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Discriminating Green Supply Chain Performance Levels Based on Priority Factors Using an Ann Model Evidence from Accommodation Businesses in Quang Ninh, Vietnam

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Abstract
Green supply chain practices (GSCP) have become increasingly central to the sustainability transition of the hospitality industry, yet prior studies have mainly ranked the priority of antecedent factors without assessing their capacity to discriminate between performance levels across firms. Building on a set of priority weights for ten GSCP factors, derived from expert assessments using the fuzzy analytic hierarchy process (FAHP), this study applies an artificial neural network (ANN) to identify the factors with the strongest discriminating power for GSCP performance among accommodation businesses in Quang Ninh, based on the fuzzy-AHP output of expert interview data. A multilayer ANN with two hidden layers, validated through 10-fold cross-validation, was trained to classify these performance levels, combined with the Garson algorithm extended through the connection-weight method to rank the relative importance of the ten input factors. The model achieved strong and stable classification performance, with institutional pressure and climate change pressure emerging as the two most discriminative factors. These findings reveal a complementary dual mechanism: external pressures act as activating drivers, while internal organizational capacity serves as the conversion condition that translates pressure into implementation. The study contributes an ANN-based approach combined with the Garson algorithm for classifying and identifying the factors that discriminate GSCP performance using small-sample expert data, while offering practical managerial implications for prioritizing resources amid growing environmental and institutional pressure in heritage tourism destinations.
Keywords: *Green supply chain practices; Artificial neural network (ANN); Garson algorithm; Variable importance; Hospitality sustainability; Quang Ninh*

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I. Introduction

Supply chain operations are among the key factors influencing global environmental and social impacts (Safaei et al., 2026). Sustainable development has therefore become a critical strategic imperative in corporate supply chain management, aimed at mitigating environmental impacts and integrating economic, social, and ecological objectives into business operations. Accordingly, sustainability is only meaningful when all members of the supply chain engage in environmentally responsible activities (Xu, Gursoy, 2015). Green supply chains thus emerge when environmental concerns are integrated into supply chain activities (Sarkis, 2012). At the same time, green supply chain practices (GSCP) have increasingly become an essential component of sustainable development in the tourism and hospitality sector.

One important research direction concerns identifying the factors and mechanisms that drive firms to develop environmental management initiatives and practices within their supply chains. Alreahi et al. (2023) and Trujillo-Gallego et al. (2022) highlighted two sources of factors motivating firms to adopt GSC initiatives: intrinsic drivers, encompassing internal factors, and pressures from stakeholders and environmental regulations. These factors include institutional pressure, market orientation, and managerial commitment (Gonzalez et al., 2022), as well as internal capabilities and organizational conditions that support the translation of green orientation into operational outcomes, such as top management commitment and green organizational resources in the hotel context (Alreahi et al., 2023). Regarding these factors, prior studies have mainly clarified their level of impact and priority ranking, without assessing their contributing role in classifying GSCP performance.

Recent publications in supply chain and sustainability management have increasingly explored the predictive and classificatory capacity of machine learning methods. In this regard, Hezam et al. (2025) showed that artificial neural networks (ANN) are the most widely used classification algorithm in this line of research, outperforming alternative methods owing to their ability to capture nonlinear relationships among performance variables. In the sustainable supply chain domain, Eraña-Díaz et al. (2026) applied ANN to classify industrial sustainability profiles for policy design purposes. In the hospitality and tourism context, Pérez López et al. (2025)

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further affirmed the value of nonlinear machine learning models for classifying the sustainability practices of small accommodation businesses. However, most of these studies rely on large-scale secondary data or publicly disclosed indicators, whereas the application of ANN to classify GSCP performance based on multi-criteria expert assessments particularly in the data-constrained hospitality sector of emerging economies remains a research gap.

Building on this analysis, the present study addresses this gap by applying an ANN model to identify the factors that discriminate GSCP performance among accommodation businesses in Quang Ninh province. Endowed with rich natural and cultural resources, Quang Ninh is a renowned tourist destination that occupies an important position on Vietnam's tourism map (Quang Ninh Department of Tourism, 2024). Notably, Ha Long Bay- a UNESCO World Natural Heritage Site has been recognized three times, in 1994, 2000, and most recently in 2023 when it was extended together with the Cat Ba Archipelago (Hai Phong), thereby reaffirming the outstanding universal value of the region's tourism resources. With these notable advantages, tourism in Quang Ninh is also gaining momentum and becoming a spearhead economic sector, progressively supporting the province's transition from a “brown” to a “green” development model (Quang Ninh Department of Tourism, 2024).

Accordingly, this study addresses the following research questions: (1) What classification performance does the ANN model achieve when trained on data simulated and augmented from small-sample MCDM weights? (2) How should the ANN network structure be selected and trained to ensure stable and reliable classification performance on simulated small-sample data? The paper therefore offers practical contributions that help managers and accommodation businesses identify and prioritize the factors capable of discriminating against GSCP performance, thereby enhancing implementation effectiveness under conditions of limited resources and growing pressure for green transition.

