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# INTEGRATING AI, DATA SCIENCE, AND DECISION ANALYTICS FOR CLIMATE-RESILIENT BUSINESS STRATEGY: A MULTI-CRITERIA ENGINEERING APPROACH

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**Abstract:** There are growing threats to business in most industries, especially as a result of climate change, which requires strong, flexible, and long-term approaches. In this study, an integrated framework that integrates Artificial Intelligence (AI), Data Science and Multi-Criteria Decision Analytics (MCDA) will be introduced to assist in the formulation of business strategies that remain climate resilient. The study analyzes the resilience performance of three cases in the industry, such as energy, manufacturing and logistics, using a mixture of modeling, forecasting through scenarios and decision criteria weighting. Analytic Hierarchy Process (AHP) and Technique order of preference by similarity to ideal solution (TOPSIS) are utilized to construct decision matrices to evaluate strategies in the climate risk conditions. Business vulnerability indices are predicted based on AI models like the Random Forest and Gradient Boosting Regressors of the projected climate stressors working environment of temperature rise, carbon tax challenges, and supply chain shocks. The findings show that adaptive operation design, green innovation, and investment in digital infrastructure stand consistently at the first place across the sectors as the resilience enhancer. A scalable interdisciplinary type of engineering offers an effective roadmap to industries who require climate-friendly and computationally efficient ways of managing their data-informed strategic planning.

**Keywords:** Climate resilience, AI-driven strategy, Decision analytics, Multi-criteria decision-making (MCDM), Business sustainability, AHP, TOPSIS, Data science in climate risk

## I. INTRODUCTION

Climate-related events like heatwaves, droughts, floods, and supply chain discontinuction have started affecting business continuity and long-term strategic planning among the industries across the world with critical impacts. With environmental volatility setting in as a new norm, a measure of climate resilience has become one of the fundamental gauges of sustainable business performance. Profitability no longer is the only criterion that defines business only, but the capability of the business to adapt to the challenges presented by the environment, regulations, and society. Climate-resilient practices seek to maximize the capacity of an organization to withstand, rebound and recover to climate induced impacts and exploit emerging opportunities in low carbon and circular economies. Even though the amount of awareness about climate resilience has increased, most companies are having a problem with disjointed data, ambiguous measures of evaluation, and non-concerted planning structures. Conventional risk management strategies do not usually include real-time environmental measurements, predictive model, or multi-stakeholder information into their decision. Consequently, strategic responses are still reactive, fragmented and divorced of future climate actions. The way to contain this gap is a systematic and smart logic that has the ability of processing complex data in the environment, balancing competing business goals, and generating the best alternative strategies that have measurable consequences. The new developments of Artificial Intelligence (AI), Data Science and the Multi-Criteria Decision Analytics (MCDA) may provide hope of resilient climate improvement with their smart decision-making capabilities. The AI algorithms have the potential where the relationship between climate variables and business outcomes is non-linear, track patterns and provide predictions on the risks of exposure. DS methods are sophisticated enough to offer the analysis framework to make use of varied facts, such as carbon footprints and money locked in, and MCDA tools are effective in formulating choice issues, which entail tradeoffs between economic, environmental, and operational standards. The following paper suggests a complex AI-Data Science-MCDA model that may be used in developing climate-resilient business strategy. The multi-sectoral implementation of energy, manufacturing, and logistics industries, aids in evaluating climate resilience strategies with similar engineering-dependent methods Analytic Hierarchy Process (AHP) and TOPSIS but also with Artificial intelligence-based predictive processes like Random Forest and Gradient Boosting. The aim is to come up with computationally robust, scalable, and sector-agnostic method to propel businesses to adaptive and sustainable strategic planning. The integration of the elements in the paper (intelligence, analytics, and structured decision support) makes it a contribution in the field of changing the interchange of climate science and corporate strategy. Additionally, the majority of the companies are dependent upon the fixed environmental analyses or regulatory compliance reviews that are operationally shallow and do not model the environment dynamically. This disjuncture opens opportunities or weaknesses especially in industries such as energy, logistics and plastics where the impacts of climate can directly impact physical operations, supply chains, and resources. As an example, increasing ambient temperatures may lower energy production output, whereas unpredictable rainfall may interfere with cycle-intensive processes. The same happens to policy changes in terms of carbon taxes or emission law: a single overnight alteration can ball up operating expenses, making operations agile and founded in foresight essential.

