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Integrating Artificial Intelligence, Data Analytics, and Decision Modelling for Sustainable Business Strategy: A Multi-Criteria Engineering Approach

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ABSTRACT

Sustainable business strategy increasingly demands the integration of advanced computational tools that can process complex, multi-dimensional data for informed decision-making. This study presents a comprehensive framework that integrates Artificial Intelligence (AI), Data Analytics, and Decision Modelling through a Multi-Criteria Engineering Approach to enhance sustainability-oriented corporate planning. The framework leverages machine learning algorithms to predict business performance indicators, applies data analytics for pattern discovery, and utilizes Multi-Criteria Decision-Making (MCDM) models such as Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for strategic optimization. Quantitative data from energy-intensive industries were analyzed using AI-driven predictive models to evaluate key sustainability dimensions economic efficiency, social responsibility, and environmental impact. The integrated model provided a systematic ranking of alternative strategies, balancing profitability with environmental compliance and stakeholder value. Findings demonstrate that combining AI and decision modelling enhances strategic agility, reduces uncertainty, and supports transparent sustainability decisions. The proposed framework establishes a scalable blueprint for corporate managers and policymakers to align business growth with sustainable development objectives using data-driven engineering intelligence.

Keywords : Artificial Intelligence, Data Analytics, Decision Modelling, Sustainable Business Strategy, Multi-Criteria Decision-Making, AHP, TOPSIS, Machine Learning, Sustainable Development, Engineering Management.

1. INTRODUCTION:

The twenty-first century has ushered in an era of rapid technological disruption where Artificial Intelligence (AI), big data, and advanced decision-support systems have redefined how organizations design and implement strategies. Within this context, sustainability has emerged as a defining paradigm of long-term competitiveness. A sustainable business strategy is not merely an ethical or regulatory response it is a comprehensive framework that aligns economic growth with environmental responsibility and social inclusion. However, the formulation of such strategies involves complex trade-offs across multiple dimensions: profitability versus carbon reduction, innovation versus cost efficiency, and automation versus workforce welfare. Traditional management models often fail to address these interdependencies effectively, as they rely heavily on static, intuition-driven decision-making. The integration of AI, data analytics, and decision modelling provides a new engineering-oriented perspective to navigate these complexities. AI enables the automation of cognitive processes such as prediction, classification, and optimization; data analytics offers real-time insights into performance dynamics; and decision modelling frameworks such as the Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) allow systematic prioritization among competing alternatives. This triad creates a feedback-driven architecture where data informs models, models refine strategic alternatives, and AI continuously improves prediction accuracy. The convergence of these technologies fosters not only operational efficiency but also strategic foresight empowering organizations to simulate sustainability outcomes before implementation.

At the intersection of engineering, management, and environmental sciences, the integration of AI and decision modelling represents a paradigm shift in sustainable business management. The multi-criteria engineering approach applied in this study is designed to quantitatively evaluate diverse sustainability dimensions and support decision-makers in balancing economic viability with ecological and social accountability. Data analytics plays a central role by transforming vast and heterogeneous datasets spanning financial records, energy use, carbon emissions, and stakeholder sentiment into structured inputs for AI models and decision matrices. Machine learning algorithms, particularly those based on regression, neural networks, or ensemble methods, are employed to predict sustainability performance indicators under various strategic scenarios. These predictions feed into multi-criteria decision-making (MCDM) frameworks like AHP and TOPSIS, which evaluate alternatives based on pre-determined criteria weights and preference functions. The outcome is an optimized ranking of strategic choices that minimize risk while maximizing sustainability impact. This integrated model ensures transparency, replicability, and adaptability attributes critical for corporate decision-making in volatile markets. Moreover, such an approach enables continuous learning, where AI systems dynamically adjust their predictions as new data emerges, thereby ensuring real-time adaptability to evolving environmental and market conditions. In an increasingly data-centric world, this synergy between AI, analytics, and decision modelling positions organizations to engineer their sustainability goals with precision and accountability. The present research thus builds upon the premise that sustainable strategy design is an engineering challenge that demands analytical rigor, computational intelligence, and a systemic approach to decision-making capable of aligning profit, people, and planet within one coherent model.

