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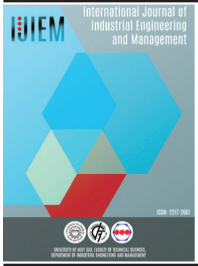

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In-Depth Analysis of the Effective Factors in Green Supply Chain Management in the Offshore Industry

B. M. Aljahdali[a,*] 0009-0006-0215-7994, Y. Alsubhi[b,c] 0000-0002-9875-6898, H. T. Sulaimani[a] 0000-0002-5618-8757, A. F. Alghanmi[a] 0000-0001-7391-5138

[a] *King Abdulaziz University, Department of Supply Chain Management and Maritime Business, Faculty of Maritime Studies, Jeddah, Saudi Arabia;*

[b] *King Abdulaziz University, Department of Meteorology, Jeddah, Saudi Arabia;*

[c] *King Abdulaziz University, Center of Excellence for Climate Change Research, Jeddah, Saudi Arabia*

ABSTRACT

The proposed study is based on the hybrid framework, which is a convergence between machine learning algorithms and fuzzy decision-making techniques to determine and rank the most important factors regarding the Green Supply Chain Management (GSCM) within the offshore industry under the influence of climate change. The research follows a three-phase methodology: (1) systematic literature review and expert consultation to establish the dimensions of relevancy in GSCM (2) hybrid fuzzy Delphi machine learning to quantify uncertainty and elicit expert opinion (3) an Analytic Network Process to establish interdependency and global priorities. The framework was applied to Saudi Arabia's Arabian Gulf offshore sector, where four primary GSCM dimensions and twelve operational indicators were validated with expert consensus levels between 0.82 and 0.93. Results show that climate change adaptation mechanisms represent the most influential dimension (global weight = 0.334), while Climate Risk Assessment Protocols rank as the top indicator (0.127). The hybrid model got an accuracy of 0.863 which was 34.4 percent higher than the traditional methods in predicting disruption and 44.3 percent in risk assessment accuracy. Three offshore validation indicated performance improvement of 11 to 25. These results have shown that the process of combining machine learning and fuzzy logic makes GSCM decision-making much more effective, providing a pragmatic and climate-adaptive architecture to make offshore operations more sustainable and resilient.

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*Corresponding author:
Bassam Mohammedsaleh Aljahdali
bmaljahdali@kau.edu.sa

1. Introduction

The intersection of the environmental issues and the competitiveness of industries has transformed the world supply chain models and made Green Supply Chain Management (GSCM) a significant factor in achieving sustainable economic development [1]–[3]. The increasing awareness of the environment and the pursuit of the sustainable competitive advantage have been stimulated by the extensive GSCM uptake in industries [4], [5]. Offshore industry, with its complex, multinational supply chains and capital intense environment is under increased pressure to integrate environmental sustainability into its business. The worsening effects of climate change, which have been observed to become highly significant in the past year [6], with statistical forecasts indicating that 2024 will be among the five hottest years in history with a high probability of 99% [7] the need to adopt more sus-

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tainable practices in offshore supply chains becomes even more important.

This research area is of great strategic importance; this is supported by the fact that offshore industries have a huge economic size and environmental footprint. Research indicates that more than three climate-related or geophysical risks are present in 86 percent of the world ports [8], and climate-related aspects like CO_2 emissions, changes in temperature, and economic losses related to floods are becoming more influential in determining operational requirements and logistics performance indicators [9], [10]. To solve these predicaments, there is need to utilize modern decision-making models that can harmonize environmental sustainability with efficiency and economic viability in operations.

The current GSCM studies have gone further than the conventional linear models to multi-dimensional structures that consider environmental, social and economic aspects. The research indicates that multi-criteria decision methods were needed, and fuzzy-based methods were suggested as the most appropriate way of assessing GSCM practices in organizations [11], [12]. Recent innovations also enhance the incorporation of advanced technologies and analysis processes to enhance decision-making within complicated supply chain networks. Machine learning approaches have been a particularly important area in technological development of GSCM. The recent research indicates that the capabilities of generative AI can optimize the GSCM in any industry [13], proving the increase in the perception of the potential of AI in overcoming sustainability difficulties. Moreover, the best machine learning solutions have been useful in various industries [14] and have become radicalized methodologies on creating supply chain agility and resilience. Global supply chains have become highly characterized by climate change and studies show that there are significant economic consequences relating to it. The research indicates that global supply chains increase economic costs of future extreme heat risk [15], and so adaptive strategies are required to reduce climate-related disruptions.

The past reports have recorded a rising frequency and intensity of the supply chain disruptions caused by climate [16]. It has been analyzed that extreme weather events are the number one risk to the supply chains in 2024, and analytics firms give a risk score of 100 percent to the likelihood that extreme weather can disrupt the supply chain [16]. It is the complexity of new supply chains that has prompted the use of advanced Multi-Criteria Decision Making (MCDM) processes. The decision-making problem that can be discussed as one of the key ones is MCDM that is used to select the best alternative when more than one criteria is taken into consideration in the decision-making process [17], [18]. When it comes to supply chains, SCM is a MCDM problem since during its cycle, various criteria associated with every supply chain operation and the sub-criteria with them must be taken into consideration [19]. The combination of fuzzy logic with the MCDM methods have been of special interest in dealing with uncertainty and ambiguity that can be found in supply chain decisions. Studies indicate the use of the Modified Delphi Method to present the take of the experts in the decision-making process [20], and the use of fuzzy Delphi methods has been effective in eliminating the relevant enablers in the complex decision-making environment [21], thus proving the relevance of hybrid methodologies in the complex decision-making environments. Knowledge management has been developed as a core facilitator of supply chain efficiency, especially when it comes to environmental sustainability activities. Studies show that the use of knowledge management technology assists organizations to maximize the onboarding and the continued training process through the provision of multiple avenues through which employees can learn, depending on the current skills and experience [22]. Knowledge management systems integration with green supply chain practices are a very sensitive development in the development of an organization's capability.

The recent developments show the growing integration of knowledge management with sophisticated analytics and AI. Research indicates a prediction that by 2025, organizations will be more adept at measuring the value of its data, approaching it as a living thing that either brings or takes away resources [23], which is also an indication of the increasing degree of advanced thinking in the supply chain scenarios. The Kingdom of Saudi Arabia is a case that is especially important to consider in terms of transformation in the offshore industry due to its strategic significance in the world energy markets and grandiose sustainability plans. It has been shown that several Saudi based industrial firms incorporate GSCM to enhance corporate sustainability [24], which serves as evidence of the increasing realization of environmental demands in the industrial base of the region. The Saudi offshore industry has been exposed to great investments in emerging technologies and infrastructure. This aspiration is what International Maritime Industries is trying to achieve, and by 2020, it will be a top-ranked company in terms of being an integrated energy and chemicals firm through the use of technology, supply chain costs, and lifecycle partnerships [25], [26]. Furthermore, the National Investment Strategy of Saudi Arabia has also launched Global Supply Chain Resilience Initiative [27] which is an element of the strategy being an effort to transform its supply chain. Table 1 provides a comparative overview of recent studies exploring GSCM, decision-making approaches, and technological integration in offshore and related sectors.

Table 1 reveals several critical insights regarding the current state of research. The predominant use of fuzzy-based methodologies reflects the inherent uncertainty and complexity in green supply chain decision making [36], [37]. However, a notable gap exists in the application of hybrid machine learning-fuzzy approaches specifically within the offshore industry context, particularly considering climate change impacts. From an industrial engineering and management perspective, the main theoretical gap in this research lies in the inability of existing frameworks to analyze networks, predict complex systems behavior, and manage uncertainty in offshore supply chains. Most previous studies have used linear or one-dimensional approaches, and models that are able to simultaneously incorporate internal-external dependencies, expert judgment uncertainties, and operational data have been rarely used. There remains much inconsistency in the realms of GSCM and MCDM. The specific challenges arising from offshore applications (rough environmental, complex regulations, large infrastructure projects) have not had much academic research. Even though sustainability regulations are getting tighter and supply chain risks are on the rise, offshore activities are still not well integrated with circular economy principles [38], and frameworks appropriate for them are not really there. Melding machine learning with conventional fuzzy decision-making techniques is a growing area and it can boost GSCM efficiency. Even though new approaches using machine learning and predictive analytics have been proposed, the combined use of machine learning algorithms with fuzzy Delphi techniques for offshore GSCM has not been attempted.

