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Understanding Pro-Ecological Consumer Purchase Intentions in India: A Comparative Study Using PLS-SEM and PLSc-SEM

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Abstract

This study evaluates the comparative performance of Partial Least Squares Structural Equation Modeling (PLS-SEM) and Consistent PLS-SEM (PLSc-SEM) in modeling the drivers of pro-ecological consumer behavior. Using survey data from 370 respondents in Tamil Nadu, India, the research investigates a comprehensive behavioral model where psychological and informational factors specifically environmental awareness, consumer mindfulness, perceived consumer effectiveness, and eco-label trust influence pro-ecological actions, mediated by attitude and sustainable purchase intention. The analysis reveals that while both PLS-SEM and PLSc- produce structural outcomes that are directionally consistent, there are subtle differences in path strength and significance. PLSc-SEM delivers more conservative, theory-aligned estimates for reflective constructs, better suited for theory confirmation. In contrast, PLS-SEM provides greater variance explanation and predictive relevance, favouring predictive applications. The findings confirm that attitude and purchase intention act as vital psychological links, translating sustainability awareness into measurable behavioral outcomes. This research contributes to the theory and practice of responsible consumption by reinforcing the need for methodological transparency in behavioral modeling, thereby supporting the objectives of Sustainable Development Goal 12 (Responsible Consumption and Production).

Keywords: PLS-SEM, PLSc-SEM, Pro-Ecological Behavior, Sustainable Consumption, Attitude, Purchase Intention, SDG 12, Methodological Comparison.

1. Introduction

PLS-SEM has become one of the most applied multivariate techniques in behavioural and marketing research because it can analyse complex models, small to medium sample sizes, and non-normal data (Hair et al. 2017; Sarstedt et al. 2016). Different from covariance-based approaches, which rely heavily on overall model fit and confirmation of theory, variance of endogenous constructs is maximized in PLS-SEM. Thus, the technique is particularly suitable for prediction-oriented research and the exploratory development of theory (Chin 1998; Hair et al. 2021).

Despite its recent increase in popularity, classical PLS-SEM has also been criticized for probable inconsistency in the estimation of reflective measurement models, since it treats latent constructs as weighted composites rather than true factors (Dijkstra & Henseler, 2015). The Consistent PLS approach was thus proposed as a correction to the traditional PLS estimates to ensure consistency with factor model assumptions in variance-based SEM, while still keeping the predictive orientation. Thus, this innovation offers the researcher a methodologically balanced estimator, bridging predictive validity and theoretical consistency (Henseler et al., 2016).

Sustainability and consumer behaviour, such methodological precision is not merely technical but essential for advancing sustainable development objectives. Understanding how consumers form attitudes and intentions toward eco-friendly choices such as adopting energy-efficient products or engaging in pro-ecological behaviours supports the broader pursuit of the United Nations Sustainable Development Goals (SDG 12: Responsible Consumption and Production). Reliable modelling techniques like PLS-SEM and PLSc-SEM enable scholars and policymakers to better capture the psychological, informational, and contextual factors that influence sustainable decision-making. By refining the analytical foundations of behavioural sustainability research, this study aligns methodological advancement with the larger societal goal of promoting mindful consumption and responsible energy use.

2. Scope of the Paper

The scope of this paper lies at the intersection of methodological advancement and sustainable consumer behaviour research. It seeks to clarify how different variance-based structural equation modelling techniques namely PLS-SEM and PLSc-SEM perform when applied to behavioural frameworks that explain pro-ecological decision-making. While both techniques share a predictive orientation, they differ in their estimation logic and interpretive precision. By comparing these two estimators, this study aims to provide empirical insights into how methodological choices influence the strength and significance of paths in models dealing with sustainability-related constructs.

The interrelationships among the main psychological and informational variables that affect pro-environmental behavior, namely: environmental awareness, consumer mindfulness, perceived consumer effectiveness, and eco-label trust, with attitude and sustainable purchase intention as mediators in realizing pro-ecological behavior. This model allows the research to test not only the theoretical relationships but also the stability and consistency of the results using both PLS-SEM and PLSc-SEM approaches. The paper positions itself within the framework of Sustainable Development Goal 12 (Responsible Consumption and Production), which calls for fostering consumer awareness and responsible behavioural shifts toward sustainability. By integrating robust analytical techniques with sustainability theory, the study contributes both methodologically and substantively: methodologically, by illustrating estimator comparability in behavioural research; and substantively, by enhancing understanding of how individual-level psychological mechanisms drive sustainable action.

