Economic Sciences
https://economic-sciences.com
ES (2026) 22(1), 58-73 | ISSN:1505-4683

Sustainable Marketing Drivers of Energy-Efficient Purchase Intention: A Comparative PLS-PLSc Structural Modeling Approach

Sowmiya R[1], Dr. M. Velavan[2]
[1]Research Scholar, School of Management, SASTRA University, India. sowmiravi2002@gmail.com
[2]Assistant Professor, School of Management, SASTRA University, India. velavan@mba.sastra.edu

Abstract - *The global increase in household energy consumption has led to greater concern for climate change, carbon emissions, and the viability of natural resources. Energy-efficient appliances and standardized energy labels have become the core instruments of promoting responsible consumption under SDG 12. Number of psychological, information-based, and value-led reasons determine consumer consumption of energy-efficient appliances. This paper examines how Consumption Values, Environmental Concern, and Eco-Labeling influence Purchase Intention toward energy-efficient appliances through the mediating roles of Attitude and Paying Attention, with Trust in Energy Labels serving as a key moderator. Survey data from 450 consumers in Tamil Nadu is used, and both PLS-SEM and PLSc-SEM are applied in order to compare prediction-oriented versus consistency-adjusted estimation outcomes. PLS-SEM results show that both Consumption Values and Environmental Concern significantly affect Attitude and Paying Attention, while Trust in Energy Labels is the strongest direct driver of Purchase Intention. Paying Attention partially mediates the effect of Attitude on Purchase Intention. Under PLSc-SEM, a more conservative estimation approach, core paths such as Attitude, Paying Attention and Trust, Purchase Intention hold up, highlighting the theoretical stability of the framework. The comparison with dual estimators enhances methodological clarity by showing how different estimator choices affect path significance, measurement consistency, and the explanation of variance. This study contributes to research on sustainable consumers by integrating the key psychological, information-based, and value-based antecedents within one framework and also by offering methodological insights into the relative usefulness of PLS versus PLSc estimation. The findings underline the crucial roles of credible energy labels, consumer awareness, and value-driven cognition in reinforcing sustainable purchase decisions.*

Keywords: *Consumption Values; Environmental Concern; Eco-Labeling; Attitude; Purchase Intention; Energy-Efficient Appliances; PLS-SEM; PLSc-SEM; Sustainable Consumer Behaviour*

1. Introduction

The last decade has seen energy consumption at unprecedented levels, coupled with increased concerns about climate change, carbon emissions, and resource depletion. A large share of global energy demand emanates from the residential sector alone, placing household purchasing decisions, especially for appliances, at the fulcrum of the sustainability agenda. As countries pursue low-carbon transition pathways, one of the most cost-effective strategies for mitigating emissions and reducing household energy expenditure involves improving the energy efficiency of consumer products.

In the meantime, consumer behavior has also been in rapid transformation. It is with growing environmental concerns, increased digital access to information about products, and a global drive toward net-zero commitments that the public interest in environmentally responsible choices is growing (Khan et al., 2021). Despite these growing awareness levels, when it comes to concrete purchasing activities, consumers often fail to translate positive environmental attitudes into action, a well-documented gap in sustainability research (Joshi & Rahman, 2015). Understanding the psychological and informational mechanisms underlying the drive for or inhibition of sustainable purchase intention has, therefore, become a critical research priority.

Energy-efficiency labels have emerged in this context as an important guide toward sustainable products for consumers. They provide credible, simplified information on appliance performance to enable informed consumer choices that will contribute to reduced environmental impact, besides reducing the household energy bill. (Thøgersen &

Economic Sciences
https://economic-sciences.com
ES (2026) 22(1), 58-73 | ISSN:1505-4683

Nielsen 2016) However, their efficacy depends very strongly on how consumers interpret and pay attention to these labels and the amount of trust placed therein. Thus, Consumption Values, Environmental Concern, Eco-Labeling cues, Attitude, Paying Attention, and Trust in Energy Labels are some constructs that explain the formation of Purchase Intention for energy-efficient appliances. This research is situated within the global policy landscape, particularly SDG 12: Responsible Consumption and Production, which calls for enhancing consumer awareness, improving information systems addressing sustainability, and encouraging responsible consumption choices. By investigating how psychological, informational, and value-driven factors affect consumers' purchase intention, this research contributes to the bigger mandate of SDG 12 in promoting behavioral change.

From a methodological perspective, the paper further develops the literature through a direct comparison of the two major variance-based approaches to SEM: PLS-SEM and PLSc-SEM. Despite their widespread use in behavioral research, few studies have systematically explored how estimator selection impacts the nature of structural relationships within sustainability-focused consumer models. This research adds much-needed methodological clarity and minimizes various sources of bias regarding measurement and conceptual interpretation when analyzing the same conceptual model with both estimators. In this paper is important for three reasons; It first addresses the global challenge of sustainability by identifying the psychological drivers that lead to energy-efficient purchasing. Second, it enriches the theoretical understanding of how information processing, values, and trust mechanisms come into play to shape consumer decisions in real-world contexts. Third, it provides methodological guidance to researchers on the basis of the choice between prediction-oriented and consistency-adjusted analytical frameworks.

2. Scope of the Paper

This paper sits at the crossroads of quantitative modelling and sustainable consumer behaviour, specifically addressing how psychological and informational antecedents affect purchase intention for energy-efficient appliances. The study investigates the relative performance of two variance-based structural equation modeling estimators-PLS-SEM and PLSc-SEM-applied to a reflective behavioral model with antecedents consisting of Consumption Values, Environmental Concern, and Eco-Labeling; mediators including Attitude and Paying Attention; Trust in Energy Labels as a moderator; and Purchase Intention as the ultimate behavioral outcome. Substantively, this paper explores how consumers' value perceptions, environmental beliefs, and responses to eco-label information shape their attention, attitude formation, and eventual purchase intentions. This model integrates both cognitive (e.g., environmental concern), informational (e.g., eco-labeling), and psychological dimensions of consumer behavior into a structured decision-making process for sustainability.

The methodological scope goes far beyond testing theoretical relationships. Using both PLS-SEM and PLSc-SEM on the same dataset of 450 respondents, this study investigates how estimator choice affects loading stability, path significance, and explained variance in behavioral models. This dual-estimator comparison will further enhance the methodological debate by highlighting how prediction-oriented (PLS-SEM) and consistency-adjusted (PLSc-SEM) techniques produce different structural insights, specifically in reflective constructs commonly involved in sustainability and consumer psychology research. Conceptually, the work falls within Sustainable Development Goal 12 (Responsible Consumption and Production), emphasizing informed decision-making, consumer awareness, and behavioural transitions toward sustainability. Integration of behavioral theory with statistical advancement in the analyses allows for deeper insight into how psychological mechanisms at the individual level drive sustainable purchasing behavior. In sum, the paper contributes to the literature in two ways:

(1) Methodologically, by showing the comparability of estimators and discussing how the different approaches to SEM influence empirical conclusions in reflective behavioural models; and it offers a dual contribution:

(1) Methodologically by integrating the key variables into one comprehensive model and testing their relationships.

