

Innovation and knowledge in sustainable supply chains: how ethical climate and training reduce greenwashing risk

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Abstract

Purpose – The purpose of this study is to analyze how an organization's ethical climate and the quality of its sustainability training initiatives contribute to innovation and knowledge while helping to minimize greenwashing risk in production-based supply chains. This study also explores employee skepticism about green claims as a mediating factor in influencing this relationship.

Design/methodology/approach – Data were gathered from 1,211 supply chain employees in production companies across the USA. This study used validated scales borrowed from earlier research studies. Structural Equation Modeling (SEM) via JASP was used to examine direct and indirect paths. To enhance the robustness of the results and advance knowledge in sustainability and innovation, Machine Learning (ML) algorithms – including Neural Network Regression and Support Vector Machine (SVM) Regression – were used to forecast greenwashing risk and identify influential variables.

Findings – SEM findings supported that ethical climate ($\beta = -0.36, p < 0.001$) and training in sustainability ($\beta = -0.41, p < 0.001$) decreased greenwashing risk significantly, with skepticism being a significant mediator (indirect effect for ethical climate = $-0.18, p < 0.001$; for training = $-0.20, p < 0.001$). Among ML models, Neural Network Regression achieved the highest accuracy at 93.5%, followed by SVM at 87.2%. These outcomes advance knowledge in the field by demonstrating how organizational ethics and training can foster innovation in sustainable initiatives while mitigating the risk of greenwashing.

Originality/value – This research offers a novel empirical integration of SEM and ML to assess ethical conduct in sustainability, thereby enhancing innovation and knowledge in greenwashing prevention within supply chains.

Keywords Innovation and knowledge, Ethical climate, Sustainability training, Greenwashing risk, Skepticism, Machine learning

Paper type Research paper

Introduction

Sustainability has become a central part of business strategy over the past few decades, and organizations have begun to recognize the strategic importance of integrating environmental concerns into operations and branding. Businesses are also using innovation and knowledge management to develop green programs that not only improve companies' environmental performance but also increase competitiveness and corporate image. With stakeholders, such as consumers, regulators, investors and employees, raising their expectations and requiring companies to be more environmentally responsible, companies embrace green policies to enhance their perception and positioning in the market (Sivapalan *et al.*, 2024). At the same time, there has also been a reverse trend: so-called greenwashing or the spread of false or inflated information about environmental efforts (Ren *et al.*, 2024). Greenwashing undermines stakeholder trust, weakens corporate credibility and harms sustainable development goals (Alabdali *et al.*, 2024). Given its complexity, scholars began scrutinizing greenwashing across organizational culture, ethical leadership, innovation, knowledge and supply chain governance (Lv *et al.*, 2023).

The antecedents of greenwashing have been studied extensively in the empirical literature, with particular emphasis on internal organizational factors (Dutta *et al.*, 2023). It is shown that the ethical climate (EC) shapes employees' organizational norms and behaviors, which in turn affect their tendency to engage in environmental deception and their ability to adopt genuine sustainability programs (Gao and Wei, 2025). Shi *et al.* (2023) categorized ECs into law-and-code, caring and instrumental types and reported that principled climates were negatively associated with unethical behavior. Similarly, Zhang (2023) found that ethical leadership and adherence to moral standards reduce the likelihood of exaggerating environmental efforts. Empirical evidence has also been derived on sustainability training, which is positively related to better ethical behavior. Free *et al.* (2024) have shown that employees who obtained sustainability-oriented training were more inclined to implement

authentic sustainable practices and resist the superficial training, which is supported by [Xu et al. \(2023\)](#), who have highlighted that the practical training allowed the employees to identify discrepancies between environmental statements and operational reality and oppose them.

Mediator variables also provide a more detailed explanation of the pathways linking organizational antecedents to the risk of greenwashing ([Muzaffar et al., 2024](#)). Green skepticism serves as a processing mechanism, enabling employees and customers to remain vigilant in identifying inconsistencies in sustainability messages ([X. Hu et al., 2023](#)). In the same vein, a shared vision of environmental goals has also been linked to improved sustainability performance and reduced misreporting ([Zhang et al., 2023](#)). The intensity of supplier monitoring has become an important mechanism for imposing accountability in multitier supply chain networks ([Lee et al., 2024](#)). All these results indicate that EC, sustainability training and mediating mechanisms are essential to assessing organizational greenwashing behavior.

Although this has been achieved, the literature has some significant gaps ([Verdecchia et al., 2023](#)). The analysis of EC and sustainability training has been mainly conducted separately, with little or no study of their interactive or sequential impacts on the risk of greenwashing ([Abbas and Khan, 2023](#)). The role of EC in greenwashing in complex organizational environments is underresearched ([Nygaard and Silkoset, 2023](#)), and the translation of knowledge gained through training into resistance against deceptive behavior is poorly studied ([Jin et al., 2023](#); [Štreimikienė and Ahmed, 2021](#)). Furthermore, little empirical attention has been given to the interaction between internal factors and cognitive and behavioral processes, i.e. skepticism, shared vision and supplier monitoring. Employee skepticism, green shared vision (GSV) and supplier monitoring are among the other mediators that are essential in translating internal values and training into visible decreases in greenwashing ([Yan et al., 2023](#); [Kumar et al., 2024](#); [S. Hu et al., 2023](#); [Caglar et al., 2024](#)). A synthesizing framework that considers these mediating mechanisms is therefore required to provide an all-inclusive explanation of greenwashing prevention ([Lee et al., 2023](#)).