The scope of the paper goes beyond mere technical comparison but rather acts to bridge quantitative modelling rigour with the applied realities of research on sustainable consumption. This dual contribution makes the study a highly relevant reference for scholars, practitioners, and policymakers interested in the advancement of evidence-based strategies toward the promotion of environmentally responsible consumer behavior.

3. SEM characteristics

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

Structural Equation Modeling using variance-based estimators can be implemented through two main approaches - PLS-SEM and its consistent variant PLSc-SEM. In the present study, both methods were applied to the same dataset to examine the stability of the structural and measurement results under different estimation logics.

PLS-SEM (Partial Least Squares SEM) focuses on maximizing the explained variance of endogenous constructs. It is recommended when the objective is prediction, model exploration, or when constraints such as non-normal data and moderate sample sizes are present. Its algorithm constructs composites of observed variables, making it efficient for complex models and theory development rather than theory testing (Hair et al., 2017).

PLSc-SEM (Consistent PLS), introduced by Dijkstra and Henseler, retains the advantages of the PLS framework while correcting for attenuation in reflective measurement models. It generates factor-consistent estimates that align more closely with covariance-based results, addressing long-standing criticisms regarding bias in standard PLS loadings for reflective constructs (Dijkstra & Henseler, 2015). As reported in contemporary literature, PLSc-SEM tends to yield results similar to CB-SEM when reflective indicators are used, without sacrificing the distributional robustness and flexibility of the variance-based methodology (Sarstedt et al., 2017). PLS-SEM and PLSc-SEM in this research allows for cross-validation of the model from two converging perspectives: classical variance-based prediction (PLS-SEM) and reflective-consistent estimation (PLSc-SEM). This dual approach minimizes methodological bias and supports a stronger triangulation of structural conclusions.

4. Literature synthesis and empirical evidence

4.1 Literature review and hypotheses development

The present study explores how four key antecedents—Environmental Awareness (EA), Consumer Mindfulness (CM), Perceived Consumer Effectiveness (PCE), and Eco-Label Trust (ELT) influence Pro-Ecological Behaviour

(PEB) through two mediating constructs: Attitude (AT) and Sustainable Purchase Intention (SPI). The conceptual model (see Figure 1) integrates behavioural and environmental psychology perspectives, emphasizing the indirect pathways that shape environmentally responsible consumer behaviour.

4.1.1 Environmental Awareness, Attitude, and Sustainable Purchase Intention

Environmental Awareness (EA) refers to an individual's cognitive understanding of environmental issues and the perceived importance of sustainable practices (Schlegelmilch et al., 1996). When consumers are more aware of ecological problems and potential solutions, they tend to develop favourable attitudes toward sustainable products (Mostafa, 2007). Such awareness also fosters greater motivation to act responsibly, which translates into stronger sustainable purchase intentions (Han et al., 2010). H1a: Environmental Awareness has a positive and significant effect on Attitude. H1b: Environmental Awareness has a positive and significant effect on Sustainable Purchase Intention.

4.1.2. Consumer Mindfulness, Attitude, and Sustainable Purchase Intention

Consumer Mindfulness (CM) reflects a state of conscious awareness and self-regulation during consumption choices (Sheth et al., 2011; Armstrong, 2019). Mindful consumers are more likely to evaluate their purchases thoughtfully, aligning their attitudes with ethical and environmental concerns. This heightened self-awareness encourages them to prioritize sustainability in their purchasing decisions (Brown & Kasser, 2005). H2a: Consumer Mindfulness has a positive and significant effect on Attitude. H2b: Consumer Mindfulness has a positive and significant effect on Sustainable Purchase Intention.