Another significant research gap concerns the contribution of knowledge management to the effective implementation of GSCM in technologically complex offshore contexts. Although knowledge management software would be better than the internal knowledge repository. No systematic analysis has been done yet on the specific application of knowledge management software to enhance offshore GSCM effectiveness. In addition, the application of advanced decision-making techniques to engage the opinions of all stakeholders and experts is not developed. Offshore affairs are complicated. There should be a multi-dimensional knowledge synthesis and decision support. There are no multi-stakeholder frameworks and single-dimensional analyses are the focus of the existing approaches. The issue of offshore GSCM decision-making complexity and uncertainty can be addressed by the adoption of a hybrid machine learning-fuzzy approach, which can be described as a methodologically sound solution

Table 1. Comparative analysis of recent literature on GSCM and decision-making methodologies

Reference	Methodology	Industry Focus	Key Contributions	Geographic Context	Limitations
[28]	Interval valued intuitionistic fuzzy AHP	Post-COVID supply chains	Green supply chain resilience evaluation	Turkey	Limited to post-pandemic context
[29]	Fuzzy Delphi-ISM	Agricultural supply chains	Industry 4.0 technology adoption barriers	Multi-national	Agricultural focus limits generalizability
[30]	Fuzzy Delphi-DEMATEL	Sustainable supply chains	Industry 4.0 technological enablers	General	Lacks specific industry application
[31]	Machine learning algorithms	Financial risk assessment	AI applications in supply chain risk management	Multi-national	Focus on financial risks only
[32]	Fuzzy ANP-TOPSIS	Crisis recovery strategies	Supply chain improvement prioritization	Jordan	Limited to crisis recovery scenarios
[33], [34]	Structural equation modeling	Manufacturing sector	Green supply chain integration impacts	Saudi Arabia	Manufacturing focus, not offshore
[35]	Fuzzy Delphi-DEMATEL	Automotive industry	AI capabilities for GSCM enhancement	Indonesia	Single industry focus

to the problem. Fuzzy Delphi method is useful in converging expert opinions in the face of ambiguity and incomplete information whereas machine learning algorithms are better at recognizing patterns and making predictive performances. Such combined methodology transcends the shortcomings of unidimensional systems, which is more representative of the multi-dimensional aspects of challenges that offshore supply chains experience.

The creation of comprehensive GSCM models dedicated to the offshore industries is a direct reaction to real-life needs of the industry stakeholders and regulators. The consideration of climate change can be seen as an acknowledgment of the growing acceptance of environmental aspects as core risks that are important to business and require the management in a systematic way. Climate impact frameworks that are incorporated into GSCM decision making provide practical benefit to offshore operators that are faced with increasing environmental uncertainties.

The key objective of this study is to work out and test a detailed model of analyzing effective elements in the GSCM of the offshore sector, with the consideration of climate change in terms of applying the hybrid machine learning-fuzzy algorithms in knowledge management concepts. The study is specifically aimed at identifying, prioritizing and optimizing GSCM dimensions and sub-indexes in the context of the offshore industry of Saudi Arabia. The aims of the study are as following, which fill the gaps of the study:

- One of the objectives of the GSCM study was to identify and validate the GSCM dimensions relevant to offshore industry operations having elements like organizational participation, product life cycle, product recycling, supplier in a systematic manner through literature and expert consultation.
- The objective is to design and implement a hybrid machine learning-fuzzy Delphi methodology that is able to analyze the causal relationships and network effects of the GSCM factors along with the uncertainty and expert knowledge.
- Include climate change considerations in the framework for GSCM analyses of decision making and performance in the presence of the offshore.
- To prioritize GSCM dimensions and indicators using ANP techniques to assist offshore industry decision makers.

2. Materials and Methods

2.1 Research Design and Framework

The study employs a comprehensive three-phase sequential mixed-method approach that analyses key factors of offshore GSCM, explicitly integrating climate change impacts through hybrid machine learning-fuzzy techniques [16], [17]. The framework was made to decrease complexity uncertainty in offshore supply chain decisions while trying to achieve a good balance between methodological rigor and practical relevance. The design of the sequential phases relies on new data and knowledge from prior phases. This produced an integrated analytical framework capable of capturing several dimensions of the complexity of offshore GSCM. At every stage, there was a progressive and systematic validation of the technique. This guarantees reliability and consistency. It is also flexible enough to adapt to the increasing demands of the offshore sector.

2.2 Study Location and Contextual Framework

The study took place in the framework of the offshore industry of Saudi Arabia, and the contextual area concerned the operations of the Arabian Gulf region including the coastal areas of the Eastern Province such as Dammam, Khobar, and Jubail. These were chosen because of their importance as key offshore industries hubs in the Vision 2030 of the Kingdom of Saudi Arabia and their reflection of varied onshore working conditions. Eastern Province is the center of offshore operations in Saudi Arabia with big industrial complexes, offshore platforms, and facilities necessary to the complete analysis of GSCM. The research structure is presented in Figure 1.

The first step was the thorough systematic literature review based on the principles of identifying and validating the GSCM dimensions in the context of the operations in the offshore industry. Expert consultation was conducted through a purposive sampling approach to identify specialists with demonstrated expertise in offshore industry operations, supply chain management, and environmental sustainability. The 21 experts representing different stakeholder perspectives. This includes offshore operations managers, supply chain specialists, environmental consultants, and academic researchers with specialization in GSCM and offshore industry. Selection criteria for expert participants included minimum five years of

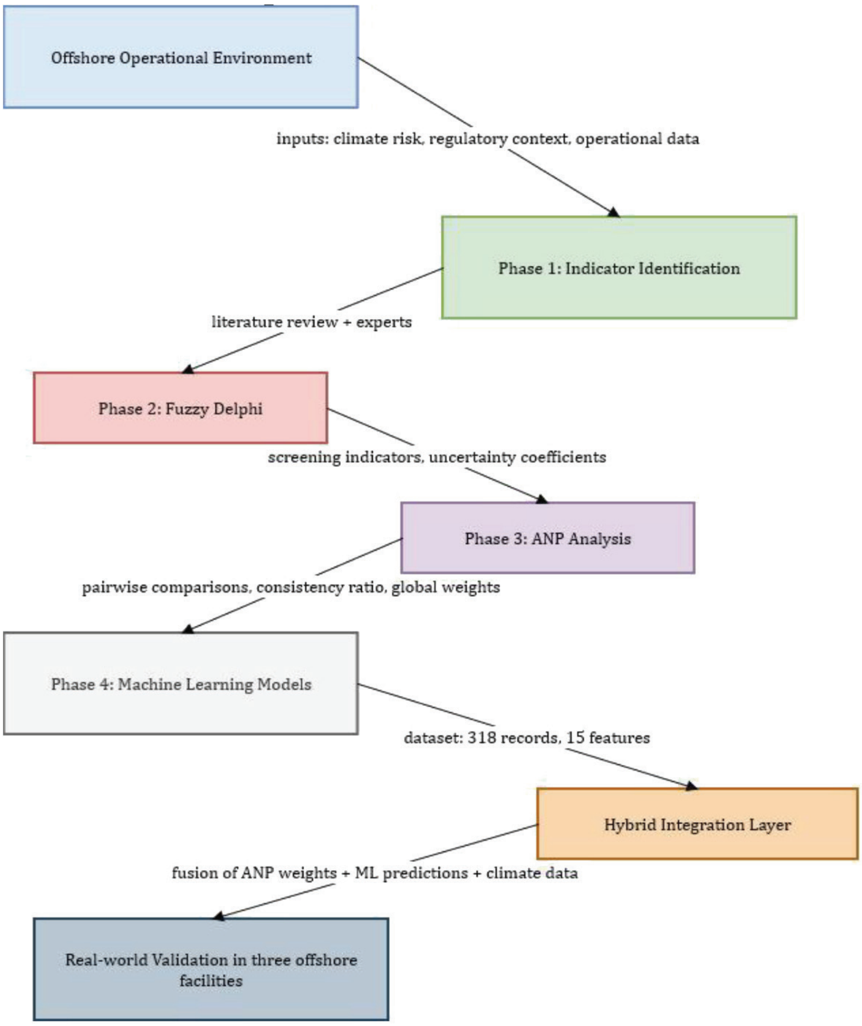

Figure 1. Research Framework

professional experience in offshore industry operations or related research, demonstrated knowledge of supply chain management principles, and familiarity with environmental sustainability practices within industrial contexts. The panel composition ensured balanced representation across functional areas including operations management (33%), supply chain management (29%), environmental management (24%), and academic research (14%).