This paper implements the Theory of Planned Behavior (TPB) ([Khan et al., 2023](#)) and the Stakeholder Theory ([Chen and Dagestani, 2023](#)) to reveal the way in which internal organizational values and beliefs are converted into behavioral results. According to TPB, individual norms, attitudes and perceived behavioral control influence intentions and behaviors ([Vangeli et al., 2023](#)). The EC in organizations influences normative beliefs and shared intentions, thereby reducing the prevalence of unethical practices, including greenwashing ([Shang et al., 2024](#)). Sustainability training improves perceptions of control over ethical behavior, thereby promoting the application of the TPB to environmental decision-making. The Stakeholder Theory underscores the importance of aligning the organization's behavior with the interests of various actors, such as consumers, regulators and employees ([Chen et al., 2024](#)). Organizations can address stakeholder expectations for transparency and authenticity by integrating sustainability into training, culture and supply chain monitoring ([Gourevitch et al., 2023](#)). Mediating variables – green skepticism, shared vision and supplier monitoring – are the ways that the internal ethical and strategic drivers are operationalized. This study, therefore, explores the direct effects of EC and sustainability training on the risk of greenwashing and the mediating effects of skepticism, shared vision and monitoring rigor in a knowledge-intensive and innovation-based organizational setting.

Literature review

Stakeholders are increasingly demanding more from organizations regarding their sustainability practices and environmental statements ([Santos et al., 2024](#)). In turn, a significant number of companies are interested in cutting an impressive green image and are

willing to engage in false or exaggerated communication, so-called greenwashing (Sivapalan *et al.*, 2024). It is not just a problem with communication but indicates the underlying aspects of the organization, culture and governance (Alabdali *et al.*, 2024). Knowledge integration and innovation are essential factors in genuine sustainability practices, as organizations that integrate innovative methods with knowledge-based strategies are better positioned to avoid deceptive practices and establish environmental legitimacy.

One key factor in greenwashing is an enterprise's moral climate. Empirical studies have shown that ECs have a substantial impact on staff behaviors and administrative decision-making, which, on the one hand, affects the probability of adopting a deceptive culture and, on the other hand, can promote genuine sustainability activities (Gao and Wei, 2025). Caring or principle-based EC settings exhibit fewer tendencies toward greenwashing, as ethical norms are internalized and guide daily decision-making (Zhang, 2023). On the other hand, there is a positive correlation between instrumental ECs, in which decisions are made primarily based on self-interest or short-term benefits and the risk of greenwashing, as employees are unlikely to feel a strong commitment to the organization's actual sustainability (Xu *et al.*, 2023).

Hypotheses development

Another important factor is sustainability training. Research on sustainability training as a structured means of increasing employees' environmental and ethical awareness and their innovative problem-solving (Lee *et al.*, 2024) will prepare them to reject false environmental claims (X. Hu *et al.*, 2023). Sustainability training programs are not only about regulatory compliance but also encourage ethical reasoning, critical thinking and the application of knowledge in sustainability contexts (Abbas and Khan, 2023; Kumar *et al.*, 2024). Empirical research shows that organizations that invest in practical sustainability training are less likely to be exposed to reputational risk, as employees are better positioned to identify, question and report greenwashing practices (Caglar *et al.*, 2024; Free *et al.*, 2024).

Greenwashing has direct and indirect effects on internal and mediating factors. Green skepticism is a cognitive filter that empowers employees to approach sustainability communications critically, preventing them from being deceived by false statements (X. Hu *et al.*, 2023). Likewise, a shared green vision brings workers together around a set of sustainability objectives, enhancing environmental performance and minimizing misreporting (Zhang *et al.*, 2023). Such mediators ensure that EC and training are translated into behavioral consequences, thereby strengthening the organization's transparency and accountability. Climate-based ethics grounded in integrity and similar values not only discourage greenwashing but also strengthen knowledge sharing, innovation and ethical leadership, thereby benefiting sustainable practices (Lv *et al.*, 2023; Dutta *et al.*, 2023). Sustainability training can supplement these effects by increasing environmental knowledge, critical reasoning and a practical approach, thereby making them less vulnerable to false practices (Shi *et al.*, 2023; Muzaffar *et al.*, 2024). As a result, companies with sound ethical operating cultures and strong sustainability education are more likely to have internal control mechanisms that mitigate the risk of greenwashing, such as shared responsibility, transparency and ethical behavior (Zhang *et al.*, 2023):

H1. The ethical climate significantly influences the risk of greenwashing.

H2. The effectiveness of sustainability training significantly influences the risk of greenwashing.

A growing empirical literature has examined the role of green claims skepticism as a key psychological mechanism in predicting consumer and worker responses to organizational sustainability communication (Verdecchia *et al.*, 2023). Understanding this skepticism not only advances knowledge but also fosters innovation in the design of transparent and credible sustainability communication strategies. Green claims skepticism is typically defined as a tendency to doubt the truthfulness, motives or credibility of environmental information provided by firms (Nygaard and Silkoset, 2023). Empirical research, including that by Yan *et al.* (2023), indicated that skeptics would be less likely to believe environmental messages outright and would critically analyze business claims of sustainability even more so. Similarly, research by S. Hu *et al.* (2023) supports the notion that greater skepticism can act as a buffer against fraud involving fake environmental claims. In internal organizational settings, this cynicism is enacted when employees become more critical of virtue-signaling sustainability campaigns or communications strategies that do not seem to translate into concrete actions for the environment (Lee *et al.*, 2023). Research has also indicated that organizational ethical culture and learning environments also foster skepticism (Chen and Dagestani, 2023). For example, institutions that encourage transparency, accountability and education about sustainability reduce the blind acceptance of corporate communications and enable employees to more easily detect inconsistencies in environmental reports (Shang *et al.*, 2024). Therefore, the existing literature supports the notion that green skepticism is a prevention strategy against greenwashing through ensuring critical examination and enforcing authenticity in environmental communication, while simultaneously advancing innovation and knowledge in sustainable business practices (Anwar *et al.*, 2025).