With this objective, the paper is structured as follows: Section 1 introduces the study; Section 2 reviews the literature and develops the theoretical framework; Section 3 describes the research methodology; Section 4 presents the results; Section 5 discusses the findings; and Section 6 concludes the paper and highlights implications as well as directions for future research.

II. Literature Review

2.1. Green supply chain practices

GSC practices emerged from growing global awareness of environmental protection and the need to integrate ecological considerations throughout the entire supply chain flow, rather than confining them to a firm's internal boundaries. Geng et al. (2017) emphasized that GSC arose from increasing worldwide environmental consciousness. According to Gilbert (2001), greening the supply chain refers to the process of integrating environmental criteria into firms' procurement decisions and into establishing and maintaining long-term cooperative relationships with suppliers. In this vein, green supply chain management (GSCM) extends beyond mere compliance with environmental management requirements to encompass more proactive practices such as reduction, reuse, recycling, and reverse logistics. From a process and functional perspective, GSCP refers to the application of GSCM methods to improve a firm's economic and environmental performance, thereby generating beneficial effects on operational performance (AlBrakat et al., 2023).

Alongside identifying these practice groups, a substantial body of research has focused on explaining the factors that drive firms to develop environmental management initiatives and practices within their supply chains. These studies have identified two groups of factors that promote GSCP: external and internal environmental factors (Neumayer, Perkins, 2005; Alreahi et al., 2023). External factors relate to institutional pressure, legal requirements, and pressure from customers, suppliers, and other stakeholders (Alreahi et al., 2023). These factors are regarded as relational drivers arising from an organization's desire to legitimize and improve its existing relationships with various stakeholders (Neumayer, Perkins., 2005). Internal factors relate to a set of business strategic drivers, leadership commitment, organizational capabilities, environmental awareness, and operational efficiency goals (Alreahi et al., 2023). This group of factors functions as an efficiency-oriented intrinsic driver aimed at enhancing productivity and profitability.

To determine the priority levels of factors influencing GSCP, numerous studies have applied various methods grounded in diverse approaches to support corporate decision-making. Overcoming the linear limitations of traditional methods has given rise to a growing trend of integrating multi-criteria decision-making methods with intelligent computational models. One of the earlier studies to combine AHP, fuzzy set theory, and artificial neural networks (ANN) into a group decision-support system for supplier selection was conducted by Kar (2015). This approach was subsequently extended to the green supply chain context: (Shabanpour et al., 2017)combined dynamic data envelopment analysis (DEA) with ANN to forecast green supplier performance, while (Tavana et al., 2017) integrated goal programming with dynamic DEA to evaluate sustainable suppliers. More recently, Shabanpour et al. (2025) extended the dynamic network DEA framework combined with ANN to forecast the sustainability of entire supply chains in the circular economy context.

Overall, this systematic review of the literature reveals two research gaps. First, existing studies have not fully explained the differential roles of external pressures and internal resources. Second, from a methodological standpoint, integrated MCDM–ANN frameworks have mainly been validated in industrial manufacturing settings, whereas their application to GSCP in accommodation businesses characterized by small-sample expert data remains unexplored.

2.2. Theoretical foundations

To explain the factors that drive or hinder the implementation of green supply chain practices, numerous international scholars have jointly applied classic theoretical frameworks, most notably Institutional Theory (IT), Stakeholder Theory (ST), and the Resource-Based View (RBV). These three theories are considered to explain different stages of the same process: IT explains why firms are compelled to respond; ST clarifies who generates the pressure and the support required; and RBV explains firms' internal capabilities for translating such pressures into operational practice. Combining these three theories provides a more precise explanation of GSCP as the outcome of external activation and internal conversion, whereby IT accounts for the pressure itself, ST accounts for the agents generating the pressure, and RBV accounts for the capability that converts pressure into GSCP.

Drawing on stakeholder theory, institutional theory, and the resource-based view, this theoretical framework conceptualizes GSC as being shaped by three closely interrelated groups of factors: external pressures, internal capabilities, and organizational barriers. External pressures include institutional pressure (IP), customer pressure (CuP), competitive pressure (CP), institutional support (IS); internal capabilities include green commitment of management (GCM), green training (GT), technological and digital capabilities (TDC); barriers to green supply chain practices (BGSCP) refer to the constraints hindering the adoption and implementation of GSCP. Building on this structure, the study applies an ANN approach to capture the predictive, potentially nonlinear influence of these factors on GSCP based on the FAHP-derived data. This integrated approach provides a more robust assessment of the determinants of GSCP performance than conventional linear techniques, by combining theoretical grounding, multi-criteria prioritization, and predictive modeling. The resulting theoretical framework, comprising ten factors along with their definitions and associated indicator systems, is presented in Appendix 1.