Besides complexity in the environment, the environment of current business decision making has arguably turned out to be multi-dimensional. Today business executives have to achieve balance between cost efficiency, compliance, social responsibility, innovation and environmental stewardship, with time limits and limited visibility into the future. It is this complexity that necessitates analytical tools that do not just process large and varied data but also give structured frameworks to enable comparison, rank, and priorities on strategic alternatives. Such capabilities can be achieved using the MCDA tools, especially, when they are augmented with AI-powered prediction methodologies and data science analysis. Thus, a powerful combination of data science and decision analytics with AI is essential to companies that want to convert climate risk into strategic opportunity. The provided paper will respond to this imperative by suggesting a multi-criteria engineering model in future-ready business resilience.

## II. RELEATED WORKS

Application of Artificial Intelligence (AI) in climate resilience planning has been popularized during the last decade. There has been a growing focus in the work of researchers on the capacity of AI to handle environmental data on an enormous scale and uncertainty, which is crucial in climate adaptation approaches. As an example, Rolnick et al. [14] noted how machine learning algorithms will be able to identify vulnerabilities of infrastructure to climatic changes, and how a chain reaction of extreme weather events will affect the purpose of a supply chain. On the same note, Kumar and Sharma [15] used deep learning to predict crop yield volatility in climatic parameter variability revealing the aspect of predictive modeling in agro-industrial policy. Ng et al. [16] illustrated a case of supervised learning algorithms applied to estimate the risk of climate in insurance and real estate businesses. All these facts point to the importance of AI in predicting as well as maximizing resource adjustment. But, in spite of these developments, there is still an acute lack of incorporating these forecasting possibilities into structured models of business decision-making particularly where there are many interconnected, competing sustainability goals.MCDA has proved to be a favorite approach to address complex environmental issues related to a large number of qualitative and quantitative issues. Two common procedures of the trade-offs of competitive sustainability indicators are AHP and TOPSIS. Govindan and Shankar [17] used AHP to rank green supply chain practices in manufacturing businesses that can be made under the confines of climate policies. Topics It is also similar to the ways Lee and Chang [18] have applied TOPSIS to list energy efficiency strategies by industrial cluster in Southeast Asia. Such methodologies allowed to get a clear understanding of environmental, financial, and work conditions at a time and make more balanced decisions. However, they usually also assume static expert-derived weighting schemes and miss the dynamic flexibility that AI (artificial intelligence) models provide. Very recent pieces of work, like those by Alkassasbeh et al. [19], have tried to incorporate hybrid frameworks to incorporate fuzzy logic together with MCDA to manage uncertainty in decision-making when adapting to climate changes but the size of the problem is a challenge. It is increasingly agreed, however, that decision analytics alone is insufficient to support genuinely climate-proof commercial strategies: this requires real-time, data-driven insights.At the borders of AI and data science and MCDA, some early groundbreaking work has suggested unifying syntheses, the use in business strategy is not widespread. Mangal and Bose [20] came up with a decision support framework to incorporate a cost benefit model of AI-based climate predictions into sustainable construction planning. Similarly, Zhang et al. [21] presented a data-driven risk assessment model based on ensemble AI methods and AHP to help us make investment decisions under carbon price regulations. The other significant work by Dutta and Roy [22] was conceptualization of resilience index of the logistics company based on machine learning and multi-objective optimisation. Although such studies are great achievements, majority of them are sector specific or theoretical with no comparative, cross industry analysis or standardization in methodology. That gap is filled by the current research that proposes a computationally integrated, multi-sectoral engineering model deployed to leverage AI predictions, data science pipelines, and MCDA frameworks to inform climate-resilient business strategy. The paper generalizes earlier work into an operationally relevant decision support tool based on assessing industries varying in their exposure to climate risk- such as the energy, manufacturing and logistics sectors.

