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The green mirage of machines: how perceived AI transparency shapes perceived ethics in sustainability messages

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ABSTRACT

Artificial intelligence (AI) is increasingly integrated into sustainability communication, offering opportunities for enhanced transparency while simultaneously introducing risks of algorithmic greenwashing. This study examines how AI-generated environmental messages influence consumer ethics, trust, and green purchasing intentions. A conceptual model incorporating perceived artificial intelligence transparency (PAT), perceived greenwashing risk (PGR), ethical perception of artificial intelligence communication (EPAC), trust in automated sustainability information, and green purchase intention (GPI) was empirically tested using data from 375 consumers exposed to AI-enabled sustainability content. Partial least squares structural equation modelling (PLS-SEM) was used to assess the hypothesized relationships. Results indicate that PAT significantly increases ethical perception and trust, while reducing PGR. Ethical perception and trust strongly predict GPI and function as key mediators linking PAT to sustainable consumer behavior. The findings highlight AI's dual potential as a mechanism for authentic sustainability communication or a source of digital deception. This study provides actionable insights for organizations adopting AI-driven communication and contributes to the emerging literature on ethical AI governance in sustainability marketing.

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1. INTRODUCTION

The rapid integration of artificial intelligence (AI) into sustainability communication has revolutionized how organizations create and share environmental messages. AI-driven tools are increasingly used to automate content creation, personalize sustainability narratives, and support environmental reporting, enabling firms to communicate their green commitments more efficiently and at scale [1], [2]. However, alongside these advantages, AI-enabled communication introduces significant ethical concerns related to transparency, accountability, and authenticity [3]. When sustainability messages are generated or curated by opaque AI systems, the risk of misleading or exaggerated environmental claims increases, extending established greenwashing concerns into algorithmically mediated communication [4], [5].

In today's digital world, consumers increasingly encounter AI-driven sources like chatbots, recommendation systems and automated content when evaluating corporate and product information [6], [7]. However, the limited explainability of AI decision-making complicates their ability to assess the accuracy, balance and selective framing of environmental claims [8]. This ethical opacity blurs the boundary between genuine sustainability commitment and algorithmically optimized persuasion. Because green purchasing

decisions depend strongly on perceived risk and trust, such opacity can heighten skepticism, erode trust, and weaken willingness to engage in sustainable consumption [9], [10].

While traditional greenwashing has been widely examined in the marketing and business ethics [4], [5], [11], [12], algorithmic greenwashing remains conceptually and empirically underdeveloped. Traditional greenwashing concerns misleading claims authored and disseminated through identifiable human or organizational actors; algorithmic greenwashing additionally arises from automated generation, ranking, personalization, and optimization processes whose data sources, decision rules, and uncertainty may be opaque. Existing AI-ethics research emphasizes fairness, accountability, transparency, and explainability [13], [14], whereas most greenwashing studies focus on human-generated environmental claims [4], [5], [11]. The distinctive novelty of this study is therefore to model algorithmic greenwashing as a consumer-perception mechanism and empirically connect perceived artificial intelligence transparency (PAT) to perceived greenwashing risk (PGR), ethical evaluation, trust, and green purchase intention (GPI) [15], [16].

This study addresses a research gap by exploring the relationship between PAT and PGR. It also examines how ethical perceptions of artificial intelligence communication (EPAC) and trust in automated sustainability information (TASI) influence GPI [9], [10], [13]. Drawing on insights from AI ethics, green marketing and consumer behavior research, the study proposes and empirically tests a conceptual model using partial least squares structural equation modelling (PLS-SEM) and survey data from consumers exposed to AI-generated sustainability messages. By focusing on ethical perception and trust as key psychological mechanisms, the study explains how technological transparency can either support or hinder sustainable consumer behavior. Accordingly, this study makes the following key contributions.

- It develops a novel conceptual model linking PAT with ethical perception, trust, PGR, and GPI, thereby extending green marketing theory into domain of AI-enabled sustainability communication [9], [10], [15].
- It empirically tests the proposed associations using PLS-SEM and provides survey-based evidence regarding consumers' perceptions of AI-generated sustainability communication [6], [7].
- It reveals the mediating roles of ethical perception and trust, demonstrating how PAT indirectly influences GPI by reducing greenwashing concerns and strengthening moral and credibility judgments [9], [10], [16].

By integrating AI ethics with sustainability marketing, this study advances theoretical understanding of algorithmic greenwashing and offers practical insights for organizations seeking to deploy AI responsibly in sustainability communication [13]–[16].

2. LITERATURE REVIEW

2.1. Artificial intelligence in sustainability communication

AI has become a central infrastructure for sustainability communication, enabling firms to automate the creation, personalization, and dissemination of environmental claims across digital channels [1], [2], [17]. AI is increasingly being used in customer-facing applications like chatbots and recommender systems. It's also being employed in corporate practices such as automated sustainability reporting environmental, social, and governance (ESG) analytics and content optimization [3], [6], [17]. While these applications may improve message consistency and reach, they also introduce governance challenges because AI-generated sustainability narratives can be optimized for engagement rather than accuracy or accountability [3], [13], [14]. In response, scholars have begun to examine how AI-enabled sustainability marketing reshapes consumer interpretation of information and brand credibility [7], [15]. Evidence from AI-mediated marketing and green-advertising research indicates that algorithmic interfaces, disclosure cues, and perceived corporate performance can influence consumer evaluations and purchase responses [6], [7], [12]. AI is therefore not only a delivery mechanism; it can also shape the persuasive structure of sustainability communication.

2.2. Traditional greenwashing vs. algorithmic greenwashing

Greenwashing traditionally refers to misleading environmental communication that creates unjustifiably positive impressions of an organization or product [4], [5], [11]. In conventional settings, deception often stems from human-authored claims, selective disclosure, vague terminology, or exaggerated environmental benefits [5], [11]. The emergence of AI-driven communication may intensify these risks by introducing automation, personalization, and opacity into sustainability messaging [3], [13], [15].

Algorithmic (or AI-enabled) greenwashing refers to misleading sustainability impressions that arise when algorithmic systems generate, amplify, or curate environmental claims in ways that obscure uncertainty, omit negative information, or strategically frame content to maximize persuasion. Research on AI, systemic sustainability risks, and algorithmically mediated communication remains less developed than real-world adoption, underscoring the need for empirical models that explain consumer responses to

AI-mediated sustainability claims [3], [17]. This distinction matters because AI can produce sustainability messages that appear coherent, confident, and credible even when evidence is weak or incomplete—thereby increasing ethical ambiguity and perceived manipulation risk, particularly when transparency cues are absent [8], [13], [15], as shown in Table 1.