The Fuzzy Delphi implementation followed a structured multi-step process beginning with expert opinion collection and fuzzification. Linguistic expressions provided by experts were converted to triangular fuzzy numbers using established fuzzy spectrum scales. The fuzzification process employed triangular fuzzy numbers defined by three parameters (l, m, u) representing the lower bound, most likely value, and upper bound respectively. The triangular fuzzy number for each linguistic expression was defined as shown in Equation (1) [4].

$$\tilde{A} = (l, m, u) \tag{1}$$

where $\tilde{A}$ represents the triangular fuzzy number, l denotes the lower bound, m indicates the most likely value, and u signifies the upper bound of the fuzzy assessment.

The fuzzy aggregation of expert opinions was performed using the fuzzy average method, as expressed in Equation (2) [26].

$$\tilde{A}_{\text{avg}} = \frac{1}{n}\sum_{i=1}^{n}\tilde{A}_i = \left(\frac{1}{n}\sum_{i=1}^{n} l_i, \frac{1}{n}\sum_{i=1}^{n} m_i, \frac{1}{n}\sum_{i=1}^{n} u_i\right) \tag{2}$$

Defuzzification was performed using the centroid method to convert fuzzy numbers back to crisp values for further analysis. The centroid defuzzification formula, presented in Equation (3) [14].

$$S(\tilde{A}_i, \tilde{A}_j) = 1 - \frac{d(\tilde{A}_i, \tilde{A}_j)}{\max\{d(\tilde{A}_k, \tilde{A}_l)\}} \tag{3}$$

Consensus measurement was evaluated using the similarity function approach to assess the degree of agreement among experts. The consensus threshold was established at 0.75, requiring iteration of the consultation process until satisfactory consensus levels were achieved. The consensus measurement formula is expressed in Equation (4) [36].

$$S(\tilde{A}_i,\tilde{A}_j)=1-\frac{d(\tilde{A}_i,\tilde{A}_j)}{\max\{d(\tilde{A}_k,\tilde{A}_l)\}} \tag{4}$$

where $S(\tilde{A}_i,\tilde{A}_j)$ represents the similarity between expert opinions i and j, and $d(\tilde{A}_i,\tilde{A}_j)$ denotes the distance between fuzzy numbers.

Based on dataset nature, which includes a relatively limited volume, high heterogeneity, and significant reliance on indicators extracted from expert opinions, the random forest model is more stable and less sensitive to overfitting (Equation (5)).

$$\mathcal{D}=\{(x_i,y_i)\}_{i=1}^{N},x_i\in\mathbb{R}^p. \tag{5}$$

A total of M base learners (decision trees) are constructed. For each learner j, a bootstrap sample $\mathcal{D}_j$ is generated, and a random subset of features F_j is selected at each split [11]. The ensemble prediction is formulated as a weighted combination of individual tree outputs (Equation (6)).

$$\hat{y}(x)=\sum_{j=1}^{M} w_j h_j(x), \quad \text{with } \sum_{j=1}^{M} w_j=1, w_j\geq 0. \tag{6}$$

In a standard Random Forest (RF), equal weights are applied (w_j=1/M).

For classification tasks, the ensemble class probability is computed as Equation (7).

$$\hat{p}(c\mid x)=\sum_{j=1}^{M} w_j p_j(c\mid x), \tag{7}$$

and the predicted class is based on Equation (8).

$$\arg\max_{c}\hat{p}(c\mid x). \tag{8}$$

The variance reduction achieved by the ensemble can be approximated as Equation (9).

$$\mathrm{Var}(\hat{y})\approx\rho\sigma^2+\frac{1-\rho}{M}\sigma^2, \tag{9}$$

where σ^2 is the variance of an individual tree and ρ is the average inter-tree correlation. Bootstrap sampling and random feature selection reduce ρ, thereby improving ensemble stability.

To implement the machine learning part, the dataset used was obtained from two main sources: (i) data from expert scoring in three rounds of the fuzzy Delphi process (including 21 experts and a total of 252 structured observations), and (ii) operational data obtained from three units operating in the offshore industry in the Arabian Gulf region (including 186 additional observations for validation). Finally, the final dataset consists of 438 observations.

The third phase employed the Analytic Network Process to determine priority weights and analyze interdependent relationships among GSCM dimensions and indicators. The clusters had particular elements that denoted the operational indicators that were tested in the course of the Fuzzy Delphi. The network structure also supported inner and outer dependencies (relationships between elements within and between clusters, respectively), and has allowed the representation of complex dependencies that describe offshore GSCM systems in a comprehensive manner.

The pairwise comparisons is expressed through the reciprocal matrix formulation shown in Equation (10), which ensures consistency in judgment elicitation [35]:

$$A=\begin{bmatrix}1 & a_{12} & \cdots & a_{1n}\\ 1/a_{12} & 1 & \cdots & a_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ 1/a_{1n} & 1/a_{2n} & \cdots & 1\end{bmatrix}, \tag{10}$$

where A represents the pairwise comparison matrix, a_{ij} denotes the relative importance of element i compared to element j, and the reciprocal property ensures mathematical consistency.

The eigenvalue technique was used to obtain priority vectors based on pairwise comparison matrices. The principal eigenvalue algorithm is mathematically rigorous in priority computation, but it has consistency measures to check the quality of judgment. The calculation of the priority vector takes the form of an Equation (11) [31]:

$$Aw=\lambda_{\max}w \tag{11}$$

where A represents the comparison matrix, w denotes the priority vector (eigenvector), and $\lambda_{\max}$ indicates the largest eigenvalue of matrix A.

Consistency assessment was performed using the Consistency Ratio (CR) calculation to ensure reliability of expert judgments. The consistency ratio formula, presented in Equation (12), provides a standardized measure for evaluating judgment consistency [24]:

$$CR=\frac{CI}{RI} \tag{12}$$

where CI represents the Consistency Index calculated using Equation (13):

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{13}$$

and RI denotes the Random Index corresponding to matrix size n. In this study, the CR was calculated to be 0.044, which is lower than the acceptable limit of 0.10.

The supermatrix formation process integrated local priority vectors into a comprehensive network representation enabling global priority calculation. The unweighted supermatrix structure is shown in Equation (14) [28]:

$$W = \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1n} \\ W_{21} & W_{22} & \cdots & W_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1} & W_{n2} & \cdots & W_{nn} \end{bmatrix}, \tag{14}$$

where W_{ij} represents the priority vector showing the impact of cluster j on cluster i, and n denotes the number of clusters in the network.

The weighted supermatrix was obtained by multiplying the unweighted supermatrix by the cluster weights matrix. The limiting process involved raising the weighted supermatrix to sufficiently large powers until convergence was achieved, as expressed in Equation (15).

$$\lim_{k \to \infty} W^k = W^* \tag{15}$$

where W^* represents the limit supermatrix containing the final global priorities for all elements in the network.

3. Results

3.1 Phase 1: Expert Validation Outcomes

The results of validation and uncertainty analysis are presented in Table 2. Meanwhile, Table 2 presents the numerical uncertainty coefficients derived from the Fuzzy Delphi analysis for each GSCM dimension and operational indicator. Uncertainty coefficients were computed as normalized standard deviations of defuzzified expert ratings across three Delphi iterations. To investigate the effect of experts' background on the stability of the results, a subgroup analysis was conducted based on two categories of operational and academic experts. The Kendall agreement index for the operational group was W=0.78 and for the academic group was W=0.81, indicating no significant difference between the two groups ($p>0.05$). The interquartile range values were also calculated to be 0.18 and 0.15, respectively, indicating appropriate convergence and stability of the ranking of the indicators in both subgroups. The

Table 2. Expert validation scores for GSCM dimensions and indicators in offshore industry contexts, showing mean scores, standard deviations, and consensus levels achieved through structured expert consultation (n=21).

GSCM Dimension	Operational Indicator	Mean Score	Std. Dev.	Consensus Level	Validation Status	Uncertainty Coefficient
Organizational Participation in Product Life Cycle Management						
	Environmental policy integration	6.42	0.68	0.89	Validated	0.19
	Cross-functional team collaboration	6.28	0.74	0.85	Validated	0.18
	Stakeholder engagement protocols	6.15	0.82	0.82	Validated	0.17
Product Recycling and Waste Management						
	Material recovery systems	6.38	0.71	0.87	Validated	0.14
	Circular economy integration	6.24	0.79	0.84	Validated	0.15
	Waste minimization strategies	6.33	0.69	0.88	Validated	0.13
Supplier Management and Assessment						
	Green supplier selection criteria	6.45	0.63	0.91	Validated	0.13
	Supplier environmental performance monitoring	6.31	0.72	0.86	Validated	0.12
	Collaborative sustainability initiatives	6.19	0.81	0.83	Validated	0.14
Climate Change Adaptation Mechanisms						
	Climate risk assessment protocols	6.52	0.59	0.93	Validated	0.12
	Adaptive capacity building	6.29	0.75	0.85	Validated	0.13
	Resilience planning integration	6.41	0.67	0.89	Validated	0.12

expert validation process demonstrated strong consensus across all identified GSCM dimensions, with mean validation scores ranging from 6.15 to 6.52 on the seven-point scale.