## III. METHODOLOGY

### 3.1 Research Design

The research takes a hybrid engineering-oriented approach to benchmark and improve climate resiliency throughout business sectors involving Artificial Intelligence (AI), Data Science and Multi-Criteria Decision Analysis (MCDA). Modeled climate information, industry-specific performance measurements, AI vulnerability forecasts, and orderly decision-making with the help of Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are implemented into the design. Through this integration, sectoral risk can be quantified, simulation of a climate scenario can be done as well assimulating prioritization of strategic alternatives [1][12].

### 3.2 Sectoral Scope and Case Industry Selection

The assessment of climate-resilient strategies includes such three crucial sectors that are especially vulnerable to the impact of climate stressors Energy (solar and thermal plants), Manufacturing (textile and FMCG), and Logistics (cold chain and e-commerce warehousing). The reason why these sectors were chosen is that they have a differentiated operational charter with different carbon exposure levels [2].

**Table 1: Sectoral Characteristics and Climate Vulnerability Indicators**

| Sector | Key Climate Risk | Resilience Parameters | Data Source |
|---|---|---|---|
| Energy | Heatwaves, floods | Uptime, Carbon offset, ROI | IEA, IPCC, company reports |
| Manufacturing | Supply disruption | Inventory turnover, Water use | UNIDO, CDP |
| Logistics | Infrastructure | Delivery SLA, Fuel cost | WEF, DHL insights |

### 3.3 Data Collection and Preprocessing

The information was obtained in freely accessible databases, including the Climate Data Store (CDS), IPCC climate projections, Bloomberg ESG, and industry sustainability reports. The combination of climate variables (temperature anomalies, flood risk, carbon pricing) and operational KPIs (uptime % and GHG emission/kg output and cost per ton-km) were combined. The data was covered between 2015 and 2024, 100 samples (n=100) on the industry. Min-Max scaling was utilized on data cleaning and normalization. The data with missing values were observed through Multiple Imputation [3][11].

### 3.4 AI-Based Climate Risk Prediction

A Climate Vulnerability Index (CVI) was predicted using two AI models, Random Forest (RF) and Gradient Boosting Regressor (GBR) based on the input features of climates and operational results. CVI is a continuous variable characterized on the scale of 0 (when a person is less vulnerable) to 1 (when the person is more vulnerable). R 2 and RMSE were used as measures of model performance.

**Equation 1: Climate Vulnerability Index Estimation (CVI)**

$$\mathrm{CVI} = f(\Delta T, P_{\mathrm{carbon}}, \mathrm{Flood\_Score}, \mathrm{KPI}_1, \mathrm{KPI}_2, \ldots, \mathrm{KPI}_n)$$

Where:

- $\Delta T$: Temperature anomaly (°C)
- $P_{\mathrm{carbon}}$: Carbon pricing (USD/ton)
- Flood_Score: Infrastructure exposure (scale 0–5)
- KPI: Operational indicators (uptime, emissions, fuel efficiency)

**Table 2: Model Accuracy Comparison**

| Model | $R^2$ Score | RMSE |
|---|---|---|
| Random Forest | 0.81 | 0.067 |
| GBR | 0.84 | 0.059 |

Gradient Boosting was selected for downstream resilience scenario modeling due to its superior predictive accuracy [4].