Table 1. Distinguishing traditional greenwashing from algorithmic greenwashing

Dimension	Traditional greenwashing	Algorithmic greenwashing
Primary agent	Human communicator (brand/marketer)	AI system + brand governance choices
Scale and speed	Limited by human production	High-volume, real-time, multi-channel
Mechanism of deception	Exaggeration, vagueness, and selective claims	Automated framing, selective ranking, personalization, "black-box" justification
Detectability	Content can be audited using disclosure evidence	Harder to audit due to opaque models/data and dynamic outputs
Accountability	Typically, attributable to organizations/individuals	Diffused across developers, data pipelines, brand, and platform
Consumer risk	Confusion, skepticism, reduced trust	Confusion amplified by opacity; risk of "authenticity illusion" via AI fluency

2.3. Explainable artificial intelligence, transparency, and trust

Transparency has become a cornerstone principle in AI ethics and governance, closely associated with explainability, auditability, accountability, and responsible disclosure [13], [14]. Research on algorithmic transparency further emphasizes providing meaningful, context-appropriate information about system operation, limitations, and oversight mechanisms [18]. In marketing and human–computer interaction contexts, explainable artificial intelligence (XAI) is positioned as a practical route to improve user understanding and confidence by offering comprehensible reasons for AI outputs [8]. Empirical and conceptual work indicates that appropriately designed transparency and explanation can reduce perceived opacity and strengthen trust, especially when users evaluate credibility-sensitive information [16], [18]–[20].

Within sustainability communication, trust in automated information depends on whether consumers believe AI-generated claims are accurate, complete, and non-manipulative. When transparency signals are strong—such as traceable sources, explanation interfaces, and disclosure of uncertainty—consumers face less information asymmetry and may be more likely to accept sustainability messages as credible [15], [16], [19], [20]. Conversely, opaque AI systems can heighten suspicion and strengthen perceptions that sustainability narratives are engineered to persuade rather than inform.

2.4. Ethical perception in artificial intelligence-mediated sustainability messages

Ethical perception refers to consumers' moral evaluation of whether AI-enabled sustainability communication is fair, honest, and socially responsible [21]. In sustainability contexts, ethical judgments are particularly influential because consumers often interpret green purchasing as value-driven behavior. When AI is perceived as obscuring the truth, exaggerating benefits, or selectively presenting information, consumers are more likely to judge the message as ethically questionable, which can translate into skepticism, distrust, and reduced behavioral intention [9], [12]. AI-ethics scholarship increasingly argues that transparency and explainability are not only technical features but also ethical signals that shape perceived accountability and legitimacy [13]–[16]. Transparent AI communication can operate as a moral cue—indicating that a firm is willing to be scrutinized—while non-transparent AI may imply concealment, thereby elevating ethical concerns and greenwashing-risk perceptions [15], [21].

2.5. Synthesis and research gap

Taken together, prior research establishes that greenwashing undermines credibility and that AI transparency can support trust, yet it does not adequately explain how these streams intersect when sustainability claims are generated, curated, or personalized algorithmically. The present study addresses this gap by distinguishing algorithmic greenwashing from traditional claim-level deception and by testing a process model in which PAT reduces PGR and shapes purchase intention through ethical perception and trust. This mechanism-based integration constitutes the study's principal theoretical contribution.

Accordingly, this study advances the literature by integrating these streams into a unified model. The model explains PAT shapes PGR, ethical perception, TASI, and GPI, including the mediating roles of ethical perception and trust. Based on the synthesis above, the following hypotheses are proposed to empirically test the relationships between PAT, PGR, ethical perception, trust, and GPI.

3. HYPOTHESIS DEVELOPMENT

3.1. Perceived artificial intelligence transparency and trust in automated sustainability information

PAT measures how well consumers comprehend how an AI system generates processes and presents sustainability information. Transparency may include disclosure of the system's data sources, decision logic, level of AI involvement, underlying assumptions, evidential boundaries, and limitations. Such disclosures reduce information asymmetry and enable consumers to assess whether automated sustainability claims are credible and appropriately supported. Previous research indicates that transparency and explainability can bolster trust in algorithmic systems. This is achieved by reducing uncertainty, enhancing perceived accountability and fostering appropriate reliance on automated outputs [15], [16], [19], [20]. Furthermore, in sustainability communication, transparent explanations suggest an organization's willingness to allow scrutiny of its environmental claims. Consequently, consumers are more likely to trust automated sustainability information when they comprehend its generation process and the supporting evidence. Therefore, the following hypothesis is proposed:

H1: PAT positively impacts TASI.

3.2. Perceived artificial intelligence transparency and perceived greenwashing risk

PGR arises when consumers suspect an organization's environmental communication is exaggerated, selective, unsubstantiated or deliberately misleading. The use of AI may intensify such concerns because automated systems can generate, personalize, and distribute environmental claims at considerable scale while concealing how those claims were produced. Transparency can reduce this uncertainty by revealing the sources, assumptions, processes, and limitations underlying AI-generated sustainability information. When organizations explain how environmental claims are generated and verified, consumers are better able to evaluate their credibility. Conversely, opaque AI systems may increase suspicion because consumers cannot determine whether environmental information has been selectively framed or manipulated. Fairness, accountability, transparency, and explainability therefore provide governance cues that may reduce perceptions of algorithmic greenwashing [9], [12], [13], [15]. Consequently, the following hypothesis is proposed:

H2: PAT negatively influences PGR.

3.3. Perceived greenwashing risk and ethical perception of artificial intelligence communication

PGR measures how much consumers feel AI-generated sustainability messaging is misleading, overstated, lacking in detail, or unsupported by verifiable environmental evidence. When consumers suspect that an organization is using AI to create a misleading impression of environmental responsibility, they are likely to evaluate the communication as less honest, less fair, and less ethically responsible. Previous research on greenwashing and consumer ethical evaluations demonstrates that misleading environmental communication damages organizational credibility, increases consumer skepticism, and generates negative moral judgments [4], [9], [12], [21]. The perceived use of AI to automate or personalize such claims may further intensify ethical concerns because responsibility for the communication can become unclear. Therefore, higher PGR is expected to weaken consumers' ethical evaluations of AI-mediated sustainability communication. Accordingly:

H3: PGR negatively influences EPAC.

3.4. Ethical perception of artificial intelligence communication and green purchase intention

The EPAC involves how consumers view the honesty, fairness, accountability, and social responsibility of AI-generated sustainability messages. Ethical evaluations are particularly important in environmental communication because green purchase decisions often depend on consumers' confidence that sustainability claims are genuine and not designed merely to create a favorable environmental image. When AI-generated sustainability communication is perceived as truthful and morally responsible, consumers may evaluate both the environmental claim and the communicating organization more favorably. Such positive ethical judgments can strengthen consumers' willingness to purchase environmentally positioned products. In contrast, communication perceived as manipulative or deceptive may reduce credibility and weaken purchase intention [10], [12], [21]. Therefore:

H4: EPAC positively influences GPI.

