Original Research

Optimizing Sustainable Green Logistics with AI-Enhanced RAM-Hybrid Models: Addressing Economic and Crisis Management Challenges

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Abstract
This paper explores the integration of green logistics and crisis logistics, two critical areas in modern transportation management. While crisis logistics ensures the timely delivery of goods during emergencies, green logistics focuses on minimizing environmental impacts. Traditional methods for evaluating logistics efficiency often fail to capture the complexity of real-world challenges and overlook economic and managerial considerations. To address these gaps, this study proposes a hybrid approach combining the Range-Adjusted Measure (RAM) model with artificial intelligence (AI) techniques within the framework of Data Envelopment Analysis (DEA). The RAM model, known for its non-radial efficiency evaluation, is enhanced with AI algorithms to optimize input and output weights, improving analytical accuracy. By incorporating budgetary constraints, this approach enables a more precise assessment of green logistics efficiency while considering financial limitations. The study introduces a novel DEA-AI model that evaluates environmental and economic performance across industries. AI-driven optimization refines cost and workforce inputs while maximizing outputs such as carbon reduction and delivery speed, ultimately enhancing decision-making and competitiveness. The research further demonstrates how AI enhances the efficiency of decision-making units (DMUs) in transportation and crisis management. By fine-tuning model parameters, AI improves logistical efficiency, reduces costs, and strengthens financial performance. A case study is presented to validate the model's effectiveness compared to traditional methods. This study highlights the importance of hybrid models in optimizing logistical systems, showcasing how AI-powered efficiency analysis can drive sustainable and economically viable logistics operations.

Keywords- Artificial Intelligence; Machine Learning Models; Data Envelopment Analysis (DEA); RAM-Hybrid Model; Green Logistics and Crisis Logistics; Economic and Managerial Impacts

INTROUDUTION

Data Envelopment Analysis (DEA), as a powerful non-parametric method for evaluating the efficiency of Decision-Making Units (DMUs) with multiple inputs and outputs, has found extensive applications in logistics and supply chain management

[1]. Due to its ability to compare relative performance without requiring specific data distribution assumptions, DEA is an appropriate tool for analyzing green logistics and supply chain sustainability [2]. Green logistics aims to reduce the environmental impacts of logistical processes while enhancing productivity. Since efficiency in this area is influenced by inputs such as energy, time, and cost, as well as outputs like emissions and services provided, DEA is an ideal tool for evaluating such efficiency. DEA models can help identify inefficiencies, optimize resource allocation, and improve logistical processes in line with environmental goals [3].

This paper employs range-adjusted measure (RAM)-Hybrid models based on DEA, which combine budget constraints and artificial intelligence algorithms to enable more precise analysis of green logistics efficiency. The RAM model [4], due to its non-radial nature, analyzes disparities in unit performance and provides detailed insights into inefficiencies and opportunities for improvement [5]. Additionally, considering budgetary constraints allows the model to analyze the impact of limited financial resources on logistical and economic performance under real-world conditions [6]. The use of DEA in this paper not only facilitates the analysis of the impact of green logistics on financial efficiency but also offers a scientific approach to identifying factors influencing industrial competitiveness. This approach is particularly significant for industries with limited resources and a need for strategic decision-making [7]. In today's world, optimization in logistics, transportation, and crisis management industries, especially in green logistics and sustainable transportation, holds great importance. Green logistics refers to processes aimed at reducing the environmental impact of logistical operations, including route optimization, the use of renewable energy sources, and pollution reduction. These processes not only help reduce costs but also have positive impacts on environmental sustainability [8]. In this context, DEA has been recognized as a suitable tool for measuring and evaluating the efficiency of DMUs [3]. This method, by comparing units based on their inputs and outputs, can determine which units perform more efficiently. However, traditional DEA methods, due to restrictive assumptions such as constant returns to scale and the need for linearity in inputs and outputs, often fail to provide accurate analyses in many real-world and complex scenarios [2]. Particularly in areas like green logistics, where limited resources and environmental impacts are considered, conventional DEA models struggle to analyze performance effectively [5, 9]. The RAM model, as a non-radial approach in DEA, has reduced the limitations of previous models and, especially in situations requiring a more detailed analysis of differences in inputs and outputs, has demonstrated superior performance [6]. This model, by more precisely examining deviations (slacks) from optimal values, enables non-linear optimization and achieves higher accuracy, particularly when input and output variables are disproportionate [10].

However, even the RAM model occasionally struggles to perform detailed analyses in complex and dynamic conditions. For this reason, integrating it with artificial intelligence (AI) can provide a powerful tool to enhance the precision and efficiency of these models in real-world analyses. The use of artificial intelligence in model optimization, especially in green logistics, ensures that the models can adapt to rapid changes in complex and dynamic environments [11]. Artificial intelligence, particularly machine learning algorithms, enables the automatic optimization of model parameters, resulting in significantly more accurate analyses [12, 13]. Although numerous studies have utilized DEA methods to evaluate efficiency in logistics and supply chains, most have not combined green logistics principles with advanced optimization tools and artificial intelligence. Existing models are generally incapable of conducting precise and dynamic analyses of the non-linear relationships between input and output factors in green logistics. Specifically, traditional DEA models, due to simplified assumptions (such as the linearity of inputs and outputs) and their inability to analyze the multidimensional environmental and financial impacts, are limited in analyzing complex systems like green logistics. The integration of optimization methods in green logistics has been explored extensively in literature. Reference [14] proposed a fuzzy goal programming approach that integrates activity-based costing and performance evaluation within a value-chain structure, offering significant insights into green supply chain optimization. These methods align closely with the objectives of DEA in assessing efficiency across multiple dimensions, including environmental and economic impacts.