III. Research methodology

This study further applies to the ANN method to classify and assess the relative predictive prominence of the factors within a simulated dataset expanded from interviews with 15 experts using the triangular fuzzy analytic hierarchy process (FAHP). The ANN data consists of data simulated from the FAHP output, and the implementation procedure comprises the following steps:

Step 1: Generating simulated data

Because the ANN method requires large and diverse datasets for effective training (Goodfellow I. et al., 2016), whereas the FAHP analysis relies on a small dataset, this study constructs additional simulated observations to support the ANN training process. The FAHP weights are augmented with a controlled random-noise component (ε) that reflects a plausible degree of variation in expert assessments while preserving closeness to the original data structure:

$$x_{new} = x + \varepsilon, \quad \varepsilon \sim U(-\delta, \delta) \qquad (7)$$

where δ denotes the noise amplitude, typically set at δ = 0.05, ensuring that the new data remains close to the original characteristics (Shorten & Khoshgoftaar, 2019)

The weights are then classified into three levels high, medium, and low based on their relative position with respect to the mean (μ) and standard deviation (σ) of the entire weight set:

$$\begin{aligned} &\text{High}, \quad x > \mu + \sigma \\ &\text{Medium}, \quad \mu - \sigma \leq x \leq \mu + \sigma \\ &\text{Low}, \quad x < \mu - \sigma \qquad (8) \end{aligned}$$

where μ is the mean of the weights generated by FAHP and σ is their standard deviation (Han, Kamber, Pei, 2012). This approach synchronizes the FAHP weights with the ANN training structure, thereby enabling the model to classify factor priority levels consistently.

Step 2: Developing and training the ANN model

Once generated, the simulated dataset was normalized to ensure stability during network training. After normalization, the data were split into two parts: 80% for model training and 20% for out-of-sample validation. Within the training set, 10-fold cross-validation was used to select the optimal network structure and hyperparameter set. The study employs a multilayer perception (MLP) model. This optimal model was trained with a learning rate of 0.3, a momentum of 0.2, and 500 epochs. The training set comprised 300 simulated observations, generated through the controlled noise-addition technique with an amplitude of δ = 0.05 to preserve coherence with the original data structure (Shorten & Khoshgoftaar, 2019). The ANN architecture consists of (1) an input layer of 10 neurons corresponding to CCP, IP, CuP, CP, IS, GCM, GT, TDC, BGSCP, and PBS; (2) two hidden layers containing 6 and 3 neurons, respectively; and (3) a GSCP output layer of 3 neurons corresponding to the three weight categories: "high," "medium," and "low" (Figure 1). This structural design ensures that the ANN model can effectively capture and generalize the underlying patterns in the data. The model was trained using the Cross-Entropy Loss function:

$$L = 1/L \ \Sigma_{i=1}N \ \Sigma_{j=1}C \ y_{ij} \log(\hat{y}_{ij}) \qquad (9)$$

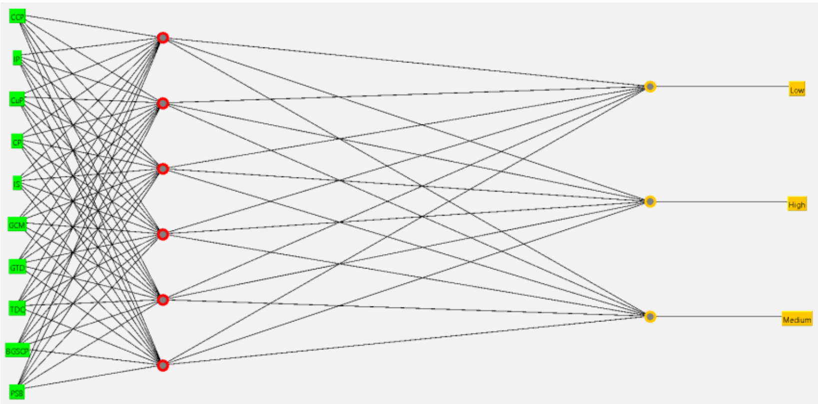

Figure 1. Architecture of the ANN model matrix

Source: Authors' synthesis and data processing using the ANN method (2026)

Step 3: Model evaluation and optimization

The effectiveness of the ANN model was evaluated through classification accuracy, the confusion matrix, and class-level performance metrics. The confusion matrix was used to identify correctly and incorrectly classified cases, thereby supporting fine-tuning of the network structure. In addition, hyperparameters such as the number of hidden neurons, learning rate, momentum, and number of epochs were systematically adjusted to optimize model performance. The final structure was selected based on three criteria: predictive accuracy, convergence stability, and robustness across cross-validation. The data were subsequently processed using the resampling procedure in WEKA to reduce class imbalance.

