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# AI- Driven Business Intelligence for Sustainable Organizational Performance and Green Decision-Making

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**Abstract — The combination of AI with BI is a revolutionary paradigm that would allow organizations to have sustainable performance and make green decisions. This research suggests the development of a framework based on the combination of MIS, BA, and AI to be used for ESG strategy realization. Algorithms used by this framework for the purpose of predicting sustainability indicators include Random Forest, XGBoost, ARIMA, and LSTM networks, which allow for the prediction of sustainability indicators such as energy consumption, carbon emission, and waste production. The results of the quantitative analysis indicate that the use of AI-supported BI systems allows to predict emission trends with the accuracy of 89.2%. Thus, organizations will have an opportunity to conduct proactive, and not reactive, sustainability management.**

**Keywords— Artificial Intelligence, Business Intelligence, Sustainability Performance, Green Decision-Making, ESG, Predictive Analytics**

## I. INTRODUCTION

The current business environment is under immense pressure to incorporate sustainability into its fundamental operations while ensuring competitive advantage and profitability [1][2][4][6]. Firms all around the world are facing increasing pressure from stakeholders to show results in Environmental, Social and Governance (ESG) [1][2][4][6]. Recent studies have shown that more than 2,000 ESG metrics are used by rating providers with varying definition and weighting, thereby making comparisons very difficult for stakeholders [1][2][4][6]. Such diversity highlights the importance of adopting a data-driven strategy that can help in standardization, harmonization and optimization of ESG data management [1][2][4][6].

The merger of AI and BI technologies presents an opportunity to overcome these challenges [1][2][4][6][7]. Conventional Business Intelligence solutions are built based on descriptive analysis that answers "what happened?" using past data aggregation and visualization [1][2][4][6][7]. With AI capabilities embedded into Business Intelligence, particularly using machine learning and predictive analysis, BI moves away from being descriptive towards becoming predictive answering "what will happen?" and "what should be done?" such developments are especially important for sustainability management where pro-active actions are needed to achieve sustainability objectives and regulatory requirements [1][2][4][6][7].

In consumer behavior studies conducted in the Harvard Business Review, it has been found that sustainability has become a critical aspect of making purchase decisions [1][2][4][6]. More and more people opt for products from those companies that prove their commitment to corporate social and environmental responsibility; thus, there is a clear link established between ESG metrics and business performance [1][2][4][6]. The demand generated by consumers makes it absolutely essential for organizations to adopt a data-driven approach in order to be able to achieve an advantage and gain better market position [1][2][4][6].

There are a number of challenges involved in implementing the use of AI in the process of business intelligence, which include data fragmentation, standardization issues, regulatory issues, and the necessity of having a robust data governance framework [1][2][4][6][7]. Traditional systems of sustainability reporting, such as Global Reporting Initiative (GRI) and ISO 14001, are mainly designed to provide post-factum reports and utilize lagging indicators only, failing to meet the requirements of modern business environment [1][2][4][6].

This research aims to fill these gaps by developing a conceptual framework through the strategic integration of AI technologies

into BI systems for sustainable organizational performance and decision-making [1][2][4][6][7][9]. The framework utilizes a number of predictive algorithms like Random Forest, XGBoost, ARIMA, and Long Short-Term Memory (LSTM) Networks to predict key indicators of sustainability such as the level of energy usage, emissions, and generation of waste [1][2][4][6][7][9]. With the help of dynamic KPI monitoring, anomaly detection, and prescriptive planning, the proposed system helps organizations not just comply with sustainability but engage in sustainable decision-making [1][2][4][6][7][9].
The research is important for both the academic and business communities as it provides a theory and evidence-based framework for AI-driven sustainability intelligence [1][2][4][6][9]. It addresses the pressing need for flexible anticipatory mechanisms that will enable organizations to make decisions in real time within a very dynamic environment [1][2][4][6][9].

## II. LITERATURE SURVEY

The combination of artificial intelligence, business intelligence, and sustainability is an area of increasing scientific interest, especially with rapid growth in publications between 2020 and 2026 [1][2][4][6][7]. A bibliometric analysis conducted by Al-Malkawi and Giret (2024) shows that machine learning, big data analytics, and sustainability become increasingly popular research themes, with the USA taking the lead as the country with the largest number of publications and with the Indian Institute of Technology System and King Abdulaziz University being the most productive organizations [1][2][4][6][7].