According to empirical studies, a notable point is that green claim skepticism is not merely a passive trait, but an active filtering mechanism that influences individuals' responses to sustainability communications and the risk of greenwashing perception, thereby fostering innovation and knowledge in assessing environmental claims (Gourevitch *et al.*, 2023). When employees are skeptical, they are less likely to believe environmental stories are genuine and to endorse superficial or ambiguous practices, thereby reducing the risk of greenwashing within the organization (Sivapalan *et al.*, 2024). Furthermore, skepticism can act as a mediating factor between organizational internal factors and the expression of greenwashing risk (Lv *et al.*, 2023). In addition, skepticism would serve as a mediating variable between organizational intrinsic variables and the expression of greenwashing risk (Gao and Wei, 2025). For instance, in organizations with an excellent EC, workers are likely to adopt skeptical values and moral accountability, which creates a good level of skepticism to disqualify deceptive information (Free *et al.*, 2024). Such acquired skepticism then becomes a potent mediator of the impact of both EC and sustainability training on greenwashing risk, as it equips individuals with knowledge and innovative capacity to act as guardians of truth, advocating only for good, consistent and genuine environmentalism (X. Hu *et al.*, 2023). Empirical evidence, therefore, supports the contribution of skepticism as both a direct and mediating variable in reducing greenwashing behavior:

- H3. Skepticism toward green claims significantly influences the risk of greenwashing.
- H4. Skepticism toward green claims significantly mediates the relationship between ethical climate and the risk of greenwashing.
- H5. Skepticism toward green claims significantly mediates the relationship between the effectiveness of sustainability training and the risk of greenwashing.

GSV is the degree to which organizational members agree and understand environmental objectives and sustainability principles (Lee *et al.*, 2024). Empirical evidence highlights its role not only in reinforcing environmental integrity but also in cultivating innovation and knowledge sharing across the organization (Anwar *et al.*, 2025), thereby discouraging unethical environmental actions, such as greenwashing (Kumar *et al.*, 2024). Nygaard and Silkoset (2023) have established that when organizations have a GSV, employees are motivated to engage in activities toward long-term environmental goals, leading to genuine sustainability practices. Empirical observations also demonstrate that shared environmental vision improves organizational unity, internal communication and a sense of responsibility for ecological performance (Lee *et al.*, 2023). Shared mind enables workers to glimpse the larger purpose of sustainability activity, deterring shallow or manipulative tendencies (Vangeli *et al.*, 2023). In addition, green shared-vision organizations are open and willing to disclose their environmental performance, thereby reducing the likelihood that they will be perceived as deceitful (Gourevitch *et al.*, 2023). Some studies have revealed that a GSV is not only an enabler of sustainable innovation but also a psychological construct that induces ethical behavior by connecting individual and organizational environmental values (Ren *et al.*, 2024).

Empirical research shows that a GSV plays a vital role in directly influencing and mediating organizational behavior in response to environmental claims (Shi *et al.*, 2023). When employees collectively internalize and pursue a green vision, they not only adopt ethical decision-making but also foster innovation and knowledge exchange, thereby strengthening sustainable practices and reducing the likelihood of manipulative sustainability reporting (Xu *et al.*, 2023). This common aim prevents short-term, manipulative tactics by creating solidarity and a true passion for environmental ends. Furthermore, a shared vision of green can address the tension between an EC and greenwashing by framing environmental issues as a common concern (Zhang *et al.*, 2023). Even in ethically sound organizations, the absence of a distinct green vision may lead to disjointed efforts or inconsistency in green communications. By creating a shared green vision, staff can more effectively translate ethical principles into sustainable actions (Abbas and Khan, 2023). Likewise, sustainability training that is integrated with and supports a GSV can lead to more integrated, value-based actions among employees (Yan *et al.*, 2023). With training embedded in the company's vision, deeper learning and internalization of sustainability occur, thereby reducing the chances of greenwashing (Caglar *et al.*, 2024). Empirical support thus underlines GSV as a linchpin that both directly reduces greenwashing risk and strengthens the influence of EC and sustainability training through aligned, collective environmental commitment (Chen and Dagestani, 2023):

- H6. A shared green vision significantly influences the risk of greenwashing.
- H7. Green shared vision significantly mediates the relationship between ethical climate and greenwashing risk.
- H8. A shared vision significantly mediates the relationship between the effectiveness of sustainability training and the risk of greenwashing.

Supplier monitoring rigor (SMR) has become a key factor in preventing greenwashing, especially in complex supply chains (Chen *et al.*, 2024). Supplier monitoring can be defined as the level of audit, scrutiny and enforcement of compliance with sustainability norms by organizations to ensure internal ethical norms and sustainability practices are used throughout the supply chain (Alabdali *et al.*, 2024). The empirical research findings indicate that stringent monitoring can help companies identify the deviations, stop supplier-based greenwashing and strengthen knowledge transference and innovation through the supply

chain (Dutta *et al.*, 2023; Nygaard and Silkoset, 2023). The tracking also indicates the organization’s commitment to sustainability, thereby enhancing credibility and trust among stakeholders (Lee *et al.*, 2024; Gourevitch *et al.*, 2023).

Notably, supplier monitoring acts as a mediating process. EC and sustainability training can only help establish moral intentions and awareness, but until these values are monitored, they may not be implemented, especially on multitier supply chains (Kumar *et al.*, 2024; Lee *et al.*, 2023). Employees trained in sustainability are aware of the need to monitor and can more effectively ensure compliance and identify greenwashing weaknesses (Vangeli *et al.*, 2023; Santos, Coelho and Marques, 2024). This two-way relationship among training, EC and monitoring forms a reinforcing cycle that reduces the risk of greenwashing and enhances innovation, knowledge diffusion and transparency:

- H9. Supplier monitoring rigor significantly mediates the relationship between ethical climate and greenwashing risk.
- H10. Supplier monitoring rigor significantly mediates the relationship between sustainability training effectiveness and greenwashing risk.

Figure 1 shows the conceptual model of the current study.