Step 4: Variable importance analysis using the Garson algorithm

After the ANN model was trained and optimized (Steps 2 and 3), the study applied the Garson algorithm (Garson, 1991) to quantify the relative contribution of each input factor to the classification of GSCP performance. This is one of the most widely used neural network interpretation methods in the machine learning literature, owing to its ability to directly convert learned connection weights into comparable contribution indices across variables, without requiring assumptions about the functional form of the relationship between input and output variables, as is the case in conventional linear regression models. The core principle of the algorithm is to decompose the connection weights between the network's layers into distinct contribution shares for each input variable, based on the premise that the larger the absolute value of a connection weight, the stronger the influence of the corresponding input variable on the model's output. For a single-hidden-layer network structure, the relative importance RI_i of input variable i is determined by Garson's (1991) original formula:

$$RI_i = [\Sigma_h (|W_{ih}| / \Sigma_i|W_{ih}|) \times |W_{ho}|] / \Sigma_i\{\Sigma_h (|W_{ih}| / \Sigma_i|W_{ih}|) \times |W_{ho}|\} \times 100\% \qquad (10)$$

Where is the connection weight between input neuron i and hidden neuron h, and W_{ho} is the connection weight between hidden neuron h and output neuron o. Because formula (10) is formulated only for single-hidden-layer networks, whereas the ANN architecture of this study comprises two hidden layers with 6 and 3 neurons, respectively (Step 2), Garson's (1991) original formula cannot be applied directly. The study therefore adopts the extension proposed by Olden and Jackson (2002) the connection weight method in which the raw contribution of input variable i is computed as the product of the absolute weights across all layers of the network, from the input layer through the first and second hidden layers to the output layer:

$$CW_i = \Sigma_{h1} \Sigma_{h2} (|W_{i,h1}| \times |W_{h1,h2}| \times |W_{h2,o}|) \qquad (11)$$

where h1 and h2 denote the neuron indices of the first hidden layer (6 neurons) and the second hidden layer (3 neurons), respectively; $W_{i,h1}$ is the connection weight between input variable i and neuron h1 of the first hidden layer; $W_{h1,h2}$ is the connection weight between neuron h1 and neuron h2 of the second hidden layer; and $W_{h2,o}$ is the connection weight between neuron h2 and output neuron o. The value CW_i is then normalized into the relative percentage contribution of each variable to the total contribution of the entire model:

$$RI_i = CW_i / \Sigma_i CW_i \times 100\% \quad (12)$$

It should be noted that, because this approach uses the absolute values of the connection weights, it (consistent with Garson's (1991) original formula) reflects only the magnitude of each factor's contribution to the model's classification capacity, without indicating the direction of influence (positive/negative) as in conventional regression coefficients.

IV. Results

The results show that the model achieved an average classification accuracy of 90.0%, with a Kappa statistic of 0.830 (Table 1). According to the classification scale of Landis and Koch (1977), this Kappa value falls within the high range (almost perfect agreement, 0.81–1.00), indicating that the agreement between the model's predictions and the actual labels far exceeds chance level. In addition, the mean absolute error (MAE = 0.0687) and root mean squared error (RMSE = 0.2254) were both low, reflecting that the model's predicted probabilities were well calibrated across the validation folds (Witten, I. H., Frank, E., Hall, M. A., & Pal, 2016). However, because the simulated observations were generated using the controlled noise-addition technique from the same small-sample set of original weights, the performance metrics reported above may partly reflect structural similarity between the training and validation folds rather than a fully independent generalization capacity on new expert data.

Table 1. Overall classification performance metrics of the ANN model (10-fold cross-validation, n = 300)

Metric	Value
Accuracy	90.0%
Kappa Statistic	0.830
Mean Absolute Error (MAE)	0.0687
Root Mean Squared Error (RMSE)	0.2254

Source: Authors' synthesis and ANN data processing (2026)

Regarding the stability of the ANN, Table 2 shows that the model achieved strong and balanced classification performance across all three GSCP performance classes. The weighted-average Precision, Recall (TP Rate), and F-Measure all reached 0.913, while the false positive rate (FP Rate) remained low at 0.044. These indicators demonstrate that the model maintains high stability and limits classification errors evenly across classes. Moreover, the average ROC area reached 0.942, reflecting the model's very strong discriminative ability across GSCP performance levels. These metrics confirm the robustness and stability of the ANN model in the multi-class classification task concerning the GSCP performance levels of accommodation businesses.