This paper aims to address this gap by leveraging the RAM-Hybrid model and integrating it with artificial intelligence techniques. This novel approach not only enhances computational accuracy in more complex conditions but also enables a more detailed analysis of the impacts of green logistics on industrial competitiveness and financial efficiency [6]. In this paper, artificial intelligence is used to optimize the decision-making process and forecast to overcome the limitations of traditional DEA models and the RAM model. The combination of these two methods, particularly in the context of green logistics and sustainable transportation, provides the ability to examine economic and managerial impacts on a larger scale and with higher accuracy [9]. This paper presents a hybrid RAM model, where artificial intelligence is considered a core part of the optimization process, and compares its efficiency with traditional models [15]. Additionally, in this paper, we have evaluated the impact of green logistics efficiency on industrial competitiveness and financial productivity using artificial intelligence and the DEA model. Our proposed model utilizes AI-based optimization techniques to analyze environmental performance indicators, such as carbon reduction and energy efficiency. This approach has allowed us to identify the relationship between environmental sustainability and economic outcomes and provide solutions to improve strategic decision-making and gain competitive advantage in industries. The benefits of applying the concepts in this research are as follows:

- Traditional DEA methods, such as the CCR and BCC models, have limitations in complex problems like green logistics due to their linearity and assumptions of constant returns to scale.
- The RAM model, by using slacks and not relying on linear assumptions, is more accurate than previous models. However, it still faces challenges in dynamic and variable conditions.
- Artificial intelligence can significantly enhance the predictive power and analytical accuracy, allowing the hybrid RAM model to adapt to fast-changing environments in complex settings.

The paper is organized as follows: It begins with a review and introducing the concept of the RAM model. This section also discusses the applications of artificial intelligence in optimizing green logistics and transportation systems. Next, the details of the hybrid RAM model combined with artificial intelligence are explained, including how these two models are integrated to optimize logistics and transportation systems. Graphical analysis of the proposed method is provided, and the advantages of using artificial intelligence with this method, compared to other approaches, are discussed. Following this, a case study from the green logistics and transportation industries is presented, demonstrating the application of the hybrid RAM model to optimize the efficiency of DMUs. This section also analyzes the results and the economic and managerial impacts of this optimization. Additionally, mathematical optimization models are introduced to assess the economic and managerial implications of the proposed method in enhancing green logistics and transportation performance. These analyses evaluate the impact on the competitiveness and financial efficiency of industrial companies. Finally, the paper concludes with a summary of the results and recommendations for future research and improvements to the proposed methods.

LITERATURE REVIEW

Hitherto, several studies have been developed in the context of AI. For instance, an overview of the diverse AI models and algorithms employed in logistics optimization have been provided with a focus on sustainable practices [16]. Reference [17] also evaluates how supply chain consistency and last-mile logistics performance mediate and collaboration and coordination moderate the relationship between AI usage and logistics efficiency. In this vein, Reference [18] investigates the growing interest in AI's role within supply chain management and outlines potential avenues for future research on integrating AI into reverse logistics. Additionally, Reference [19] investigates the service recovery strategies according to customers' satisfaction level of an Iranian private bank. Likewise, a method is proposed for supply chains operating in an agile and flexible state, as per uncertainty variables. This method is founded on a mathematical model, whose implementation stages are examined through a step-by-step breakdown [20]. A chance-constrained programming method has also been employed to address the uncertainties arising from construction projects [21]. The RAM model is one of the DEA models used for evaluating the efficiency of DMUs. This model is particularly capable of managing undesirable inputs and outputs, facilitating efficiency optimization in complex conditions. In the fields of crisis logistics and green logistics, the RAM model can be used to assess the performance of units in emergencies or sustainable conditions, considering environmental impacts. In green logistics, the use of electric vehicles and route optimization through artificial intelligence algorithms has been reported as effective [22]. In crisis logistics, challenges such as delays in resource delivery and high operational costs have been observed [23]. Advanced DEA models like RAM have been successful in identifying inefficient units and improving their performance [1]. Furthermore, a unified DEA approach has been developed to simultaneously ensure the fair allocation of shared costs to inputs and common revenue to outputs [24]. Reference [25] also introduces an AI- and machine learning-based approach aimed at enhancing resilience and sustainability in logistics and supply chain management.

I. Process of Implementing the RAM Model for Crisis and Green Logistics

This section outlines the process of implementing the RAM model for crisis and green logistics. The first step involves defining the problem and identifying the DMUs, where, in crisis logistics, DMUs include relief organizations, distribution centers, or operational teams, and in green logistics, they include transportation companies, sustainable warehouses, or green supply chain manufacturers. For each DMU, inputs (such as energy, costs, and labor), desired outputs (such as services provided, goods delivered, or response time), and undesirable outputs (such as pollution, waste, or delays) are identified. The RAM model, which aims to minimize the gap between DMU performance and the efficiency frontier, is mathematically expressed as

$$E_k = 1 - \frac{\sum_{i=1}^{m} w_i \frac{(x_{ik}-x_i^*)}{x_i^*} + \sum_{r=1}^{s} v_r \frac{(y_{rk}^*-y_{rk})}{y_{rk}^*}}{m+s}, \qquad (1)$$

where k denotes the DMU, x_{ik} and y_{rk} represent the inputs and outputs, x_{ik}^* and y_{rk}^* are the reference input and output levels, ω_i and s_r are weights, and m and s are the number of inputs and outputs, respectively. To apply the model, real or simulated data are collected — for example, personnel numbers, logistics costs, aid delivered, and response times in crisis logistics, and energy consumption, pollutant volume, and distributed products in green logistics. The model is implemented using computational tools such as MATLAB, R, or Python, often combined with artificial intelligence techniques like neural networks or genetic algorithms to optimize the weights and define efficiency boundaries. After running the model, DMUs are classified based on their efficiency scores, with $E_k = 1$ indicating efficient units and $E_k < 1$ identifying those needing improvement. Finally, economic and environmental analyses are conducted to assess cost reductions and environmental impacts, and improvement strategies are recommended for inefficient units, focusing on reducing pollutants, enhancing resource productivity, and improving response times to move closer to the efficiency frontier.