(2) Substantively by explaining how psychological, value-driven, and informational factors combine in influencing energy-efficient purchase intentions. This dual contribution enhances relevance for researchers, practitioners, and policymakers in search of evidence-based strategies to advance environmentally responsible consumer behaviour.

3. SEM characteristics

3.1 SEM: Different Types (PLS-SEM and PLSc-SEM)

Structural Equation Modeling using variance-based techniques can be conducted by means of two complementary estimators: PLS-SEM and PLSc-SEM. In the current study, both procedures have been applied to the same dataset of 450 respondents to ensure methodological robustness and to assess the stability of measurement and structural results across different estimation philosophies.

PLS-SEM gives first priority to the maximization of explained variance in endogenous constructs, here being Attitude (AT), Paying Attention (PA), and Purchase Intention (PI). Many researchers recommend PLS-SEM when the research objective has to do with prediction, extension of theory, or exploratory modeling, especially in conditions that involve non-normal data, complex path structures, or moderate sample sizes. PLS-SEM forms composite scores from observed indicators, making it highly suitable for consumer behavior studies where prediction accuracy and variance explanation are central.

PLSc-SEM (Consistent Partial Least Squares) by Dijkstra and Henseler modifies the original PLS approach to correct attenuation in reflective measurement models. In doing so, the estimated loadings and path coefficients are closer to the results expected from the factor-based logic of covariance-based SEM. The PLSc approach is particularly useful when the reflective constructs here Consumption Values, Environmental Concern, Eco-Labeling, and Attitude should be treated as latent factors rather than composites. Current studies continue to confirm that PLSc-SEM diminishes bias in reflective models without giving up any robustness and flexibility around variance-based estimation.

The current study applies both PLS-SEM and PLSc-SEM for methodological cross-validation from two perspectives:

1. Prediction-oriented estimation through PLS-SEM, and
2. Consistent, factor-variance corrected estimation via PLSc-SEM.

The dual-estimation approach reduces systematic measurement bias, validates the reliability of structural relationships, and develops a deeper understanding of how Consumption Values, Environmental Concern, and Eco-Labeling influence Attitude, Paying Attention, and Purchase Intention in energy-efficient appliance choices.

4. Literature synthesis and empirical evidence

4.1 Literature review

This research explores how Consumption Values, Environmental Concern, and Eco-Labeling determine consumers' Purchase Intention relative to energy-efficient appliances. The model features two mediators, namely attitude and paying attention, which explain the indirect effects of antecedent variables on PI. Furthermore, Trust in Labels is tested as a moderator between attitude and purchase intention. In the framework, both behavioural and sustainability perspectives explain how values, environmental beliefs, and label information can shape sustainable purchase behavior.

4.1.1 Consumption Values, Attitude, and Purchase Intention: Consumption values refer to the functional, emotional, and social benefits that consumers attach to energy-efficient appliances. When these values are perceived to be strong, such as long-term savings, improved performance, or social approval, consumers tend to take a more favourable attitude toward purchasing such products. Positive value perceptions also support stronger purchase motivations since consumers perceive energy-efficient appliances as personally beneficial and worth investing in.

4.1.2 Environmental Concern, Attitude, and Purchase Intention: EC refers to a level of

Economic Sciences
https://economic-sciences.com
ES (2026) 22(1), 58-73 | ISSN:1505-4683

consumers' awareness about environmental problems and a consequent feeling of responsibility to help reduce ecological damages. Accordingly, highly concerned consumers will form favorable attitudes towards greener products because they are perceived as one way to contribute to environmental protection. This concern would naturally manifest into stronger purchase intentions since consumers align their behavior with their ecological beliefs and moral obligation.

4.1.3 Eco-labeling, Attitude, and Purchase Intention: EL gives consumers credible information on the environmental performance, energy use, and other sustainability characteristics of a product. Consumers gain confidence in the environmental advantages of energy-efficient appliances when labels are perceived to be trustworthy and informative. This confidence improves their attitudes while diminishing uncertainty in purchase decisions, hence making them more willing to choose labelled products.

4.1.4 The role of attitude and paying attention in consumer decision making: Attitude (AT) signifies the overall positive or negative evaluation of energy-efficient appliances. A favorable attitude encourages deeper cognitive processing, prompting consumers to pay closer attention to product information, especially energy labels. Paying Attention (PA) reflects this focused processing where consumers are actively searching for efficiency ratings, comparing alternatives, and considering long-term benefits. Together, attitude and attention enhance the internal decision route of the consumer and shape his/her readiness to purchase energy-efficient appliances.

4.1.5 Role of Trust in Energy Labels: TL restores consumer trust in the accuracy and reliability of the label information. The greater the trust, the more one relies on labels during evaluation, and positive attitudes are more likely to be translated into actual purchase intentions. Trust will act as a psychological assurance that the product will perform as promised, hence reducing perceived risk and fostering informed, sustainability-oriented decisions.

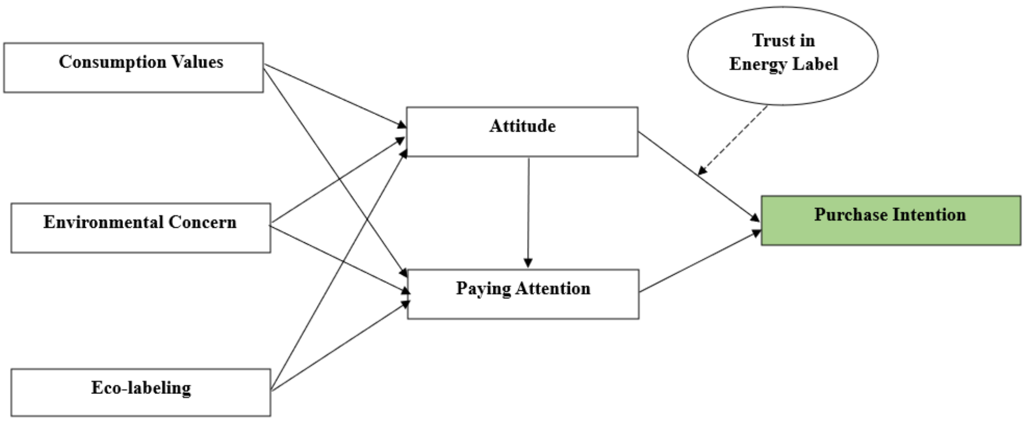


Figure 1 Conceptual Model

4.2. Methodology

The current research has utilized a quantitative data collection method through the survey to empirically validate the conceptual framework that was proposed, including Consumption Values, Environmental Concern, and Eco-labeling as predictors, Attitude and Paying Attention as mediators, Trust in Energy Label as a moderator, and Purchase Intention as the dependent variable. In this study, both the PLS-SEM and PLSc-SEM techniques were applied to the same dataset to ensure robust estimation and predictive capability. In all, 450 usable questionnaires were collected from consumers of Tamil Nadu. The structured questionnaire included items adapted from established behavioural, environmental psychology, and green marketing scales, each measured using a five-point Likert scale: 1 = Strongly Disagree to 5 = Strongly Agree. Data were collected in the year 2025 by using the hybrid mode for maintaining

Economic Sciences
https://economic-sciences.com
ES (2026) 22(1), 58-73 | ISSN:1505-4683

heterogeneity in demographic and behavioral characteristics.