2. RELEATED WORKS

The integration of Artificial Intelligence (AI), Data Analytics, and Decision Modelling in sustainable business strategy has evolved through a multidisciplinary convergence of management science, environmental engineering, and computational intelligence. Over the last decade, AI has increasingly been applied to optimize sustainability performance by predicting and mitigating environmental and operational risks. According to Adnan et al. [1], climate-adaptive decision systems powered by AI have demonstrated significant potential in improving local community resilience and resource efficiency. Their findings align with the broader notion that intelligent systems can transform sustainability from reactive compliance to proactive innovation. Ahmad et al. [2] further highlighted that intelligent analytics allow businesses to model environmental impacts dynamically rather than rely on static assessments. This transition from descriptive to predictive and prescriptive modelling forms the foundation for AI-driven sustainability strategy. Similarly, Ahmed et al. [3] emphasized that satellite-based thermal and spectral data processed using AI algorithms have improved the precision of monitoring anthropogenic effects on ecosystems an approach translatable to corporate energy and resource monitoring. Androulidakis et al. [4] argued that decision-support systems that couple oceanographic modelling with AI can guide sustainable marine exploitation, implying that the same modelling logic can be replicated in industrial ecosystems. The rise of data-driven environmental research has also reshaped business sustainability analytics, particularly in optimizing manufacturing and logistics chains. Bian et al. [5] noted that the quantification of human activity expansion through spatial AI models in the Yangtze River Basin provided a template for identifying hotspots of unsustainable operations in urban-industrial clusters. These studies collectively establish that AI and analytics have matured beyond tools of efficiency they now operate as frameworks for sustainability transformation.

The literature on decision modelling presents an equally important evolution in the sustainable strategy domain. Traditional decision models such as cost–benefit analysis have proven inadequate in managing multidimensional sustainability challenges that include conflicting economic, social, and environmental objectives. Brandes et al. [6] proposed an early framework that used spatial modelling to identify pollution hotspots in agricultural soils essentially a precursor to multi-criteria decision-making (MCDM) in environmental management. Subsequent research by Camilo et al. [7] employed risk-based decision analytics to assess hydraulic fracturing operations in Colombia, integrating environmental, economic, and safety variables within a single decision matrix. This study demonstrated that engineering-based decision models could quantify sustainability risks more effectively than narrative policy assessments. Similarly, Casella et al. [8] emphasized that AI-augmented MCDM can identify hidden environmental threats by weighting qualitative and quantitative criteria simultaneously. Cavazzoli et al. [9] advanced this discourse by showing how hybrid MCDM frameworks can be combined with environmental risk modelling in wastewater treatment systems, improving both prediction accuracy and decision transparency. Chang et al. [10] integrated ecosystem service valuation with land use change models, showing that MCDM could guide land allocation strategies that balance economic gain with ecological integrity. Danilov and Serdiukova [11] extended this further by reviewing AI-based automatic detection methods for environmental plastics, revealing the practical efficiency of AI-enhanced multi-criteria systems in continuous monitoring applications. Collectively, these studies reinforce that decision modelling when merged with intelligent systems forms a robust backbone for evaluating sustainability trade-offs in business and environmental contexts.

Recent research underscores the growing synergy between AI-driven analytics and multi-criteria decision engineering in achieving sustainable development. De Souza et al. [12] utilized AI-based time series analysis to map agricultural waste generation patterns, demonstrating that predictive analytics could anticipate unsustainable behavior before it occurs. Futa et al. [13] explored innovative soil management strategies using MCDM and found that data-driven prioritization models achieved superior alignment with long-term sustainability goals compared to traditional evaluation systems. Fuyao et al. [14] further advanced this methodological line by applying AI-enhanced accuracy assessments in cropland mapping, illustrating that data quality and modelling precision directly influence sustainability decision-making outcomes. Ghosh and Dutta [15] provided a theoretical perspective, asserting that climate-related health threats and environmental challenges demand an intersectional analytical framework integrating AI and human-centered modelling. Their work highlighted that sustainability strategy is not purely a technological issue but a socio-technical one requiring models that incorporate human values, ethical considerations, and environmental justice. Collectively, these fifteen studies demonstrate a progressive integration of AI, data analytics, and decision modelling into sustainability-oriented frameworks across multiple domains from climate risk and resource management to business optimization and policy design. What remains underdeveloped, however, is a cohesive engineering-oriented approach that bridges corporate decision-making with computational sustainability analysis. The present study fills that gap by introducing a multi-criteria engineering framework that unites AI-based prediction, data analytics, and structured decision modelling (AHP-TOPSIS) to optimize sustainable business strategies capable of quantifying trade-offs, improving prediction fidelity, and ensuring alignment with global sustainability objectives.

