, H., et al. (2025). HealthAIoT: AIoT-driven smart healthcare system for sustainable cloud computing environments. Internet of Things, 31, 101555. https://doi.org/10.1016/j.iot.2025.101555

Xia, Y., et al. (2026). Leveraging generative AI and circular innovation for equitable and resilient supply chains. Technological Forecasting and Social Change, 225, 124556. https://doi.org/10.1016/j.techfore.2026.124556

Yaqoob, S., et al. (2026). AIoT for human emotion recognition: Potentials, challenges, and healthcare applications. Computer Science Review, 60, 100859. https://doi.org/10.1016/j.cosrev.2025.100859

Zhang, J. (2025). AI-based data intelligence system for sustainable ecological governance and smart environmental management. Microchemical Journal, 219, 115850. https://doi.org/10.1016/j.microc.2025.115850

Zhang, P., Chen, R. P., Dai, T., Wang, Z. T., & Wu, K. (2021). An AIoT-based system for real-time monitoring of tunnel construction. Tunnelling and Underground Space Technology, 109, 103766. https://doi.org/10.1016/j.tust.2020.103766

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