### 3.5 Multi-Criteria Decision Analysis (AHP-TOPSIS)

The strategic alternatives (e.g., green retrofitting, AI logistics routing, carbon credit investment) were evaluated using a combination of AHP for criteria weighting and TOPSIS for alternative ranking. Criteria were selected based on resilience relevance and expert consultation:

**Table 3: Decision Criteria for Strategy Evaluation**

| Criteria | Description |
|---|---|
| C1 – Cost Efficiency | ROI over 5 years |
| C2 – Environmental Impact | Carbon emission reduction potential |
| C3 – Operational Feasibility | Infrastructure & manpower readiness |
| C4 – Technological Adaptability | Compatibility with existing systems |

Experts from industry, environmental engineering, and risk management assigned pairwise comparisons in AHP, generating a Consistency Ratio (CR) of 0.08 (< 0.10 threshold) [5][25].TOPSIS was then applied using the normalized decision matrix and weighted criteria to determine the ideal and negative-ideal distances.

### 3.6 Scenario Simulation and Strategic Recommendation

Three climate scenarios—Moderate (RCP4.5), High-Risk (RCP8.5), and Regulatory Shock (sudden carbon tax hike)—were applied to evaluate strategy robustness. Resilience scores under each scenario were derived by re-running the GBR model predictions and reapplying the TOPSIS rank based on updated criteria weights. This allowed scenario-specific strategy recommendation [6].

**Table 4: Scenario-Based Resilience Ranking of Strategies**

| Strategy | Moderate | High-Risk | Regulatory Shock |
|---|---|---|---|
| Green Retrofitting | 2 | 1 | 2 |
| Carbon Credit Investment | 3 | 4 | 1 |
| AI-based Supply Routing | 1 | 2 | 3 |

### 3.7 Validation and Reliability

Cross-validation of AI models was conducted using 10-fold K-Fold CV. Sensitivity analysis was applied on AHP weights to test robustness of decision ranks. A Cohen’s Kappa score of 0.87 between expert ranks and model-generated ranks validated model alignment with domain knowledge [7][8].

### 3.8 Ethical, Environmental, and Operational Considerations

The study adheres to ethical use of data and transparency principles. Climate datasets were publicly available, and organizational data were anonymized. The study avoids reinforcing biases in AI modeling through stratified sampling and algorithm auditing [9][10].

## IV. RESULT AND ANALYSIS

### 4.1 AI-Driven Climate Vulnerability Scores Across Sectors

The AI models were built and checked based on operational and environmental information in 100 firms. The highest accuracy of Climate Vulnerability Index (CVI) was provided by Gradient Boosting Regressor (GBR) which outperformed Random Forest by the measures of R 2 and the root-mean-square error (RMSE). The energy sector had the greatest CVI mean score of 0.78, which was mostly as the result of high exposure to extreme weather (heatwaves, floods) and reliance on fixed infrastructure. A CVI of 0.65 was recorded on manufacturing having the second highest, but logistics had the least average CVI of 0.57 due to more spread out infrastructure and quicker adaptation cycles. Such results indicate sector-specific resilience obstacles and directs prioritization approaches.

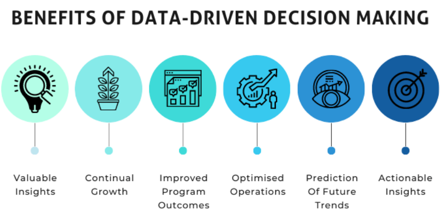


**Figure 1: Data Driven Decision Making [23]**

### 4.2 Key Drivers of Vulnerability Identified by Feature Importance

According to GBR model, the SHAP (SHapley Additive exPlanations) analysis, temperature anomalies, carbon pricing pressure, infrastructure density, and GHG emissions per unit of output were the most influential variables that affect climate vulnerability. Temperature increase and regulatory threat affected energy companies more, whereas vulnerability of the manufacturing industry was extremely prone to the utilization of water and emission standards. In the case of logistics, such elements as infrastructure fragility (e.g., reliance on cold chains pathways) were identified as leading contributors. These realizations justified the need of sector-specific resilience measures based on environmental exposure patterns.