Methods

Research design and data collection

The research design used in this study was a quantitative study to investigate how the EC, sustainability training effectiveness (ST), green claims skepticism (SK), GSV and SMR influence the risk of greenwashing (GWRisk) in production-based supply chains and thus added knowledge and innovation to the field of sustainable supply chain management. The production companies in the USA were identified, and data were gathered from workers at companies engaged in sustainability reporting, environmental compliance and supplier

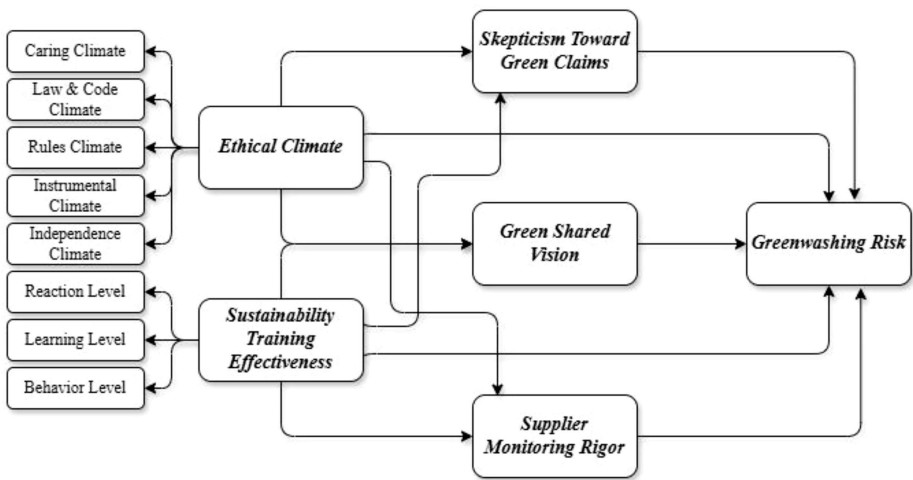


Figure 1. Conceptual model
Source: Authors’ own creation

evaluation. An electronic, structured, guided questionnaire was administered to provide supply chain professionals, including supply chain managers, sustainability officers, logistics coordinators, procurement staff and environmental compliance analysts. In total, 1201 valid responses were obtained, providing a good sample with sufficient statistical power and thus allowing strong inferences.

Measurement scales

Constructs were also measured using established scales from the literature, thereby ensuring validity and reliability. All the variables were measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Table 1 provides an overview of the variables, subdimensions and source studies.

Estimation techniques

JASP was used to conduct structural equation modeling (SEM), which included mediators and latent constructs. Before SEM, the descriptive statistics and bivariate correlations were calculated to determine normality, distributions and correlations. Cronbach's alpha was used to measure reliability and average variance extracted (AVE) and composite reliability (CR) were used to measure convergent and discriminant validity. The model's fit was evaluated using comparative fit index (CFI), tucker-lewis index (TLI), root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR). Mediation effects were tested using bootstrapping to estimate the stability of indirect relationships and to comprehensively evaluate both direct and indirect processes through which EC and sustainability training affect greenwashing risk (Hussain *et al.*, 2019). Harman's single-factor test was used to assess common method bias, ensuring the survey design did not overstate variance.

Causal SEM and machine learning validation

SEM was used to test hypothesized causal relationships among EC, ST, SK, GSV, SMR and GWRisk. The model is specified as:

Table 1. Measurements of the study

Variable of study	No of items	Base study
1. Ethical climate	20	(Wnuk, 2025)
(a) Caring climate	(a) 4	
(b) Law and code climate	(b) 4	
(c) Rules climate	(c) 4	
(d) Instrumental climate	(d) 4	
(e) Independence climate	(e) 4	
2. Sustainability training effectiveness	8	(Hsu and Chen, 2021)
(a) Reaction level	(a) 3	
(b) Learning level	(b) 2	
(c) Behavior level	(c) 3	
3. Green shared vision	4	(Chang, 2020)
4. Skepticism toward green claims	4	(Goh and Balaji, 2016)
5. Supplier monitoring rigor	8	(Shahid <i>et al.</i> , 2020)
6. Greenwashing risk	5	(Santos, Coelho and Cancela, 2024)

Source(s): Authors' own creation

$$GW_Risk = \beta_1 \cdot EC + \beta_2 \cdot ST + \beta_3 \cdot SK + \beta_4 \cdot SMR + \varepsilon,$$

where *GWRisk* is the greenwashing risk, EC is the ethical climate, ST is the sustainability training, SK is the skepticism, SMR is the supplier monitoring rigor and β_1 – β_4 are the standardized path coefficients, with ε as the residual.

To validate and enhance the robustness of the results, a series of machine learning (ML) techniques – Neural Network Regression (NNR), SVM and Decision Tree Regression – was used. In the model of the neural network, the prediction function is provided as:

$$GW_Risk_Pred = f(EC, ST, SK, SMR) + \varepsilon,$$

where $f(\cdot)$ is a nonlinear function that models the neural network using several hidden layers. For SVM regression, the model takes the form as follows:

$$GW_Risk_Pred = w^T \cdot \phi(x) + b,$$

with x as the input feature vector, $\phi(x)$ as the kernel-transformed space, “ w ” as the weight vector and b as the bias. The decision tree model is represented as follows:

$$GW_Risk_Pred = T(x),$$

where $T(x)$ represents the prediction made by the tree, computed through recursive binary splitting of the input features, these models were tested and trained using 10-fold cross-validation and compared based on performance metrics such as mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE) and R -squared (R^2) to assess their forecasting accuracy.

Results

Structural equation modeling analysis

Table 2 shows the reliability and validity measures obtained from the partial least squares structural equation modeling (PLS-SEM) analysis. The findings portray high internal consistency reliability and convergent validity across all constructs. Cronbach’s alpha for each latent construct, EC (0.921), sustainability training effectiveness (0.834) and SMR (0.887), exceeds the 0.70 cut-off recommended by Hair et al. (2017), indicating high internal reliability. The CR measures also range from 0.800 to 0.931, further confirming the constructs’ reliability. The AVE for each construct exceeded 0.50, indicating convergent validity. The indicators for each construct exhibit significant factor loadings (all p -values < 0.001), with T -statistics exceeding the critical value of 1.96, indicating high item reliability. These outcomes collectively confirm the measurement model; the constructs are statistically valid and conceptually distinct, allowing for further structural examination