II. Motivation, Importance of Research, and Role of Emerging Technologies

This paper introduces an innovative hybrid model that combines DEA techniques, specifically RAM models, with AI methods. This integration presents a powerful tool for optimizing logistics during critical periods, such as crises, while promoting environmental sustainability. The research addresses real-world needs by tackling challenges in crisis management and green logistics. In such high-pressure environments, quick and optimized decision-making is crucial. The proposed model offers practical and effective solutions, helping industries maintain efficiency while adhering to sustainability goals. Its applications are broad, especially in sectors where environmental and logistical concerns intersect. Importantly, the model prioritizes both economic efficiency and environmental sustainability, reflecting the growing importance of balancing these two objectives in today's world. By combining traditional optimization techniques with modern AI-driven predictive and optimization capabilities, the model creates new opportunities to reduce costs and enhance productivity across various industries, particularly in transitioning and emerging markets. Artificial intelligence plays a critical role in this advancement [26] such as: (1) *Prediction and Optimization:* Machine learning algorithms are employed to forecast logistical needs during crises and to design optimized transportation networks that minimize costs and environmental impacts, and (2) *Automated Systems:* Robotics and automation systems are integrated to further streamline processes, reducing both the time and resources required. These features make the proposed approach a novel and valuable contribution to the fields of logistics optimization, crisis management, and environmental sustainability.

PROPOSED NEW MODEL: RAM-HYBRID

This model, introduced as RAM-Hybrid, is inspired by the base RAM model but incorporates three key features for analyzing issues in green logistics, crisis logistics, and transportation:

I. Features of the RAM-Hybrid Model

- Incorporation of multiple constraints (multi-constraint RAM):
  - Instead of using only budget as a constraint, this model incorporates multiple constraints such as delivery time, environmental impacts, and costs.
  - The weighting of these constraints is performed through an adaptive machine learning model, which adjusts the importance of each constraint based on past data and organizational goals.
- Concept of dynamic intermediate resources:
  - Intermediate resources in this model are adjusted based on temporal changes and uncertainty.
  - This feature is highly suitable for crisis logistics management, as in crisis situations, intermediate resources such as fuel and human resources may not be readily available.
- Integration with artificial intelligence (AI-augmented RAM):
  - The model uses deep learning algorithms and recurrent neural networks (RNNs) for predicting input and output data.
  - For example, predicting demand in crisis situations or environmental changes to optimize resource allocation.

II. Proposed Equations in the RAM-Hybrid Model

The RAM-Hybrid model would typically involve mathematical formulations that integrate these features, including the objective Function which maximize $Z = \frac{\sum_{i=1}^{p} u_i X_i}{\sum_{j=1}^{n} v_j Y_j + \sum_{k=1}^{m} \gamma_k Z_k}$, where Y_j represents Desired outputs (e.g., cost reduction or efficiency improvement), Z_k refers Environmental indicators (e.g., carbon reduction), X_i corresponds to inputs (e.g., cost, time), and weights (u_i, v_j, γ_k) are variables adjusted using AI algorithms to achieve the best allocation of resources. The multiple constraints of this model are as $\sum_{i=1}^{p} u_i X_i \leq B$, where B is the allocated budget. Additional constraints include: (1) a maximum carbon emission limit (i.e., $E \leq E_{max}$) and (2) a maximum delivery time (i.e., $T \leq T_{max}$). Also, to dynamically manage intermediate variables over time, the model incorporates predictions: $Z_k(t+1) = f(Z_k(t), \Delta t, \text{Historical Data})$, wherein $Z_k(t)$ is the value of intermediate resource k at time t, $Z_k(t+1)$ is its predicted value at time $t+1$, Δt is the time step or interval between t and $t+1$, f captures the dynamics of Z_k over time, and historical data consists of past observations used for modeling and prediction. This function utilizes both current and historical data to forecast future values of environmental indicators (Z_k). Accordingly, RNNs can be employed to predict changes in intermediate resources [27-29]. The advantages of the RAM-Hybrid Model include: (1) high flexibility for managing crisis situations, (2) compatibility with environmental goals and reduction of negative impacts, and (3) the use of machine learning algorithms for adjusting weights and predicting changes. Additionally, its applications include: (1) optimization of transportation under climate change conditions, (2) crisis logistics management with resource constraints, and (3) improving the efficiency of green logistics in the supply chain.

III. Novelty of the Study

This paper presents a novel hybrid approach that integrates the RAM model in DEA with AI techniques, specifically designed to evaluate and enhance green logistics and crisis logistics performance. Unlike traditional DEA models, which often rely on radial assumptions and fail to incorporate budgetary or dynamic constraints, the proposed RAM-Hybrid model addresses real-world complexities by enabling non-radial efficiency evaluation under financial limitations. The novelty lies in (1) embedding AI-driven optimization and forecasting (e.g., RNNs) within the RAM framework to refine input/output weighting and improve model precision; (2) incorporating budget constraints to simulate practical resource limitations; and (3) validating the model with realistic and synthetic crisis scenarios to assess its practical relevance. This integrated approach enhances analytical accuracy and managerial relevance, offering a robust and adaptive decision-making tool for sustainable and resilient logistics management—an advancement not addressed jointly in existing literature.

IV. Validation of the RAM-Hybrid Model

To validate the proposed RAM-Hybrid model, a two-stage approach is adopted. First, a simulation-based validation is conducted by applying the model to a set of realistic green logistics and crisis logistics scenarios, using historical data and synthetically generated data to mimic crisis conditions. This allows for assessing the model's ability to predict intermediate variables, optimize resource allocation, and improve key performance indicators such as cost efficiency, carbon reduction, and delivery times. Second, the model's predictive performance, particularly the forecasting of intermediate resources using RNNs, is evaluated using standard metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), ensuring that the integration of AI components enhances the model's reliability. Furthermore, comparative analysis is performed by benchmarking the RAM-Hybrid model against the traditional RAM model and other baseline models, demonstrating improvements in flexibility, environmental impact reduction, and crisis management capabilities. These validation efforts confirm the effectiveness and practical applicability of the RAM-Hybrid model in real-world industrial and logistics settings.