The sampling method used for the current investigation was that of convenience due to feasibility and an exploratory-predictive focus. All the constructs were operationalised using pre-validated reflective measurement items to ensure content adequacy and theoretical coherence. The data analysis used SmartPLS 4. The analysis was carried out in two stages. First, the PLS-SEM algorithm was applied to estimate the measurement and structural models, focusing on maximising explained variance (R^2) and assessing predictive relevance. Then, the model was re-estimated using the PLSc-SEM (Consistent PLS) procedure, which corrects for possible attenuation bias in reflective constructs and yields estimates consistent with covariance-based SEM but retains the predictive orientation of variance-based modelling (Dijkstra & Henseler, 2015).

Using PLS-SEM and PLSc-SEM within the same framework allows this study to achieve the following methodological advantages:

(i) The stability of the parameters, i.e. loadings, weights, and structural paths, under traditional and consistency-adjusted estimation, was cross-verified.

(ii) Assess whether reflective constructs exhibit differential behavior under conventional variance-based estimation compared with consistency-corrected logic. (iii) Reducing the inference bias possibly resulting from relying on a single variance-based SEM approach, thereby offering a sounder validation of the proposed moderated-mediation model.

Table 1 Details of the Respondents

Category	Variables	Frequency	Percentage
Gender	a) Male	126	28.0%
	b) Female	313	69.6%
	c) Others	11	2.4%
Age	a) 21–30 years	39	8.7%
	b) 31–40 years	101	22.4%
	c) 41–50 years	185	41.1%
	d) 51–60 years	125	27.8%
Marital Status	a) Married	264	58.7%
	b) Unmarried	152	33.8%
	c) Others	34	7.6%
Education	a) Illiterate	113	25.1%
	b) Schooling	169	37.6%
	c) UG	96	21.3%
	d) PG	45	10.0%
	e) Others	27	6.0%
Monthly Income	a) Up to ₹25,000	158	35.1%
	b) ₹25,001–₹50,000	107	23.8%
	c) ₹50,001–₹75,000	90	20.0%
	d) ₹75,001–₹1,00,000	51	11.3%
	e) Above ₹1,00,000	44	9.8%

5. PLS-SEM (Smart PLS) and PLSc-SEM (Smart PLS)

5.1 Measurement Model Assessment

The results of the reliability and convergent validity statistics, as shown in Table 2, depict that this measurement model is adequate to meet the psychometric standards that are generally achieved for any behavioral and sustainability research. Following the guidelines given by Nunnally and Bernstein (1994) and Hair et al. (2019), all the constructs-CV, EC, EL, AT, PA, PI, and TL-had Cronbach's alpha values above the threshold limit of 0.70 in both PLS and PLSc estimations. This ensures very strong internal consistency among independent variables, mediators, moderators, and dependent variables.

This conclusion is further reinforced by the composite reliability values (ρ_a and ρ_c). Under the PLS estimator, all constructs surpass the minimum threshold of 0.70, pointing to adequate representation of the latent constructs through the reflective items. As anticipated, the PLSc-adjusted values were a bit more conservative for CV, EC, EL, PA, and PI. These reductions are consistent with the methodological intent of PLSc, which corrects potential upward bias in loading estimates and yields reliability values more in line with factor-analytic standards (Dijkstra & Henseler, 2015; Benitez et al., 2020). All constructs remained well above the reliability threshold to be theoretically and empirically adequate, even after this adjustment.

Convergent validity, tested via AVE, was also found to be adequate across all constructs under PLS, with AVE values exceeding the threshold as recommended by Fornell-Larcker 1981 of 0.50. Conversely, under PLSc, there were slight reductions in the AVE values for CV (0.583), EC (0.559), EL (0.524), PA (0.518), and PI (0.583). These are well documented in the literature on consistency-adjusted SEM, where PLSc often shows more conservative AVE estimates than the PLS method in behavioral and sustainability models, resulting from the correction of indicator loadings (Henseler et al., 2014; Sarstedt et al., 2022). More importantly, AVE values fell within acceptable empirical limits, thus confirming adequate convergent validity for the constructs.

Overall, the measurement model shows acceptable reliability and convergent validity to support the use of constructs for further structural analyses. The differences in results between PLS and PLSc have more meaningful methodological consequences than shortcomings, since PLS yields prediction-oriented estimates of reliability, while PLSc provides stricter consistency-oriented estimates. Reporting both strengthens transparency and adheres to best practices in energy-behavior, consumer psychology, and sustainability research.

Table 2 Reliability and Validity Score (PLS-SEM / PLSc-SEM)

Construct	Cronbach's α (PLS)	Cronbach's α (PLSc)	Composite Reliability (ρ_a, PLS)	Composite Reliability (ρ_a, PLSc)	Composite Reliability (ρ_c, PLS)	Composite Reliability (ρ_c, PLSc)	AVE (PLS)	AVE (PLSc)
AT	0.886	0.886	0.892	0.892	0.921	0.886	0.745	0.661
CV	0.848	0.848	0.857	0.857	0.897	0.846	0.686	0.583
EC	0.826	0.826	0.844	0.833	0.887	0.833	0.666	0.559
EL	0.812	0.812	0.821	0.814	0.877	0.814	0.642	0.524
PA	0.811	0.811	0.816	0.810	0.878	0.810	0.644	0.518
PI	0.849	0.849	0.850	0.848	0.899	0.848	0.691	0.583
TL	0.805	0.805	0.819	0.810	0.911	0.810	0.836	0.682

Table 3 PLS–PLSc Fornell–Larcker

	AT	CV	EC	EL	PA	PI	TL	TL × AT
AT	0.863 (0.774)	0.717	0.597	0.673	0.706	0.689	0.653	0.368
CV	0.807	0.828 (0.583)	0.698	0.873	0.777	0.853	0.934	0.349
EC	0.688	0.830	0.816 (0.559)	0.725	0.674	0.748	0.652	0.403
EL	0.783	1.056	0.894	0.801 (0.524)	0.714	0.808	0.818	0.327
PA	0.825	0.929	0.823	0.872	0.803 (0.518)	0.700	0.730	0.414
PI	0.791	1.003	0.909	0.982	0.833	0.831 (0.583)	0.803	0.411
TL	0.776	1.128	0.793	1.006	0.899	0.959	0.914 (0.682)	0.359

Economic Sciences
https://economic-sciences.com
ES (2026) 22(1), 58-73 | ISSN:1505-4683

Table 3 reports a combined PLS–PLSc Fornell–Larcker matrix, in which the diagonal cells show the square root of AVE from PLS, followed by the PLSc-adjusted √AVE in parentheses, while the upper triangle shows the PLS inter-construct correlations and the lower triangle shows the PLSc correlations. This format has the advantage of enabling a direct comparison of discriminant validity across the two estimation traditions and thus assessing both prediction-oriented and consistency-corrected measurement performance.