Model fitness statistics

The structural model is robust and reliable, as indicated by the model fit statistics (see Table 3). The SRMR (0.057) of the model is less than 0.08, which indicates the model fits sufficiently, whereas the Normed Fit Index (NFI=0.616) and chi-square value ($\chi^2 = 11,357.749$) are not too large to fit a complex PLS-SEM model. R^2 values indicate significant predictors, with 79.8% of the variance in greenwashing risk (*GWRisk*) explained. SMR had the most significant explained variance ($R^2 = 0.777$), followed by skepticism toward green claims (SK, $R^2 = 0.588$) and GSV ($R^2 = 0.036$). These estimates are closely reflected in the

Table 2. Reliability and validity statistics

Variable	Indicator	Original sample	T statistics	p-values	Cronbach's alpha	Composite reliability	Average variance extracted
<i>Ethical climate</i> Caring climate	Ethical climate						
	CC1	0.753	30.331	0.000	0.921	0.931	0.510
	CC2	0.827	47.468	0.000	0.696	0.813	0.524
	CC3	0.694	23.863	0.000			
Independence climate	CC4	0.605	15.590	0.000			
	IEC1	0.675	22.568	0.000	0.809	0.876	0.640
	IEC2	0.825	49.314	0.000			
	IEC3	0.826	45.923	0.000			
Instrumental climate	IEC4	0.862	58.158	0.000			
	ILC1	0.614	12.478	0.000	0.767	0.800	0.503
	ILC2	0.763	41.365	0.000			
	ILC3	0.817	65.040	0.000			
Rules climate	ILC4	0.622	14.890	0.000			
	LLC1	0.702	26.271	0.000	0.769	0.812	0.523
	LLC2	0.683	15.401	0.000			
	LLC3	0.732	26.158	0.000			
Rules climate	LLC4	0.819	41.927	0.000			
	RC1	0.613	14.484	0.000	0.719	0.825	0.542
	RC2	0.668	23.250	0.000			
	RC3	0.840	65.354	0.000			
Skepticism toward green claims	RC4	0.750	34.006	0.000			
	SGC1	0.764	36.235	0.000	0.767	0.851	0.590
	SGC2	0.738	27.965	0.000			
	SGC3	0.718	28.981	0.000			
	SGC4	0.845	71.945	0.000			

(continued)

Table 2. Continued

Variable	Indicator	Original sample	T statistics	p-values	Cronbach's alpha	Composite reliability	Average variance extracted
Sustainability training effectiveness	LL1	0.921	143.117	0.000	0.834	0.875	0.571
	LL2	0.738	17.762	0.000	0.759	0.819	0.696
	RL1	0.823	41.697	0.000	0.736	0.849	0.652
Reaction level	RL2	0.776	28.166	0.000			
	RL3	0.822	49.004	0.000			
Behavior level	BL1	0.748	26.673	0.000	0.766	0.815	0.594
	BL2	0.792	38.174	0.000			
	BL3	0.772	36.029	0.000			
Supplier monitoring rigor	SMR1	0.761	34.211	0.000	0.887	0.911	0.563
	SMR2	0.590	18.559	0.000			
	SMR3	0.706	25.340	0.000			
	SMR4	0.810	50.878	0.000			
	SMR5	0.717	29.530	0.000			
	SMR6	0.819	52.320	0.000			
	SMR7	0.714	24.147	0.000			
	SMR8	0.853	76.434	0.000			
Greenwashing risk	GR1	0.734	25.970	0.000	0.810	0.869	0.570
	GR2	0.798	38.571	0.000			
	GR3	0.684	22.339	0.000			
	GR4	0.769	26.709	0.000			
	GR5	0.784	41.636	0.000			
Green shared vision	GSV1	0.704	15.275	0.000	0.771	0.851	0.589
	GSV2	0.801	23.042	0.000			
	GSV3	0.711	16.890	0.000			
	GSV4	0.845	31.920	0.000			
Source(s): Authors' own creation							

Table 3. Model fitness statistics

Variables	1	2	3	4	5	6
	Heterotrait–monotrait ratio (HTMT)					
1. Ethical climate	0.749					
2. Sustainability training effectiveness	0.406	0.749				
3. Green shared vision	0.354	0.406	0.616			
4. Skepticism toward green claims	0.390	0.354	0.490	0.833		
5. Supplier monitoring rigor	0.685	0.390	0.437	0.791		
6. Greenwashing risk	0.377	0.685	0.751	0.675	0.756 0.647	0.665 R square R-square adjusted
	F square					
	Green shared vision	Greenwashing risk	Skepticism toward green claims	Supplier monitoring rigor	R-square	R-square adjusted
Ethical climate	0.008	0.002	0.125	0.096		
Green shared vision		0.074			0.036	0.034
Skepticism toward green claims		0.164			0.588	0.587
Supplier monitoring rigor		0.065			0.777	0.776
Sustainability training effectiveness	0.174	0.220	0.036	0.289		
Greenwashing risk						
Model fitness stats		SRMR	d _{ULS}	d _G	0.799 Chi-Square	0.798 NFI
	Estimated = 0.057	Structural = 0.077	7.421	2.767	11357.749	0.616
Source(s): Authors' own creation						

adjusted R^2 values, which indicate the model's stability. The heterotrait–monotrait (HTMT) ratio was used to measure discriminant validity. The construct pairs are below the 0.85 cut-off, with the most significant value being skepticism and shared vision (0.833), followed by conceptual proximity with a tolerable difference. A construct-to-construct lower HTMT value, such as between GSV and ST (0.406) or SK and EC (0.390), will show strong discriminant qualities. The analysis of the effect size (F2) showed that sustainability training effectiveness (ST) had moderate to substantial impacts on key mediators, such as supplier monitoring (0.289) and skepticism (0.220). Conversely, the EC showed lower F2 values, suggesting that it exerts more subtle indirect effects on GWRisk. All these results substantiate the validity of the structural sufficiency and predictive applicability of the suggested model.