Table 2. Classification performance of the ANN model

Metric	Medium	High	Low	Weighted Avg.
TP Rate (Recall)	0.911	0.896	0.932	0.913
FP Rate	0.044	0.040	0.047	0.044
Precision	0.907	0.923	0.908	0.913
F-Measure	0.909	0.909	0.920	0.913
MCC	0.866	0.862	0.880	0.869
ROC Area	0.932	0.938	0.955	0.942
PRC Area	0.840	0.934	0.941	0.906

Source: Authors' synthesis and ANN data processing (2026)

At the class level, the "Low" category exhibited the strongest performance, with the highest Recall (0.932), F-Measure (0.920), MCC (0.880), and ROC area (0.955) (Table 2). This indicates that firms with low GSCP performance possess more distinctive characteristics, making them easier for the ANN model to identify. In contrast, the "high" category achieved the highest Precision (0.923), reflecting a high degree of reliability in the predictions for this class that is, when the model predicts a firm as belonging to the high-performance group, the likelihood of that prediction being correct is very high. The "medium" category showed relatively good overall performance, although its PRC area was noticeably lower than the other two classes (0.840 compared with 0.934 and 0.941), reflecting greater overlap between this class and its neighboring categories consistent with the findings from the confusion matrix analysis.

Table 3. Factor importance ranking

Rank	Variable	Importance (%)	Rank	Variable	Importance (%)
1	IP	23.27	6	GCM	8.62
2	CCP	21.67	7	SGN	5.05
3	GT	11.25	8	TDC	3.58
4	CuP	10.46	9	PBS	3.29
5	CP	10.41	10	BGCSP	2.40

Source: Authors' synthesis and ANN data processing (2026)

To clarify the relative contribution of each input factor to the classification of GSCP performance, the study applied the Garson algorithm (Garson, 1991), extended for the two-hidden-layer network structure via the connection weight method of Olden and Jackson (2002). The results in Table 3 show that the input factors can be grouped into three tiers according to their level of contribution. The highest-contributing group comprises institutional pressure (IP, 23.27%) and climate change pressure (CCP, 21.67%), jointly accounting for over 44% of the model's total contribution. This indicates that these two factors exert the strongest dominant influence in discriminating GSCP performance levels. The moderate-contributing group comprises green training (GT, 11.25%), customer pressure (CuP, 10.46%), competitive pressure (CP, 10.41%), and green management commitment (GCM, 8.62%), reflecting a substantial but non-decisive supporting role. The lowest-contributing group comprises institutional support (IS, 5.05%), technological and digital capability (TDC, 3.58%), perceived sustainability benefits of GSCP (PBS, 3.29%), and barriers (BGSCP, 2.40%), indicating the relatively limited role of this group within the ANN's learned structure in discriminating against GSCP performance levels.

Examination of the confusion matrix shows that the ANN model performed well in classifying GSCP performance levels, with most observations correctly predicted across all three classes (Table 4). Specifically, 54 cases in the "high" class were correctly classified, with only 8 cases misclassified as "medium" and none misclassified as "low." Likewise, the "low" class was also clearly identified, with 63 cases correctly classified and only 5 cases misclassified as "medium." For the "medium" class, the model correctly classified 153 cases, while 8 cases were misclassified as "high" and 9 as "low."

Table 4. Confusion matrix of the ANN model

Actual \ Predicted	Medium	High	Low
Medium	153	8	9
High	8	54	0
Low	5	0	63

Source: Authors' synthesis and ANN data processing (2026)

Another notable finding is that misclassification errors mainly occurred between adjacent classes, particularly between "medium" and "high," with no direct confusion observed between "high" and "low." This suggests that the ANN model captured the hierarchical structure of the target variable reasonably well and effectively distinguished between the two extreme levels. Nevertheless, separating the intermediate class remains a greater challenge for this model. Overall, the relatively low misclassification rate and the concentration of errors among neighboring classes demonstrate the model's good generalization capacity with respect to GSCP performance levels.

In summary, the ANN model achieved strong and stable classification performance with respect to GSCP performance levels. The three-class model exhibited even Precision, Recall, and F-Measure across classes, although the "medium" class showed greater overlap with its neighboring classes. The Garson analysis identified institutional pressure (IP) and climate change pressure (CCP) as the two most dominant factors, reflecting the central role of external drivers relative to firms' internal capabilities. The confusion matrix shows that errors were concentrated mainly among adjacent classes, with no confusion between the two extreme classes, confirming that the model effectively captured the hierarchical structure of the target variable.

V. Discussion

The findings of this study offer important methodological contributions, in that the use of the ANN method enables a clearer identification of the relative role and predictive capacity of the factors influencing GSCP. This study extends this line of inquiry into the hospitality sector, building on prior research integrating fuzzy

MCDM with intelligent computational models, such as Mavi (2015), who applied fuzzy AHP combined with fuzzy ARAS, and Gegovska et al. (2020), who directly integrated fuzzy MCDM with ANN in a manufacturing context. The results show that the ANN achieved high classification accuracy (90%) and a high weighted average MCC value (0.869). These findings demonstrate that the model reliably captures the underlying structure of GSCP performance, particularly in distinguishing between adjacent performance levels. The results therefore carry not only technical significance but also academic value in extending the GSCP research approach from factor-priority assessment toward data-driven performance forecasting and classification, contributing a quantitative analytical tool that has been lacking in the GSCP literature on accommodation businesses.