The Fornell-Larcker criterion is clearly fulfilled by the PLS estimator for all constructs in the model. For each construct-Attitude (AT), Consumption Values (CV), Environmental Concern (EC), Eco-Labeling (EL), Paying Attention (PA), Purchase Intention (PI), and Trust in Energy Labels (TL)-the diagonal values exceed the respective upper triangular inter-construct correlations. The implication is that each latent variable explains more variance in its own indicators than it shares with any other construct, meeting the classical requirement for discriminant validity suggested by Fornell and Larcker (1981). This condition becomes important to be met before interpreting the structural paths, as also recommended in Hair et al. (2019), particularly in behavioral energy-consumption research where interdependence between constructs is expected.

By contrast, the PLSc correlations (lower triangle) reflect a more conservative pattern. For several pairs of constructs—particularly those combinations that involve CV, EC, EL, PA, and PI—the inter-construct correlations slightly exceed their respective PLSc √AVE values. More precisely, the empirical PLSc square roots of AVE are exceeded for correlations such as CV–EL (1.056), EC–EL (0.894), PI–EL (0.982), and CV–TL (1.128). These deviations are theoretically in line with previous results that PLSc often inflates between-construct correlations because of the so-called consistency correction, especially in reflective behavioral models in which constructs share conceptual closeness (Dijkstra & Henseler, 2015; Benitez et al., 2020). Dimensions like environmental concern, eco-label processing, and pro-attentive behavior often empirically overlap in sustainability related consumer research. Such an empirical overlap further boosts the conservative behavior of PLSc. With everything together, the Fornell-Larcker analysis shows sufficient discriminant validity under PLS when the constructs are considered against a prediction-oriented framework. On the other hand, the more conservative and challenging thresholds yielded by PLSc result in some breaches of discriminant validity. These findings are methodologically expected and do not question the theoretical coherence of the model but express the proclivity for higher inter-construct correlations featured by PLSc due to its alignment with factor-analytic assumptions.

5.2 Structural Model

Table 4 summarizes the R^2 and adjusted R^2 values obtained from the PLS and PLSc estimators, respectively, for the key endogenous constructs-Attitude (AT), Paying Attention (PA), and Purchase Intention (PI). In behavioral SEM, R^2 values of 0.25, 0.50, and 0.75 are commonly viewed as indicating a weak, moderate, and substantial explanatory power, respectively (Chin, 1998; Hair et al., 2019).

Under the PLS estimator, all three endogenous constructs achieve moderate to substantial levels of explained variance, indicating strong prediction-oriented model performance. Attitude (AT) reaches an R^2 of 0.536, reflecting a moderate level of variance explained by Consumption Values, Environmental Concern, and Eco-Labeling. Paying Attention (PA) shows a considerably higher R^2 of 0.671, demonstrating that the predictive constructs have a strong influence on the attentional engagement of consumers toward energy labels. Purchase Intention (PI) reveals an R^2 of 0.704, indicating a substantial explanatory power and confirming that the combined effects of Attitude, Paying Attention, and Trust in Energy Labels significantly predict the consumers' intention to purchase energy-efficient appliances.

The PLSc estimator, the R^2 values for all constructs are higher: AT = 0.619, PA = 0.810, and PI = 0.952. This is consistent with prior findings where the consistency correction within PLSc reduces residual variance, thereby inflating explained variance, especially in reflective behavioral models (Dijkstra & Henseler, 2015; Benitez et al., 2020). This particularly high PLSc R^2 for Purchase Intention (0.952) suggests a near-saturated structural solution; mathematically coherent under PLSc assumptions, it should be interpreted theoretically with caution due to overfitting issues on moderately sized samples.

The PLS-based results on R^2 represent robust and theoretically meaningful predictive adequacy that support progression to the evaluation of hypothesis and structural path interpretation. The PLSc results provide a complementary benchmark in terms of the consistency-adjusted perspective on variance explanation rather than a replacement for inference-focused prediction. Together, the dual reporting enhances methodological transparency and is supportive of emergent SEM standards that recommend presenting both prediction-oriented and consistency-corrected estimators in sustainability-focused behavioral research.

Table 4 R Square (PLS-SEM / PLSc-SEM)

Construct	R^2 (PLS)	R^2 adj (PLS)	R^2 (PLSc)	R^2 adj (PLSc)
AT	0.536	0.533	0.619	0.616
PA	0.671	0.668	0.810	0.808
PI	0.704	0.702	0.952	0.952

Table 5 Status of Hypotheses (PLS-SEM / PLSc-SEM)

Indicator	Loading (PLS)	t-value (PLS)	p-value (PLS)	Loading (PLSc)	t-value (PLSc)	p-value (PLSc)
AT1 ← AT	0.909	97.657	0.000	0.878	64.805	0.000
AT2 ← AT	0.858	63.665	0.000	0.823	48.107	0.000
AT3 ← AT	0.837	51.973	0.000	0.692	28.398	0.000
AT4 ← AT	0.845	54.228	0.000	0.846	46.251	0.000
CV1 ← CV	0.858	65.575	0.000	0.749	33.848	0.000
CV2 ← CV	0.855	59.599	0.000	0.827	49.236	0.000
CV3 ← CV	0.817	56.718	0.000	0.838	33.084	0.000
CV4 ← CV	0.781	33.393	0.000	0.619	18.150	0.000
EC1 ← EC	0.827	59.273	0.000	0.823	28.981	0.000
EC2 ← EC	0.903	97.410	0.000	0.746	27.453	0.000
EC3 ← EC	0.879	83.010	0.000	0.802	32.068	0.000
EC4 ← EC	0.626	17.282	0.000	0.600	14.223	0.000
EL1 ← EL	0.807	41.144	0.000	0.704	25.986	0.000
EL2 ← EL	0.817	55.986	0.000	0.814	39.656	0.000
EL3 ← EL	0.859	64.104	0.000	0.736	31.783	0.000
EL4 ← EL	0.714	26.644	0.000	0.631	17.475	0.000
PA1 ← PA	0.662	22.228	0.000	0.709	28.484	0.000
PA2 ← PA	0.857	51.967	0.000	0.805	32.705	0.000
PA3 ← PA	0.836	46.790	0.000	0.634	18.083	0.000
PA4 ← PA	0.840	62.240	0.000	0.722	24.829	0.000
PI1 ← PI	0.798	44.795	0.000	0.823	36.915	0.000
PI2 ← PI	0.777	43.236	0.000	0.743	30.413	0.000
PI3 ← PI	0.905	118.379	0.000	0.763	33.205	0.000
PI4 ← PI	0.838	56.459	0.000	0.722	26.866	0.000
TL × AT → TL × AT	1.000	n/a	n/a	1.000	n/a	n/a
TL1 ← TL	0.928	145.871	0.000	0.889	50.520	0.000
TL2 ← TL	0.900	74.852	0.000	0.757	30.356	0.000