3.5. Mediating role of trust in automated sustainability information

TASI represents consumers' confidence that AI-generated environmental information is credible, reliable, accurate, and suitable for supporting purchase decisions. Although transparency may directly increase consumers' understanding of an AI system, its influence on behavioral intention may operate primarily through the trust created by transparent communication. When organizations disclose the sources, processes, limitations, and level of AI involvement underlying sustainability claims, consumers may perceive

the information as more reliable and accountable. Increased trust can subsequently reduce uncertainty and encourage consumers to rely on the information when making environmentally oriented purchase decisions. Previous research identifies trust and perceived risk as important antecedents of GPI, while appropriate trust also determines consumers' willingness to rely on automated systems [10], [16], [20]. Consequently, PAT is expected to bolster TASI. This increased trust is anticipated to elevate GPI. Trust therefore serves as the psychological mechanism through which transparency influences consumer behavior.
H5: TASI mediates the positive relationship between PAT and GPI.

3.6. Perceived artificial intelligence transparency and ethical perception of AI communication

Transparency may function not only as an informational mechanism but also as an ethical signal. Organizations that disclose the sources, reasoning processes, evidential limitations, and degree of AI involvement in sustainability communication demonstrate openness and accountability. Such disclosure allows consumers to evaluate whether the communication is honest, fair, and consistent with responsible AI practices. Conversely, limited transparency may raise doubts regarding authenticity, accountability, and the possibility that AI is being used to conceal unsupported or selectively presented environmental claims. Existing research suggests that transparency, explainability, accountability, and perceived system integrity contribute to favorable ethical evaluations of algorithmic communication [13]–[16], [21]. Therefore:
H6: PAT positively influences EPAC.

3.7. Ethical perception of AI communication and trust in automated sustainability information

Ethical perception is a crucial foundation for consumer trust. When consumers believe AI-generated sustainability communication is honest, fair, accountable, and socially responsible, they're more likely to find it credible and reliable. Ethical communication also signals that the organization is not intentionally using AI to manipulate consumer perceptions or conceal unsupported environmental claims.

Previous research indicates that ethical evaluations, transparency cues, perceived integrity, and accountability contribute to trust formation and appropriate reliance on automated systems [15], [20], [21]. Consumers who evaluate AI-generated sustainability communication favorably from an ethical perspective should therefore demonstrate greater trust in the information presented. Accordingly:
H7: EPAC positively influences TASI.

4. CONCEPTUAL MODEL

Figure 1 shows conceptual model linking of PAT, PGR, ethical perception, trust, and GPI. The model specifies that PAT reduces PGR while enhancing EPAC and TASI. PGR is expected to negatively affect EPAC, EPAC to strengthen TASI, and both EPAC and TASI to positively influence GPI.

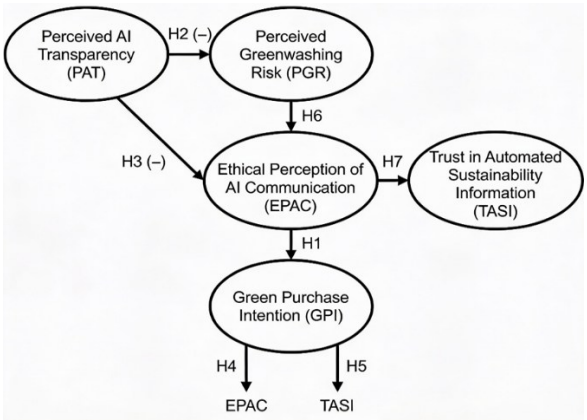

Figure 1. Proposed model of AI transparency and algorithmic greenwashing

5. RESEARCH METHODOLOGY

5.1. Research design

This study employs a quantitative cross-sectional survey design to explore the impact of AI-enabled sustainability communication on consumers' ethical perceptions, trust in PGR and GPI. Respondents familiar

with AI-generated sustainability content completed a structured questionnaire. The proposed model was subsequently tested using PLS-SEM.

5.2. Sampling strategy and rationale

A purposive sampling technique was used because the study needed respondents familiar with or having prior exposure to AI-driven sustainability communication. This included AI-generated adverts, chatbots, recommendation systems and automated environmental messages. Random sampling would have risked including respondents with no meaningful interaction with AI-based sustainability content, thereby weakening the validity of construct measurement. Purposive sampling is appropriate when researchers need information-rich respondents who meet predefined experience criteria; by targeting participants with relevant exposure, the study aligns the sample with the phenomenon being investigated [22].

Potential sampling bias may arise from the non-probability sampling strategy and the concentration of young, digitally literate respondents. The sample is also gender-imbalanced (75.73% male) and geographically situated in India; therefore, the findings should not be interpreted as population estimates or assumed to generalize automatically across cultures, older age groups, rural consumers, or individuals with low AI literacy. These boundaries are explicitly considered when interpreting the results and defining future validation priorities [23].

5.3. Instrument development and validation

The survey instrument was developed by adapting established construct domains from previous research on greenwashing, green trust and purchase intention, algorithmic transparency, explainability and consumer-perceived ethicality. These domains were sourced from references [9], [10], [15], [16], [21]. Before full-scale data collection, the questionnaire underwent a two-stage pre-testing process to assess content validity and clarity.

Before full-scale data collection, the questionnaire underwent a two-stage pre-testing process. First, three academic experts in sustainability marketing and digital communication reviewed it for clarity, relevance, and construct alignment. This led to minor wording revisions for items related to PAT and ethical perception. A second pilot study with 35 respondents then assessed item clarity, completion time and preliminary reliability. Respondents reported no major difficulties, and the average completion time was around 8–10 minutes. Cronbach's alpha values exceeded the recommended 0.70 threshold for all constructs (PAT 0.81, PGR 0.78, EPAC 0.84, TASI 0.80, and GPI 0.82). This confirmed satisfactory internal consistency and supported the instrument's suitability for large-scale administration.

5.4. Respondent demographics

Table 2 presents the demographic profile of the 375 respondents. The sample predominantly consists of young digitally literate consumers. These respondents have frequent exposure to AI-enabled communication, making them suitable for exploring AI-mediated sustainability messages.