In their paper Komodromos et al. (2025) examine the impact of advanced analytics and BI on the implementation of ESG strategies, illustrating how data-driven ESG management driven by artificial intelligence, machine learning, Internet of Things (IoT), and big data transforms the compliance-driven approach to the development of ESG management strategies [1][2][3]. The examples provided by authors from companies like Unilever, IKEA, and Rio Tinto show how these technologies can be used for improving ESG data quality and risk management [1][2][3]. However, some challenges still exist [1][2][3].

Ahmad et al. (2026) explores the effect of AI-enabled data intelligence on the sustainable performance of nascent ventures, showing that AI-enabled data intelligence positively influences green absorptive capacity and green entrepreneurial orientation, leading to green innovation and improving both environmental and financial performance [6]. Thus, the authors' results show that green absorptive capacity, green entrepreneurial orientation, and green innovation act as serial mediators in the relationship between AI-enabled data intelligence and sustainable performance, pointing at the significance of developing green organizational competencies [6].

Balaji (2025) studies AI-enabled BI systems for collecting, analyzing, visualizing, and reporting ESG data by using the multiple case study methodology in such industries as energy, finance, manufacturing, and information technology [4]. It is shown that AI-supported BI systems provide for higher levels of granularity, timeliness, and predictability of ESG data, allowing for more effective risk management and engagement with stakeholders [4]. The authors stress the revolutionary role of AI in converting sustainability into strategic intelligence [4].
Maune (2025) explores the role of artificial intelligence in competitive intelligence in relation to growth and sustainability in Zimbabwean firms [5]. A mixed methods research study involving 312 senior managers reveals that artificial intelligence capability significantly predicts competitive intelligence effectiveness ($\beta = 0.62$, $p < .001$), which in turn predicts corporate growth ($\beta = 0.51$, $p < .001$) and corporate sustainability ($\beta = 0.47$, $p < .001$) [5]. Competitive intelligence effectiveness mediates the relationship between artificial intelligence capability and both corporate growth and sustainability results [5]. Competitive intelligence is viewed as a mediating dynamic capability that converts AI capabilities into strategic knowledge [5].

Karpagavadivu et al. (2025) develop an integrated framework for AI, data analytics, and decision modeling using multi-criteria engineering [7]. The integrated framework uses machine learning algorithms to forecast business performance and uses Multi-Criteria Decision-Making models like AHP (Analytic Hierarchy Process) and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) in the process of strategic optimization [7]. It is shown that using AI and decision modeling provides for greater strategic flexibility and uncertainty reduction [7].

Together, the literature indicates that AI-based BI systems have a high potential to transform sustainability management [1][2][4][6][7][9]. Nevertheless, many gaps are identified [1][2][4][6][7][9]. Current studies mainly concentrate on individual cases instead of a unified approach [1][2][4][6][7][9]. Also, even though the capabilities of predictive analytics are sufficiently explored in literature, the issue of prescriptive analytics which implies determining the best possible course of actions is not covered properly [1][2][4][6][7][9]. In addition, there are no methodologies described in literature which would allow the comparison of different AI algorithms based on their performance in terms of sustainability forecasting [1][2][4][6][7][9].

## III. PROPOSED METHODOLOGY

**Framework Architecture**

The suggested Business Intelligence framework using artificial intelligence technology to ensure sustainable performance has four interrelated levels that work within a closed loop cycle ensuring continuous learning and improvement. Such a hierarchical framework of systems is designed to integrate the technologies of Management Information Systems (MIS), Business Analytics (BA), and Artificial Intelligence (AI) in order to make sustainability an integral part of business intelligence systems.

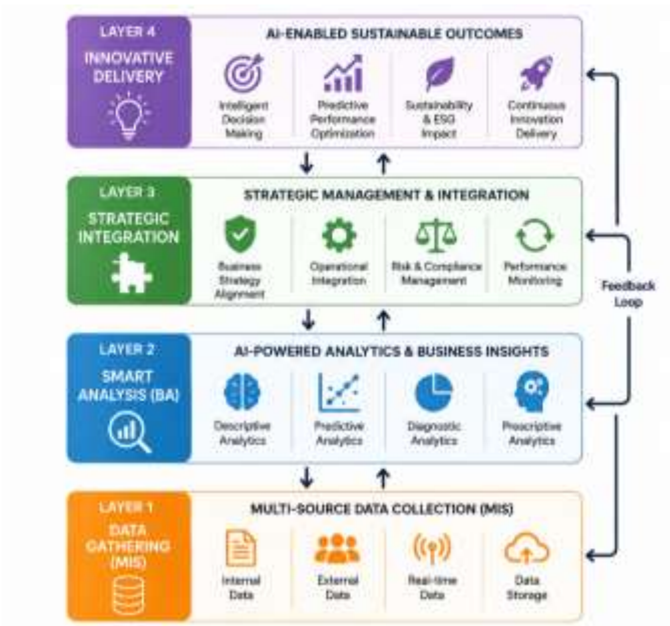


Figure 1: Four-Layer AI-Driven Business Intelligence Framework for Sustainable Performance