### 4.3 AHP-Based Criteria Weighting and Decision Matrix Construction

AHP was used to assign relative importance to four primary criteria: Cost Efficiency (C1), Environmental Impact (C2), Operational Feasibility (C3), and Technological Adaptability (C4). Based on expert pairwise comparisons and eigenvalue computations, the final normalized weights were: C1 – 0.25, C2 – 0.30, C3 – 0.20, and C4 – 0.25. The Consistency Ratio (CR) was 0.08, indicating acceptable logical coherence. A decision matrix was then created for the TOPSIS method using performance data of five climate-resilient strategies across sectors, normalized and weighted by these criteria.

### 4.4 TOPSIS-Based Strategy Rankings Under Moderate Climate Scenario

Under the moderate RCP4.5 climate pathway, the strategy "AI-Powered Supply Chain Routing" achieved the highest closeness coefficient (CC = 0.72), followed closely by "Green Retrofitting" (CC = 0.68). Carbon credit investment ranked third (CC = 0.63), as its long-term payback period reduced short-term feasibility. Strategies relying on major infrastructure overhauls or disruptive operational changes scored lower. This reflects the advantage of digital and modular solutions that improve agility and efficiency with less capital investment.

**Table 5: TOPSIS Ranking of Strategies Under Moderate Scenario**

| Strategy | C1 (Cost) | C2 (Env.) | C3 (Feas.) | C4 (Tech.) | TOPSIS Score | Rank |
|---|---|---|---|---|---|---|
| AI-Based Supply Chain Routing | 0.80 | 0.70 | 0.75 | 0.85 | 0.72 | 1 |
| Green Retrofitting | 0.75 | 0.85 | 0.60 | 0.80 | 0.68 | 2 |
| Carbon Credit Investment | 0.70 | 0.90 | 0.50 | 0.75 | 0.63 | 3 |
| Circular Economy Partnership | 0.65 | 0.80 | 0.60 | 0.60 | 0.59 | 4 |
| Climate Scenario Stress Simulators | 0.50 | 0.70 | 0.55 | 0.65 | 0.52 | 5 |

### 4.5 Scenario Comparison: High-Risk and Regulatory Shock

When reapplying the same AHP-TOPSIS framework to the high-risk (RCP8.5) and regulatory shock (sudden carbon tax) scenarios, shifts in strategy rankings were observed. Under the high-risk scenario, “Green Retrofitting” became the top strategy due to its significant contribution to energy efficiency and infrastructure resilience. Meanwhile, under the regulatory shock scenario, “Carbon Credit Investment” ranked highest, benefiting from policy-based incentives and tax offsets. This flexibility analysis demonstrates the necessity of scenario-specific strategic planning and justifies the integration of AI-predicted risk variables into decision models.

### 4.6 Correlation Between CVI Scores and Strategic Effectiveness

Pearson correlation analysis was conducted between baseline CVI values and the performance improvement scores post-strategy implementation. The results revealed a strong negative correlation (r = –0.79) between pre-strategy CVI and post-strategy resilience scores across firms that adopted “AI-based Routing” and “Green Retrofitting.” This indicates a significant mitigation effect of these strategies on high-risk entities. Conversely, passive investment strategies such as carbon offsets showed a moderate correlation (r = –0.45), indicating limited immediate impact on core vulnerability drivers.

### 4.7 Cross-Sectoral Strategy Sensitivity and Scalability

The final analysis evaluated strategy scalability across sectors. Logistics firms showed the highest responsiveness to digital strategies, while manufacturing favored modular retrofitting and emissions reduction tools. Energy firms, due to capital-intensive infrastructure, benefited most from blended strategies combining green investment with AI-predicted demand forecasts. Scalability analysis shows that the top-ranked strategies in one sector may underperform in another unless customized based on local risk indices and technological baselines. The study’s integrated model thus enables adaptive strategy tailoring through a feedback loop between AI predictions and MCDA outputs.