At the same time, the Garson analysis reveals two groups of factors with clearly distinct roles. The first, high-contributing group comprises institutional pressure (IP) and climate change pressure (CCP), reflecting the role of external activating drivers. The second, moderately prominent group comprises green management commitment (GCM), green training (GT), and technological and digital capability (TDC), reflecting the significance of internal organizational capabilities in translating green orientation into GSCP implementation. This finding is consistent with prior studies that have emphasized external pressure as the primary antecedent of GSCP (Neumayer, 2005; Saeed et al., 2018; Alreahi et al., 2023). However, these studies have largely treated the two factor groups as co-equal companion elements without clarifying the differential magnitude of their contributions. The Garson results in this study suggest that the two groups may instead play distinct role oriented toward activation, the other toward implementation and directly testing this sequential relationship represents an important direction for future research.

The prominence of CCP and IP, occupying a central role within the classification structure, is a noteworthy finding, consistent with Gonzalez et al. (2022) on the substantial role of institutional pressure in GSCP, as well as with hospitality-focused studies such as Alreahi et al. (2023) on the role of external pressure in shaping environmental behavior. However, although the contribution of this group is high, it does not dominate absolutely over the internal-condition group (accounting for only about 45% of the model's total contribution), with the remainder allocated substantially to firm-resource factors. This suggests that institutional pressure, while central, must be accompanied by internal organizational capability to translate into actual implementation effectiveness in the accommodation business context.

In another respect, the Garson analysis also clarifies the supporting role of GT and GCM. This finding aligns with Gonzalez et al. (2022) regarding the complementary role of managerial commitment alongside institutional pressure, while also extending the arguments of Alreahi et al. (2023) and Haldorai et al. (2025) on the joint influence of stakeholders and governance conditions on GSCM in the hotel industry. An additional contribution of this study is to clarify the role of the internal factor group as an implementation condition, thereby helping explain why accommodation businesses facing relatively similar levels of external environmental pressure can nonetheless exhibit very different levels of GSCP implementation. Notably, the GT factor was emphasized by the ANN to a degree exceeding its typical position in the prior literature, consistent with the argument of Jabbour and de Sousa Jabbour (2016) that green human resource management practices, including training, constitute an important foundation for integrating GSCM into firm operations. Whereas earlier studies have mainly regarded training as a supporting factor, the results of this study show that GT functions as an almost core implementation variable within the GSCP model in the hospitality sector.

Within the lowest-contributing group, institutional support (IS), technological and digital capability (TDC), perceived sustainability benefits (PBS), and implementation barriers (BGSCP) exhibited a relatively limited role in discriminating GSCP performance levels according to the ANN's learned structure. This result warrants cautious interpretation along two lines. First, for IS and PBS, the low contribution may reflect the fact that institutional support resources (preferential policies, technical consultancy) and benefit awareness in the study area are not yet sufficiently widespread or differentiated across firms to generate clear classificatory power. This finding carries more of a policy implication than a methodological limitation. Second, for TDC and BGSCP, the low contribution may also partly reflect the limitations of the simulated data, which may not have fully captured the real-world diversity of technological capability and implementation barriers across accommodation businesses of different sizes.

Overall, the study's findings both confirm and extend prior findings in the GSCP literature. Compared with earlier studies, which have largely viewed external pressure as a direct and relatively uniform driver of GSCP adoption, the results of this study provide additional evidence that external pressure is a necessary but not sufficient condition, since the effectiveness of converting such pressure into action depends substantially on firms' internal capabilities.

VI. Conclusion and implications

This study applied an artificial neural network (ANN) combined with the Garson algorithm to assess and rank the relative contribution of ten factors to the classification of green supply chain practice (GSCP) performance among accommodation businesses in Quang Ninh province. The results show that institutional pressure (IP) and climate change pressure (CCP) are the two highest-contributing factors, reflecting the central role of external activating drivers. Meanwhile, green management commitment (GCM) and green training (GT), belonging to the internal organizational capability group, made a substantial contribution. This indicates that the process of translating green orientation into concrete action depends considerably on a firm's internal conditions. These findings suggest a view of GSCP in the hospitality industry as a two-layer structure of factors with distinct roles one layer oriented toward external activation, the other toward internal implementation conditions rather than a set of co-equal, companion factors with comparable influence, as commonly assumed in prior research.

6.1. Academic contributions

This study contributes to the academic literature on GSCP in two ways. Methodologically, it is among the few studies to apply an artificial neural network combined with the Garson algorithm to assess variable importance in the context of small-sample, multi-criteria expert assessment data, a common characteristic of management research on small and medium-sized enterprises in emerging economies. In doing so, the study extends the literature on integrating fuzzy multi-criteria decision-making (fuzzy MCDM) with intelligent computational models (Mavi, 2015; Gegovska et al., 2020) into a new application domain: the hospitality sector at a heritage destination. Theoretically, by providing classificatory evidence of the differential contribution between the external-activation factor group and the internal-implementation factor group, the study enriches the understanding of GSCP, which has previously been largely confined to confirming the parallel roles of the two factor groups (Neumayer & Perkins, 2005; Saeed et al., 2018; Alreahi et al., 2023) without quantifying their relative contributions within a single model.