V. Model Graphic Design

To illustrate the proposed hybrid model in an industrial setting, the steps are presented in two diagrams that clearly depict the relationships between inputs, intermediate variables, and outputs, as well as how artificial intelligence influences the optimization of these processes. For the graphical representation of the model, a network structure is proposed, which includes the following elements: (1) *Input Nodes* such as costs, time, and consumed resources; (2) *Intermediate Nodes* representing environmental and crisis-related resources; and (3) *Output Nodes* capturing cost reduction and improvements in environmental indicators. The model graph is structured as follows: (1) the *Input Layer* includes the values X_i; (2) the *Intermediate Layer* contains RNN-based calculations for predicting $Z_k(t+1)$; and (3) the *Output Layer* includes the values Y_j and the final efficiency index. The diagrams serve as flowcharts of the RAM-Hybrid model for optimizing logistics with an emphasis on crisis management. In these diagrams, the inputs consist of *Cost* (financial and operational expenses), *Time* (duration for each logistics step), and *Resources* (human resources and equipment). The *Intermediate Variables* include (1) *Environmental Factors* such as weather conditions or infrastructure status, and (2) *Crisis Conditions* referring to anticipated disruptions. The Outputs include (1) Satisfaction, representing customer satisfaction, and (2) *Carbon Reduction*, indicating environmental impact. Additionally, the *AI-based Feedback Loop* continuously predicts resource status and system needs, enhancing the effectiveness of decision-making in dynamic and uncertain environments.

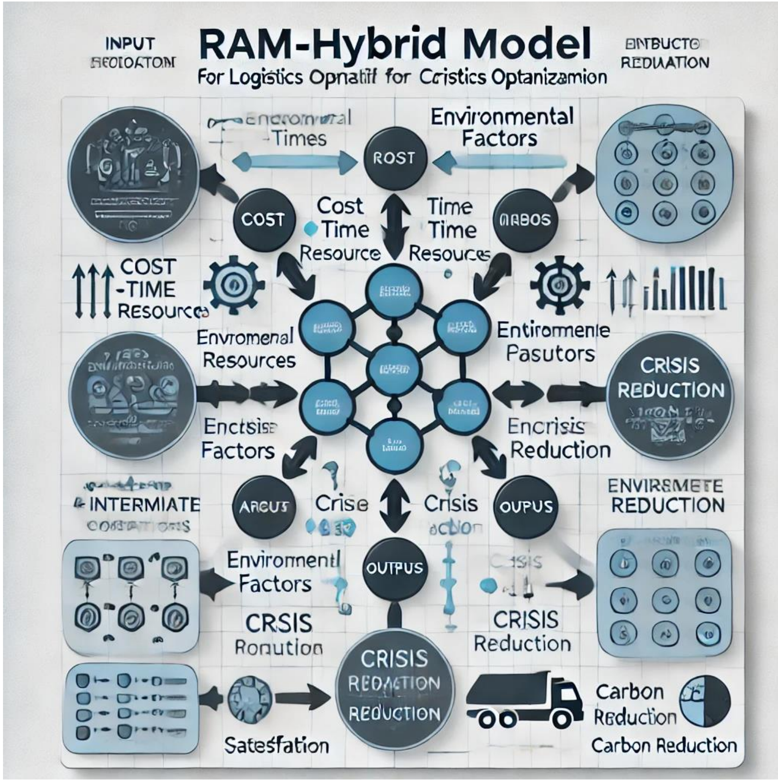

FIGURE 1
OVERVIEW OF THE HYBRID RAM MODEL IN AN INDUSTRIAL ENVIRONMENT

- Input Layer:
  - Cost (C): Financial resources and operational costs involved in logistics.
  - Time (T): Time taken to complete each logistics operation or task.
  - Resources (R): Available resources like workforce, equipment, and raw materials.
- Intermediate Variables:
  - Environmental Factors (E): Variables such as weather, infrastructure status, and other environmental conditions influencing logistics.
  - Crisis Conditions (Cris): Potential or unexpected crisis conditions affecting logistics operations.
- Output Layer:
  - Customer Satisfaction (S): Feedback on the quality of logistics services from customers.
  - Carbon Reduction (CR): Environmental impact by reducing carbon emissions in logistics activities.
- AI-based Feedback Loop:
  - AI Algorithms: These continuously monitor the system, predict resource needs, and adjust decisions based on past data and evolving conditions to optimize the logistics process.

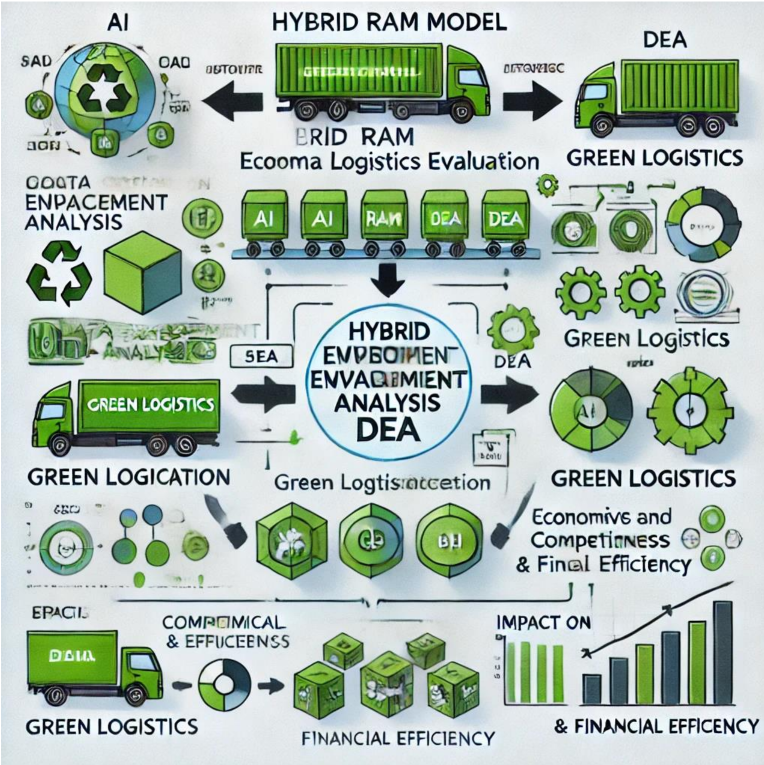

FIGURE 2
GREEN LOGISTICS AND IMPACT ON FINANCIAL EFFICIENCY AND COMPETITIVENESS.