Table 2. Demographic profile of the 375 survey respondents

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	284	75.73
	Female	91	24.27
Age group	18–21 years	158	42.13
	22–25 years	203	54.13
	Others	14	3.74
Education level	Pre-university	69	18.40
	Undergraduate	192	51.20
	Postgraduate	114	30.40

5.5. Ethical considerations

This study adhered to established ethical research standards. Participation was voluntary, and participants were fully informed about the study's purpose, the anonymous nature of data collection, and their right to withdraw at any time without penalty. Informed consent was obtained from all participants before completing the survey. No personally identifiable information was collected, and all responses were used solely for academic research.

6. DATA ANALYSIS

Data analysis utilized SmartPLS 4.0 and the PLS-SEM technique. This choice was based on PLS-SEM's suitability for prediction-focused research and complex models involving multiple latent constructs as per [24].

i) Mathematical model: PLS-SEM comprises two sub-models, as expressed in (1).

$$= \Lambda_x \xi + \delta y = \Lambda_y \eta + \varepsilon \quad (1)$$

Where x, y is observed indicators; ξ, η is latent variables; Λ is loading matrices; and δ, ε is measurement errors.

ii) Structural model: the structural model describes the relationships among latent variables, as expressed in (2).

$$\eta = B\eta + \Gamma\xi + \zeta \quad (2)$$

Where B is relationships among endogenous constructs; Γ is effects of exogenous constructs; and ζ is residual errors. For this study, the main structural equations are formulated as (3).

$$EPAC = \beta_1 PAT - \beta_2 PGR + \zeta_1 TASI = \beta_3 PAT + \beta_4 EPAC + \zeta_2 GPI = \beta_5 EPAC + \beta_6 TASI + \zeta_3 (3)$$

iii) Measurement model evaluation: the following criteria were assessed. Internal consistency was assessed with Cronbach's alpha ≥ 0.70 [24] and composite reliability (CR) ≥ 0.70 [24]. Convergent validity was confirmed by average variance extracted (AVE) ≥ 0.50 [24], [25] and discriminant validity was evaluated using the Fornell–Larcker criterion and heterotrait–monotrait (HTMT) ratio [25], [26]. Structural model evaluation involved assessing the structural relationships (H1–H7) using bootstrapping with 5,000 resamples, path coefficients and significance levels, coefficient of determination (R^2) values for explanatory power, f^2 for effect sizes, and Q^2 for predictive relevance. Mediation analysis was conducted to explore the indirect effects of PAT on GPI through EPAC and TASI.

7. RESULTS AND DISCUSSION

7.1. Measurement model evaluation

The measurement model was assessed to evaluate the reliability and validity of the reflective constructs before testing the structural relationships. This involved examining internal consistency reliability, convergent validity and discriminant validity for the five latent constructs: PAT, PGR, EPAC, TASI, and GPI. Indicator reliability was evaluated using standardized outer loadings. Figure 2 shows that the indicators generally meet the recommended 0.70 benchmark. This measurement model displays the standardized outer loadings for indicators related to PAT, PGR, EPAC, TASI, and GPI. Internal consistency was assessed using Cronbach's alpha and CR, while convergent validity was measured using AVE following established PLS-SEM guidelines [24], [25]. Overall, the results confirm the measurement model's satisfactory reliability and convergent validity. This supports its suitability for further structural model analysis.

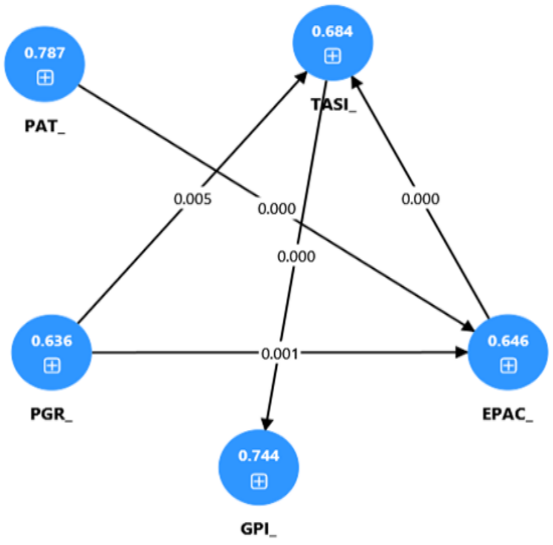

Figure 2. Measurement model and standardized outer loadings

Figure 3 presents a structural model with standardized path coefficients and explained variance. The standardized coefficients are shown on the arrows while the explained variance within each endogenous construct is indicated by the R^2 values. Figure 3 presents a structural model with standardized path coefficients and explained variance. The figure displays the PLS-SEM structural model linking PAT, PGR, EPAC, TASI, and GPI, showing standardized path coefficients on all hypothesized relationships (H1–H7) and R^2 values for the endogenous constructs.