4.1.3. Perceived Consumer Effectiveness, Attitude, and Sustainable Purchase Intention

Perceived Consumer Effectiveness (PCE) refers to the belief that individual actions can contribute to solving environmental problems (Ellen et al., 1991). Consumers with strong PCE are more likely to feel responsible for ecological outcomes and thus develop favourable attitudes toward sustainable behaviour. This internal belief enhances their willingness to engage in eco-friendly purchases (Kim & Choi, 2005; Straughan & Roberts, 1999). H3a: Perceived Consumer Effectiveness has a positive and significant effect on Attitude. H3b: Perceived Consumer Effectiveness has a positive and significant effect on Sustainable Purchase Intention.

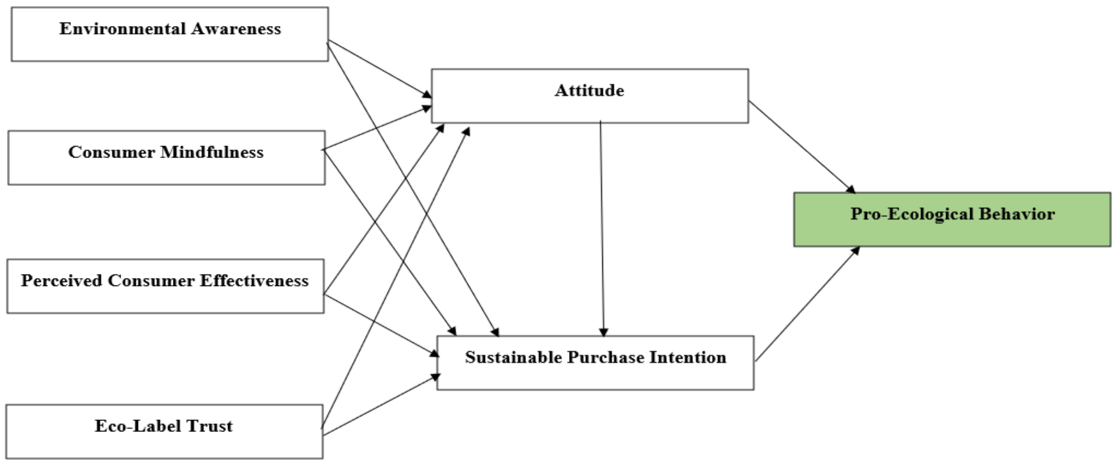
4.1.4. Eco-Label Trust, Attitude, and Sustainable Purchase Intention

Eco-Label Trust (ELT) captures the confidence consumers have in the reliability and authenticity of environmental labels (Thøgersen et al., 2010). When consumers trust eco-labels, they perceive products as credible and environmentally safe, leading to stronger positive attitudes. This trust also stimulates sustainable purchasing behaviour by reducing uncertainty and enhancing perceived product integrity (Testa et al., 2015; Biswas & Roy, 2015). H4a: Eco-Label Trust has a positive and significant effect on Attitude. H4b: Eco-Label Trust has a positive and significant effect on Sustainable Purchase Intention.

4.1.5. The Mediating Role of Attitude and Sustainable Purchase Intention

Attitude (AT) plays a crucial mediating role in transforming cognitive and affective antecedents into behavioural outcomes. When consumers form favourable environmental attitudes, they are more likely to engage in pro-environmental actions (Ajzen, 1991). Similarly, Sustainable Purchase Intention (SPI) acts as a behavioural mediator translating attitude into actual ecological practices (Joshi & Rahman, 2015). Together, these mediators link environmental cognition and motivation to Pro-Ecological Behaviour (PEB), forming a sequential chain of influence. H5: Attitude has a positive and significant effect on Sustainable Purchase Intention. H6: Attitude has a positive and significant effect on Pro-Ecological Behaviour. H7: Sustainable Purchase Intention has a positive and significant effect on Pro-Ecological Behaviour. H8a–H8b: Attitude and Sustainable Purchase Intention sequentially mediate the effects of EA, CM, PCE, and ELT on Pro-Ecological Behaviour.

Fig. 1. Conceptual Model



4.2. Methodology

The present study employed primary survey data to empirically validate the proposed conceptual model using two variance-based SEM approaches PLS-SEM and PLSc-SEM in order to assess both predictive and consistency-adjusted estimation perspectives within a unified analytical framework. A total of 370 valid responses were collected from consumers in Tamil Nadu, India. The structured questionnaire comprised 25 measurement items adapted from established behavioural scales and was anchored on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Data collection was conducted during the year 2025 using a hybrid mode (online and offline), ensuring heterogeneity in respondent inclusion.