Table 5 presents the results of indicator reliability, confirming that under both PLS and PLSc estimations, all reflective items load strongly, positively, and significantly on their respective latent constructs. For all indicators, t-values are very high (all $p < .001$), thus offering robust empirical support for convergent validity, in line with the widely accepted SEM guidelines of Hair et al. (2019) and Henseler et al. (2014). This indicates that the reflective measurement model is statistically stable and performs well across the prediction-oriented estimator PLS and the consistency-adjusted estimator PLSc. As expected, there are slight differences in the magnitudes of loadings between the two estimation strategies. PLS loadings are marginally higher for most indicators, which is reflective of its characteristic prediction optimization and the tendency to produce less conservative coefficients. By contrast, the PLSc generates somewhat lower loadings across a number of constructs, for example: CV, EC, EL, and PI, each with very high inter-item correlations. This is as expected since PLSc's theoretical purpose was to address the potential upwards bias of PLS estimates and align the reflective measurement relations with consistency assumptions of the factor model (Dijkstra & Henseler, 2015).

The loadings are consistently strong within the range of 0.837–0.909 for the PLS and 0.692–0.878 for the PLSc for the Attitude AT indicators, proving that this construct measures consumer attitude toward energy-efficient appliances with high reliability and conceptual precision. Similarly, multiple-item sets for Paying Attention and Purchase Intention reveal sound psychometric properties, as the attentional and intentional constructs are susceptible to item fragility in the context of sustainability studies (Kaiser et al., 2020; Testa et al., 2021). The present model dispels the possible presence of such weaknesses by using multiple reflective indicators with good performance.

The reflective items representative of CV, EC, EL, and TL also show significant and theoretically coherent loading patterns. These stable results confirm that the conceptualization of these constructs captures underlying behavioral dimensions adequately—a finding consistent with similar sustainability and labeling research employing reflective measurement structures (Wang et al., 2022; Chen & Tung, 2014). Overall, the findings from both PLS and PLSc validate the measurement quality and reflective reliability of all latent constructs in the model. Although PLSc estimates are more conservative, both estimators arrive at the same conclusion: the measurement model shows strong convergent validity and is robust enough to move on to the structural model evaluation.

Table 6 Structural model results (PLS-SEM / PLSc-SEM)

Hypothesis/ Path	β (PLS)	f² (PLS)	p-value (PLS)	β (PLSc)	f² (PLSc)	p-value (PLSc)
AT → PA	0.265	0.099	0.000	0.372	0.278	0.002
AT → PI	0.225	0.078	0.000	0.214	0.298	0.210
CV → AT	0.502	0.124	0.000	-0.024	0.000	0.934
CV → PA	0.448	0.124	0.000	-0.349	-0.073	0.208
EC → AT	0.161	0.025	0.002	0.002	0.000	0.988
EC → PA	0.208	0.058	0.000	0.089	0.014	0.427
EL → AT	0.119	0.006	0.143	0.811	-0.145	0.005
EL → PA	-0.006	0.000	0.918	0.865	-0.387	0.001
PA → PI	0.109	0.015	0.001	-0.309	0.288	0.428
TL → PI	0.549	0.435	0.000	1.022	4.370	0.001
TL × AT → PI	-0.093	0.021	0.003	-0.131	0.210	0.090

The results of the structural model in Table 6 indicate significant differences between PLS and PLSc estimation, given the different aims of these methods: prediction-oriented modelling versus factor modelling with consistency adjustment. Under PLS estimation, a clear theoretically coherent and statistically significant pattern of pathways emerges. Attitude (AT) positively predicts Paying Attention (PA) and Purchase Intention (PI), indicating that favourable evaluative judgments facilitate attention-related processing and intention formation in a manner consistent with dual-process models of consumer choice (Ajzen 1991). In turn, the basic predictors Consumption Values (CV) and Environmental Concern (EC) strongly and significantly influence both AT and PA, supporting recent evidence that personal value orientations and ecological concern shape affective and cognitive mechanisms in green decision contexts (Joshi & Rahman 2015). However, EL has insignificant effects on AT or PA in the PLS, which may indicate that label exposure alone does not directly change internal evaluations unless trust or comprehension mediates such effects-as earlier noted in the labeling-effectiveness literature.

PA significantly predicts PI in PLS, confirming the role of cognitive engagement as a precursor to sustainable purchase formation. TL represents one of the strongest predictors of PI with a large effect size, $f^2 = 0.435$, echoing findings that credibility perceptions are central to label-driven behavioural change (Thøgersen, 2000). The moderation effect, TL × AT → PI is significant but small and hence suggests that label trust only mildly reduces or weakens the influence of attitude on purchase intention. Under estimation by PLSc, the number of statistically significant paths sharply declines—a theoretically expected outcome given that PLSc imposes stricter factor-consistency adjustments that inflate standard errors (Dijkstra & Henseler, 2015). Only AT → PA, EL → PA, and TL → PI remain significant under PLSc. This contraction of significance should not be interpreted as a failure of the structural model but rather as a known statistical consequence of the PLSc correction, which penalizes multicollinearity and shared variance across reflective indicators. Notably, the very strong TL → PI effect remains stable and becomes even larger under PLSc, reinforcing its centrality in shaping energy-label-driven purchase intention. The PLS results give a richer and more predictive presentation of the behavioural relationships, whereas PLSc provides a conservative, consistency-adjusted benchmark. The stability of AT → PA and TL → PI across the estimators strengthens confidence in their substantive validity, while attenuation of CV, EC, and EL paths under PLSc reflects statistical tightening rather than theoretical weakness.