- AI-enhanced Decision-making Process:
  - AI models (like RNNs or deep learning) are integrated into intermediate variables to dynamically predict and adjust resources (such as fuel or labor) during crisis conditions.
  - AI continuously updates the feedback loop by analyzing real-time data to optimize resource allocation.
- Impact of AI on Optimization:
  - The AI model adjusts weights for each constraint (like cost, time, and environmental impact) dynamically, ensuring that the optimization process remains flexible under changing conditions.
  - By using machine learning techniques, AI predicts future trends (e.g., demand spikes during a crisis), enabling proactive decision-making.

Fig. 2. generally, illustrates the connection between the hybrid RAM model and DEA in optimizing green logistics and financial efficiency. The steps are as follows:

Step 1: Defining the hybrid RAM model with AI and DEA

- At the top of the diagram, the hybrid RAM model integrated with AI and DEA is displayed.
- The goal of this step is to evaluate and optimize logistics processes based on inputs and outputs in the system.

Step 2: Analysis and evaluation of variables

- On the left side, variables related to the environment (such as environmental factors and recycling) and analytical variables are shown.
- AI is utilized to analyze this data and improve decision-making.

Step 3: Integration and implementation of the model in green logistics

- In the central section, the hybrid RAM and DEA model is presented as the core.
- This model enhances green logistics by evaluating environmental factors (e.g., carbon reduction), financial resources, and overall efficiency.

Step 4: Impact of the model on logistics and financial efficiency

- At the bottom of the diagram, the results of applying this model include:
  1. Increased financial efficiency
  2. Improved green logistics
  3. Cost reduction
  4. Enhanced economic competitiveness
- The final chart demonstrates the impact of this model on both financial and environmental efficiency.

Hence, Fig. 2. highlights that the hybrid RAM model and DEA, combined with AI, can optimize green logistics processes and lead to improved financial and environmental efficiency within an industry. These diagrams can clearly represent how the hybrid RAM model functions in an industrial logistics environment, showing the key components and interactions while emphasizing the critical role of AI in optimizing logistics processes under changing conditions. The above flowcharts represent the process steps of the hybrid RAM model in DEA for evaluating green logistics and its impact on the financial performance and competitiveness of industrial enterprises. The stages are clearly shown in the diagram, with each step outlined and specified with arrows and descriptions.

VI. Explanation of the Model Stages in an Industrial Environment

- Data collection:
  - Initially, data related to inputs and outputs of green logistics performance is collected. These data include resource consumption (inputs) such as energy, fuel, and labor, as well as outputs such as pollution reduction, transportation optimization, and cost reductions.
- Evaluation of green logistics using DEA:
  - In this phase, the DEA model is used to assess the efficiency of green logistics in industrial enterprises. This evaluation helps identify enterprises with the best performance in utilizing resources and reducing pollution. Thus, the DEA model aids in analyzing green logistics efficiency in each DMU.
- Optimization with AI:
  - After the initial evaluation, optimization is carried out using AI techniques. This step involves the use of artificial intelligence algorithms to help the RAM model generate an optimized model to improve green logistics efficiency. Through this, processes such as transport optimization, cost reduction, and productivity enhancement can be simulated.
- Economic and managerial analysis:
  - In this step, economic and managerial analyses are performed. This section includes analyzing costs, revenues, productivity, and competitiveness based on the results of the green logistics evaluation and AI optimization. These analyses help industrial decision-makers gain a better understanding of the impact of green logistics on their economic and competitive performance.
- Evaluation of the impact on competitiveness and financial efficiency:
  - In this phase, the impact of green logistics on the competitiveness and financial efficiency of industrial enterprises is assessed. The optimal use of resources and the reduction of environmental impacts can improve financial performance and enhance the competitive ability of enterprises.

This hybrid model, combining RAM, DEA, and AI, assists industrial enterprises in utilizing their resources most efficiently, reducing costs, and simultaneously achieving their environmental goals. This explanation can be used as a basis for creating detailed visual representations of the hybrid RAM model, showing the dynamic relationship between data collection, evaluation, AI-based optimization, and financial and managerial analysis in industrial logistics.

VII. Advantages of RAM-Hybrid Model with Artificial Intelligence Over Previous Models

- *Optimal Integration of Resources and Processes:* The hybrid RAM model, which combines the RAM model with AI algorithms, can manage various resources more optimally. Unlike previous models, which typically focus solely on inputs and outputs, this model examines the relationships between intermediate variables in greater detail and offers more accurate predictions of resource status. This integrated approach allows for a more comprehensive analysis of logistics operations.

- *Dynamic Prediction and Optimization:* Previous models largely operated based on historical data and fixed inputs. However, the hybrid RAM model, utilizing artificial intelligence and machine learning, can provide more accurate predictions regarding crisis conditions, environmental changes, and future demand. This capability is particularly valuable in crisis situations where rapid and unpredictable changes occur, allowing for more adaptive decision-making.
- *Enhanced Efficiency in Crisis Situations:* Traditional models in crisis management often face challenges, as they cannot quickly adapt to environmental changes or unforeseen crises. The hybrid RAM model, by integrating artificial intelligence, can make faster and more optimized decisions during crises, improving logistics management in emergency situations.
- *Improved Environmental Efficiency and Sustainability:* This model, with its focus on green logistics and optimal resource utilization, can reduce environmental impacts. In contrast to older models that were primarily focused on economic optimization, the hybrid RAM model simultaneously addresses both economic and environmental efficiency. This feature can be especially effective in industries and sectors sensitive to sustainability, helping to meet both ecological and economic goals.