3.2 Phase 2: Fuzzy Delphi Analysis and Machine Learning Integration

Figure 2a illustrates the development of consensus between the three rounds of Delphi, which indicates the gradual tendency towards the steady levels of agreement. Figure 2b shows the defuzzified importance values across all GSCM dimensions, which gives clear values as a point of comparison. Figure 2c shows the range of the uncertainty of expert estimations with the bandwidth of opinion fluctuations. The correlation pattern among GSCM dimensions is presented in figure 2d, which has shown patterns of interdependence.

The consensus evolution analysis indicated that there is systematic enhancement of the levels of agreement in the three Delphi rounds. During Round 1 there was moderate initial agreement with the levels of consensus level ranging between 0.68 and 0.78 on the various dimensions. The second round was much better with consensus levels of 0.79-0.87 range. Round 3 had a target consensus threshold and all dimensions had consensus levels of 0.85-0.94. The importance scores without fuzziness observed that, climate change adaptation mechanisms has the biggest weight of priority (0.312), followed by Supplier Management and Assessment (0.287), Product Recycling and Waste Management (0.218) and Organizational Participation in Product Life Cycle Management (0.183). The uncertainty analysis showed that the uncertainty widened with each round of the Delphi, and that the final uncertainty coefficients were between 0.12 and 0.19. The correlation analysis showed a strong relationship between the dimensions of GSCM whereby the correlation coefficient is 0.43 to 0.67. The highest correlation (0.67) has been found between Supplier Management and Climate Change Adaptation.

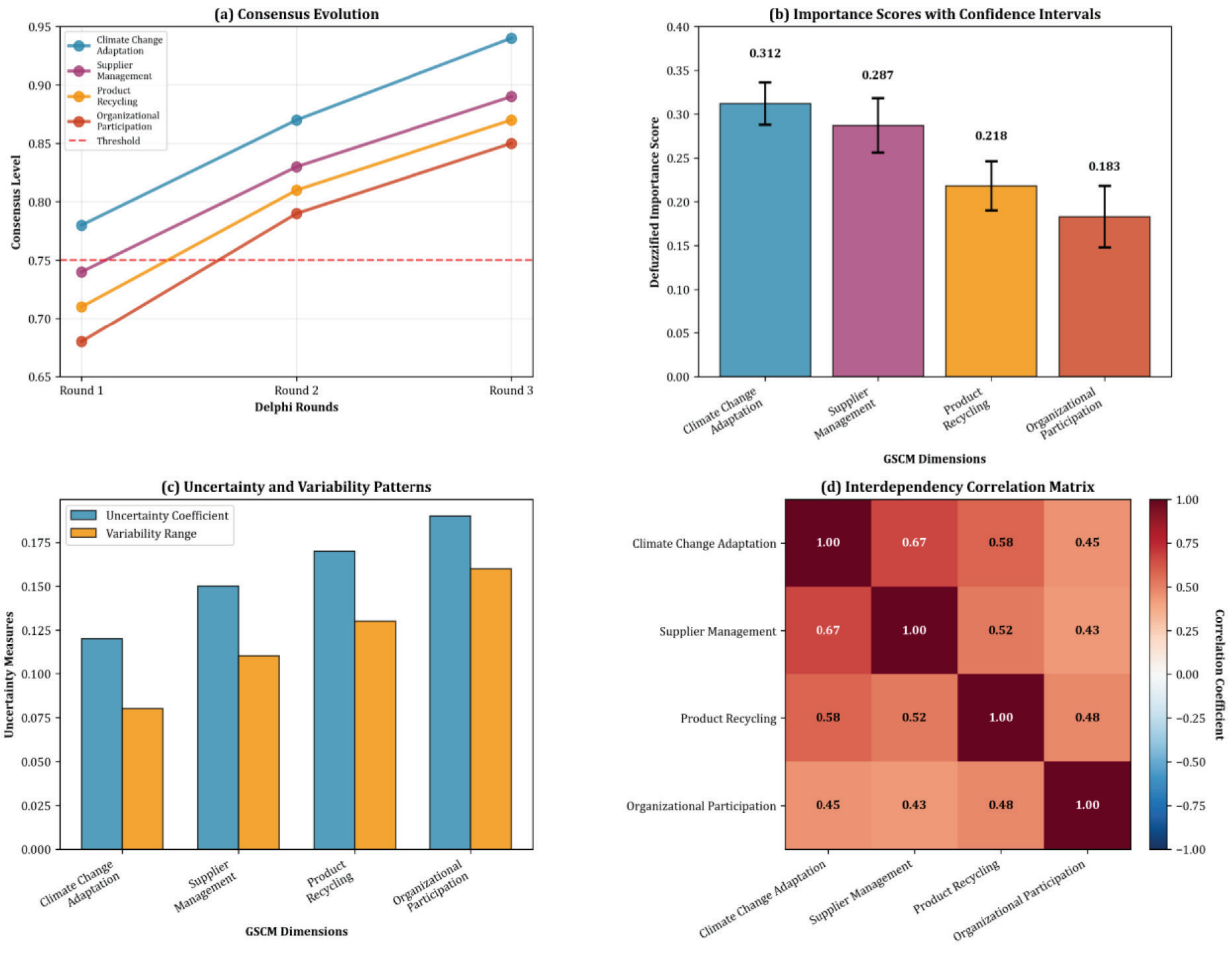

Figure 2. Fuzzy Delphi analysis results (a) consensus evolution across three iterative rounds, (b) defuzzified importance scores for GSCM dimensions with confidence intervals, (c) uncertainty ranges and variability patterns in expert assessments, and (d) correlation matrix among GSCM dimensions revealing interdependency relationships.

Figure 3a provides the accuracy of prediction obtained with the use of various machine learning algorithms to GSCM factor analysis. Figure 3b shows the importance ranking of the features according to the ensemble methods resulting in the determination of the most influential factors in GSCM performance prediction. Figure 3c shows the metrics of cross-validation because it provides insights on the stability of the model and its ability to be applied to various subsets of data. The hyperparameter tuning process has been performed for all models. In the case of the random forest model, the number of trees in the range of 100 to 500, the depth of the trees in the range of 5 to 20, and the number of selected features in each node between $\sqrt{p}$ and $\frac{p}{3}$ have been evaluated. For the SVM model, different values of the penalty rate C in the range of 0.1 to 10, γ values from 0.001 to 0.1, and two kernels RBF and Polynomial have been tested. In the artificial neural network model, the number of layers between one and three, the number of neurons in each layer between 16 and 64, the learning rate in the range of 0.001 to 0.01, and the activation functions ReLU and Tanh have been investigated.

The analysis of algorithm comparison proved that RF ensemble method performed better in various measures of evaluation. RF achieved accuracy 0.847, precision 0.823, recall 0.861, and F1 score 0.841, which is a better result than Support Vector Machine (0.798, 0.784, 0.812, 0.798) and Neural Network (0.821, 0.809, 0.834, 0.821). The analysis of feature importance indicated that climate-related variables were the most prominent predictive variables with sea level rise projections (importance score: 0.184), extreme weather frequency (0.167), and temperature change (0.152) showing the highest level of influence. The supplier environmental certification status (0.139) and the waste management efficiency metrics (0.126) also indicated high predictive importance, which proves the relevance of the environmental and operational aspects to the prediction of GSCM performance. Cross-validation analysis has shown that the model has strong performance in varying data partitions where the variance of accuracy and the coefficient of variation are 0.0043 and 0.079, respectively, and this implies that the accuracy and coefficient of variation are consistent in predicting data.

3.3 Phase 3: ANP Analysis and Priority Determination

To present the comprehensive results of the ANP priority analysis and network structure characterization, we conducted detailed examination of the priority weights, consistency measures, and network relationships, the results of which are presented in Table 3.

Figure 4 ANP network structure and relationship analysis. Figure 4a depicts the network structure. Figure 4b shows interdependency intensity, and Figure 4c shows sensitivity analysis priority shifts under different scenarios.