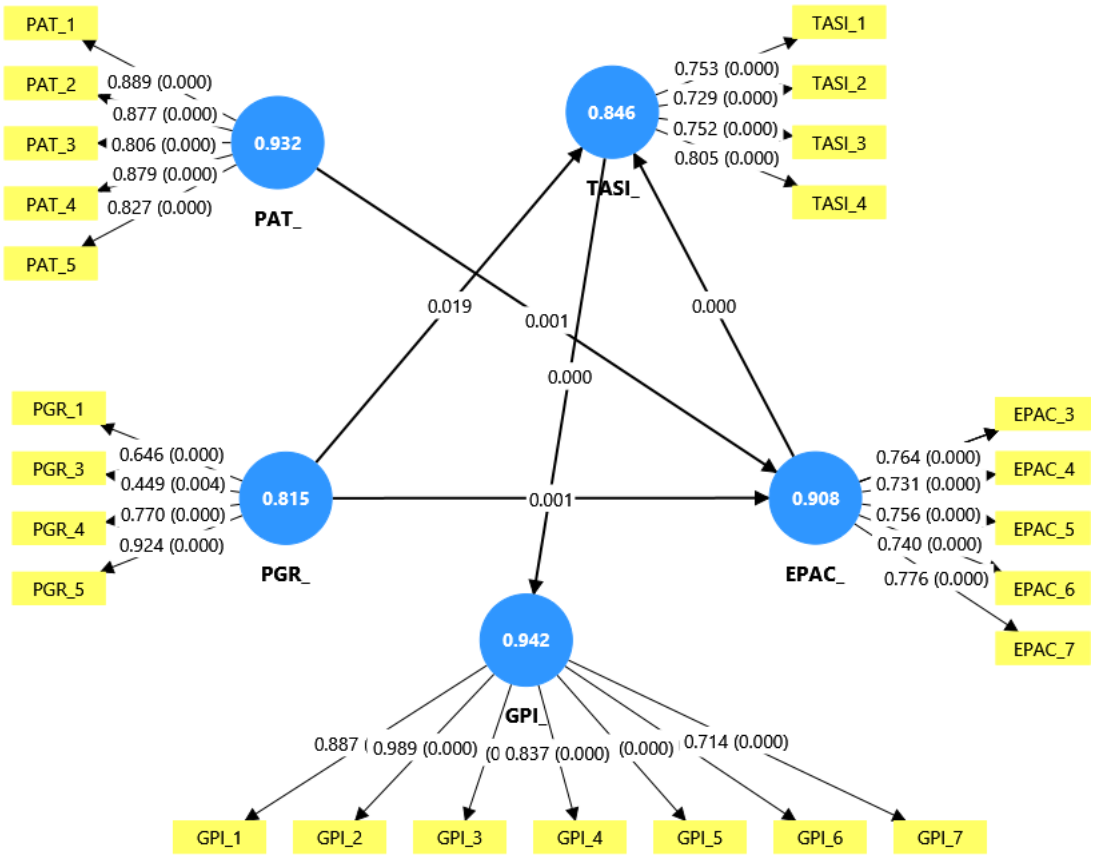

Figure 3. PLS-SEM structural model showing standardized path coefficients for the hypothesized relationships (H1–H7) and R² values for the endogenous constructs

7.2. Reliability and convergent validity

Table 3 presents the Cronbach's alpha, CR, and AVE values for all constructs. All Cronbach's alpha and CR values exceed the 0.70 threshold, indicating adequate internal consistency and construct reliability, while all AVE values exceed 0.50, confirming adequate convergent validity. Reliability and validity were further confirmed using (4). Convergent validity was confirmed as all CR values exceeded 0.70 and AVE values exceeded 0.50. VIF was used to assess multicollinearity, as shown in (4).

$$CR = \frac{(\sum\lambda_i)^2}{(\sum\lambda_i)^2+\sum(1-\lambda_i^2)} AVE = \frac{\sum\lambda_i^2}{n} VIF = \frac{1}{1-R_i^2} \quad (4)$$

Table 3. Construct reliability and convergent validity statistics

Constructs	Cronbach's alpha	CR (rho_a)	CR (rho_c)	AVE
EPAC_	0.908	0.908	0.927	0.646
GPI_	0.942	0.948	0.953	0.744
PAT_	0.932	0.933	0.949	0.787
PGR_	0.815	0.847	0.875	0.636
TASI_	0.846	0.846	0.896	0.684

7.3. Discriminant validity (Fornell–Larcker criterion)

Table 4 presents the HTMT ratios for the ten construct pairs. The ratios range from 0.230 for PGR–EPAC to 0.799 for TASI–EPAC. All values are below the 0.85 threshold [26], supporting discriminant validity under the HTMT criterion. Table 5 presents the Fornell–Larcker matrix, which compares the square root of each construct's AVE with its correlations with other constructs. As reported in Table 5, the EPAC–TASI correlation of 0.802 exceeds the diagonal values for EPAC (0.764) and TASI (0.760). The Fornell–Larcker criterion is therefore not met for this pair in the reported matrix.

Table 4. Discriminant validity HTMT ratio

Construct pairs	HTMT ratio
GPI_ <-> EPAC_	0.612
PAT_ <-> EPAC_	0.240
PAT_ <-> GPI_	0.240
PGR_ <-> EPAC_	0.230
PGR_ <-> GPI_	0.319
PGR_ <-> PAT_	0.422
TASI_ <-> EPAC_	0.799
TASI_ <-> GPI_	0.590
TASI_ <-> PAT_	0.237
TASI_ <-> PGR_	0.302

Table 5. Fornell–Larcker discriminant validity matrix (diagonal values are square roots of AVE)

Constructs	EPAC	GPI	PAT	PGR	TASI
EPAC_	0.764				
GPI_	0.612	0.838			
PAT_	0.240	0.241	0.856		
PGR_	0.246	0.316	0.415	0.718	
TASI_	0.802	0.591	0.238	0.307	0.760

7.4. Structural model evaluation

Bootstrapping with 5,000 subsamples was employed to evaluate the significance of the hypothesized relationships. In response to the review, 95% confidence intervals are reported for direct effects, indirect effects, and explained-variance estimates wherever the manuscript provides the required bootstrap standard deviations. Figures 4 to 8 show the bootstrap sampling distributions of the standardized path coefficients. In each chart, the horizontal axis represents the bootstrapped standardized path coefficient and the vertical axis represents frequency; the overlaid curve indicates the approximate distributional shape and stability of the estimate.

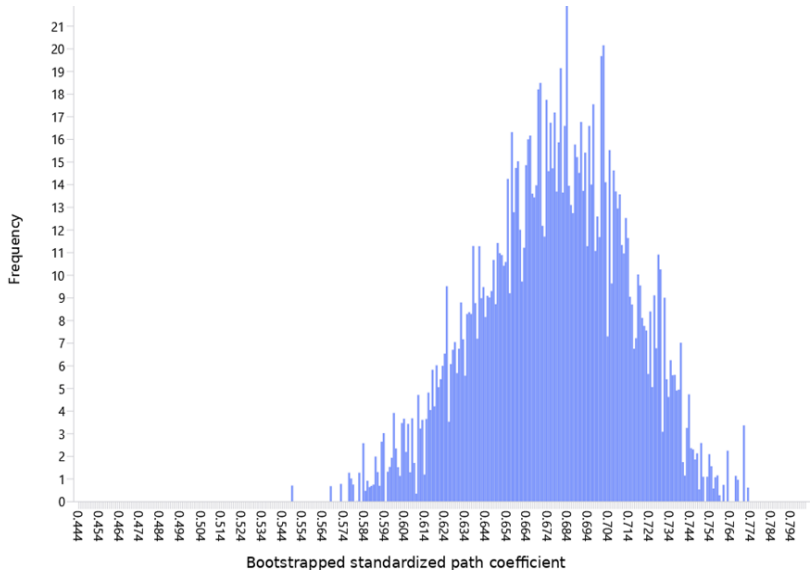

Figure 4. Bootstrap distribution for the EPAC → TASI path (5,000 resamples)