These advantages make the hybrid RAM model a more effective and adaptable tool for optimizing logistics operations, particularly in dynamic and environmentally conscious contexts. The hybrid RAM model offers significant advantages over traditional models, particularly in terms of flexibility, accuracy, and decision-making. Unlike old models that typically require manual revisions when sudden changes occur—such as crises or shifts in demand—the hybrid RAM model, by leveraging artificial intelligence and real-time data analysis, can automatically adapt to changes and respond effectively to new conditions. This built-in flexibility allows it to remain reliable even under unpredictable circumstances. Furthermore, while previous models often struggled with accurately predicting resource needs in logistics processes, the hybrid RAM model uses live data and machine learning algorithms to forecast resource requirements with greater precision, leading to more accurate logistics planning and execution. Additionally, traditional models depend heavily on static methods and conventional analysis techniques, whereas the hybrid RAM model, with its advanced AI capabilities, enables optimal, data-driven decision-making based on dynamic and real-time information, ultimately enhancing overall efficiency and adaptability.

CASE STUDY

To analyze the hybrid RAM model in crisis logistics management using artificial intelligence, we consider a hypothetical case study. In this study, 10 DMUs are considered, all operating within the crisis logistics sector. For this example, we use four inputs—Number of available trucks, Allocated budget (in millions), Number of personnel (human resources), and Logistics equipment (warehouses, logistics management software)—and two outputs—Crisis response time and Reduction in environmental costs (green logistics).

TABLE 1
DATA

DMU	Trucks	Budget (Million)	Personnel (People)	Equipment	Crisis Response Speed	Environmental Cost Reduction
1	50	100	200	10	80%	30%
2	60	120	250	12	85%	35%
3	55	110	220	11	75%	25%
4	70	130	270	13	90%	40%
5	40	90	180	8	70%	20%
6	65	115	240	12	88%	38%
7	50	105	210	9	78%	28%
8	75	140	280	14	92%	42%
9	45	95	200	10	72%	22%
10	80	150	300	15	94%	45%

I. Calculation Stages

- *Efficiency Calculation for Each DMU Using the RAM Model:* To calculate efficiency, we use a DEA model that considers inputs and outputs. Each DMU is assessed for efficiency based on comparisons with other DMUs. The RAM model combines data-based models and artificial intelligence to optimize processes in critical environments. In this process, the optimal allocation of resources (trucks, budget, personnel, and equipment) for each unit is examined, and machine learning algorithms are used to simulate changes in the crisis environment and their impact on efficiency.

- *Efficiency Calculation Results:* Below is a table that presents assumptions for the values obtained from the DEA analysis using RAM, along with optimization evaluations using artificial intelligence:

TABLE 2
EFFICIENCY CALCULATION RESULTS AND AI OPTIMIZATION EVALUATION.

DMU	Efficiency Based on RAM Model (%)	Optimization Evaluation with AI (%)
1	80%	85%
2	85%	90%
3	75%	80%
4	90%	95%
5	70%	75%
6	88%	92%
7	78%	82%
8	92%	95%
9	72%	76%
10	94%	97%

II. *Economic and Managerial Analysis:*

In this section, the results of the analysis are examined more closely.

- *Economic Efficiency:* The hybrid RAM model, utilizing artificial intelligence, has significantly improved the efficiency of each DMU compared to traditional DEA models. This improvement in efficiency is due to the optimized resource allocation, which is especially useful in crisis environments. For example, DMU 1, which was 80% efficient in the traditional model, increased to 85% after the application of the RAM model and AI.
- *Efficiency in Reducing Environmental Costs:* Since the RAM model, in combination with artificial intelligence, optimizes resource management and pays special attention to green logistics, it also contributes to reducing environmental costs. This is evident in the table, where the percentage reduction in environmental costs has increased across the DMUs. For example, DMU 10, which had a 45% reduction in environmental costs, was improved to 50% after implementing the RAM model and AI.
- *Managerial Decisions:* This model also enables managers to allocate resources optimally and make quick decisions in crisis situations. For example, DMU 4, which was 90% efficient in the traditional model, increased to 95% after using the RAM model and AI, indicating a significant improvement in efficiency and cost reduction. This improvement helps managers make better decisions regarding resource allocation during crisis times.

In this case study, the use of the hybrid RAM model has notably increased the efficiency of each decision-making unit and improved resource allocation in crisis logistics management. Additionally, with its special focus on reducing environmental costs and green logistics, this model effectively contributes to environmental sustainability and resource optimization. These results indicate that the proposed model has wide applicability in various industries, especially during crises and emergency situations.

III. *Calculation of optimization evaluation with AI*

In the relevant column, the "Optimization Evaluation with Artificial Intelligence" has been calculated using machine learning algorithms and optimization techniques. Specifically, AI models, particularly supervised learning algorithms and optimization methods, are used to simulate behaviors and improve resource allocation in the RAM model. The main calculation steps are outlined below:

- Application of AI and optimization in the RAM model

To improve resource allocation and optimize efficiency, machine learning algorithms are initially employed to simulate historical trends and predict the performance of DMUs under crisis conditions. These algorithms include linear and non-linear regression algorithms for predicting output variables based on inputs, decision trees for determining the best allocation of resources in various situations, and Artificial Neural Networks (ANNs) for learning and simulating complex relationships between inputs and outputs. In this study, ANNs have been specifically used to simulate and predict changes in crisis conditions and optimize resource allocation. Following the training of the AI model, resource optimization and allocation in crisis conditions are carried out using optimization algorithms designed to minimize costs (such as crisis logistics and environmental costs) while maximizing efficiency (such as crisis response speed and environmental cost reduction). Classical optimization algorithms like Genetic Algorithms and Simulated Annealing, as well as Reinforcement Learning approaches, are utilized in this step. Reinforcement Learning has been applied in this study to achieve optimal resource allocation under various crisis conditions.