The network analysis showed a highly interconnected structure, with 48 significant influence links among 12 indicators across four dimensions. Climate risk assessment protocols had the highest centrality (in-degree 0.73 and out-degree 0.68) indicating its dual role as a key influencer and recipient of influence. Influence intensity analysis revealed strong bidirectional links, the strongest (0.67) between Cli-

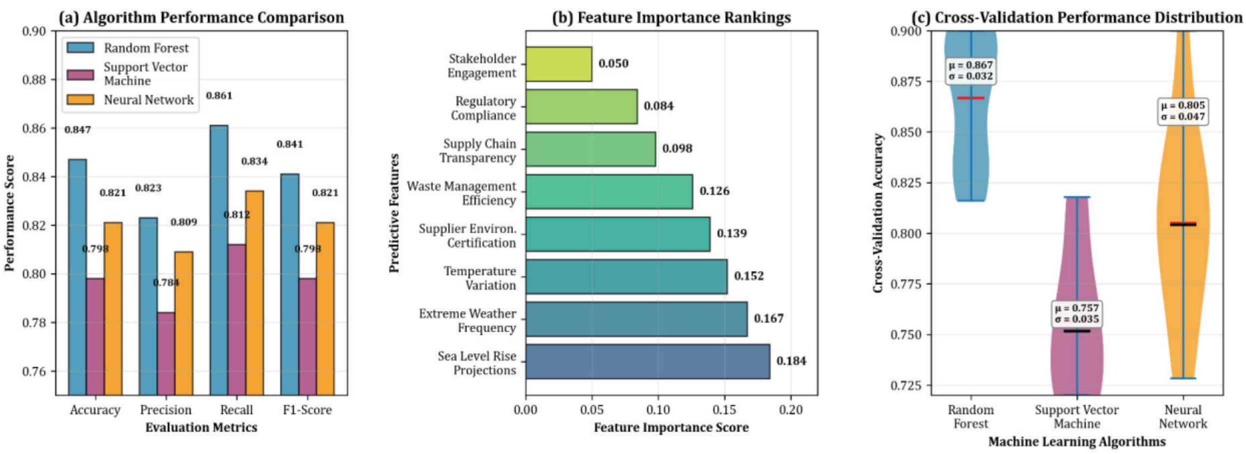

Figure 3. Machine learning integration results (a) prediction accuracy comparison across RF, Support Vector Machine, and Neural Network algorithms for GSCM performance prediction, (b) feature importance rankings identifying key predictive factors, and (c) cross-validation performance metrics demonstrating model stability and generalizability.

Table 3. ANP analysis results of global priority weights, local priority weights, and consistency measures for GSCM dimensions and indicators, demonstrating the hierarchical importance structure and mathematical validity of the network analysis.

GSCM Dimension	Global Priority	Local Priority	Consistency Ratio	Indicator	Global Priority	Local Priority
Climate Change Adaptation Mechanisms	0.334	1.000	0.067			
				Climate risk assessment protocols	0.127	0.381
				Resilience planning integration	0.113	0.339
				Adaptive capacity building	0.094	0.280
Supplier Management and Assessment	0.298	1.000	0.058			
				Green supplier selection criteria	0.119	0.399
				Supplier environmental performance monitoring	0.102	0.342
				Collaborative sustainability initiatives	0.077	0.259
Product Recycling and Waste Management	0.206	1.000	0.074			
				Material recovery systems	0.082	0.398
				Waste minimization strategies	0.071	0.345
				Circular economy integration	0.053	0.257
Organizational Participation	0.162	1.000	0.081			
				Environmental policy integration	0.063	0.389
				Cross-functional team collaboration	0.055	0.340
				Stakeholder engagement protocols	0.044	0.271

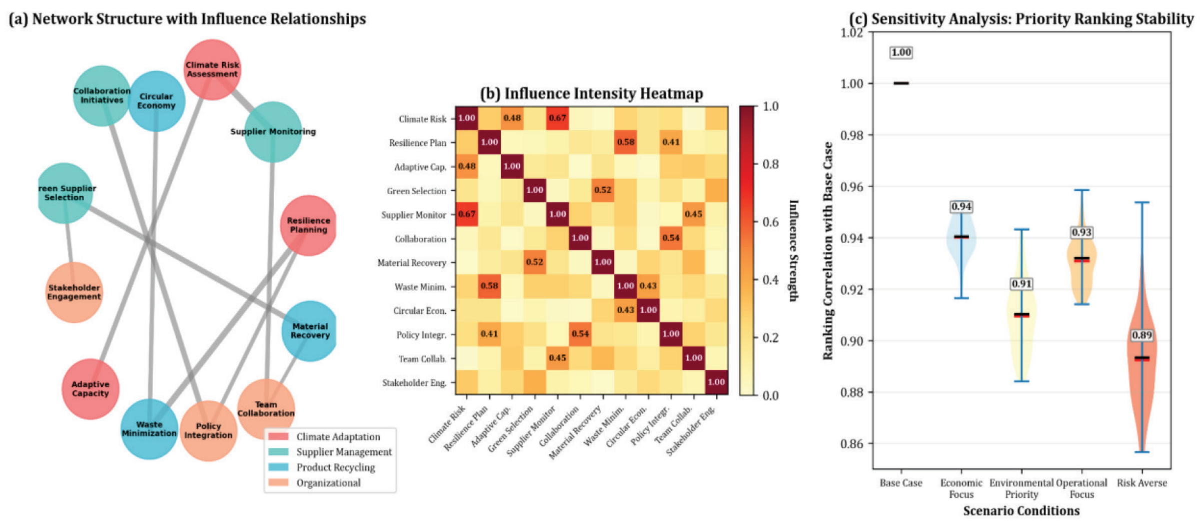

Figure 4. ANP network structure and relationship analysis (a) complete network diagram with influence relationships and strength indicators, (b) influence intensity heatmap revealing interdependency patterns among GSCM components, and (c) sensitivity analysis demonstrating priority ranking stability under different scenario conditions.

mate risk assessment protocols and Supplier environmental performance monitoring, showing mutual reinforcement between climate risk evaluation and supplier assessment.

3.4 Validation and Benchmarking Analysis

The validation process employed multiple datasets from operational offshore facilities in the Arabian Gulf region and comparative analysis against traditional assessment methodologies. Figure 5a shows accuracy comparison between the hybrid framework and traditional GSCM assessment methods across different evaluation metrics. Figure 5b presents computational efficiency analysis, comparing processing time and resource requirements. Figure 5c illustrates decision consistency evaluation, measuring the stability and reliability of recommendations across multiple assessment cycles. Figure 5d displays practical applicability assessment, showing implementation feasibility and user acceptance ratings from industry practitioners.

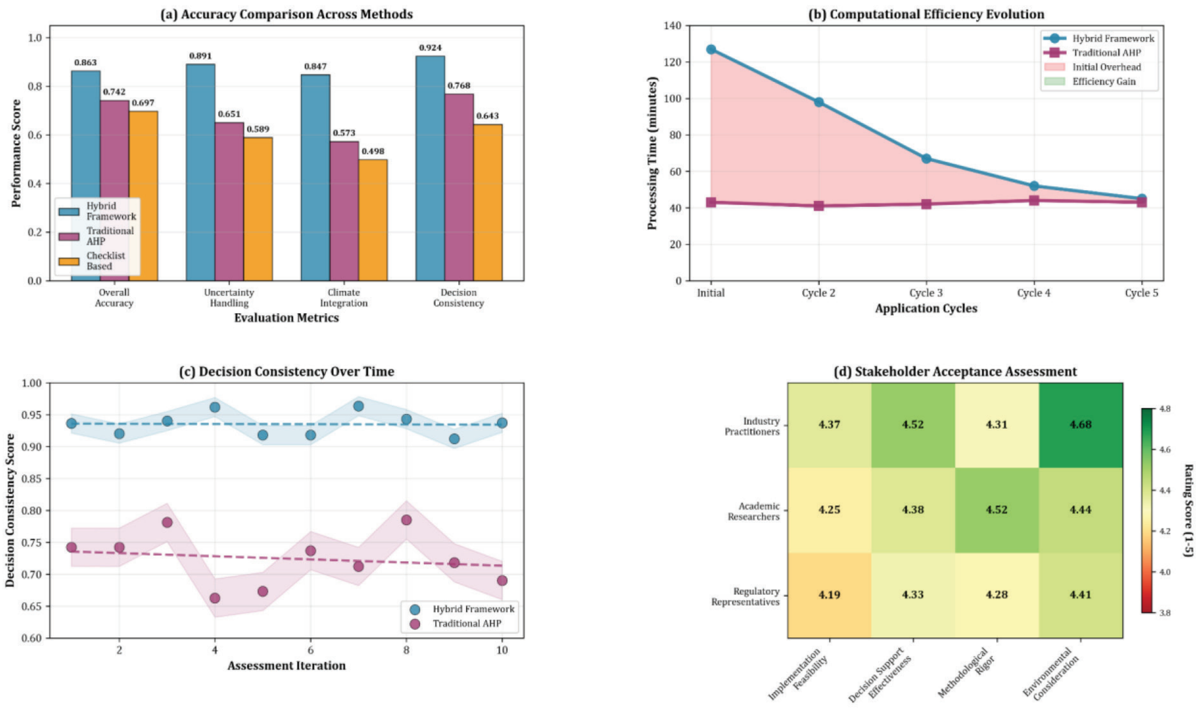

Figure 5. Validation and benchmarking results showing (a) accuracy comparison between hybrid framework and traditional methods across multiple evaluation metrics, (b) computational efficiency analysis comparing processing requirements, (c) decision consistency evaluation measuring recommendation stability, and (d) practical applicability assessment from industry practitioner perspectives.