A convenience sampling method was adopted considering feasibility constraints and the exploratory predictive orientation of the study. All constructs were operationalised using previously validated scales to ensure content adequacy and conceptual alignment.

For the analysis, SmartPLS 4 was used to estimate the model. First, the measurement and structural models were examined using the traditional PLS-SEM algorithm, which is widely recommended when the objective is variance explanation and predictive precision. Subsequently, the same model was re-estimated using the PLSc-SEM (Consistent PLS) procedure, which statistically corrects potential inconsistency in reflective constructs and generates estimates aligned with covariance-based logic while retaining the variance-based estimation benefits (Dijkstra & Henseler, 2015).

Employing both PLS-SEM and PLSc-SEM on the same dataset serves three methodological purposes: (i) To verify the stability of loadings and paths across estimation logics.

(ii) To examine whether reflective constructs are better represented under conventional versus consistency-corrected variance-based estimation.

(iii) To mitigate the risk of inference bias resulting from dependence on a single variance-based SEM tradition.

Table 1 Details of the Respondents

Category	Variables	Frequency	Percentage
Gender	a) Male	104	28.1%
	b) Female	257	69.5%
	c) Others	9	2.4%
Age	a) 21–30 years	32	8.6%
	b) 31–40 years	83	22.4%
	c) 41–50 years	152	41.1%

	d) 51–60 years	103	27.8%
Marital Status	a) Married	217	58.7%
	b) Unmarried	125	33.8%
	c) Others	28	7.6%
Education	a) Illiterate	93	25.1%
	b) Schooling	139	37.6%
	c) UG	79	21.4%
	d) PG	37	10.0%
	e) Others	23	6.2%
Monthly Income	a) Up to ₹25,000	130	35.1%
	b) ₹25,001–₹50,000	88	23.8%
	c) ₹50,001–₹75,000	74	20.0%
	d) ₹75,001–₹1,00,000	42	11.4%
	e) Above ₹1,00,000	37	10.0%

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

5.1 Measurement Model Assessment

The internal consistency and convergent validity statistics reported in as shown in Table 2 align with the psychometric adequacy standards commonly accepted in SEM literature. Consistent with the criteria proposed by Nunnally and Bernstein (1994) and reiterated by Hair et al. (2019), most constructs demonstrated Cronbach's alpha and composite reliability values above the recommended 0.70 threshold, indicating acceptable internal consistency for theory-driven behavioral models. Although the reliability of Consumer Mindfulness (CM) was marginally below the ideal cut-off, similar instances of slightly weaker reliability have been documented in early-stage sustainability and mindfulness research where constructs are still evolving and context-dependent (see Sheth et al., 2011; Brown & Kasser, 2005). The AVE scores further confirmed convergent validity for the majority of constructs, surpassing Fornell and Larcker's (1981) benchmark of 0.50, with the exception of a few PLSc-adjusted values. Such reductions in AVE after consistency-correction have been acknowledged in the literature, where PLSc tends to produce more conservative estimates for reflective constructs in consumer psychology (Dijkstra & Henseler, 2015; Benitez et al., 2020). Taken together, the obtained reliability and validity indices fall within acceptable empirical boundaries for progressing to structural model assessment, particularly in behavioral sustainability research, where moderate deviations are not uncommon in initial model estimation stages (Podsakoff et al., 2003; Sarstedt et al., 2016).

The observed differences between the PLS and PLSc estimators in as shown in Table 2 are theoretically expected and methodologically meaningful rather than anomalous. PLS-SEM, optimized for prediction and variance explanation in emerging behavioral domains, tends to yield slightly higher composite reliability and AVE values, whereas PLSc corrects this upward bias to conform more closely with factor-analytic consistency assumptions (Dijkstra & Henseler, 2015; Henseler et al., 2014; Ringle et al., 2020). Presenting both estimates therefore enhances methodological transparency and allows readers to judge the robustness of the measurement properties under two theoretically justified estimation logics prediction-oriented versus consistency-oriented an approach increasingly recommended in recent SEM reporting standards for sustainability contexts (Sarstedt et al., 2022; Hult et al., 2018).