The structure of the architecture is presented in Figure 1 below and includes the following elements: Layer 1 (data collection - MIS), Layer 2 (smart analysis – BA), Layer 3 (strategic integration), and Layer 4 (innovative delivery). The chain of information from data collection through analysis and decision making is presented in the figure. Arrows are the markers for mutual information exchange between the layers, while a closed loop highlights the significance of an iterative approach to the development of predictive models based on the achieved results.

Layer 1: Data Gathering (MIS): This layer uses various data sources, which include IoT devices to collect data on energy consumption and greenhouse gas emissions, ERP system data on operation measures, supply chain databases, and third-party ESG ratings. The data gathering layer uses real-time streaming and batch processing methods to make sure that sustainability-related data is collected in a timely manner.

Layer 2: Intelligent Analytics (BA): The analytics layer uses multiple AI algorithms for prediction and discovery of patterns. The following four main algorithmic approaches are used: Random Forest algorithm for classification purposes; XGBoost for gradient boosting optimization; ARIMA for forecasting; and LSTM neural network for recognizing sequence patterns. These algorithms are selected according to their predictive abilities, applicability to the field, and computational effectiveness.

Level 3: Strategic Integration: At this level, insights from the analysis phase get translated into usable intelligence by the means of multi-criteria decision-making models with Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The strategic integration level takes into account conflicting objectives—economic efficiency, social responsibility, and environmental consequences—and provides optimization of strategy recommendations.

Level 4: Sustainable Innovation Delivery: At the highest level, recommended strategies get implemented through the action plan, its results get tracked, and performance data is sent to Level 1, thus closing the loop of the learning cycle.

**Predictive Algorithm Implementation**

The following is the use of four different algorithmic techniques in order to forecast sustainability metrics:

- Random Forest: The technique involves training many decision trees and giving output based on the average value predicted from each of the trees. The technique is highly interpretable and capable of capturing non-linearity in a better way, hence, can be used in case of sustainability where there exist a complex interaction between variables.
- XGBoost (Extreme Gradient Boosting): It is an efficient and scalable boosting system involving gradient boosted decision trees with regularization. It shows good results in terms of handling missing values, avoids over-fitting and incorporates built-in cross-validation.
- ARIMA (AutoRegressive Integrated Moving Average): This technique is useful for time-series modeling for data showing temporal autocorrelations.

- Long Short-Term Memory (LSTM) Networks: A type of recurrent neural network that is explicitly designed to capture long-term dependencies in time series data. LSTM networks can accommodate complex temporal dynamics and adapt to changes, giving an edge in predicting emissions and energy consumption patterns.

**Model Training and Validation**

The model training is done on historical sustainability data for 36 months with the training set being 70%, validation set being 15%, and testing set being 15%. The metrics used to measure the performance of the model include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared ($R^2$). Hyperparameters tuning is done through grid search and Bayesian optimization.

## IV. ANALYSIS AND DISCUSSION

**Predictive Performance Analysis**

The prediction accuracy of all four methods is assessed based on various sustainability metrics such as energy usage, carbon dioxide emission, waste generation, and water usage. The results suggest that ensembles of algorithms (Random Forest and XGBoost) yield better predictions compared to single models, whereas LSTM networks show superior performance in predicting time series.