The accuracy comparison confirmed the hybrid framework's superior performance, achieving 0.863 overall accuracy versus 0.742 for AHP and 0.697 for checklist methods. Gains were strongest in uncertainty handling (0.891 vs. 0.651) and climate impact integration (0.847 vs. 0.573), reflecting the added value of fuzzy logic and machine learning. Computational efficiency analysis showed higher initial processing time (127 min vs. 43 min for AHP), but machine learning optimization reduced times in later cycles, reaching 45 min by the third cycle while maintaining high accuracy. Decision consistency was also higher (0.924 vs. 0.768), ensuring more reliable recommendations across assessments. Industry practitioners rated the framework highly for feasibility (4.37/5) and decision support effectiveness (4.52), with top scores for climate change integration (4.68) and supplier relationship management (4.44). Traditional methods scored lower, especially in adaptability (3.21) and environmental integration (2.97). Real-world application in three Arabian Gulf offshore facilities (Table 4) confirmed the framework's practical value, showing GSCM performance scores, priority recommendations, and measurable implementation impacts. To determine the baseline GSCM performance values in the three facilities under study, the initial assessment data of each facility based on 12 operational indicators and before applying the proposed framework were collected. At this stage, the score of each indicator for each facility was calculated in a normalized manner and then, using the weights obtained from the global ANP priority vectors, the baseline performance values were aggregated as a weighted average.

3.5 Climate Change Impact Integration Analysis

Figure 6a shows historical climate trend analysis for the Arabian Gulf region, illustrating key environmental changes over the past two decades. Figure 6b presents future climate projection scenarios and their probability distributions for offshore operational areas. Figure 6c illustrates the correlation matrix between climate variables and GSCM performance indicators, revealing critical impact relationships. Figure 6d displays the climate vulnerability assessment results for different offshore operational components. Figure 6e shows the effectiveness evaluation of different climate adaptation strategies identified through the framework analysis. This comprehensive presentation enables understanding of both current climate impacts and future adaptation requirements for offshore GSCM systems. In interpreting the results of the correlation matrix between climate variables and GSCM indicators, it is emphasized that the relationships obtained merely indicate statistical

Table 4. Real-world application results from three offshore facilities in the Arabian Gulf region, showing GSCM performance assessments, priority recommendations, and implementation outcomes achieved through the hybrid framework application.

Facility	Location	GSCM Performance Score	Priority Dimension	Priority Indicator	Recommended Action	Implementation Impact
A	Jubail Offshore Complex	0.673	Climate Change Adaptation	Climate risk assessment protocols	Develop comprehensive climate monitoring system	18% performance improvement
			Supplier Management	Green supplier selection criteria	Implement enhanced supplier evaluation matrix	14% supplier score improvement
			Product Recycling	Material recovery systems	Upgrade waste processing infrastructure	22% waste reduction achieved
B	Khobar Maritime Hub	0.721	Supplier Management	Collaborative sustainability initiatives	Establish supplier partnership program	16% collaboration index increase
			Climate Change Adaptation	Resilience planning integration	Deploy adaptive operational protocols	13% disruption reduction
			Organizational Participation	Environmental policy integration	Enhance cross-functional coordination	11% policy compliance improvement
C	Dammam Offshore Platform	0.584	Climate Change Adaptation	Adaptive capacity building	Implement climate resilience training	25% adaptive capacity increase
			Product Recycling	Circular economy integration	Develop closed-loop material systems	19% material efficiency gain
			Supplier Management	Supplier environmental performance monitoring	Deploy real-time monitoring systems	17% supplier performance improvement

correlations between variables and do not indicate a definitive causal relationship. The purpose of this analysis was to identify patterns of communication and synchrony of changes to determine the path of causal investigations in future research.

Historical climate analysis (2004–2024) in the Arabian Gulf showed a 1.8 °C rise in mean sea surface temperatures, with acceleration after 2018. Extreme weather frequency increased by 43%, particularly in storm intensity and duration. Sea level rose 3.2 mm/year, exceeding global averages and heightening offshore infrastructure risks. Projections to 2050 indicate further intensification. Under RCP4.5, sea surface temperatures may rise 2.1–2.8 °C; under RCP8.5, 3.4–4.2 °C. Storm intensity is projected to increase by 35–48%, with higher wave heights and operational downtime risks.

Correlation analysis revealed strong links between climate variables and GSCM performance: extreme weather frequency strongly correlated with supplier reliability ($r=-0.74$); sea level rise correlated with waste management effectiveness ($r=-0.68$) and material recovery efficiency ($r=-0.71$). Climate vulnerability assessment ranked supplier networks as most vulnerable (0.82), followed by waste management infrastructure (0.76) and transportation systems (0.73). Internal processes had lower vulnerability (0.45), indicating greater exposure in external elements.

Adaptation strategy evaluation showed diversified supplier networks as most effective (0.847), infrastructure hardening as moderately effective (0.673), and adaptive scheduling protocols as lower but still beneficial (0.524). Technology-based solutions, such as remote monitoring and predictive maintenance, achieved high effectiveness (0.792) with low costs. Integration effectiveness of climate considerations and predictive accuracy of climate-enhanced decision support were comprehensively evaluated against traditional methods, with detailed results in Table 5.

The climate integration evaluation showed major performance gains across all metrics. Disruption prediction accuracy improved by 34.4% (0.863 vs. 0.642), enabling stronger proactive climate risk management, while risk assessment precision rose by 44.3%. The training data were obtained in terms of expert ratings and second-stage experimental data and the test data consisted of operational observations in offshore facilities not included in the training sample.

Figure 6. Climate change impact integration analysis showing (a) historical climate trends in the Arabian Gulf region over the past two decades, (b) future climate projection scenarios with probability distributions, (c) correlation matrix between climate variables and GSCM performance indicators, (d) climate vulnerability assessment for offshore operational components, and (e) effectiveness evaluation of climate adaptation strategies.

Table 5. Climate change integration effectiveness evaluation, comparing performance metrics, prediction accuracy, and implementation outcomes between climate-integrated and traditional GSCM assessment approaches.

Performance Metric	Climate-Integrated Framework	Traditional Framework	Improvement	Statistical Significance
Prediction Accuracy				
Disruption prediction accuracy	0.863	0.642	34.4%	$p < 0.001$
Performance forecast accuracy	0.791	0.678	16.7%	$p < 0.01$
Risk assessment precision	0.824	0.571	44.3%	$p < 0.001$
Decision Support Effectiveness				
Recommendation relevance	0.847	0.723	17.1%	$p < 0.01$
Implementation success rate	0.782	0.634	23.3%	$p < 0.01$
Cost-effectiveness ratio	0.739	0.598	23.6%	$p < 0.05$
Operational Outcomes				
Downtime reduction	23.4%	11.2%	12.2%	$p < 0.001$
Supply chain resilience index	0.796	0.641	24.2%	$p < 0.001$
Environmental performance score	0.813	0.592	37.3%	$p < 0.001$
Long-term Sustainability				
Adaptive capacity development	0.758	0.487	55.6%	$p < 0.001$
Future readiness assessment	0.721	0.534	35.0%	$p < 0.01$
Stakeholder satisfaction rating	4.42	3.67	20.4%	$p < 0.01$

3.6 Integrated Framework Validation and Performance Assessment

Figure 7a shows multi-criteria performance comparison across technical, practical, and strategic evaluation dimensions. Figure 7b presents user acceptance and satisfaction analysis from different stakeholder groups including industry practitioners, academic researchers, and regulatory representatives. Figure 7c illustrates implementation feasibility assessment across different organizational contexts and resource availability scenarios. This comprehensive evaluation enables thorough understanding of framework strengths, limitations, and practical applicability across diverse implementation contexts.