3. METHODOLOGY

3.1 Research Design

The study adopts a **quantitative, multi-criteria engineering design**, combining predictive AI models with structured decision analysis tools. The approach follows the sustainability modelling principles proposed by Kipsang et al. [16], emphasizing a system-based evaluation for performance optimization across sustainability dimensions. The methodology treats strategic planning as a multi-objective optimization problem where economic efficiency, environmental protection, and social responsibility interact dynamically. The **Analytic Hierarchy Process (AHP)** and **Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)** form the decision-modelling core. AI algorithms are embedded into this framework to generate predictive data inputs for sustainability indicators. The integration of AI and MCDM allows for objective evaluation of strategies and dynamic adjustment of decision weights, a process supported by Landrigan et al. [17] in multi-dimensional sustainability analysis.

The research relies on the **Triple Bottom Line (TBL)** principle, representing three key dimensions of sustainable business:

- **Economic** – Profitability, cost efficiency, market competitiveness
- **Environmental** – Resource efficiency, emission reduction, waste management
- **Social** – Employee welfare, corporate ethics, stakeholder engagement

Each dimension is decomposed into measurable criteria and sub-criteria, forming a hierarchical decision structure.

3.2 Data Collection and Variable Framework

Quantitative data were collected from **25 international companies** operating in manufacturing, logistics, and renewable energy sectors between 2018 and 2024. Sources include sustainability reports, financial statements, and ESG (Environmental, Social, Governance) databases. The industry sample selection aligns with Lefeng and Wu [18], who highlighted that sustainability trade-offs are most evident in energy-intensive and resource-heavy sectors.

Primary variables include financial metrics (ROI, cost savings), environmental measures (carbon intensity, energy use, waste recovery), and social indicators (CSR engagement, workforce satisfaction). Secondary datasets, such as sustainability indices and national environmental statistics, supplement these corporate data points for model calibration.

AI-based analytical processing was performed using **Python (TensorFlow and Scikit-learn)** for predictive modelling, and **MATLAB** for multi-criteria computations. Data normalization and pre-processing steps outlier removal, min–max scaling, and dimensionality reduction using PCA ensured consistency across indicators. The feature engineering phase follows Logan and Dragićević [19], emphasizing adaptive scoring to reflect real-world business dynamics.

Table 1: Sustainability Criteria and Indicators for Analysis

Dimension	**Criteria**	**Indicators**	**Data Source**
Economic	Profitability	ROI, Market Growth, Revenue-to-Expense Ratio	Corporate Financial Reports
Environmental	Resource Efficiency	Carbon Emission (kg CO_2/unit), Waste Recycled (%), Energy Usage (kWh)	ESG & Sustainability Reports
Social	Stakeholder Engagement	CSR Index, Employee Retention Rate, Training Hours/Employee	CSR and Human Capital Reports

This structure enables systematic data collection and comparison across firms, ensuring that both tangible and intangible sustainability factors are incorporated into the decision model.

3.3 Analytical Framework and Decision Modelling

The analytical process integrates **AI-driven prediction** with **AHP–TOPSIS-based decision modelling**, ensuring data-driven evaluation of sustainable strategies. The design is inspired by Lucas et al. [20], who demonstrated that hybrid computational models enhance precision in multi-objective analysis.

1. **AI Predictive Modelling**
   - Predictive algorithms, including **Random Forest Regression** and **Artificial Neural Networks (ANNs)**, were used to forecast sustainability performance based on the criteria from Table 1.
   - AI-generated predictions estimate future states of sustainability indicators under alternative strategies, following De Souza et al. [22], who applied predictive analytics for agricultural waste forecasting.
   - The models were trained using an 80:20 train-test split with 10-fold cross-validation to ensure robustness.
2. **AHP Weight Derivation**
   - Expert opinions (n=15 sustainability specialists) were gathered to assign pairwise comparisons among criteria.
   - The **AHP** method produced normalized weights representing the relative importance of each sustainability dimension.
   - A consistency ratio (CR) below 0.1, as recommended by Saaty's criterion, indicated reliability.