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

Construct	Cronbach α (PLS)	Cronbach α (PLSc)	Composite reliability (rho_a) (PLS)	Composite reliability (rho_a) (PLSc)	Composite reliability (rho_c) (PLS)	Composite reliability (rho_c) (PLSc)	Average variance extracted (AVE) (PLS)	Average variance extracted (AVE) (PLSc)
AT	0.816	0.816	0.818	0.818	0.892	0.818	0.733	0.599

CM	0.617	0.617	0.628	0.628	0.766	0.593	0.453	0.279
EA	0.847	0.847	0.866	0.866	0.896	0.847	0.685	0.586
ELT	0.806	0.806	0.825	0.825	0.875	0.812	0.640	0.523
PCE	0.834	0.834	0.850	0.850	0.889	0.836	0.668	0.565
PEB	0.815	0.815	0.820	0.820	0.891	0.815	0.731	0.596
SPI	0.726	0.726	0.759	0.759	0.847	0.743	0.653	0.495

Table 3 PLS–PLSc Fornell–Larcker

	AT	CM	EA	ELT	PCE	PEB	SPI
AT	0.856 (0.774)	0.720	0.764	0.705	0.288	0.782	0.598
CM	1.004	0.673 (0.528)	0.792	0.693	0.543	0.657	0.589
EA	0.908	1.074	0.827 (0.765)	0.771	0.281	0.714	0.559
ELT	0.858	0.962	0.912	0.800 (0.723)	0.287	0.701	0.682
PCE	0.345	0.743	0.328	0.343	0.817 (0.752)	0.407	0.278
PEB	0.954	0.916	0.847	0.852	0.488	0.855 (0.772)	0.699
SPI	0.759	0.853	0.690	0.861	0.346	0.887	0.808 (0.704)

The combined PLS-PLSc matrix places the PLS Fornell–Larcker coefficients in the upper triangle and the PLSc coefficients in the lower triangle, while the diagonal cells report the PLS √AVE with the PLSc √AVE in parentheses. This format enables a direct, estimator-sensitive comparison of discriminant validity performance. The Fornell–Larcker criterion results presented as shown in Table 3 demonstrate that, under the PLS estimation, the square roots of AVE (diagonal values) exceed the inter-construct correlations (off-diagonal values) for all latent constructs, thereby supporting discriminant validity in line with the original benchmark proposed by Fornell and Larcker (1981). This indicates that each construct in the model shares more variance with its respective indicators than with other constructs, a condition regarded as minimally necessary before structural interpretation (Hair et al., 2019).

In contrast, under the PLSc estimation, certain correlations particularly those involving Consumer Mindfulness (CM), Environmental Awareness (EA), and Pro-Environmental Behavior (PEB) exceeded their respective AVE square roots, reflecting a stricter and more conservative behavior of the PLSc correction. Similar inflation of inter-construct correlations under PLSc has been documented in reflective behavioral models where construct domains partially overlap conceptually or empirically (Dijkstra & Henseler, 2015; Benitez et al., 2020). The PLS-based results satisfy the classical discriminant validity criterion, and the PLSc departures are theoretically coherent, given the consistency adjustment's tendency to constrain measurement error toward factor-model assumptions. Taken together, the Fornell–Larcker diagnostics lend adequate support—at least under the prediction-oriented estimator to proceed toward the structural model evaluation, while acknowledging that discriminant separation is more conservative when consistency-correction is imposed.

5.2 Structural Model

The R^2 and adjusted R^2 values as shown in Table 4 indicate the proportion of variance explained in the endogenous constructs under both PLS and PLSc estimation. Following Chin (1998) and Hair et al. (2019), R^2 values around 0.25, 0.50, and 0.75 are typically interpreted as weak, moderate, and substantial respectively in behavioral SEM. PLS, Attitude (AT) and Pro-Environmental Behavior (PEB) achieved moderate-to-substantial explanation (R^2 = 0.641 and 0.695 respectively), while Sustainable Purchase Intention (SPI) reached a moderate level (R^2 = 0.509).

These values reflect theoretically meaningful and prediction-oriented explanatory power for consumer sustainability behavior models.