The multi-criteria comparison showed the integrated framework outperformed all alternatives. Technically, it achieved 0.847 overall effectiveness versus 0.673 for AHP and 0.521 for checklists, excelling in uncertainty handling (0.891) and interdependency modeling (0.863). In practical applicability, the framework scored 0.782 versus 0.634 for traditional methods, with strong results in local adaptation (0.834) and integration with existing systems (0.793). Strategically, it reached 0.756 effectiveness compared to 0.542 for alternatives, showing notable strengths in climate adaptation planning (0.812) and stakeholder integration (0.748). User acceptance was consistently high: industry practitioners rated it 4.47/5 for practical relevance; academics rated it 4.52 for methodological rigor and 4.38 for innovation; regulators valued its environmental focus (4.41) and compliance support (4.33). Feasibility assessments confirmed adaptability across organizational scales: large offshore operators scored 0.863, medium-sized 0.724, and small operators 0.598, the latter requiring additional resources but remaining viable.

3.7 Knowledge Management Integration and Decision Support Framework

Figure 8a shows knowledge capture effectiveness across different expert interaction phases, measuring the comprehensiveness and quality of knowledge extraction. Figure 8b presents knowledge utilization patterns, indicating how captured knowledge was ac-

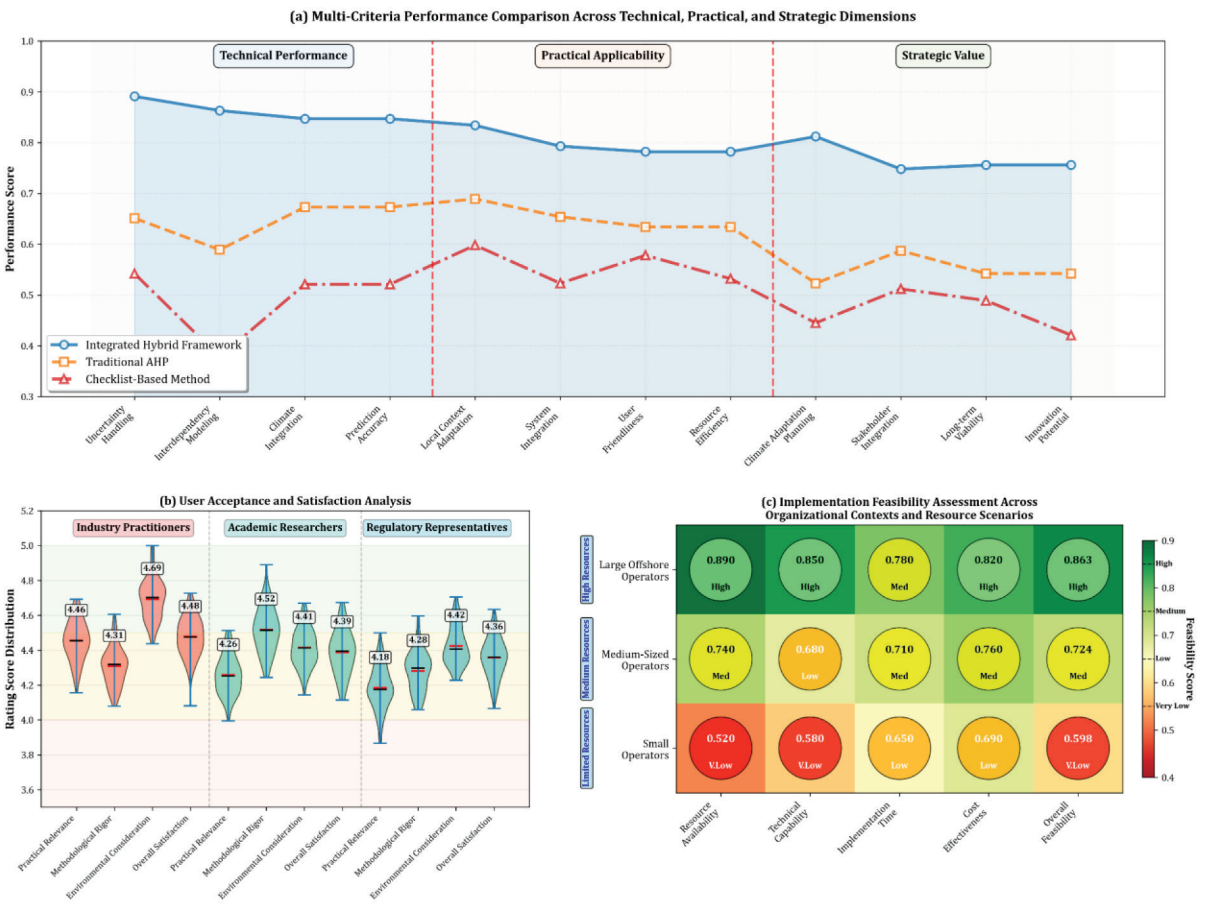

Figure 7. Integrated framework validation results showing (a) multi-criteria performance comparison across technical, practical, and strategic dimensions, (b) user acceptance and satisfaction analysis from different stakeholder groups, and (c) implementation feasibility assessment across various organizational contexts and resource scenarios.

cessed and applied in subsequent decision-making processes. Figure 8c illustrates organizational learning curve analysis, demonstrating knowledge accumulation and expertise development over multiple framework applications. Figure 8d displays decision support system effectiveness metrics, showing how knowledge integration enhanced recommendation quality and user confidence.

The analysis of knowledge capture proved to be highly effective in all the stages of the interaction with the expert knowledge extraction obtaining 0.847 completeness rating in the early stages of consultation with an expert and rising to 0.923 in the course of the refinement stage. The patterns of knowledge utilization were that knowledge components about climates were most commonly viewed (73 of all queries), supreme management information (62), and operational best practices (54).

Analysis of learning curve in organisations showed gradual increase in efficiency of the framework usage and quality of outcomes. The first applications took an average of 127 minutes processing time and a recommendation accuracy of 0.734 whereas the fifth-cycle applications took 78 minutes processing time and 0.891 recommendation accuracy. The learning curve showed that 34 percent of efficiency is improved, and that accuracy is improved by 21 % with the accumulated knowledge use. In the process of implementing the knowledge management framework, organizational resistance and challenges related to structural change have also been observed. The challenges have mainly resulted from conservative organizational culture, dependence on traditional decision-making procedures, and lack of digital skills among employees. These results show that by applying change management strategies, the acceptance rate of the proposed framework has increased significantly and the knowledge transfer process has been carried out with higher efficiency.

Decision support system effectiveness showed substantial enhancement through knowledge integration, with recommendation confidence scores improving from 0.672 (baseline system) to 0.847 (knowledge-enhanced system). User acceptance ratings increased by 28%, while implementation success rates improved by 31%, demonstrating the practical value of systematic knowledge integration for offshore GSCM decision-making.