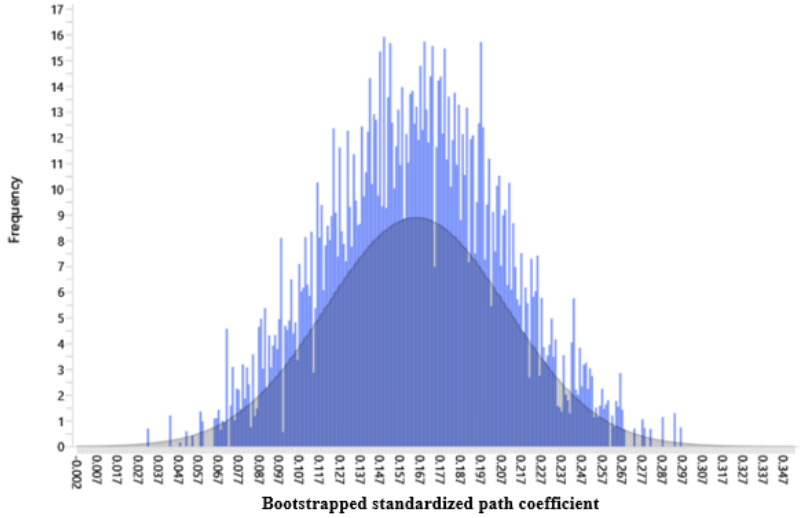

Figure 5. Bootstrap distribution for the PAT → EPAC pathway with 5,000 resamples

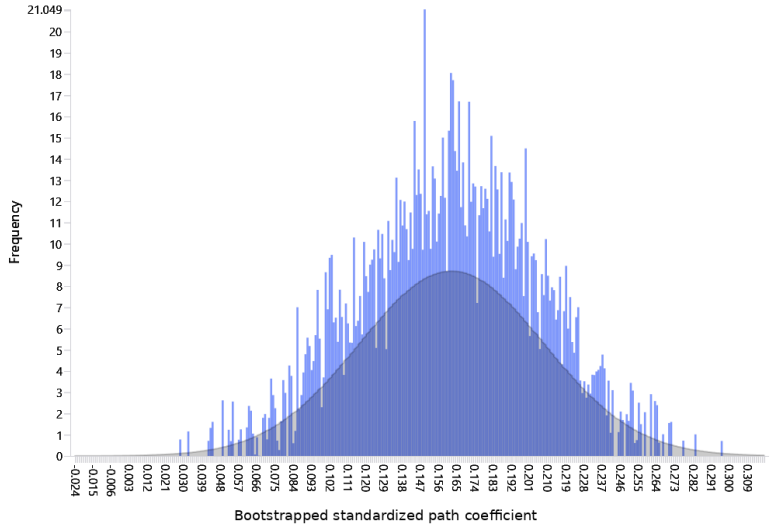

Figure 6. Bootstrap distribution for the PGR → EPAC path (5,000 resamples)

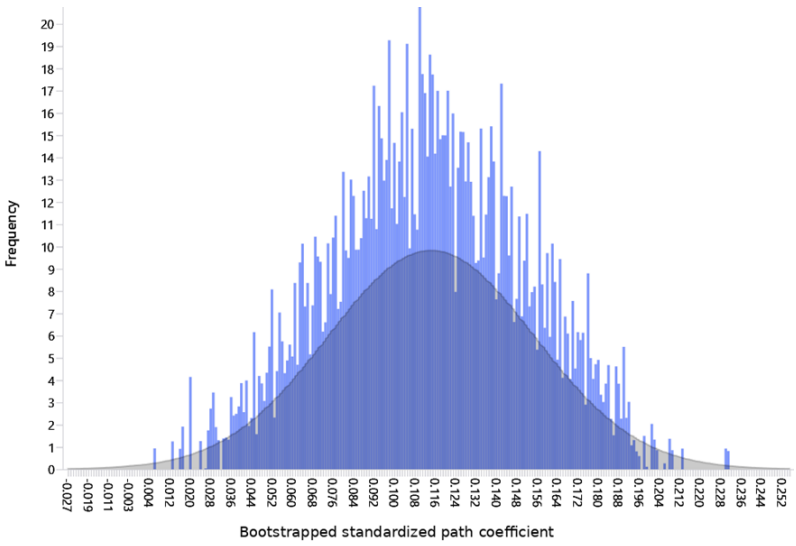

Figure 7. Bootstrap distribution for the PGR → TASI path (5,000 resamples)

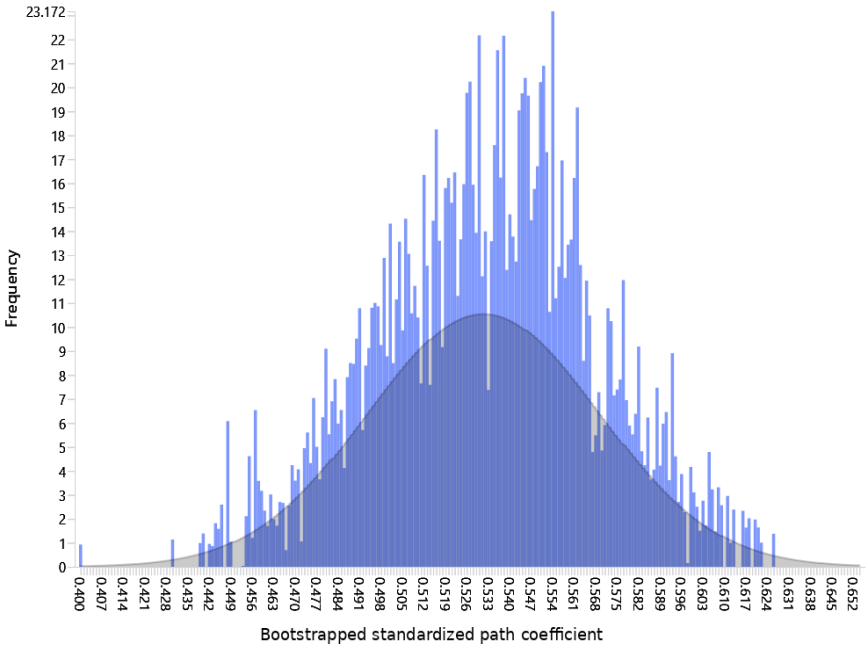

Figure 8. Bootstrap distribution for the TASI → GPI path (5,000 resamples)

Table 6 presents standardized path coefficients (β), bootstrap means, standard deviations, t-values, p-values, and percentile-based approximate 95% confidence intervals calculated as β ± 1.96 × bootstrap standard deviation. Intervals excluding zero indicate the significance of the reported direct effects. Interpretation of key findings:

- PAT strengthens trust (H1), indicating transparency enhances perceived credibility.
- Transparency reduces greenwashing risk (H2), meaning consumers associate transparent AI with lower deception.
- PGR reduces ethical perception (H3).
- Ethical perception strongly predicts GPI (H4), the strongest direct effect in the model.
- Trust also enhances purchase intention (H5).
- Transparency improves ethical perception (H6).
- Ethical perception boosts trust (H7).

Table 7 summarizes the indirect effects and significance levels for the mediating roles of ethical perception and trust, confirming partial mediation across key structural paths.