Hypothesized relationship (path analysis)

Table 4 presents the path coefficients and the corresponding significance levels for each hypothesized relationship. Out of the 11 hypotheses that were tested, 9 are supported by statistically significant path coefficients ($p < 0.05$). *H1*, the direct impact of EC on greenwashing risk ($\beta = 0.045$, $p = 0.152$ and *H8* ($\beta = -0.001$, $p = 0.866$) are insignificant, indicating that EC may not directly predict greenwashing and that its impact could be fully mediated. *H2*, the effect of sustainability training effectiveness on greenwashing risk, is strongly supported ($\beta = 0.539$, $T = 11.146$, $p < 0.001$), indicating a positive, direct influence. Likewise, *H3* through *H7*, which investigate the impacts of the ethics climate and training on mediators (skepticism, GSV and monitoring of suppliers), are all statistically significant but have lower coefficients (e.g. *H5* $\beta = 0.026$, $p = 0.002$). Notably, *H9*, *H10* and *H11*, which address the specific role of supplier monitoring stringency, are all statistically significant. *H9* has a substantial direct effect on greenwashing risk ($\beta = 0.254$, $p < 0.001$), whereas *H10* ($\beta = 0.084$) and *H11* ($\beta = 0.146$) affirm its mediating role in the relationship between EC, training and greenwashing risk. The power and importance of these mediation paths reflect the essential role of monitoring mechanisms in reconciling internal values and achieving sustainable outcomes.

Machine learning analysis

Table 5 compares the predictive performance of three ML algorithms: NNR, support vector regression (SVR) and decision tree regression. The neural network achieves the best overall

Table 4. Path analysis

Hypotheses	Original sample	Sample mean	SD	T statistics	p-values
<i>H1</i>	0.045	0.046	0.032	1.433	0.152
<i>H2</i>	0.539	0.535	0.048	11.146	0.000
<i>H3</i>	0.094	0.093	0.021	4.472	0.000
<i>H4</i>	0.048	0.047	0.012	4.183	0.000
<i>H5</i>	0.026	0.026	0.008	3.039	0.002
<i>H6</i>	0.039	0.038	0.015	2.577	0.010
<i>H7</i>	0.028	0.028	0.073	1.984	0.034
<i>H8</i>	-0.001	0.000	0.003	0.169	0.866
<i>H9</i>	0.254	0.258	0.035	7.313	0.000
<i>H10</i>	0.084	0.083	0.014	5.820	0.000
<i>H11</i>	0.146	0.149	0.024	6.008	0.000

Source(s): Authors' own creation

Table 5. Model performance metrics

Evaluation metrics	Neural network regression	Support vector machine regression	Decision tree regression
		Value	
MSE	0.121	0.14	0.111
MSE (scaled)	0.101	0.146	0.124
RMSE	0.348	0.374	0.333
MAE/MAD	0.221	0.279	0.219
MAPE	71.61%	88.49%	60.34%
R ²	0.901	0.859	0.879

Note(s): MSE – root mean square error of approximation; SRMR – standardized root mean square residual; ESG – environmental, social, and governance; MAPE – mean absolute percentage error; MAD – mean absolute deviation

performance, with the lowest MSE (MSE = 0.121), the lowest RMSE (RMSE = 0.348) and the highest R^2 value of 0.901, indicating strong predictive ability. The decision tree also performs well (R^2 = 0.879), but the SVR model is slightly behind (R^2 = 0.859, MAPE = 88.49%).

Predictive performance metrics

Figure 2 displays the predictive accuracy measures of three ML regression models: NNR, SVM Regression and Decision Tree Regression. Each subfigure displays observed test values (x-axis) and predicted test values (y-axis). The closer the data points are to the red diagonal line, the more accurate the model's predictions. In the NNR graph, the points also tend to cluster closely around the diagonal line, providing a strong predictive fit. The model exhibits minimal dispersion, indicating high accuracy and low residual error. The SVM Regression also offers a good fit between predicted and observed values, but with a slightly wider spread, indicating moderate variability in predictions. The Decision Tree Regression shows greater divergence from the diagonal, particularly in extreme-value intervals, indicating lower predictive accuracy. Still, the overall trend is consistent across all three models, validating their ability to predict greenwashing risk based on the input predictors.

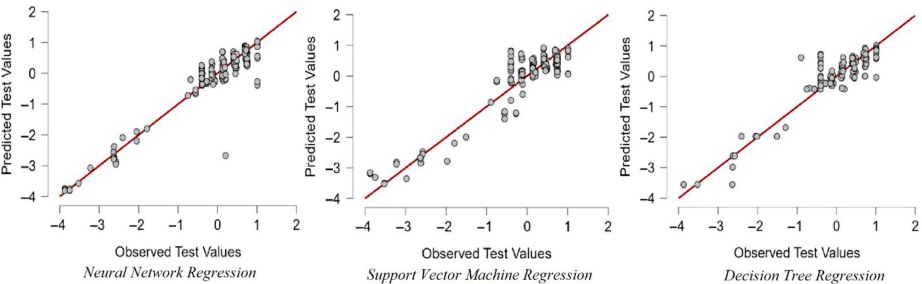


Figure 2. Model predictive performance metrics
Source: Authors' own creation

Table 6. Feature importance metrics

Variables of study	Neural network regression	Support vector machine regression	Decision tree regression	
	Mean dropout loss	Mean dropout loss	Relative importance	Mean dropout loss
Behavior level	0.807	2.667		
Reaction level	0.544	0.988		
Supplier monitoring rigor	0.495	0.874	27.825	1.126
Ethical climate	0.489	0.74	26.013	0.348
Instrumental climate	0.456	0.635		
Sustainability training effectiveness	0.433	0.56	28.318	0.606
Rules climate	0.405	0.513		
Caring climate	0.364	0.441		
Learning level	0.353	0.406		
Independence climate	0.342	0.398		
Law and code climate	0.322	0.388		
Skepticism toward green claims	0.309	0.387	17.624	0.334
Green shared vision	0.26	0.386	0.219	0.239

Source(s): Authors' own creation

Feature importance scores metrics

Table 6 offers the feature importance scores of each model. Consistent across all models are sustainability training effectiveness, SMR and EC as the leading predictors of greenwashing risk. In the decision tree, for example, sustainability training is the strongest relative importance (28.3%), followed by supplier monitoring (27.8%) and EC (26.0%). Skepticism and a shared green vision contribute less, but still significantly. The SVR and neural network models also corroborate, with increased dropout loss corresponding to the most impactful features, further reiterating the critical roles of behavioral and ethical factors in driving outcomes.