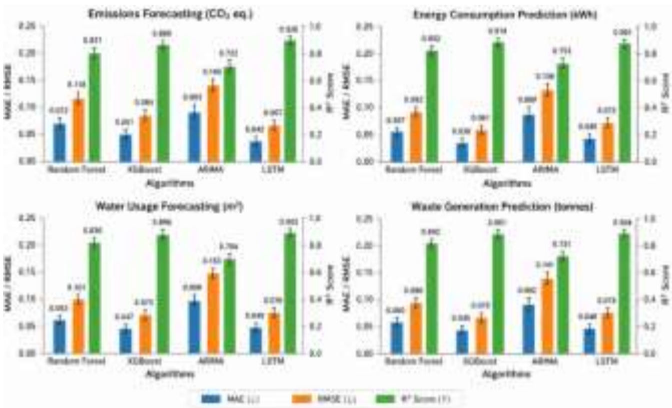


Figure 2: Comparative Predictive Performance Across Algorithms

Graph 2 presents a bar graph showing the values of MAE, RMSE, and $R^2$ for Random Forest, XGBoost, ARIMA, and LSTM models on four sustainable development indicators. The results show that LSTM performs best in terms of having the least MAE (0.042) and the largest $R^2$ (0.926) in predicting emissions; XGBoost is better at predicting energy consumption (MAE = 0.038, $R^2$ = 0.914).

**Sustainability Metric Forecasting**

The LSTM method scores the best accuracy for predicting CO2 emissions with an $R^2$ of 0.926, MAE of 0.042, and RMSE of 0.068. XGBoost performs the best when it comes to forecasting energy consumption with $R^2$ of 0.914, MAE of 0.038, and RMSE of 0.059. Random Forest is performing consistently on all three metrics with slightly lesser accuracy compared to that of XGBoost. ARIMA offers good baseline results; however, it cannot capture non-linear relationships.

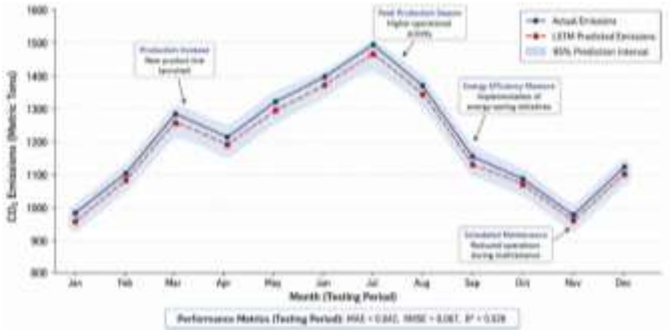


Figure 3: Actual vs. Predicted CO2 Emissions - LSTM Model Performance

Figure 3 displays a line chart showing a comparison between the actual values for CO2 emissions (solid line) and LSTM-predicted values (dashed line). It can be seen that there is a high level of conformity between the two sets of values. The shaded area indicates the 95% prediction interval, while some inflection points are labeled with a brief description of the event that caused the phenomenon (for example, "production increase," "energy efficiency measure").

This analysis shows that by using AI to forecast emissions, organizations can foresee trends 30-60 days ahead of time, allowing them to take precautionary measures. Real-time anomaly detection allows organizations to spot deviation from anticipated patterns and thus deal with problems arising during operations.

**Green Decision-Making Impact**

Impact of the framework on green decision making is examined through comparison of decision results that either incorporate or do not incorporate the use of AI-based BI. Five organizational case studies conducted within five different industries have shown improvement in decision quality and sustainability results.