6.2. Practical and managerial applications

The findings offer several practical implications for accommodation business managers and policymakers in the Ha Long Bay area. First, given that institutional pressure (IP) has the highest contribution, regulatory authorities should continue to maintain and clearly communicate the heritage area's specific environmental conservation regulations, as this is the most influential driver of firms' green supply chain practices. Second, because green management commitment (GCM) and green training (GT) also make a substantial contribution, accommodation businesses particularly small establishments with limited resources, should prioritize investment in staff training programs and in building commitment at the managerial level, rather than relying solely on regulatory compliance. Third, the low contribution of institutional support (IS) within the model is a noteworthy finding for policymakers: it may indicate that current support programs (policy incentives, technical consultancy, training provided by local authorities) are not yet sufficiently widespread or differentiated across firms, suggesting a need to strengthen and diversify support mechanisms in order to narrow the GSCP implementation gap among firms with differing internal capabilities.

6.3. Limitations and future directions

This study has several limitations that should be addressed in future research. Because the ANN training data were simulated from a small original weight set (15 experts), the 10-fold cross-validation procedure may not fully eliminate structural similarity across folds, creating a risk that the reported model performance is somewhat more optimistic than ((Kohavi, 1995). Future research should adopt a group k-fold validation strategy, ensuring that simulated observations derived from the same original weight always belong to the same fold, to provide a more objective assessment of the model's generalization capacity. In addition, this study did not conduct a sensitivity analysis of the simulation noise parameter (δ), nor did it compare ANN performance against alternative classifiers (e.g., Random Forest, SVM); these represent important extensions for further testing the robustness of the proposed methodological framework. Finally, because the Garson algorithm only provides evidence of the static contribution of each factor within the classification model, this study did not test the sequential or mediating relationship between the external-activation factor group and the internal-implementation factor group. Future studies should therefore apply mediation-testing methods (e.g., structural equation modeling with serial mediators) on larger-scale primary data to fully confirm the conversion mechanism between the two factor groups.

Reference

[1]. AlBrakat, N., Al-Hawary, S., Muflih, S. (2023). Green supply chain practices and their effects on operational performance: an experimental study in Jordanian private hospitals. *Uncertain Supply Chain Management*, 11(2), 523–532.

[2]. Alreahi, M., Bujdosó, Z., Dávid, L. D., Gyenge, B. (2023). Green Supply Chain Management in Hotel Industry: A Systematic Review. *Sustainability* (Switzerland), 15(7). https://doi.org/10.3390/su15075622

[3]. Eraña-Díaz, M. L., Enríquez-Urbano, J., Martínez-Bahena, B., Juárez-Chávez, J. Y., D'Granda-Trejo, A., De-la-Rosa-Mondragon, J. (2026). Artificial neural network-based classification of industrial sustainability profiles for differentiated fiscal policy design in remanufacturing processes. *Processes*, 14(9). https://doi.org/10.3390/pr14091501

[4]. Garson, G. D. (1991). *Interpreting neural-network connection weights*. https://api.semanticscholar.org/CorpusID:58482602

[5]. Gegovska, T., Koker, R., Cakar, T. (2020). Green supplier selection using fuzzy multiple-criteria decision-making methods and artificial neural networks. *Computational Intelligence and Neuroscience*, 2020(1), 8811834.

[6]. Geng, R., Mansouri, S. A., Aktas, E. (2017). The relationship between green supply chain management and performance: A meta-analysis of empirical evidences in Asian emerging economies. *International Journal of Production Economics*, 183(Part A), 245–258. https://doi.org/10.1016/j.ijpe.2016.10.008

[7]. Gilbert, N. (2001). *Researching social life* (2nd ed.). Sage Publications.

[8]. Gonzalez, C., Agrawal, V., Johansen, D., Hooker, R. (2022). Green supply chain practices: The role of institutional pressure, market orientation, and managerial commitment. *Cleaner Logistics and Supply Chain*, 5, 100067. https://doi.org/10.1016/j.clscn.2022.100067

[9]. Goodfellow, I., Bengio, Y., Courville, A. (2016). Deep Learning. MIT Press.

[10]. Haldorai, K., Kim, W. G., Phetvaroon, K. (2025). Top management commitment, institutional pressures and green supply chain practices: pathways to sustainable performance. *Journal of Hospitality and Tourism Insights*, 8(8), 2860–2879. https://doi.org/10.1108/JHTI-07-2024-0773

[11]. Han, J., Kamber, M., Pei, J. (2012). *Data mining: Concepts and techniques*. Morgan Kaufmann Publishers.