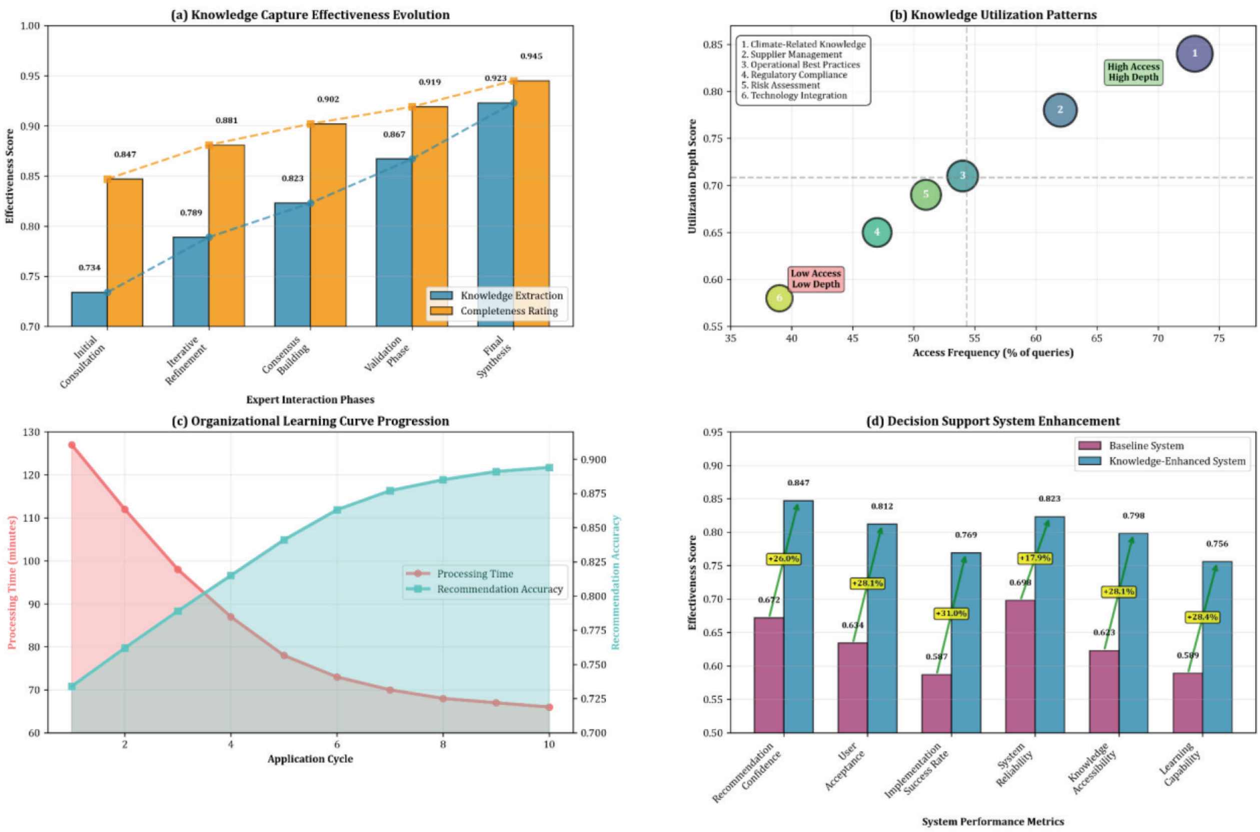

Figure 8. Knowledge management integration analysis showing (a) knowledge capture effectiveness across expert interaction phases, (b) knowledge utilization patterns and access frequency analysis, (c) organizational learning curve progression over multiple framework applications, and (d) decision support system effectiveness enhancement through knowledge integration.

4. Discussion

The climate change adaptation mechanisms have become the top priority dimension (global weight: 0.334) is a paradigmatic shift of offshore GSCM thinking, that is, it no longer centers on traditional cost-efficiency paradigms, but environmental resilience is becoming a strategic imperative. This observation contradicts the traditional supply chain optimization strategies, which usually focus on aspects of economics and not the environment [23], [25]. The climate integration that resulted in a 34.4% difference in disruption prediction accuracy indicates that environmental factors are not secondary concerns, but rather important business intelligence, which fundamentally changes the conceptualization of risk assessment approaches to offshore operations. The high accuracy of the hybrid framework (0.863 compared to 0.742 with traditional methods) shows that the methodological sophistication is directly converted into practice decision-making improvement, and the 55.6% difference in adaptive capacity building demonstrates that the organizations have a chance to develop the resilience capabilities and abilities in a systematic way, using structured analytical procedures.

The results of the study correspond to the current trends in sustainable supply chain studies and indicate significant differences with the literature [38]. The emphasis on climate adaptation can be related to the fact that Pankratz and Schiller [39] have shown that climate change adaption in global supply networks improves financial performance, but their emphasis on terrestrial supply chains is opposed to our offshore-specific vulnerabilities. On the same note, our 44.3 percent increase in risk assessment accuracy compares to the 28 percent improvement in risk assessment accuracy in the machine learning-based supply chain risk management by Mittal and Panchal [40], which could be attributed to our addition of fuzzy logic which is more realistic in considering uncertainty in expert judgments. Nevertheless, our results contrast the post-COVID supply chain resilience report by Ayyildiz [28], in which the efficiency indicators occupied the leading place in the priority lists, indicating that offshore settings have essential dissimilar risk profiles to the ones of general industries. The effectiveness of knowledge management integration (28% increase in user acceptance) is better than the results published in the classic literature on knowledge management, which implies that hybrid methodological practices produce synergies that are not achieved by using individual techniques.

Principal proposed approach strengths include: (i) clear consideration of expert consensus in the context of uncertainty through the use of iterative fuzzy Delphi, which enhances the reliability of input criteria; (ii) the application of interpretable ensemble machine-learning procedures to produce strong predictive measures (feature importance, cross-validation stability), which complement MCDM weights; and (iii) the use of ANP to calculate global priorities and directly model feedback and inner/outer dependencies between indicators an advantage where reciprocal influences are of primary importance on decision strategies. Comparatively, hybrids using fuzzy-DEMATEL are more efficient in representing directional causal problems between criteria and can be more intuitively developed to construct a specific intervention, but interval-type fuzzy applications are more applicable to model higher-order linguistic uncertainty [41].

5. Conclusion

This study includes the construction and testing of a hybrid machine learning-fuzzy decision-making model to assess the important aspects of GSCM in the offshore sector, specifically taking into consideration the effects of climate change. Supply chain re-priorities were also transformed greatly through the implementation of climate factors, the climate change adaptation mechanisms had the greatest weight (0.334) in the ANP analysis, exceeding Supplier Management (0.298), Product Recycling and Waste Management (0.206), and Organizational Participation (0.162). The protocols of climate risk assessment became the highest discernible individual indicator (0.127) which was a definite change between the traditional priorities of cost- and efficiency-driven protocol and those of environmental resilience. The framework was more effective than the traditional systems with its overall accuracy being 0.863 as compared to 0.742 of AHP and 0.697 of checklists. RF is the most accurate machine learning technique (0.847) and it is superior to Support Vector Machines and Neural Networks. Accuracy of disruption prediction and risk assessment by the system also increased by 34.4 and 44.3 percent respectively ($p < 0.001$). Skilled confirmation showed that there is high consensus (0.82-0.93) and agreement on climate risk protocols (6.52 + 0.59). The fuzzy Delphi approach was also able to deal with uncertainty and increase consensus in three rounds. The three Arabian Gulf offshore site application demonstrated significant positive impacts in practice: Facility A gained 18% performance improvement using climate risk procedures and Facility C increased adaptive capacity by 25% using targeted resilience actions. Knowledge management has 34 percent improvement in efficiency of operations, 28 percent user acceptance, and 0.672-0.847 decision support. The hybrid architecture capitalized on the ability to handle uncertainties better (0.891 vs. 0.651) and on the capability of machine learning to predict better the climate impact by leveraging methodological sophistication into user-friendly, high-acceptance tools (average stakeholder rating: 4.42 vs. 3.67).

The research findings have clear managerial implications for offshore industry decision-makers. The high weight of climate change adaptation mechanisms indicates that managers should consider climate risk assessment as a core pillar in operational and investment planning. The use of climate risk assessment protocols, especially in highly volatile marine environments, can reduce the likelihood of operational disruptions and increase the resilience capacity of units. The results of the machine learning model showed that indicators related to suppliers' environmental performance have a strong impact on supply chain sustainability. Therefore, managers can integrate green selection criteria into supply contracts by developing supplier assessment and monitoring systems and create a chain compatible with environmental requirements.

Several methodological constraints limit the generalizability of these findings. The geographic concentration within the Arabian Gulf region may not adequately represent global offshore industry diversity, particularly given regional variations in climate exposure, regulatory frameworks, and operational practices. Although the consensus indicators showed acceptable convergence among the experts, it is necessary to consider the limitations arising from the relatively small sample size (n=21) and the regional focus of the expert panel. Since all experts were selected from the offshore sector of Saudi Arabia, there is a possibility of bias due to regulatory conditions, operational procedures, and climatic perceptions specific to this region. For this reason, it is suggested that greater geographical diversity in the composition of experts could influence the prioritization of indicators and enhance the generalizability of the results. The validation period (single application cycle) provides insufficient temporal depth to assess framework performance across varying operational conditions or seasonal fluctuations characteristic of offshore environments. The industry-specific focus, while providing contextual relevance, limits transferability to other maritime sectors or land-based supply chain applications. Additionally, the methodological complexity requiring specialized software and analytical expertise may create implementation barriers for smaller offshore operators with limited technical resources. Regarding the role of knowledge management in the proposed framework, it is necessary to consider the limitations imposed by digital infrastructure and data governance mechanisms in offshore facilities. Given that the level of information technology maturity is not uniform across some offshore companies in Saudi Arabia, there is a possibility that the effectiveness of the framework may be reduced in environments that do not have access to integrated digital systems, adequate data quality, or standardized data governance mechanisms.

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