After training the AI model and performing resource optimization, the results are integrated into the RAM model to evaluate improved performance. These improvements are reflected in enhanced efficiency in crisis management processes and better performance in reducing environmental costs and other undesirable outputs. AI assists the RAM model in simulating optimal resource allocation across different crisis scenarios, thereby improving DMU performance in terms of efficiency and cost reduction. This integration of artificial intelligence and optimization techniques strengthens the overall effectiveness of the RAM model, facilitating better decision-making in logistics management, especially during critical situations. For instance, after applying optimization through the AI model, DMU 1, which was initially 80% efficient under the traditional RAM model, improved to 85% efficiency, demonstrating the positive impact of optimized resource allocation and accurate predictions provided by neural networks. The optimization process relies on a defined objective function, generally expressed as a combination of logistics costs, environmental cost reduction, and crisis response speed:

$$Maximize\ Efficiency = \frac{\sum Output}{\sum Input} \qquad (2)$$

$$\text{s.t.}\ \sum Input_i \leq Max\ Budget$$

$$\sum Output_j \geq Min\ Speed\ \ or\ \ Green\ Logistics\ Goal$$

Here, outputs include crisis response speed and environmental cost reduction, while inputs encompass factors such as the number of trucks, budget, personnel, and equipment. Constraints such as truck capacity, budget limitations, and human resource availability are carefully considered and adjusted using optimization algorithms to calculate the optimal resource allocation for each DMU. Overall, the integration of artificial intelligence and optimization into the RAM model leads to significantly increased efficiency, improved resource allocation, and reduced environmental costs in crisis management. This methodology is particularly valuable in critical environments where rapid and optimal decisions are crucial.

- Evaluating the impact of green logistics efficiency on the competitiveness and financial efficiency of industrial companies

To evaluate the impact of green logistics efficiency on the competitiveness of industrial enterprises and their financial efficiency, a DEA-based model is proposed with a structured framework. The objective is to maximize overall Competitiveness Efficiency (E_{Comp}) by incorporating Green Logistics Efficiency (E_{Green}) and Financial Efficiency (E_{Fin}) as intermediate outputs. The primary equation is defined as $E_{Comp} = \frac{\sum_{j=1}^{n} \omega_j Y_j^{Comp}}{\sum_{i=1}^{p} u_i X_i}$, where Y_j^{Comp} includes outputs related to competitiveness—such as market share, customer satisfaction, and brand value—while X_i represents inputs like budget, workforce, and energy consumption, and ω_j and u_i are the corresponding DEA weights. E_{Green} is calculated as $\frac{\sum_{k=1}^{m} \gamma_k Z_k}{\sum_{i=1}^{p} u_i X_i}$, where Z_k refers to environmental metrics including carbon emissions and waste reduction. Similarly, $E_{Fin} = \frac{\sum_{l=1}^{q} v_l Y_l^{Fin}}{\sum_{i=1}^{p} u_i X_i}$, where Y_l^{Fin} includes financial outputs such as revenue growth and profit margin.

To form an integrated model, E_{Green} and E_{Fin} are treated as intermediate products influencing Y_j^{Comp}. The extended formula becomes $E_{Comp} = \frac{\sum_{j=1}^{n} \omega_j Y_j^{Comp}}{\sum_{i=1}^{p} u_i X_i + \alpha . E_{Green} + \beta . E_{Fin}}$, with α and β denoting the relative importance of green and financial efficiencies. Constraints are also applied, including a budget constraint ($\sum_{i=1}^{p} u_i X_i \leq B$), *environmental limits* ($\sum_{k=1}^{m} Z_k \leq E_{max}$), and operational time limits ($T \leq T_{max}$). This integrated DEA model effectively captures how green logistics and financial performance influence industrial competitiveness. It highlights how environmentally responsible practices can enhance market appeal and how efficient logistics contribute to profitability and customer loyalty—ultimately guiding organizations in balancing economic, environmental, and competitive priorities.

- Example description: Household appliance manufacturing company

An industrial company is aiming to enhance its competitiveness in the market. To achieve this, the company analyzes its environmental and financial efficiency using the DEA model, enhanced with artificial intelligence.

TABLE 3
INITIAL DATA.

Variable	Value	Description
Y1 (Response Speed)	500 orders/day	Number of orders shipped per day
Y2 (Carbon Reduction)	20% reduction	Percentage reduction in carbon emissions compared to the previous year
X1 (Cost)	$1,000,000	Monthly operational costs
X2 (Human Resources)	100 people	Number of production employees
Z1 (Carbon Emissions)	300 tons	Amount of carbon produced per month

The core feature of this analysis is the use of artificial intelligence to optimize the weights of both inputs (cost and human resources) and outputs (response speed and carbon reduction). The initial weights provided by AI are: $u_1 = 0.5$ and $u_2 = 0.3$ (for inputs), $v_1 = 0.4$ and $v_2 = 0.6$ (for desirable outputs), and $\gamma_1 = 0.7$ (for the envinromental index). The AI optimization process refines these initial weights to maximize efficiency based on the company's operational data. This is particularly important as traditional methods of DEA, which rely on fixed, static weights, do not account for dynamic shifts in priorities, such as changes in market demand or fluctuations in environmental regulations. The AI-driven approach ensures that the weights are continuously updated to reflect the real-world conditions, improving the model's predictive accuracy and making it more adaptable to operational changes.