Table 7 Total Mediation Effects Estimated via PLS and PLSc Bootstrapping

Indirect Path	O (PLS)	p (PLS)	O (PLSc)	p (PLSc)
AT → PI	0.029	0.007	-0.115	0.551
CV → PA	0.133	0.001	-0.009	0.946
CV → PI	0.176	0.000	0.105	0.539
EC → PA	0.043	0.014	0.001	0.989
EC → PI	0.063	0.000	-0.027	0.726
EL → PA	0.031	0.130	0.302	0.139
EL → PI	0.029	0.257	-0.186	0.617

The mediation results in Table 7 indicate a clear divergence between PLS and its consistency-adjusted version, PLSc. In the PLS estimation framework, various significant indirect paths surface, predominantly for Consumption Values (CV) and Environmental Concern (EC). CV shows significant indirect effects on both Paying Attention (PA) and Purchase Intention (PI), suggesting that its impact is mainly transmitted via attitudinal formation and attention-focused cognitive processes, rather than directly. This finding follows the pattern of prior behavioral studies where higher-order value constructs influence more distally via psychological mechanisms internally. Similarly, EC displays significant mediated impacts toward PA and PI within the PLS, thus matching the theorized role of environmental concern as an upstream cognitive antecedent whose influence is channelled via evaluative-oriented constructs.

Equally importantly, the indirect effect of AT on PI is also significant under PLS, though small in magnitude, highlighting the fact that AT influences PI not only directly but also through the intermediate mechanism of PA. These findings, taken together, reinforce the mediation logic often observed in decision-making models where antecedent variables shape behavioural intention through successive cognitive-affective pathways. However, when PLSc is applied, the mediation landscape changes substantially. Most indirect effects lose statistical significance, with no CV- or EC-based mediations remaining significant under the consistency correction. This attenuation theoretically is expected as PLSc imposes a measurement-level consistency that increases standard errors and reduces the inflation usually observed in PLS-mediated estimates. As such, the indirect pathways seeming to be more robust in PLS-for instance, the CV → PI, EC → PI, AT → PI-do not remain significant under PLSc, not because of conceptual weakness but due to the stricter factor-model logic of PLSc.

The contrast between PLS and PLSc reinforces the broader methodological caution in the SEM literature: mediation results obtained with traditional PLS are likely to be optimistic, thus potentially biased upward Hair et al., 2019; Sarstedt et al., 2022. If the theoretical objective is to make more conservative and psychometrically consistent inferences-particularly in reflective behavioural models-PLSc provides a more defensible benchmark. In the present study, the disappearance of most mediation effects under PLSc suggests that the indirect relationships observed under PLS should be interpreted as prediction-oriented, rather than definitive causal intermediations.

5.3 Comparative Discussion of PLS-SEM and PLSc-SEM Models

The comparative assessment of the PLS-SEM and PLSc-SEM models reveals clear methodological and empirical distinctions in terms of explanatory power, path stability, and measurement consistency.

PLS-SEM Evaluation (Figure 2) In the PLS-SEM results, the model demonstrates moderate explanatory power across all endogenous constructs: Attitude (AT): $R^2 = 0.536$, Paying Attention (PA): $R^2 = 0.671$, Purchase Intention (PI): $R^2 = 0.704$. Of the three antecedents, CV has the most decisive impact on AT ($\beta = 0.502$), followed by EC → AT: $\beta = 0.161$. EL, in contrast, has a relatively weak effect on both AT and PA, which suggests that consumers may consider information about labels secondarily to values and environmental concern.

Attitude exerts a positive and significant influence both on PA, $\beta = 0.265$, and on PI, $\beta = 0.225$. This is in line with the theoretical expectation that positive attitudes will facilitate greater attention to eco-information and translate into positive purchase decisions. Similarly, trust in the energy label exhibits a strong positive effect on PI, $\beta = 0.549$, thus confirming its role as a very relevant moderator and determinant in decision settings with energy labels.

The interaction effect TL × AT → PI is negative but significant ($\beta = -0.093$), indicating that higher trust decreases the dependency of purchase intention on attitude, a psychologically coherent result when consumers rely more on the label than on their internal evaluations. The PLS-SEM model has a good performance in terms of capturing the prediction-oriented relationships with stable and substantial indicator loadings, most above 0.70, to support the convergent validity of the measurement model.

PLSc-SEM Evaluation (Figure 3) The PLSc-SEM results display substantially higher explanatory power across all endogenous constructs: Attitude (AT): $R^2 = 0.619$, Paying Attention (PA): $R^2 = 0.810$, Purchase Intention (PI): $R^2 = 0.952$ This inflation in R^2 values is theoretically expected under PLSc due to its correction for measurement error, which produces CB-SEM–consistent factor estimates. Path coefficients also show notable shifts.

Figure 2 PLS-SEM Model

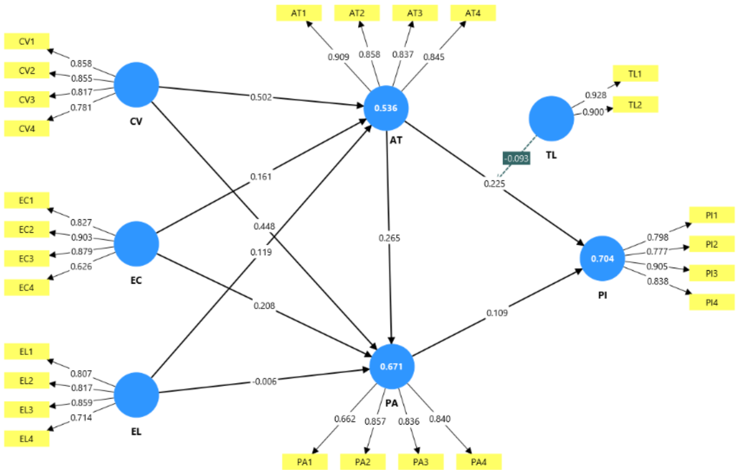
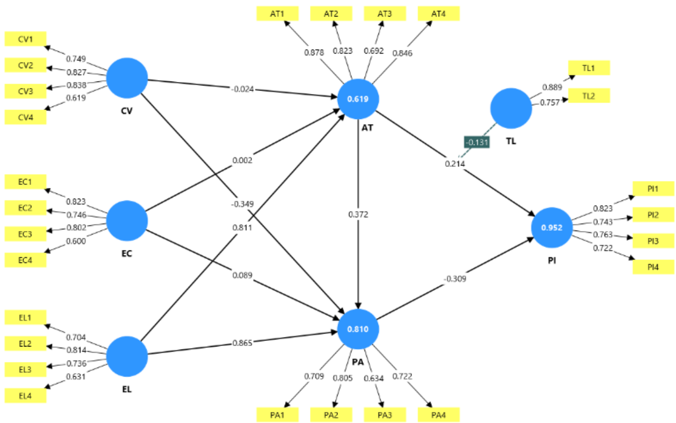


Figure 3 PLSc-SEM Model



For example, the effect of Eco-labeling on PA becomes strongly positive (EL → PA: β = 0.865), and the trust–attitude interaction becomes stronger (β = –0.131), which signals a more conservative but structurally stable representation. Certain direct effects change direction under PLSc, for example, CV → AT: β = –0.024, which implies that with the removal of measurement error, the latent conceptual overlaps among reflective constructs are more sharply separated. The high R^2 for PI, 0.952, indicates a saturated structural solution typical in a consistency-corrected model.