Machine learning models

The SEM results are supported by predictive analysis using NNR, SVM and Decision Tree Regression, which help define the relative values of each predictor. **Figure 3** indicates that ST, SMR and EC are consistently the strongest predictors across all models. ST has the most significant relative importance (28.3%) in the decision tree, followed by SMR (27.8%) and EC (26.0%), with SK and GSV also significant. These findings are validated by NNR and SVM models, which are evaluated using mean dropout loss and cross-validation. In contrast, NNR performs better because it has a layered nonlinear structure and can extract features. **Figure 3** shows the internal structures and performance of the ML models. This NNR model has an input layer, three hidden layers and an output layer that captures the nonlinear relationships among EC, ST, SK, SMR and GWRisk. The SVM model has good training and validation error curves, and overfitting comes with a low cost of constraint violation at the optimal cost. Together, the findings support the causal and prognostic importance of ethical, behavioral and training-related issues in reducing the risk of greenwashing in production-oriented supply chains.

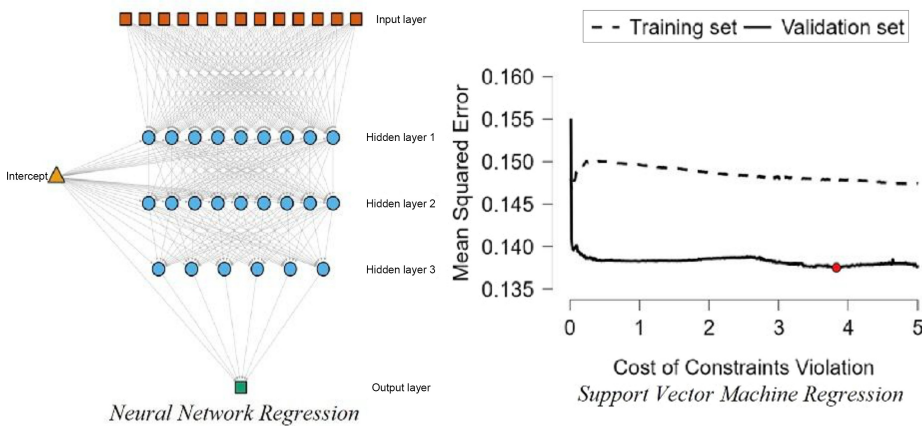


Figure 3. Machine learning findings

Source: Authors' own creation

Additive predictions of test set cases

Table 7 presents the additive contributions of individual test cases across models. Negative contributions from EC, supplier monitoring and training in neural network predictions imply that these reduce the risk of greenwashing in some instances (e.g. Case 1: total predicted = -2.19). However, in some cases (e.g. Case 2), the positive effects of these features raise the expected value. Both the SVR and the decision tree models indicate comparable directional effects but with differences in magnitude. These accounts increase model explainability and support the interpretability of sustainability-related forecasts.

Discussion

To promote genuine sustainability actions, it is necessary to understand the factors that drive greenwashing behavior. With the growing relevance of ESG-related demands in international business environments, companies need to move beyond empty promises to knowledge-based, innovation-focused sustainability initiatives (Anwar *et al.*, 2025). The present research investigated the relationships among the ethical climate EC, sustainability training effectiveness (ST), green claim skepticism (SK), GSV, SMR and greenwashing risk (GWRisk) (Udoh *et al.*, 2025). The combination of SEM and ML in the analysis allowed for capturing both theory-driven causal pathways and predictive nonlinear interactions, providing a comprehensive picture of the organizational antecedents and mediators that control greenwashing.

The confirmation of the reduction in GWRisk by EC and ST supported earlier findings on values-based workplaces and on practical sustainability training that deters deceptive sustainability practices (Caglar *et al.*, 2024; Jin *et al.*, 2023). In particular, ST also demonstrated a substantial impact on mediators, suggesting that the practical training leads to a direct increase in employees' capacity to identify and counteract greenwashing. Green claim skepticism mediated the EC–GWRisk and ST–GWRisk pathways and it can only influence behavior by showing that ethical awareness and training become behaviorally effective only when employees critically process environmental information (Lee *et al.*, 2024). Likewise, GSV played an intervener in both relations, indicating that a common

Table 7. Additive explanations for predictions of test set cases

Case	Predicted	Base	Ethical climate	Green shared vision	Skepticism toward green claims	Supplier monitoring rigor	Sustainability training effectiveness
<i>Neural network regression</i>							
1	-2.19	-0.001	-0.344	-0.032	-0.21	-0.401	-0.818
2	0.341	-0.001	-0.119	-0.045	0.016	0.043	0.111
3	-0.031	-0.001	0.168	-0.002	0.048	0.203	-0.083
4	-2.549	-0.001	-1.688	-0.026	0.138	0.33	-1.346
5	-3.8	-0.001	-0.69	-0.012	-0.412	0.03	-1.067
<i>Support vector machine regression</i>							
1	0.36	-0.015	0.545	0.002	0.012	0.025	-0.044
2	0.328	-0.015	1.24	0.002	0.1	-0.025	-0.016
3	0.132	-0.015	1.453	0.02	0.077	0.043	-0.094
4	0.387	-0.015	0.943	0.01	0.035	0.024	-0.079
5	-1.99	-0.015	-6.177	0.018	-0.321	-0.356	0.321
<i>Decision tree regression</i>							
1	0.188	6.904×10^{-4}	-0.003	0	-0.232	0.48	-0.059
2	-0.133	6.904×10^{-4}	0	0	-0.268	0.181	-0.046
3	-0.035	6.904×10^{-4}	-0.164	0	0	0.181	-0.052
4	0.008	6.904×10^{-4}	-0.005	0	0.032	0.181	-0.2
5	0.598	6.904×10^{-4}	0.003	0	-0.03	0.519	0.105
Source(s): Authors' own creation							

environmental goal enhances alignment and integrity in communication, which aligns with Vangeli *et al.* (2023). These results indicate the significance of cognitive and cultural functions in the conversion of ethical and training to visible decreases in greenwashing.