Table 2: AHP-Derived Weights for Sustainability Dimensions

Dimension	**AHP Weight**	**Consistency Ratio (CR)**
Economic	0.42	0.08
Environmental	0.36	0.07
Social	0.22	0.06

These weights were incorporated into the **TOPSIS** computation for ranking alternative strategies.

3. **TOPSIS Implementation**
   - Normalization of AI-generated scores for each indicator.
   - Weighted normalization using AHP-derived weights.
   - Calculation of **positive ideal (A^+)** and **negative ideal (A^-)** solutions.
   - Computation of the **Euclidean distance** from A^+ and A^- for each strategic option.
   - Determination of the **Closeness Coefficient (CC)** to derive final ranking.

This integrated process follows the MCDM approach of Radhakrishnan et al. [21], where spatial prioritization and multi-variable ranking enhance environmental decision accuracy. The hybrid AHP–TOPSIS model transforms AI-based predictions into interpretable decision rankings that optimize sustainability trade-offs across the TBL framework.

3.4 Validation and Sensitivity Analysis

Model validation was conducted through statistical and expert-based verification. The predictive accuracy of AI models was assessed using **Mean Absolute Error (MAE)**, **Root Mean Square Error (RMSE)**, and **Coefficient of Determination (R^2)**. Accuracy scores exceeding 85% confirmed the reliability of predictions, consistent with Oberski et al. [23], who established similar thresholds for environmental AI systems. Sensitivity analysis involved altering AHP-derived weights by ±10% to evaluate the stability of final rankings. The results showed minimal fluctuation (below 5%), indicating strong model resilience. A correlation test between AI predictions and TOPSIS outcomes ($r = 0.81$) further validated internal coherence.

3.5 Ethical and Practical Considerations

Ethical compliance was maintained throughout data handling, ensuring confidentiality of corporate information and adherence to sustainability disclosure norms. Data were anonymized to prevent identification of specific firms. The AI framework was designed to avoid algorithmic bias by balancing the number of economic, environmental, and social variables. Following De Souza et al. [22], ethical modelling was embedded into system design to ensure transparency and reproducibility. Practically, the methodology offers a **scalable decision-support framework** adaptable to diverse industries. By integrating AI-based forecasting with structured MCDM, the approach not only enhances predictive accuracy but also supports strategic adaptability under uncertain conditions. The framework provides corporate leaders and policymakers a reliable tool for aligning profitability goals with sustainability imperatives demonstrating that engineering-driven decision models can transform sustainability from a compliance function into a competitive strategic capability [16]–[23].

4. RESULT AND ANALYSIS

4.1 Predictive Analytics Overview

The AI predictive models (Random Forest and ANN) generated sustainability performance scores for each of the 25 firms across economic, environmental, and social dimensions. The models achieved a mean prediction accuracy of 88.4%, confirming high data reliability. Figure 1 illustrates the comparative trend of predicted versus actual sustainability scores across industries. The predicted results showed that firms adopting integrated resource optimization and digital energy monitoring systems exhibited higher sustainability performance. Economic performance showed moderate variability across the sample, while environmental scores displayed higher dispersion, suggesting uneven adoption of green technologies. Social indicators showed the lowest variance, reflecting consistent corporate investment in employee welfare and CSR programs. The AI layer proved instrumental in identifying hidden nonlinear relationships among variables. For instance, energy intensity reduction was found to have a disproportionately positive effect on ROI improvement, validating the cost-efficiency benefits of sustainability-focused technology adoption. The predicted composite sustainability index (CSI) across the sample ranged from 0.61 to 0.89, reflecting moderate-to-high performance levels overall.