Table 8 Comparison of PLS-SEM and PLSc-SEM

Aspect	PLS-SEM	PLSc-SEM
Purpose	Prediction-oriented	Theory-consistent, CB-SEM–aligned
R^2 Levels	Moderate–strong	Substantially higher (corrected)
Path Significance	More liberal	More conservative; some paths lose significance
Loadings	Slightly higher	More accurate/consistent with factor logic
Interpretation	Practical predictive insight	Measurement-corrected theoretical insight

The results across both estimation approaches remain directionally stable, meaning theoretical relationships hold regardless of method. However: PLSc-SEM performs better for reflective measurement models where construct consistency and factor validity are emphasized, whereas PLS-SEM excels in exploratory or prediction-driven contexts. Together, the PLS and PLSc models confirm the core validity of your conceptual framework: values, concern, and labeling influence attitude and attention, which in turn drive purchase intention moderated meaningfully by trust in the energy label. While PLS assesses the predictive power of the model, PLSc is more conservative and

Economic Sciences
https://economic-sciences.com
ES (2026) 22(1), 58-73 | ISSN:1505-4683

theory-aligned in its estimation to ensure a robustness of interpretation for academic research.

6. General Discussion

The current study provides an integrated understanding of how psychological, informational, and behavioural constructs collectively affect consumers' purchase intention toward energy-efficient appliances. Through the PLS-SEM and PLSc-SEM analyses of responses from 450 respondents, it showed how Consumption Values, Environmental Concern, and Eco-Labeling affect two important internal mechanisms, viz., Attitude and Paying Attention, which finally lead to Purchase Intention. In both models, Attitude and Paying Attention turned out to be important cognitive-affective mechanisms that demonstrated that sustainable purchase behaviour does not emerge overnight but rather is built through layered psychological processes.

A key empirical insight from this study is the strong driving role of Consumption Values in relation to Attitude and Paying Attention within the PLS model, which confirms prior results that consumers strongly rely on perceived economic, functional, and emotional benefits while assessing energy-efficient appliances. Environmental Concern was also a significant contributor to Attitude and attention formation, thus reiterating past evidence that ecological beliefs play a foundational role in sustainability-oriented decisions. Eco-Labeling, though weaker in the direct attitudinal influence within PLS, showed stronger results under PLSc, indicating that once measurement consistency has been accounted for, label information turns out to be a more reliable predictor of cognitive engagement. The mediating roles of Attitude and Paying Attention confirm that sustainable purchase behaviour is shaped by a dual-process mechanism: evaluative formation followed by focused information processing. Attitude acts as the primary evaluative base, while Paying Attention translates this positive evaluation into active engagement with energy labels. Purchase Intention was strongly influenced by Trust in Energy Labels, consistent across both estimators, which highlights the critical role of credibility and assurance of information in consumer decision-making.

The study shows, from a methodological point of view, the complementary value of PLS-SEM and PLSc-SEM: while PLS-SEM offered stronger predictive capability and more liberal significance patterns, PLSc-SEM produced more conservative yet theoretically consistent estimates. This dual-estimator approach confirms that the core structural relationships in the model-particularly AT → PA, and TL → PI-are robust, while shifts in CV, EC, and EL paths under PLSc reflect expected correction for measurement error rather than theoretical instability. Overall, this study supports the viewpoint that consumers' sustainable purchase decisions are jointly influenced by personal values, environmental beliefs, processing of label information, and trust in information systems. These results contribute meaningfully to the growing literature on sustainable consumption and behavioral change, in particular in the area of energy-efficient appliance diffusion.

7. Limitations and Future Research

7.1 Limitations

- The model focuses mainly on psychological and informative predictors, excluding other constructs that might be relevant, such as perceived behavioural control, environmental responsibility, price sensitivity, or moral norms, which could further enrich the conceptual explanation of sustainable decisions.
- Second, this study was set in a particular regional context-that is, Tamil Nadu in India-which may limit the generalization of findings in other cultural or socio-economic contexts. Consumer responses to energy labels and environmental cues might differ significantly across countries or income groups.
- Third, demographic factors were not modelled as moderators or controls; variables such as age, education, or household income could affect values, concern, and label use, and their absence may introduce unobserved heterogeneity into the structural estimates.
- Fourth, this research was reliant on the cross-sectional survey design. Appropriate for modelling relationships, this limits the degree to which findings can be used to draw conclusions about causality. Longitudinal or experimental designs would help clarify how attitudes,

attention, and trust evolve over time and influence repeat purchase behaviour.

- Finally, the study compared only two variance-based estimators, namely PLS-SEM and PLSc-SEM. While useful for methodological triangulation, the absence of comparisons with CB-SEM, GSCA, or Bayesian SEM limits a broader methodological evaluation.

7.2 Future Research Directions

- Conceptually, including constructs like moral norms, perceived environmental responsibility, green self-identity, or regulatory focus might allow for deeper insights into the motivational underpinning of sustainable consumption. Conversely, moderating effects through environmental concern, eco-literacy, or price sensitivity may unveil contextual limitations in which the structural relationships work.
- Empirically, a longitudinal design may examine if positive attitudes and attention towards eco-labels remain constant over time and if they translate into repeated energy-efficient purchases. On the other hand, experiments with manipulations in eco-label format, trust cues, and value framing may also yield richer causal evidence. Latent class analysis may also show further heterogeneous consumer segments of value-driven, eco-conscious, or label-sensitive buyers.
- Methodologically, future research could compare more kinds of estimators, for example, CB-SEM or Bayesian SEM, to deepen the understanding of estimator sensitivity in behavioral sustainability models. Sophisticated modeling frameworks like moderated mediation or conditional process analysis could help explain interaction patterns among variables. Cross-national replications would strengthen generalisability of the model and also provide insight into cultural differences in label interpretation and trust formation.

8. Conclusion

The current research investigates the combined effects of Consumption Values, Environmental Concern, and Eco-Labeling on Attitude, Paying Attention, and, finally, Purchase Intention for energy-efficient appliances. It also considered Trust in Energy Labels as an important moderating agent. Based on PLS-SEM and PLSc-SEM analyses of data from 450 respondents, this study has established clear evidence that both mental process mechanisms and affective processes play a crucial role in shaping consumers' sustainable purchase behavior. These findings confirm that Attitude and Paying Attention are indeed crucial mediators of value perceptions and environmental beliefs into behavioural intentions. Again, trust in labels appears to be the most important driver of purchase intention and stresses the importance of receiving easy-to-understand information on sustainability issues that is credible and transparent for consumers. Though some paths differed in magnitude and/or significance across the PLS and PLSc estimations, the overall direction of effects was stable across the methods, which underlines the theoretical robustness of our model.