Table 6. Direct structural effects with bootstrap significance tests and 95% confidence intervals

Construct pairs	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	The 95% confidence interval is lower	95% confidence interval upper bound
EPAC_ -> GPI_	0.359	0.361	0.037	9.716	0.000	0.286	0.432
PAT_ -> GPI_	0.059	0.060	0.018	3.332	0.001	0.024	0.094
PAT_ -> TASI_	0.111	0.112	0.032	3.502	0.000	0.048	0.174
PGR_ -> GPI_	0.116	0.120	0.028	4.188	0.000	0.061	0.171
PGR_ -> TASI_	0.106	0.110	0.032	3.320	0.001	0.043	0.169

Table 7. Indirect effects with bootstrap significance tests and 95% confidence intervals

Construct pairs	O	M	STDEV	|O/STDEV|	P values	The 95% confidence interval is lower	95% confidence interval upper bound
EPAC_ -> GPI_	0.359	0.361	0.037	9.716	0.000	0.286	0.432
PAT_ -> GPI_	0.059	0.060	0.018	3.332	0.001	0.024	0.094
PAT_ -> TASI_	0.111	0.112	0.032	3.502	0.000	0.048	0.174
PGR_ -> GPI_	0.116	0.120	0.028	4.188	0.000	0.061	0.171
PGR_ -> TASI_	0.106	0.110	0.032	3.320	0.001	0.043	0.169

Mediation formulae:

$IndirectEffect = a \times bTotalEffect = c' + (a \times b)$, example:
$PAT \rightarrow TASI \rightarrow GPI = \beta_{PAT,TASI} \times \beta_{TASI,GPI}$ mediating paths are significant.

7.5. Coefficient of determination

Table 8 presents the R^2 estimates and their 95% bootstrap confidence intervals. The structural model explains 7.0% of the variance in EPAC, 28.0% in GPI, and 50.6% in TASI. The model explains the largest share of variance in TASI and the smallest share in EPAC. The low R^2 for EPAC suggests that factors outside the model may help explain how consumers evaluate the ethicality of AI-generated sustainability messages. These estimates should be interpreted in the context of the study and its prediction-focused purpose [24].

Table 8. Explained variance (R^2) with bootstrap 95% confidence intervals

Construct	O	M	STDEV	|O/STDEV|	P values	The 95% confidence interval is lower	95% confidence interval upper bound
EPAC_	0.070	0.077	0.025	2.797	0.005	0.021	0.119
GPI_	0.280	0.284	0.040	6.990	0.000	0.202	0.358
TASI_	0.506	0.510	0.047	10.693	0.000	0.414	0.598

7.6. Model fit and predictive validity

Table 9 summarizes the standardized root mean square residual (SRMR), the R^2 for GPI, the effect size, and predictive relevance. The SRMR of 0.061 is below the threshold of 0.08 used in this study, indicating acceptable model fit. The f^2 value of 0.42 indicates a large effect for the EPAC–GPI relationship. The positive (Q^2) value of 0.417 supports predictive relevance under the criterion used in Table 9.

Tables 10 to 13 present the multi-group analysis. Table 10 compares total indirect effects, which combine the effects transmitted through all mediating paths between two constructs. Table 11 compares specific indirect effects, showing how individual mediation paths through EPAC and TASI differ between the groups. Table 12 compares total effects, which combine direct and indirect effects for each relationship. Table 13 compares f^2 effect sizes, showing how much each predictor contributes to the explained variance of its outcome in each group.

Table 9. Model fit, explanatory power, effect size, and predictive relevance

Indicator	Criterion	Observed value	Result
SRMR	≤ 0.08	0.061	Good fit
R^2 (GPI)	≥ 0.25	0.583	Strong
f^2 (EPAC → GPI)	≥ 0.35	0.42	Large effect
Q^2	> 0	0.417	Good predictive relevance

Table 10. Multi-group analysis of total indirect effects

Structural relationships	The difference between group 1 and group 2	The p-value for a one-tailed test comparing group 1 and group 2	The two-tailed p-value for the comparison between group 1 and group 2
EPAC_ -> GPI_	0.190	1.000	0.000
PAT_ -> GPI_	-0.009	1.000	0.000
PAT_ -> TASI_	-0.060	1.000	0.000
PGR_ -> GPI_	0.046	1.000	0.000
PGR_ -> TASI_	0.084	1.000	0.000

Table 11. Multi-group analysis of specific indirect effects

Structural relationships	The difference between group 1 and group 2	The p-value for a one-tailed test comparing group 1 and group 2	The two-tailed p-value for the comparison between group 1 and group 2
PAT_ -> EPAC_ -> TASI_ -> GPI_	-0.009	1.000	0.000
PGR_ -> EPAC_ -> TASI_ -> GPI_	0.065	1.000	0.000
PAT_ -> EPAC_ -> TASI_	-0.060	1.000	0.000
PGR_ -> EPAC_ -> TASI_	0.084	1.000	0.000
EPAC_ -> TASI_ -> GPI_	0.190	1.000	0.000
PGR_ -> TASI_ -> GPI_	-0.020	1.000	0.000

Table 12. Multi-group analysis of total effects

Structural relationships	The difference between group 1 and group 2	The p-value for a one-tailed test comparing group 1 and group 2	The two-tailed p-value for the comparison between group 1 and group 2
EPAC_ -> GPI_	0.190	1.000	0.000
EPAC_ -> TASI_	0.127	1.000	0.000
PAT_ -> EPAC_	-0.116	1.000	0.000
PAT_ -> GPI_	-0.009	1.000	0.000
PAT_ -> TASI_	-0.060	1.000	0.000
PGR_ -> EPAC_	0.087	1.000	0.000
PGR_ -> GPI_	0.046	1.000	0.000
PGR_ -> TASI_	0.009	1.000	0.000
TASI_ -> GPI_	0.162	1.000	0.000

Table 13. Multi-group analysis of f^2 effect-size differences

Structural relationships	The difference between group 1 and group 2	The p-value for a one-tailed test comparing group 1 and group 2	The two-tailed p-value for the comparison between group 1 and group 2
EPAC_ -> TASI_	1.032	1.000	0.000
PAT_ -> EPAC_	-0.042	1.000	0.000
PGR_ -> EPAC_	0.025	1.000	0.000
PGR_ -> TASI_	-0.032	1.000	0.000
TASI_ -> GPI_	0.386	1.000	0.000

8. DISCUSSION

The findings show that PGR significantly reduces consumers' GPI in AI-driven sustainability communication, confirming that suspected exaggeration or deception weakens willingness to buy sustainable products. This aligns with green-marketing research linking perceived greenwash and green perceived risk to lower trust, unfavorable consumer reactions, and reduced purchase intention [9], [10], [12]. The study extends this mechanism to AI-mediated contexts by showing that ethical perception and TASI help explain how consumers respond to algorithmically generated messages.