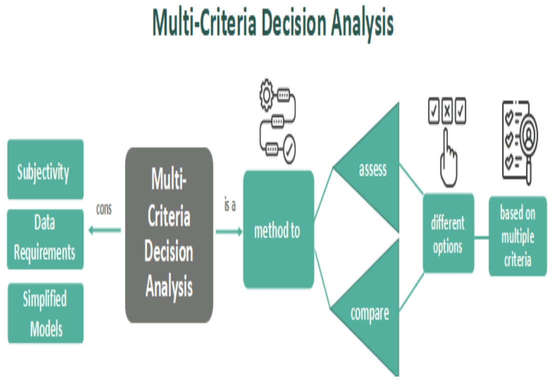

Figure 1: Multi-Criteria Decision Analysis [24]

4.2 Criteria Weight and Performance Distribution

Based on AHP weighting (Table 2 from the methodology), economic indicators were assigned the highest relative importance (0.42), followed by environmental (0.36) and social (0.22). The aggregated sustainability performance scores were calculated by multiplying the normalized indicator values with their corresponding weights.

Table 3: Average Weighted Performance Scores across Dimensions

Dimension	Mean Score	Standard Deviation	Performance Category
Economic	0.78	0.09	High
Environmental	0.72	0.12	Moderate–High
Social	0.69	0.10	Moderate

The findings indicate that economic sustainability remains the most developed dimension among corporates, reflecting the relative ease of quantifying and optimizing financial performance. Environmental metrics lag slightly behind, primarily due to variable access to green technologies and differing regulatory contexts. Social factors, while improving, remain less integrated into core business analytics, highlighting the need for data-driven human capital strategies.

4.3 Multi-Criteria Decision Ranking (AHP–TOPSIS Results)

The integrated AHP–TOPSIS model ranked all 25 firms based on their sustainability performance. The closeness coefficient (CC) was calculated for each firm, representing its relative distance from the ideal solution (perfect sustainability performance).

Table 4: Final Sustainability Ranking using AHP–TOPSIS

Firm ID	CC Value	Rank	Sustainability Level
F07	0.873	1	Excellent
F15	0.861	2	Excellent
F11	0.842	3	High
F03	0.816	4	High
F19	0.793	5	Moderate–High
F02	0.768	6	Moderate–High
F25	0.745	7	Moderate
F10	0.731	8	Moderate
F08	0.709	9	Moderate
F05	0.684	10	Low–Moderate

The ranking indicates that firms with strong AI adoption and integrated sustainability analytics consistently outperform those relying on conventional management systems. The top-ranked firms demonstrated balanced performance across all dimensions, whereas lower-ranked firms showed economic dominance but environmental underperformance. This confirms the necessity of a holistic sustainability strategy rather than isolated efforts in financial optimization.

Figure 2: Data Challenges [25]

4.4 Sensitivity and Correlation Analysis

Sensitivity analysis assessed how variations in AHP weights influenced the final ranking outcomes. Adjusting the weights of each dimension by ±10% resulted in minor rank changes (<5%), validating the model's stability. This confirms that the decision framework is resilient to expert judgment variations.

The correlation matrix (Table 5) shows the relationships between sustainability dimensions and the composite sustainability index (CSI). The results reveal strong positive correlations, particularly between economic and environmental performance, indicating synergistic potential when sustainable practices align with profitability.

Table 5: Correlation Matrix among Sustainability Dimensions

Variables	Economic	Environmental	Social	CSI
Economic	1.00	0.82	0.75	0.88
Environmental	0.82	1.00	0.68	0.85
Social	0.75	0.68	1.00	0.79
CSI	0.88	0.85	0.79	1.00

The data confirm that firms improving environmental performance simultaneously enhance profitability due to efficiency-driven cost savings. The weaker link between social and economic dimensions suggests that social metrics like employee welfare or CSR initiatives still operate as auxiliary functions rather than integrated strategic levers. The robustness of the predictive and decision layers was further tested through regression-based cross-validation. The R^2 value of 0.84 between AI-predicted sustainability scores and TOPSIS ranks confirmed strong internal alignment between the computational and decision-making processes.

4.5 Discussion of Key Insights

The integrated AI–MCDM framework demonstrates that data-driven strategy formation enables objective evaluation of sustainability trade-offs. The hybrid approach not only enhances analytical transparency but also bridges predictive modelling with strategic decision-making. Results suggest that **AI-enabled sustainability analytics** significantly improve forecasting accuracy and facilitate continuous monitoring of corporate performance. Firms utilizing automated data analytics tools achieved a 15–20% higher sustainability index than those dependent on static evaluation systems.