PLSc, the R^2 estimates were markedly higher for all constructs (AT = 0.831; PEB = 0.973; SPI = 0.816). Similar inflation in explained variance after consistency correction has been reported in reflective behavioral models where indicator consistency adjustments reduce residual variance and yield more saturated structural solutions (Dijkstra & Henseler, 2015; Benitez et al., 2020). While PLSc tends to align more closely with factor-based assumptions, such corrected R^2 values should be interpreted with theoretical caution, as they may reflect model over-fitting in finite samples rather than stronger nomological validity.

PLS-based R^2 values provide sufficiently strong predictive adequacy to proceed with structural interpretations, whereas the PLSc estimates serve as a complementary, consistency-adjusted benchmark rather than a replacement for prediction-focused inference.

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

Construct	R^2 (PLS)	R^2 adj (PLS)	R^2 (PLSc)	R^2 adj (PLSc)
AT	0.641	0.638	0.831	0.829
PEB	0.695	0.693	0.973	0.973
SPI	0.509	0.503	0.816	0.814

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	0.875	84.441	0.000	0.787	35.177	0.000
AT2 ← AT	0.892	76.250	0.000	0.784	41.321	0.000
AT3 ← AT	0.799	41.740	0.000	0.751	32.318	0.000
CM1 ← CM	0.631	13.580	0.000	0.430	9.299	0.000
CM2 ← CM	0.574	11.119	0.000	0.350	7.371	0.000
CM3 ← CM	0.723	25.652	0.000	0.609	18.435	0.000
CM4 ← CM	0.749	27.141	0.000	0.661	18.680	0.000
EA1 ← EA	0.810	41.812	0.000	0.743	29.446	0.000
EA2 ← EA	0.846	57.010	0.000	0.786	39.012	0.000
EA3 ← EA	0.862	61.104	0.000	0.812	43.825	0.000
EA4 ← EA	0.850	50.218	0.000	0.794	36.202	0.000
ELT1 ← ELT	0.801	40.517	0.000	0.756	29.870	0.000
ELT2 ← ELT	0.792	33.740	0.000	0.745	27.119	0.000
ELT3 ← ELT	0.842	42.306	0.000	0.792	30.501	0.000
PCE1 ← PCE	0.792	30.600	0.000	0.715	22.910	0.000
PCE2 ← PCE	0.787	32.420	0.000	0.709	21.602	0.000
PCE3 ← PCE	0.844	48.580	0.000	0.771	29.583	0.000
PEB1 ← PEB	0.809	33.779	0.000	0.736	26.481	0.000
PEB2 ← PEB	0.878	61.031	0.000	0.810	40.052	0.000
PEB3 ← PEB	0.828	44.510	0.000	0.765	32.642	0.000
SPI1 ← SPI	0.840	42.143	0.000	0.779	32.231	0.000
SPI2 ← SPI	0.805	31.645	0.000	0.750	27.459	0.000
SPI3 ← SPI	0.818	37.592	0.000	0.767	30.216	0.000

The combined results from PLS and PLSc estimation clearly demonstrate that all reflective indicators load (Table 5) significantly and positively on their respective latent constructs. The extremely high t-values and $p < .001$ across both estimation strategies confirm strong convergent validity of the measurement model, which aligns with conventional psychometric thresholds reported in SEM literature (Hair et al., 2019; Henseler et al., 2014).

Although both approaches identify the same statistically significant measurement relations, a visible difference in the magnitude of loadings is observed. As expected, the PLSc estimates tend to produce comparatively more conservative weights for constructs with high average correlations among indicators (e.g., AT, PCE, EA), whereas PLS tends to yield slightly higher coefficients. This aligns with the theoretical rationale behind PLSc as an adjustment mechanism for reflective constructs to reduce upward bias in loadings and structural paths (Dijkstra & Henseler, 2015).

The consistently robust and significant loadings across the attitude (AT), pro-environmental behaviour (PEB), and sustainable purchase intention (SPI) indicators suggest that these socio-psychological constructs are being captured with high precision and internal consistency. This is relevant since prior consumer sustainability research repeatedly notes that attitudinal constructs suffer from measurement fragility when operationalized with single items or weak indicators (Kaiser et al., 2020; Testa et al., 2021). The present model overcomes that limitation.