[12]. Hezam, Y., Luong, H., Anthonysamy, L. (2025). Machine learning in predicting firm performance: a systematic review. China *Accounting and Finance Review*, 27(3), 309–339. https://doi.org/10.1108/CAFR-03-2024-0036

[13]. Jabbour, C. J. C., de Sousa Jabbour, A. B. L. (2016). Green human resource management and green supply chain management: linking two emerging agendas. *Journal of Cleaner Production*, 112, 1824–1833. https://doi.org/10.1016/j.jclepro.2015.01.052

[14]. Kar, A. K. (2015). A hybrid group decision support system for supplier selection using analytic hierarchy process, fuzzy set theory and neural network. *Journal of Computational Science*, 6, 23–33. https://doi.org/10.1016/j.jocs.2014.11.002

[15]. Kohavi, R. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. *Proceedings of the 14th International Joint Conference on Artificial Intelligence*, 2, 1137–1143.

[16]. Mavi, R. K. (2015). Green supplier selection: a fuzzy AHP and fuzzy ARAS approach. *International Journal of Services and Operations Management*, 22, 165–188.

[17]. Neumayer, E., Perkins, R. (2005). Uneven geographies of organizational practice: Explaining the cross-national transfer and diffusion of ISO 9000. Economic Geography, 81(3), 237–259. https://doi.org/10.1111/j.1944-8287.2005.tb00269.x

[18]. Olden, J. D., Jackson, D. A. (2002). Illuminating the "black box": a randomization approach for understanding variable contributions in artificial neural networks. Ecological Modelling, 154(1–2), 135–150. https://doi.org/10.1016/S0304-3800(02)00064-9

[19]. Pérez López, M. del C., Plata Díaz, A. M., Martin Salvador, M., López Pérez, G. (2025). A machine learning approach to classifying sustainability practices in hotel management. *Journal of Sustainable Tourism*, 33(8), 1634–1657. https://doi.org/10.1080/09669582.2024.2397645

[20]. Quang Ninh Department of Tourism (2023). Summary report on theoretical and practical issues concerning Vietnam's 40 years of socialist-oriented reform, with respect to developing the socialist-oriented market economy in Quang Ninh. Quang Ninh.

[21]. Saeed, A., Jun, Y., Nubuor, S. A., Priyankara, H. P. R., Jayasuriya, M. P. F. (2018). Institutional pressures, green supply chain management practices on environmental and economic performance a two theory view. *Sustainability*, 10(5), 1517. https://doi.org/10.3390/su10051517

[22]. Safaei, M., Yahya, K., Al Dawsari, S. (2026). An explainable machine learning framework for sustainable supply chain performance assessment. *Frontiers in Sustainability*, 7–2026. https://doi.org/10.3389/frsus.2026.1803933

[23]. Sarkis, J. (2012). A boundaries and flows perspective of green supply chain management. *Supply Chain Management*, 17, 202–216.

[24]. Shabanpour, H., Yousefi, S., Farzipoor Saen, R. (2025). Forecasting sustainability of supply chains in the circular economy context: a dynamic network data envelopment analysis and artificial neural network approach. *Journal of Enterprise Information Management*, 38(1), 68–93. https://doi.org/10.1108/JEIM-12-2020-0494

[25]. Shabanpour, H., Yousefi, S., Saen, R. F. (2017). Forecasting efficiency of green suppliers by dynamic data envelopment analysis and artificial neural networks. *Journal of Cleaner Production*, 142, 1098–1107. https://doi.org/10.1016/j.jclepro.2016.08.147

[26]. Shorten, C., Khoshgoftaar, T. M. (2019). A survey on Image Data Augmentation for Deep Learning. *Journal of Big Data*, 6(1), 60. https://doi.org/10.1186/s40537-019-0197-0

[27]. Tavana, M., Shabanpour, H., Yousefi, S., Farzipoor Saen, R. (2017). A hybrid goal programming and dynamic data envelopment analysis framework for sustainable supplier evaluation. *Neural Computing and Applications*, 28(12), 3683–3696. https://doi.org/10.1007/s00521-016-2274-z

[28]. Trujillo-Gallego, M., Sarache Castro, W. A., & Sellitto, M. (2025). Unlocking sustainability: a hierarchical approach to environmental dynamic capabilities in supply chain transformation. *Business Strategy and the Environment*, *34*(7), 8516-8553.

[29]. Witten, I. H., Frank, E., Hall, M. A., Pal, C. J. (2016). *Data mining: practical machine learning tools and techniques* (4th ed.). Morgan Kaufmann.

[30]. Xu, X., Gursoy, D. (2015). A conceptual framework of sustainable hospitality supply chain management. *Journal of Hospitality Marketing & Management*, 24, 229–259.