The study also underscores the central role of PAT, which simultaneously enhances ethical perception and trust while lowering PGR. This supports AI-ethics and human–AI interaction research showing that fairness, accountability, transparency, explanation, and traceability can reduce information asymmetry and strengthen trust [13]–[16], [19], [20]. Transparent and accountable AI systems therefore become not only technical requirements but also communication mechanisms that improve evaluations of sustainability claims.

8.1. Interpretability of transparent and opaque AI sustainability messages

Interpretability in this context concerns whether consumers can understand how an AI-generated sustainability claim was produced, what evidence supports it, what limitations apply, and who is accountable for it. A transparent message identifies AI involvement, cites verifiable lifecycle or emissions evidence, specifies the comparison baseline and applicable conditions, communicates uncertainty, and provides a route for human review. An opaque message uses confident environmental language while leaving its sources, assumptions, or oversight unclear. Table 14 illustrates these differences through examples that disclose AI involvement and cite a lifecycle assessment, quantify an emissions reduction against a stated baseline under specified test conditions, and identify a human reviewer and a correction channel. These examples show how PAT can be assessed at the message level, drawing on established principles of explainability and algorithmic transparency [8], [18].

Table 14. Interpretability examples for AI-generated sustainability communication

Message feature	Transparent example	Opaque example	Expected consumer implication
Disclosure and provenance	"This claim was drafted with AI assistance using the cited 2025 lifecycle assessment."	"AI-verified eco-friendly product."	Disclosure supports traceability; unsupported authority cues may increase greenwashing risk.
Evidence and uncertainty	"Estimated emissions are 18–24% lower than the 2022 model under stated test conditions."	"Up to 50% greener."	Specific boundaries and uncertainty improve evaluability; vague maxima invite skepticism.
Accountability and recourse	"Reviewed by the sustainability officer; evidence and correction channel are linked."	No reviewer, evidence link, or correction mechanism.	Human oversight and recourse strengthen perceived accountability and trust.

8.2. Ethical trade-offs and AI-governance implications

AI systems used to generate, screen, or verify sustainability claims create an asymmetric ethical trade-off. A false positive—accepting a misleading claim as credible—can facilitate algorithmic greenwashing, misallocate consumer spending, and damage trust. A false negative—flagging a valid claim as misleading—can suppress legitimate sustainability communication and disadvantage firms making substantiated improvements. Governance should therefore avoid treating automated scores as final decisions. Organizations should combine calibrated risk thresholds with evidence provenance, human review for consequential claims, appeal and correction procedures, periodic audits, and disclosure of model limitations. This approach aligns transparency with broader AI-ethics principles of fairness, accountability, explainability, and human oversight [13], [14], [18].

8.3. Cross-cultural, organizational, and policy relevance

Because the sample was drawn from India, the observed relationships should be interpreted in light of local patterns of institutional trust, environmental concern, technology acceptance, and regulatory expectations. Cross-cultural studies should establish measurement invariance before comparing path coefficients across countries and recruit participants across a wider range of ages, genders, educational backgrounds, rural and urban settings, and levels of AI literacy. At the organizational level, AI-assisted ESG reporting, automated claim generation, chatbots, and personalized content provide settings for examining how governance practices shape the credibility of environmental claims.

For policymakers, the findings highlight the relevance of disclosing material AI involvement, requiring evidence for environmental claims, and ensuring auditability, human accountability, and access to correction mechanisms [13], [14], [18]. Table 15 translates these implications into practical guidelines for organizations using AI in sustainability communication. It recommends documenting the sources, methods, and comparison baselines behind environmental claims, disclosing material AI involvement, and assigning responsibility for human review and correction.

Table 15. Practical guidelines for responsible AI deployment in sustainability communication

Governance stage	Required practice	Operational indicator	Risk addressed
Data and evidence	Use traceable, current, and scope-defined environmental data.	Source, date, baseline, boundary, and method recorded for every material claim.	Unsupported or selectively framed claims.
Generation	Disclose material AI involvement and prohibit unsupported superlatives.	AI disclosure and claim-template controls applied before publication.	Authenticity illusion and vague green claims.
Explainability	Provide consumer-facing reasons, evidence links, and uncertainty.	Explanation available in plain language at point of exposure.	Opacity and information asymmetry.
Human oversight	Require qualified review for high-impact environmental claims.	Named reviewer and approval log retained.	False positives and diffusion of accountability.
Monitoring	Audit output drift, demographic effects, complaints, and corrections.	Periodic audit metrics and correction turnaround reported.	Bias, model drift, and repeated misinformation.
Recourse	Enable challenge, correction, and withdrawal of disputed claims.	Accessible contact channel and documented appeal process.	False negatives, consumer harm, and unresolved errors.

9. CONCLUSION

This study reveals that PAT is a key factor influencing consumer reactions to AI-generated sustainability communications. Increased transparency decreases PGR and bolsters the EPAC, ultimately fostering TASI. This positive perception and trust then positively impact GPI and mediate the influence of transparency on sustainable consumer behavior. Conversely, opaque AI communication fosters perceptions of deception and erodes consumer confidence. By integrating AI ethics with green consumer behavior theory, the study expands greenwashing research to AI-mediated communication. It identifies transparency, ethical perception and trust as the primary mechanisms through which AI-generated environmental claims influence purchase intention. Overall, the findings underscore the importance of transparent and accountable AI communication for credible sustainability messaging and mitigating the risk of algorithmic greenwashing.

10. LIMITATIONS AND FUTURE RESEARCH

The cross-sectional, self-reported survey identifies associations among the study constructs and may be vulnerable to common-method bias. Future experiments could compare transparent and opaque AI-generated sustainability advertisements and measure outcomes such as actual purchase choices, click-through behavior, willingness to pay, recall, and claim verification. Longitudinal studies could examine whether perceived transparency, ethical evaluations, and trust change after repeated exposure to

sustainability claims or after those claims are publicly corrected. Interviews and focus groups could complement the survey by exploring how consumers interpret AI disclosure, supporting evidence, uncertainty, and human oversight.

The purposive sample consisted primarily of young, digitally literate Indian consumers and was unevenly distributed by age and gender, limiting the generalizability of the findings. Future studies could use probability-based or stratified sampling to recruit participants across a wider range of ages, genders, educational backgrounds, rural and urban settings, and levels of AI literacy. Cross-cultural studies should establish measurement invariance before comparing structural paths across countries. Future research could also combine consumer surveys with organizational case studies and policy analysis to examine how fairness, accountability, explainability, contestability, privacy, and human oversight are applied in practice.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [SM], upon reasonable request.

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