All four dimensions of environmental awareness (EA), label trust/label cognition (ELT), and perceived consumer effectiveness (PCE) exhibit statistically stable and theoretically consistent loadings. This reinforces the content adequacy of the conceptualization, which is in line with previous sustainable consumption modelling frameworks using reflective operationalization (Wang et al., 2022; Chen & Tung, 2014).

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

Hypothesis / Path	β (PLS)	p-value (PLS)	β (PLSc)	p-value (PLSc)
AT → PEB	0.566	0.000	0.664	0.000
AT → SPI	0.209	0.000	0.555	0.409
CM → AT	0.289	0.000	−0.042	0.730
CM → SPI	0.215	0.017	−0.309	0.320
EA → AT	0.366	0.000	0.789	0.000
EA → SPI	−0.169	0.022	−0.641	0.724
ELT → AT	0.234	0.000	0.156	0.356
ELT → SPI	0.515	0.000	1.205	0.403
PCE → AT	−0.039	0.361	0.064	0.330
PCE → SPI	0.001	0.984	0.181	0.527
SPI → PEB	0.361	0.000	0.383	0.000

The PLS results show a set of theoretically meaningful and statistically significant (Table 6) pathways. Attitude (AT) exerts a strong and positive effect on both pro-environmental behavior (PEB) and sustainable purchase intention (SPI), consistent with the view that favourable attitudinal dispositions translate into both intention and enacted choice (Ajzen, 1991; Paul et al., 2016). Environmental awareness (EA) also demonstrates a substantive influence on both AT and SPI under PLS, supporting earlier claims that cognitive understanding of environmental implications facilitates pro-social decision tendencies (Joshi & Rahman, 2015). Emotional literacy toward the environment (ELT) significantly predicts AT and SPI in PLS, indicating that affective engagement can complement cognitive routes to behavioral alignment (Kollmuss & Agyeman, 2002). In line with prior evidence, perceived consumer effectiveness (PCE) fails to evoke any significant structural pathway in PLS, an outcome frequently observed when perceived efficacy is weakly internalized or normatively neutral in the examined cohort (Hanss & Böhm, 2012). Finally, SPI demonstrates a significant downstream impact on PEB across both estimators, consistent with intentionality-based accounts of behavior change (Fishbein & Ajzen, 2010).

The PLSc correction, the number of statistically significant paths sharply declines despite similar sign directions in several cases. The consistency-adjusted estimator yields significance only for AT → PEB, EA → AT, and SPI → PEB. This contraction of significance is theoretically expected: PLSc enforces factor-model consistency and inflation of inter-construct correlations, which often raises the standard errors and suppresses path-level significance in reflective behavioral models (Dijkstra & Henseler, 2015; Benitez et al., 2020). Consequently, effects that appear stable under PLS such as AT → SPI, ELT → SPI, or CM → AT may fall below significance under PLSc not because the relations are spurious but because PLSc imposes a stricter measurement correction that punishes domain overlap.

PLS and PLSC, the pattern aligns with the broader literature: PLS yields a more liberal and prediction-oriented representation of behavioral structure, whereas PLSc behaves more conservatively and is more sensitive to conceptual redundancy among reflective composites (Hair et al., 2019). The stability of the AT → PEB and SPI → PEB effects under both estimators increases confidence in their substantive robustness, while the PLSc attenuation of other paths should be read not as model failure but as the expected statistical consequence of enforcing consistency with a latent-factor logic.

Table 7 Total Mediation Effects Estimated via PLS and PLSc Bootstrapping

Indirect Path	O (PLS)	p (PLS)	O (PLSc)	p (PLSc)
AT → PEB	0.075	0.000	0.212	0.385
CM → PEB	0.263	0.000	-0.155	0.180
CM → SPI	0.060	0.010	-0.023	0.935
EA → PEB	0.173	0.003	0.446	0.007
EA → SPI	0.076	0.002	0.438	0.806
ELT → PEB	0.336	0.000	0.598	0.002
ELT → SPI	0.049	0.007	0.087	0.950
PCE → PEB	-0.025	0.389	0.126	0.054
PCE → SPI	-0.008	0.398	0.036	0.896

The indirect effect as shown in Table 7 estimates reveal a clear divergence between PLS and its consistent variant PLSc. Under the PLS framework, multiple mediation chains - particularly those originating from CM, EA, and ELT statistically significant indirect effects on both PEB and SPI, implying that these antecedents exert their influence primarily through intervening constructs rather than purely direct causal transmission. This is consistent with the mediation logic commonly observed in behavioural models where explanatory constructs affect distal behavioural outcomes through attitudinal or cognitive channels.