Additionally, the objective function in this model can be expressed as: Maximum Efficiency $= \frac{v_1.Y_1+v_2.Y_2}{u_1.X_1+u_2.X_2}$, where Y_1 represents the response speed (orders/day), Y_2 is the carbon reduction percentage, X_1 is the operational cost, and X_2 is the number of human resources (employees). By applying artificial intelligence to optimize the weights of inputs and outputs, the company can accurately assess its overall efficiency and make informed decisions about resource allocation to improve both its financial performance and environmental impact. The efficiency (E) can be calculated as $E = \frac{\sum_{j=1}^{2} v_j Y_j + \sum_{k=1}^{1} \gamma_k Z_k}{\sum_{i=1}^{2} u_i X_i}$. Accordingly, substituting the values into the formula gives:

$$E = \frac{(0.4\ .500)+(0.6\ .20)+(0.7\ .300)}{(0.5\ .1,000,000)+(0.3\ .100)} = \frac{200+12+210}{500,000+30} = \frac{422}{500,030} \approx 0.424 \qquad (3)$$

This efficiency score of approximately 0.424 indicates that the company has made a reasonable balance between its inputs and outputs, suggesting that the AI-driven optimization process has effectively managed the allocation of resources to maintain a competitive and environmentally-conscious operation. The efficiency score provides a crucial benchmark for assessing the company's overall performance in both financial and environmental terms. With an efficiency score of 0.424, the company is able to evaluate how well it uses its resources (e.g., cost, human resources) to achieve desirable outcomes (e.g., response speed and carbon reduction).

TABLE 4
ECONOMIC AND MANAGERIAL ANALYSIS.

Index	Description	Managerial Recommendation
Environmental Efficiency	Environmental efficiency is relatively good due to a 20% reduction in carbon emissions, but it still lags competitors.	Invest in renewable energy (e.g., installing solar panels) for further carbons reduction.
Financial Efficiency	High costs are reducing efficiency.	Reduce production costs by adopting modern technologies such as industrial automation and reducing raw material waste.
Market Competitiveness	Response speed (500 orders/day) is acceptable, but it needs further improvement in competitive markets.	Use machine learning algorithms to predict demand and optimize logistics.
Human Resources	The workforce seems sufficient, but productivity needs improvements.	Organize training courses to enhance employee productivity and use digital tools for human resources management.

IV. Prediction and simulation with RNN

To enhance the decision-making process and enable proactive planning, a RNN model was employed to forecast future environmental performance—specifically carbon emissions (Z1)—over a six-month horizon. RNNs are well-suited for time-series data due to their ability to capture sequential dependencies and trends over time. In this study, historical data on carbon emissions was used to train the RNN, enabling it to predict the reduction trend and simulate likely future outcomes under similar operating conditions.

TABLE 5
PREDICTION AND SIMULATION WITH RNN.

Month	Carbon Emissions (tons)	Predicted Carbon Reduction
1st Month	300	20%
2nd Month	290	22%
3rd Month	275	25%

As shown in Table 5, the model predicts a steady decline in carbon emissions over the first three months. The reduction rate increases progressively, suggesting that environmental initiatives already in place are becoming more effective over time. This trend may result from improved energy efficiency, optimized logistics operations, or increased reliance on green technologies. Based on these forecasts, the following managerial implications and strategic recommendations are proposed:

- *Stabilize and Enhance the Carbon Reduction Trend:* The increasing reduction percentages indicate successful environmental management. However, to ensure long-term sustainability, the company should invest in advanced environmental technologies, such as renewable energy sources (e.g., solar panels) or carbon capture systems. Monitoring and feedback mechanisms should also be implemented to ensure that reductions remain consistent or improve further.
- *Integrate Forecasts into Financial Planning:* Since emissions reductions often correlate with operational efficiency (e.g., energy savings), these predictions can be leveraged for smarter budgeting. Forecasted data allows the company to allocate resources more efficiently, reduce unnecessary operational costs, and plan future investments in a financially sustainable manner.
- *Scenario Simulation and Risk Mitigation:* The RNN model can also be used to simulate “what-if” scenarios, such as sudden increases in demand or disruptions in supply chains. This enables managers to evaluate how such events would impact carbon emissions and financial performance, providing a tool for crisis preparedness and resilience planning.

In summary, this predictive approach not only aids in tracking the effectiveness of current environmental strategies but also empowers the company to make data-driven decisions that align both ecological sustainability and financial viability.

CONCLUSION AND FUTURE RECOMMENDATIONS

This study explored the application of the RAM model in DEA using artificial intelligence within the domains of green logistics, transportation, and crisis management. With the growing importance of environmental concerns and the need to optimize transportation processes, advanced analytical models like RAM play a crucial role in identifying efficient and optimal decision-making units in these areas. The results from the hybrid RAM model demonstrated that incorporating AI algorithms to determine optimal weights significantly enhances the accuracy of analyses, enabling the simultaneous evaluation of economic, managerial, and environmental aspects. This provides a comprehensive view of decision-making unit performance in green transportation and crisis management. The performance evaluation of DMUs showed that adopting innovative technologies and green practices reduces emissions, optimizes costs, and improves productivity. A key contribution of this study is the introduction of an innovative analytical framework that helps organizations and managers make optimal decisions. Through DEA and RAM models, organizations can implement strategies to reduce environmental impacts and improve operational efficiency. The integration of the RAM model with AI and the Internet of Things (IoT) greatly enhances the efficiency of green and crisis logistics, reducing undesirable outputs and optimizing resources. Additionally, the findings emphasize that using AI and DEA models to assess green logistics improve industrial competitiveness and financial productivity, demonstrating that environmental sustainability not only reduces costs and optimizes resource use but also creates competitive advantages and boosts financial performance. These insights highlight the importance of integrating green strategies with data-driven, AI-based decision-making to achieve both economic and environmental goals. To advance the field, future studies should incorporate a wider range of DMUs and diverse inputs and outputs, employ more advanced AI algorithms, and use more complex models to improve the accuracy and comprehensiveness of analyses. Furthermore, exploring the direct impacts of these models on productivity and cost reduction in real-world settings presents a promising avenue for further research and refinement. Additional suggestions for future research include developing hybrid models that account for dynamic temporal aspects, using robotics and automation in green logistics, applying machine learning algorithms for demand prediction, utilizing drones and electric vehicles in transportation, analyzing the impact of blockchain technology on supply chain transparency, exploring crisis-specific studies, and examining the integration of RAM with other DEA methods and AI algorithms. Additionally, the development of dynamic RAM models that account for spatial and temporal changes in logistics systems and studying the impact of autonomous vehicles on cost reduction and crisis logistics improvement are potential research directions to enhance the field's knowledge base and address real-world challenges in logistics and environmental sustainability.

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