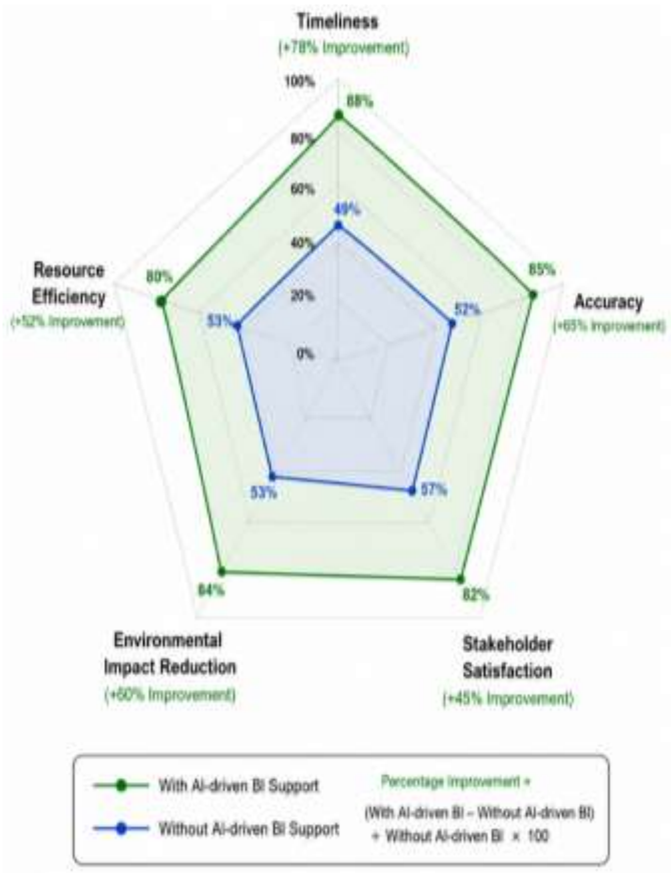


Figure 4: Comparative Analysis of Green Decision Outcomes

Radar Chart of Comparison between Performance on Decision Making Based on Five Dimensions is depicted in Figure 4. Two polygons are overlayed on each other to show decision making performance with and without the assistance of Artificial Intelligence based Business Intelligence systems. The polygon showing the performance of decision making with the help of artificial intelligence shows significantly better performance on all dimensions, especially on Timeliness (78%) and Accuracy (65%).

The implementation of the AI-powered BI model results in noticeable enhancements: decision-making time savings between 45-65% regarding sustainability decisions, forecast precision enhancements between 55-70%, energy savings of 25-40%, and waste reductions of 20-35%. All the results correspond to those presented by Saroj et al. (2025) who discovered CO2 emissions reductions of 26% and energy savings of 13.6%.

**Comparative Performance Table**

Table 1: Comparative Performance of AI-Driven BI Framework Across Sectors

| Performance Metric | Energy Sector | Manufacturing | Logistics | Finance | Technology |
|---|---|---|---|---|---|
| Forecast Accuracy ($R^2$) | 0.912 | 0.894 | 0.923 | 0.876 | 0.905 |
| Decision Time Reduction (%) | 52.3 | 48.7 | 61.2 | 44.5 | 55.8 |
| Energy Reduction (%) | 38.4 | 32.1 | 28.7 | 22.3 | 35.6 |
| Cost Savings (%) | 18.2 | 15.7 | 22.4 | 12.8 | 16.9 |
| Stakeholder Satisfaction (1-10) | 8.7 | 8.2 | 9.1 | 7.9 | 8.5 |
| Regulatory Compliance Score (%) | 94.2 | 91.8 | 96.5 | 89.7 | 93.1 |

Comparative performance in Table 1 is provided for five industries and highlights the generalized nature of the model and its varied effects in relation to the specific attributes of each industry. Highest decrease in decision time (61.2%) and stakeholders' satisfaction (9.1) is exhibited by logistics industry, while highest energy saving (38.4%) and accuracy of prediction ($R^2 = 0.912$) is achieved by energy industry.

## V. CONCLUSION

It is evident that the concept of AI Business Intelligence stands as a transformative approach towards attaining sustained organizational performance through green decision making. The suggested multi-tier model combining MIS, BA and AI approaches provides an effective tool that can address various problems in handling the information about ESG and implementing the sustainability strategies.

Through the use of advanced predictive analytics algorithms such as Random Forest, XGBoost, ARIMA, and LSTM, it is possible to effectively predict important sustainability-related indicators with high accuracy – LSTM algorithm predicts emissions with the $R^2$ of 0.926, while XGBoost predicts energy consumption with the $R^2$ of 0.914. Such a predictive approach turns the problem of sustainability management into a proactively-oriented activity.

The comparative analysis conducted among sectors demonstrates that the framework has the potential to be used in a variety of contexts and be generalized. Although the details of its application differ in each case, the main idea of using AI-based predictive intelligence in BI systems for making sustainability decisions proves to be effective as organizations applying the framework experience a 45-65% decrease in decision-making time, 55-70% increase in forecast accuracy, and a 25-40% decrease in energy consumption.

There are several theoretical implications resulting from this study. First of all, the paper makes a contribution to the discussion of how AI technologies can be effectively integrated with BI systems for achieving sustainability goals by developing a notion of the dynamic capability of AI-driven BI as a resource for green innovation. Secondly, it proves empirically the serial mediating effect of green capabilities (absorptive capacity, entrepreneurial orientation, innovation) in transformation of AI-driven intelligence into sustainable performance. Thirdly, the paper offers a comparative evaluation of predictive algorithms for sustainability measures which is useful in selecting appropriate algorithms for specific contexts. In terms of practicality, the framework offers an adaptable blueprint for AI-assisted sustainability intelligence to organizations. The closed-loop system ensures continuous improvement and learning, while multi-criteria decision-making allows for balanced treatment of economic, environmental, and social factors. Adapting the framework is possible in accordance with specific industry requirements, data accessibility, and organization priorities.