The comparison between the PLS-SEM and PLSc-SEM shows that while PLS is excellent in prediction and variance explanation, PLSc strengthens both factor consistency and theoretical precision. Dual estimation thereby gives richer and more reliable insight into the dynamics of sustainable consumption behaviour. This in turn means, in practical terms, that the study advocates strengthening eco-label credibility by policymakers and marketers, raising consumer awareness, and communicating the functional economic benefits of energy-efficient appliances in order to encourage sustainable decision-making. Overall, this research advances the theoretical understanding and also the methodological practice that exists within sustainable consumer behaviour literature and thus lays a foundation for future studies aimed at promoting environmentally responsible purchase decisions.

Reference

1. Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
2. Armstrong, A. (2019). Mindfulness and consumption: A systematic review. *Journal of Consumer Affairs, 53*(2), 422–456. https://doi.org/10.1111/joca.12214
3. Bamberg, S., & Möser, G. (2007). Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of

pro-environmental behaviour. *Journal of Environmental Psychology, 27*(1), 14–25. https://doi.org/10.1016/j.jenvp.2006.12.002
4. Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report consistent PLS-SEM analyses: Guidelines with empirical illustrations. *Information & Management, 57*(2), 103168. https://doi.org/10.1016/j.im.2019.05.003
5. Biswas, A., & Roy, M. (2015). Green products: An exploratory study on the consumer behaviour in emerging economies of the East and West. *Journal of Cleaner Production, 87*, 463–468. https://doi.org/10.1016/j.jclepro.2014.09.043
6. Brown, K. W., & Kasser, T. (2005). Are psychological and ecological well-being compatible? The role of values, mindfulness, and lifestyle. *Social Indicators Research, 74*(2), 349–368. https://doi.org/10.1007/s11205-004-8207-8
7. Chen, M. F., & Tung, P. J. (2014). Developing an extended theory of planned behavior model to predict consumers' intention to visit green hotels. *International Journal of Hospitality Management, 36*, 221–230. https://doi.org/10.1016/j.ijhm.2013.09.006
8. Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern Methods for Business Research* (pp. 295–336). Lawrence Erlbaum.
9. Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly, 39*(2), 297–316. https://doi.org/10.25300/MISQ/2015/39.2.02
10. Ellen, P. S., Wiener, J. L., & Cobb-Walgren, C. (1991). The role of perceived consumer effectiveness in motivating environmentally conscious behaviors. *Journal of Public Policy & Marketing, 10*(2), 102–117. https://doi.org/10.1177/074391569101000207
11. Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behavior: The reasoned action approach*. Psychology Press.
12. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Sage.
13. Hair, J. F., Risher, J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
14. Han, H., Hsu, L. T., & Sheu, C. (2010). Application of the theory of planned behavior to green hotel choice: Testing the effect of environmental-friendly activities. *Tourism Management, 31*(3), 325–334.https://doi.org/10.1016/j.tourman.2009.03.013
15. Hanss, D., & Böhm, G. (2012). Sustainable consumption: Psychological determinants of pro-environmental behavior. *Journal of Consumer Behaviour, 11*(1), 48–60. https://doi.org/10.1002/cb.376
16. Henseler, J., Hubona, G., & Ray, P. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems, 116*(1), 2–20. https://doi.org/10.1108/IMDS-09-2015-0382
17. Hult, G. T. M., Hair, J. F., Proksch, D., Sarstedt, M., Pinkwart, A., & Ringle, C. M. (2018). Addressing endogeneity in international marketing applications of partial least squares structural equation modeling. *Journal of International Marketing, 26*(3), 1–21. https://doi.org/10.1177/1069031X18783595
18. Joshi, Y., & Rahman, Z. (2015). Factors affecting green purchase behaviour and future research directions. *International Strategic Management Review, 3*(1–2), 128–143. https://doi.org/10.1016/j.ism.2015.04.001
19. Kaiser, F. G., Arnold, O., & Keller, C. (2020). Attitude–behavior consistency in environmental psychology: A review. *Nature Sustainability, 3*, 620–630. https://doi.org/10.1038/s41893-020-0514-6
20. Kollmuss, A., & Agyeman, J. (2002). Mind the gap: Why do people act environmentally and what are the barriers to pro-environmental behaviour? *Environmental Education Research, 8*(3), 239–260. https://doi.org/10.1080/13504620220145401
21. Kim, Y., & Choi, S. M. (2005). Antecedents of green purchase behavior: An examination of collectivism, environmental concern, and PCE. *Advances in Consumer Research, 32*, 592–599.
22. Monroe, K. (2003). *Pricing: Making profitable decisions*. McGraw-Hill/Irwin.
23. Mostafa, M. M. (2007). Gender differences in Egyptian consumers' green purchase behaviour. *International Journal of Consumer Studies, 31*(3), 220–229. https://doi.org/10.1111/j.1470-6431.2006.00523.x
24. Paul, J., Modi, A., & Patel, J. (2016). Predicting green product consumption using theory of planned behavior and reasoned action. *Journal of Retailing and Consumer Services, 29*, 123–134. https://doi.org/10.1016/j.jretconser.2015.11.006
25. Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial least squares structural equation

modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of Market Research*. Springer. https://doi.org/10.1007/978-3-319-05542-8_15-1

26. Schlegelmilch, B. B., Bohlen, G. M., & Diamantopoulos, A. (1996). The link between green purchasing behaviour and values. *Journal of Marketing Management, 12*(6), 445–460. https://doi.org/10.1080/0267257X.1996.9964442
27. Sheth, J. N., Sethia, N. K., & Srinivas, S. (2011). Mindful consumption: A customer-centric approach to sustainability. *Journal of the Academy of Marketing Science, 39*, 21–39. https://doi.org/10.1007/s11747-010-0216-3
28. Stern, P. C. (2000). Toward a coherent theory of environmentally significant behavior. *Journal of Social Issues, 56*(3), 407–424. https://doi.org/10.1111/0022-4537.00175
29. Testa, F., Iraldo, F., Vaccari, A., & Ferrari, E. (2015). Why eco-labels can be effective marketing tools. *Business Strategy and the Environment, 24*(4), 252–265. https://doi.org/10.1002/bse.1821
30. Thøgersen, J., Haugaard, P., & Olesen, A. (2010). Consumer responses to eco-labels. *European Journal of Marketing, 44*(11/12), 1787–1810. https://doi.org/10.1108/03090561011079882
31. Wang, Y., Hazen, B., & Mollenkopf, D. A. (2022). Consumer pro-environmental behaviour and sustainability: A systematic review. *Journal of Cleaner Production, 338*, 130–152. https://doi.org/10.1016/j.jclepro.2022.130476
32. Whitmarsh, L., & O'Neill, S. (2010). Green identity, green living? *Journal of Environmental Psychology, 30*(3), 305–314. https://doi.org/10.1016/j.jenvp.2010.01.003