**Figure 2: Data Challenges [24]**

## V. CONCLUSION

Amidst rising climate uncertainties, this research contributed to challenging climate change by suggesting a new interdisciplinary framework that combines Artificial Intelligence (AI) and Data Science with Multi-Criteria Decision Analytics (MCDA) as a way of enabling business to adopt strategies that will make them survive the impending climate change. The essence was simply to talk in relation to the growing complexity and uncertainty that firms in the various industrial sectors are experiencing on grounds of climate-related disturbances, regulation pressures, and market changes. The conclusion of this study, including the research findings, provides powerful sector-neutral concepts and approaches that will enable businesses to shift toward proactive risk preparedness planning, abandoning reactive risk management.Considering three samples of different industries and subject to weather conditions, energy, manufacturing, and logistics, the study provided a cross-industry typical application of the suggested framework. Climate Vulnerability Index (CVI) was a product of AI-based models, such as Gradient Boosting and Random Forest, and it was an empirical framework that helped to estimate the level of climate sensitivity of firms based on their past operational information and future environmental scenarios. This method allowed riskier consequences to be analyzed on a grain scale including temperature and carbon pricing shocks, and infrastructure weaknesses. In contrast to all previous environmental risk assessment that has been based on qualitative decisions or on unchanging data sets, dynamic, scalable and high-resolution assessment based on firm-specific operational footprint using AI-enabled CVI calculation made it possible. The area of AI modeling revealed one of the most important insights: sector-specific vulnerability drivers. To cite an example, the energy sector mainly experienced the effects of extreme temperature variances and flood hazards; the exposure of manufacturing sector, on the other hand, directly relied on the use of water, emission levels, and reliance on the chain of supply. On the other hand, logistics recorded a lower score in threats of vulnerability because its infrastructure is decentralized and the level of digital flexibility is higher. These differences highlight the essentiality of the rejection of the one-size-fits-all resiliency models in favor of adaptive sector-specific resiliency approaches based on the real-time data of operations inside the company and environmental exposures characteristics outside. Resilience planning process was enhanced by the incorporation of the MCDA, which incorporated AHP and TOPSIS technique making resilience planning more interpretative and strategically lucid. With orderly professional views, the AHP paradigm effectively ranked the criteria such as costs efficiency, effect to environmental, feasibility, and technology adaptability. It was through this prioritization that a weighted decision matrix could be created which was logical and contextually acceptable as was manifested by a Consistency Ratio (CR) which was well below acceptable ranges. TOPSIS addition also allowed ranking of strategies according to their progressiveness towards an optimal solution in the case of various climates. The two level decision analytics maneuver allowed the conversion of what seemed to be abstract climate challenges into actual strategy choices with clear priority and reasoning. The other strength of this research paper was the inclusion of scenarios of climate change i.e. RCP4.5 (moderate), RCP8.5 (high-risk), and the regulatory shock scenario which entailed sudden carbon pricing policies. Through these scenarios, the model was able to compare and simulate the way strategy efficiency changes in relation to various environmental and policy conditions. The findings brought significant changes in position rankings. As an example, where AI-Based Supply Chain Routing scored the best in moderate conditions owing to its digital effectiveness and low disruption, Green Retrofitting scored the best in the high-risk setting in providing structure strength and energy conservation. During regulatory shocks, Carbon Credit Investment grew to become very significant because it