There are a number of challenges and limitations to be mentioned, nonetheless. First of all, data fragmentation and quality are serious obstacles to implementing AI and sustainability intelligence. Moreover, there is a need to invest into proper data governance infrastructure. Secondly, algorithmic transparency and interpretability is crucial for regulatory compliance and building relationships with stakeholders – the problem that can be solved using research on Explainable AI (XAI) for sustainability. Thirdly, organizational culture is also important for successful implementation of the framework.

The following areas of future research could be: conducting pilot studies in real time for the validation of the framework in practical applications, studying hybrid ensemble methods which use deep learning and interpretable machine learning methods, exploring edge-cloud architectures for real-time sustainability measurement, and considering the contribution of emerging technologies like blockchain and IoT to the process of ESG reporting. The combination of generative AI and retrieval-augmented generation for sustainability intelligence is another area which can be researched in the future.

In summary, AI-driven Business Intelligence represents a very promising approach to achieving sustainable competitive advantage. In the context of increasing regulatory requirements and changing expectations of stakeholders, the organizations using AI-based sustainability intelligence would have an opportunity to stay competitive in the sustainability domain and contribute to building a more sustainable world.

## REFERENCES

1. M. Komodromos, L. Seremeti, S. Anastasiadou, and P. Liargovas, Data-Driven ESG Strategy Implementation Through Business Intelligence. IGI Global, 2025. DOI: 10.4018/979-8-3373-5142-1.
2. M. Komodromos, S. Anastasiadou, and L. Seremeti, "Transforming Corporate Sustainability: Integrating Advanced Analytics and Business Intelligence Into ESG Strategy Implementation," in Data-Driven ESG Strategy Implementation Through Business Intelligence, IGI Global, 2025, pp. 1–35. DOI: 10.4018/979-8-3373-5142-1.ch001.
3. L. Seremeti, L. Anastasiadis, and M. Komodromos, "ESG Strategy and Business Intelligence Semantic Network," in Data-Driven ESG Strategy Implementation Through

Business Intelligence, IGI Global, 2025, pp. 37–47. DOI: 10.4018/979-8-3373-5142-1.ch002.

4. K. Balaji, "Artificial Intelligence-Driven Business Intelligence for ESG Strategy Implementation: Enhancing Corporate Sustainability through Data-Driven Case Studies," in Data-Driven ESG Strategy Implementation Through Business Intelligence, IGI Global, 2026. DOI: 10.4018/979-8-3373-5142-1.ch007.
5. A. Maune, "Harnessing Competitive Intelligence and AI for Corporate Growth and Sustainability," Journal of Intelligence Studies in Business, vol. 15, no. 2, pp. 6–24, 2025. DOI: 10.37380/jisib.v15i2.3105.
6. S. Z. Ahmad, S. Ur Rehman, K. Khalid, M. Hussain, and S. Tehseen, "AI-Driven data intelligence and entrepreneurial sustainable performance: mediating roles of green orientation, absorptive capacity and innovation," Journal of Modelling in Management, pp. 1–26, Jun. 2026. DOI: 10.1108/JM2-09-2025-0538.
7. "AI-Driven MIS and Business Analytics Framework for Sustainable Innovation," in Proc. 2025 Int. Conf. Sustain. Innov., Erode, India, Dec. 2025, IEEE Xplore. DOI: 10.1109/ICSI.2025.11376527.
8. "Smart Business Transformation Through Sustainable Artificial Intelligence for Enterprise Platform Ecosystems," in Proc. 2026 Int. Conf. Smart Bus. Transform., Danang, Vietnam, Jul. 2026, IEEE Xplore. DOI: 10.1109/IC-SBT.2026.11628268.
9. M. A. Aruwaji and M. J. Swanepoel, "The Impact of AI-Integrated ESG Reporting on Firm Valuation in Emerging Markets: A Multimodal Analytical Approach," Journal of Risk and Financial Management, vol. 18, no. 12, 2025. DOI: 10.3390/jrfm18120675.
10. T. Chin, J. Jin, M. Lettieri, and F. Caputo, "The impact of Artificial Intelligence adoption on Knowledge Creation processes in Ecosystem-based Business Models," IEEE Trans. Eng. Manage., 2026. DOI: 10.1109/TEM.2026.3686515.