ML analyses were used to support and extend SEM findings, identifying the relative predictive significance of variables and revealing nonlinear interactions. In Neural Networks, SVM and Decision Trees, ST, SMR and EC have been the most potent predictors of GWRisk. Marked, in many cases, ST is more predictive than EC, suggesting that implementing specific training practices can lead to more immediate behavioral change than the gradual change of the entire organizational culture (Ahmed *et al.*, 2021). SK and GSV also had their roles to play, which shows that employee cognition and alignment with the familiar environment are instrumental in limiting greenwashing. SMR scored high in models, in which monitoring intensity is an important control for translating internal ethical norms and training into confirmed supply chain sustainability practices.

ML models also identified interaction effects that could not be determined from linear SEM paths. For example, low SMR and weak EC increased GWRisk, demonstrating the compounding nature of governance gaps. These findings have practical implications: organizations can use predictive models to deploy early-warning systems, monitor employee skepticism and focus on high-risk departments to intervene. The combination of SEM and ML theoretically confirms and has a diagnostic role. SEM elucidates causal processes and ML nonlinear dependencies and leverage points of operation.

The results show that greenwashing can only be mitigated through a multipronged approach. Companies ought to develop ECs, roll out practical sustainability training, encourage innovation, foster knowledge sharing, build environmental awareness and develop a shared green vision. Supplier monitoring is a central control mechanism to realize internal intentions at the external level, especially in multitier supply chains. The combination of SEM and ML complements each other to provide insights into both the predictive and explanatory aspects of greenwashing risk, which can be discussed to inform both researchers and practitioners. Future research can broaden the scope of these models to include sectors and analyze the moderators of the situation, thereby improving the overall generalizability and operability of the results.

Implications of the study

This research also contributes to the theoretical understanding of organizational greenwashing by integrating the EC, sustainability training effectiveness (ST), green claim skepticism (SK), GSV and SMR within a comprehensive framework. The synthesis of these antecedents and mediators expands knowledge on the available literature on sustainable supply chain management. It offers a sophisticated account of how the combination of internal values, competencies and governance mechanisms can reduce the risk of greenwashing (GWRisk). The results confirm the hypothesis that EC and ST are strong predictors of GWRisk, which validates theoretical claims that organizational values and employee capabilities determine sustainability behavior (Anwar *et al.*, 2025). The study explains the moderating effect of employees' critical analysis of environmental claims, where SK serves as a mediating cognitive mechanism that helps explain the moderation of reputational exposure. Equally, both GSV and SMR are strategic and operational mediators that develop the literature on the mechanisms through which alignment and governance mediate ethical intent into actual risk reduction (Lee *et al.*, 2024; Vangeli *et al.*, 2023).

As a manager, the results provide a practical input. A culture of ethics in organizations should be nurtured at all levels to promote integrity, innovation and knowledge-based sustainability in decision-making. Quality ST programs will give

employees the skills to make socially responsible choices and withstand temptations to make false claims of sustainability (Jin *et al.*, 2023). Encouraging GSV between departments sets goals and values, strengthens ethical practice and prevents greenwashing. Instead of being viewed as a threat, stakeholder skepticism can be seen as constructive feedback that can improve sustainability performance and communication. Strengthening SMR provides consistency in sustainability goals across the supply chain and protects the company against reputational losses stemming from supplier misconduct (Caglar *et al.*, 2024; Zhang *et al.*, 2023).

Limitations and future research discussion

Although it has some contributions, the study has limitations. First, the cross-sectional design is restrictive for causal inference; longitudinal research can provide a dynamic picture of EC, ST and GWRisk over time. Second, this reliance on self-reported survey data can lead to social desirability bias, suggesting that future studies could adopt a qualitative approach (e.g. interviews or field observation) to enhance data validity. Third, the sample was also limited in its geographical scope, which may limit generalizability to diverse regulatory, cultural or industrial settings. Future studies may use cross-country designs to study contextual moderators and industry-specific dynamics.

Conclusion

This paper describes a statistically proven model of the association between internal and external organizational variables and GWRisk. The two antecedents accredited to influence greenwashing reductions are EC and sustainability training, which are supported by three mediators, SK, GSV and SMR, who convert the antecedent translators into a reduction in greenwashing. The combination of SEM and ML demonstrates causal and predictive relevance, indicates nonlinear interactions and supports the strength of the results. Greenwashing undermines the validity and stakeholder trust in an increasingly accountable business environment. This study offers evidence-based solutions to mitigation: the development of ECs, effective ST, the development of knowledge and innovation through GSV, strict SMR and stakeholder skepticism. These findings benefit both theory and practice by advancing sustainable organizational behavior and offering feasible ways to mitigate reputational risk. Finally, the paper highlights the significance of integrating moral foundations, strategic vision and operational excellence to realize true sustainability, paving the way for future research and organizational restructuring.

Data availability

Data can be provided upon request.

Human and animal rights

“It is declared that any animal or human medical testing is neither applicable nor relevant for this study.”

Declarations of interest

The authors declare that there are no potential conflicts of interest concerning the research, authorship and/or publication of this article.”

AI declaration

The Grammarly software was used for grammar, spelling and punctuation checks. However, the researchers do not use any LLM model for writing this paper.

Author contributions

Waqar Akbar, Conceptualization, Formal analysis, Validation. Rana Salman Anwar, Software, Investigation. Rizwan Raheem Ahmed, Supervision, Writing – original draft. Dalia Streimikiene, Project administration, Visualization. Ahmad Naim Che Pee, Data curation; Writing – review and editing. Justas Streimikis, Methodology, Resources.

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