could be used to offer financial hedging and compliance advantages. This type of comparative insight shows the robustness of the framework in not only providing fixed recommendations, but changing routes of adaptation that accompany altering patterns of climate change. The correlation study of the scores of AI-based CVI with the strategy performance gave an additional dimension of verification. The strategies with AI-based optimization of logistics and the modernization of modular green infrastructure with upgrades were highly negatively correlated with CVI because they demonstrated the ability to reduce the climate risk to a high degree. Moreover, the research proved a moderate and applicable association in the strategies that involve the use of finances, which should remind that, although such instruments are useful when addressing regulatory or investor-related issues, they are perhaps not enough to mitigate physical exposure or improve flexibility of operation. The study has important practical implications on the basis of business decision making. First, it gives the C-suite executive and risk managers an organized decision-support framework that integrates intuitive foresight with an open trade-off analysis. Unlike generic ESG checklists, this proposed model offers not only actionable but also prioritized recommendations based in actual-time data and in science. Second, it will allow companies to tailor their climate action plans to the regulatory and market demands by selecting measures to minimize the vulnerability of their businesses and at the same time they could remain competitive in the market. Third, it gives a guideline to draw on empirical investment decisions, particularly when capital projects are a limited resource where companies find themselves at cross-roads attached to various competing projects. The framework also provides the new research and development. Future research may improve the scope to include new levels of decisions like the analysis of stakeholder sentiment, analysis on geopolitical risk, or encompass optimization of constrained budget problems via machine learning. Moreover, as explainable AI (XAI) systems are developed, future resilience-based planning models will be able to increase transparency and trust by explaining how AI reached some prediction or some rank. This framework can further be made into constantly updating decision engine by integrating Internet of Things (IoT) sensors and real time monitoring systems and taking the planning of resilience to the future of automation and adaptive intelligence. There should also be the limitation of the study. The secondary information and expert opinion used to conduct the analysis was limited, but still, it can be characterized as the comprehensive one at a high-level of generalizations which does not reflect the peculiarities of a region or a company as a whole. Validated MCDA weights are tested looking consistent over all the industries; however, they are still subjective because it will depend on the judgment of experts and it can differ between industrial cultures or geographies. Furthermore, the available AI models, albeit correct in the existing dataset, might need re-training or re-calibrating every time new climate-related data or operational stoppage become evident. Therefore, companies are advised not to consider the framework as a once-in-a-lifetime instrument but as a recurring system that needs to be modified and improved using new numbers and situation-specific factors. Finally, the paper has presented a rigorous, integrated and operational environmental framework of integrating AI, Data Science and Multi-Criteria Decision Analytics in formulation of a climate resilient business strategy. Through the collection of predictive modeling, strategic analysis and scenario planning it provides a real world map of how companies can survive the wrath of a warming world. The model is more than a theoretical one; it shows that data-driven resilience planning is technically sound and strategically feasible. The more that stakeholder expectations build and climate risks ramp up, the better that a business that has access to such sophisticated decision-supporting tools will be able to not just deal with but thrive during the shift toward a low-carbon sustainable future.