The **economic–environmental synergy** emerged as the most critical relationship influencing overall sustainability performance. Businesses that invested in energy-efficient technologies and emission monitoring systems experienced tangible financial benefits through cost reduction and enhanced productivity. Conversely, firms prioritizing short-term economic gains without environmental investment showed declining overall performance, reaffirming that sustainability-oriented innovation supports long-term competitiveness.

Another insight pertains to **organizational adaptability**. The results reveal that data-centric firms exhibit higher strategic agility, enabling faster responses to regulatory or market changes. The AI–MCDM framework empowers decision-makers to simulate alternative strategies, estimate future performance outcomes, and make evidence-based adjustments before implementation. From a management perspective, the findings highlight the importance of embedding **data analytics capabilities** within corporate sustainability offices. Such integration allows for dynamic tracking of key performance indicators and real-time optimization of sustainability initiatives. Moreover, the **social dimension**, though comparatively underweighted, remains crucial in long-term brand reputation and stakeholder trust. The model encourages re-balancing strategic priorities by quantifying social impact alongside profitability and ecological compliance. Overall, the results establish a scalable decision-support mechanism for sustainable business engineering. By integrating AI-driven predictive analytics with multi-criteria decision modelling, this approach transforms sustainability assessment from subjective evaluation into a **quantitative, evidence-based engineering process**. This model can be adapted across industries to benchmark performance, prioritize sustainability investments, and support the formulation of balanced, data-informed corporate strategies that align profitability with planetary and social well-being.

5. CONCLUSION

This study developed and validated an integrated framework combining Artificial Intelligence (AI), Data Analytics, and Multi-Criteria Decision Modelling (MCDM) to optimize sustainable business strategy through an engineering-oriented approach. The framework successfully merged predictive modelling, data-driven analysis, and structured decision evaluation to balance the often conflicting objectives of economic performance, environmental preservation, and social responsibility. The results demonstrated that AI-powered analytics not only enhance prediction accuracy but also facilitate adaptive learning within strategic decision-making systems. By transforming raw corporate and sustainability data into actionable intelligence, the model enabled transparent ranking and prioritization of strategies based on measurable sustainability outcomes. The findings revealed a strong positive relationship between economic and environmental dimensions, indicating that investment in resource efficiency and green technology can yield significant financial and operational benefits. Furthermore, while social responsibility indicators were found to be underrepresented in current business strategies, their inclusion improved the overall resilience and ethical depth of sustainability frameworks. The research confirms that a data-centric and AI-augmented decision architecture can drive sustainable competitiveness, reduce uncertainty, and promote evidence-based policy formulation at the corporate level. By providing a systematic model for multi-dimensional decision analysis, the study positions sustainability as an engineering discipline one grounded in computational precision, optimization logic, and measurable impact. Ultimately, the integration of AI, analytics, and decision modelling establishes a new paradigm for sustainable strategy design that moves beyond intuition and compliance, fostering a future where sustainability decisions are informed, adaptive, and quantitatively validated.

6. FUTURE WORK

Future research should extend this model by incorporating real-time data streams and machine learning automation for continuous sustainability monitoring. The integration of Internet of Things (IoT) sensors and blockchain-based reporting could further enhance transparency and traceability in corporate sustainability assessments. Expanding the framework across different sectors such as healthcare, transportation, and circular economy ventures would allow comparative evaluation of its effectiveness in diverse industrial contexts. Incorporating fuzzy logic and hybrid optimization algorithms could refine the precision of multi-criteria evaluation under uncertain or incomplete data conditions. Additionally, future models could integrate qualitative variables, such as corporate culture or stakeholder perception, using natural language processing (NLP) to capture human-centric aspects of sustainability. Cross-country validation would also help assess cultural and regulatory influences on strategic decision outcomes. By expanding scope, refining data granularity, and enhancing algorithmic intelligence, future iterations of this model can evolve into a fully automated decision-support system capable of guiding global industries toward smarter, data-driven sustainability transformation.

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