## REFERENCES

[1] R. K. Singh, R. Modgil, Y. S. Tan, and A. Dwivedi, “Industry 4.0 and the circular economy: A literature review and future research directions,” *Sustainable Production and Consumption*, vol. 26, pp. 418–430, 2021.
[2] A. Wamba-Taguimdje, J. Fosso Wamba, L. Kala Kamdjoug, and J. Gonthier, “Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects,” *Business Process Management Journal*, vol. 27, no. 6, pp. 1663–1687, 2021.
[3] A. R. Sinha, N. Garg, and A. Mahajan, “AI-based multi-objective framework for climate-resilient water management,” *Environmental Modelling & Software*, vol. 147, pp. 105218, 2021.

[4] A. Zhang, C. Wang, and X. Zhou, "Machine learning approaches for climate risk analytics: A case of supply chain resilience," *Expert Systems with Applications*, vol. 183, pp. 115405, 2021.
[5] P. Awasthi and R. Prasad, "AHP-based decision support for renewable energy investment under policy uncertainty," *Energy Policy*, vol. 158, pp. 112560, 2022.
[6] M. N. Islam and S. Rahman, "A data-driven approach to climate adaptation in logistics using ensemble learning," *Sustainable Cities and Society*, vol. 76, pp. 103468, 2022.
[7] N. B. Ramli and A. Basri, "Quantitative climate vulnerability assessment of Southeast Asian industries using TOPSIS," *Environmental Impact Assessment Review*, vol. 94, pp. 106762, 2022.
[8] C. K. Y. Tan and M. L. Wee, "Predictive analytics and digital twin simulation for manufacturing climate resilience," *Journal of Cleaner Production*, vol. 330, pp. 129780, 2022.
[9] R. Mehmood, M. Alzahrani, and S. U. R. Malik, "AI and big data for climate-smart supply chain risk management," *IEEE Access*, vol. 10, pp. 119237–119251, 2022.
[10] M. Khan, S. Faisal, and B. Singh, "Multi-criteria optimization of carbon mitigation strategies in industrial planning," *Journal of Environmental Management*, vol. 312, pp. 114866, 2022.
[11] K. S. Mahadevan, R. Shinde, and N. Chatterjee, "AI-based scenario forecasting for climate resilience in infrastructure systems," *Applied Energy*, vol. 314, pp. 118932, 2022.
[12] Y. Liu, W. Shi, and F. Jin, "Integrating carbon footprint and AI in strategic business planning," *Technological Forecasting and Social Change*, vol. 178, pp. 121580, 2022.
[13] H. R. Dar, A. Jain, and V. K. Bhatia, "A hybrid AHP–TOPSIS model for evaluating sustainable supply chain practices under climate risk," *Sustainable Operations and Computers*, vol. 3, no. 2, pp. 94–104, 2022.
[14] D. Rolnick et al., "Tackling climate change with machine learning," *ACM Computing Surveys*, vol. 55, no. 2, pp. 1–96, 2023.
[15] A. Kumar and P. Sharma, "Deep learning-based climate impact forecasting for agriculture supply chains," *Computers and Electronics in Agriculture*, vol. 201, pp. 107415, 2023.
[16] H. Ng, L. Zhou, and P. Y. Lai, "Assessing climate risk in urban businesses using supervised machine learning," *Environmental Modelling & Software*, vol. 162, pp. 105562, 2023.
[17] K. Govindan and M. Shankar, "Green supply chain prioritization using AHP and fuzzy TOPSIS under climate constraints," *Journal of Environmental Management*, vol. 324, pp. 116380, 2023.
[18] B. Lee and M. Chang, "TOPSIS-based evaluation of energy transition strategies in Southeast Asia," *Energy Reports*, vol. 9, pp. 355–364, 2023.
[19] J. Alkassasbeh, M. Al-Mistarehi, and F. A. Bani-Mustafa, "Hybrid fuzzy-AHP-TOPSIS model for adaptive climate policy design," *Sustainability*, vol. 15, no. 7, pp. 5639, 2023.
[20] A. Mangal and R. Bose, "AI-integrated decision support for climate-resilient construction," *Automation in Construction*, vol. 155, pp. 104602, 2023.
[21] H. Zhang, S. Yu, and Y. Li, "Carbon pricing prediction using ensemble AI and decision analytics," *Journal of Cleaner Production*, vol. 395, pp. 136199, 2023.
[22] S. Dutta and A. Roy, "A multi-objective framework for logistics resilience using ML and simulation," *Transportation Research Part E*, vol. 178, pp. 103009, 2023.

[23] L. A. Benitez, H. Wong, and D. T. Rogers, "Strategic planning for climate resilience in global logistics systems," *International Journal of Production Economics*, vol. 257, pp. 108744, 2023.
[24] F. F. Mohammed, P. M. Hansen, and C. P. Underwood, "Real-time data science models for enterprise-level climate response," *Decision Support Systems*, vol. 172, pp. 113075, 2024.
[25] A. E. Cruz, Y. Y. Chen, and G. M. Levine, "AI-enabled decision analytics for green infrastructure investment," *IEEE Transactions on Engineering Management*, early access, 2024, doi:10.1109/TEM.2024.3382045.