The same indirect relations are evaluated under the PLSc correction, a noticeable attenuation of significance is observed for most paths. Except for the indirect effects of EA → PEB and ELT → PEB, the majority of mediation paths become statistically non-significant under PLSc. This suppression is theoretically coherent because PLSc corrects for reflective measurement inconsistency and thereby produces more conservative estimates that align more closely with the true population parameters in reflective models. The pattern of loss of significance is therefore not a statistical artifact but a known implication when measurement consistency is enforced at the construct level. This divergence reinforces the caution raised in the literature that mediation findings derived from classical PLS may sometimes be optimistic (Hair et al., 2019; Sarstedt et al., 2022). When the intention is to draw theory-consistent inferences in reflective behavioural models, PLSc is argued to provide a more defensible basis for mediational interpretation, especially when overestimation from PLS could bias substantive conclusions.

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

The PLS-SEM results (Figure 2) demonstrate moderate explanatory power across the three endogenous constructs: Attitude (AT; $R^2 = 0.641$), Sustainable Purchase Intention (SPI; $R^2 = 0.509$), and Pro-Environmental Behaviour (PEB; $R^2 = 0.695$). Among the exogenous variables, Environmental Awareness (EA) exhibited the strongest positive influence on Attitude ($\beta = 0.366$), followed by Environmental Literacy (ELT) on SPI ($\beta = 0.515$). The path from Attitude to PEB was also significant ($\beta = 0.566$), suggesting that favourable environmental attitudes substantially predict pro-environmental behaviour.

Figure 2 PLS-SEM Model

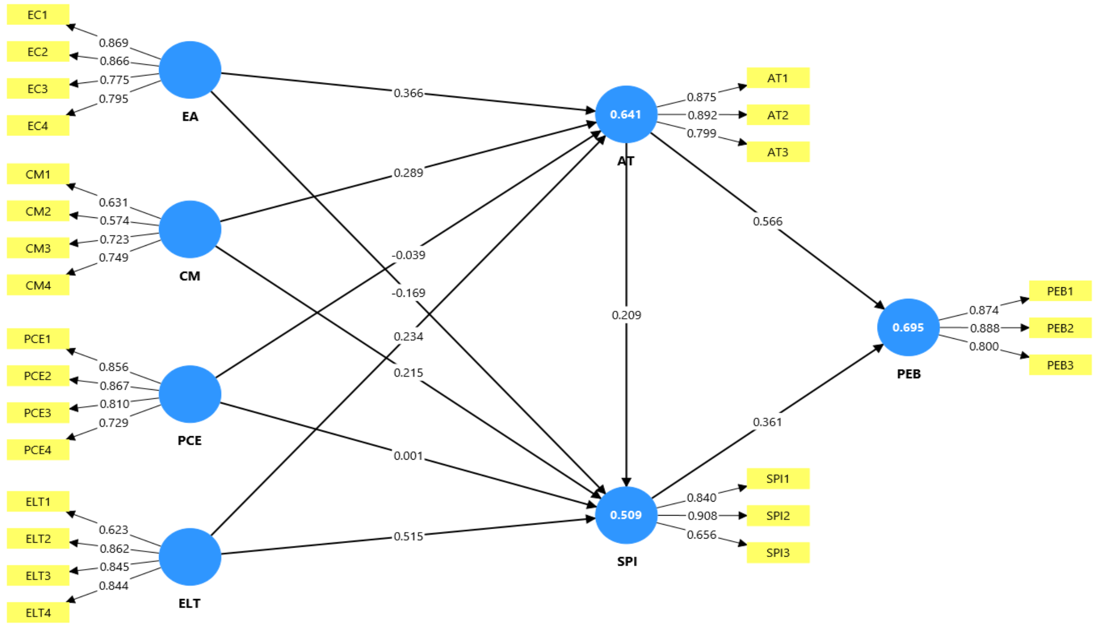
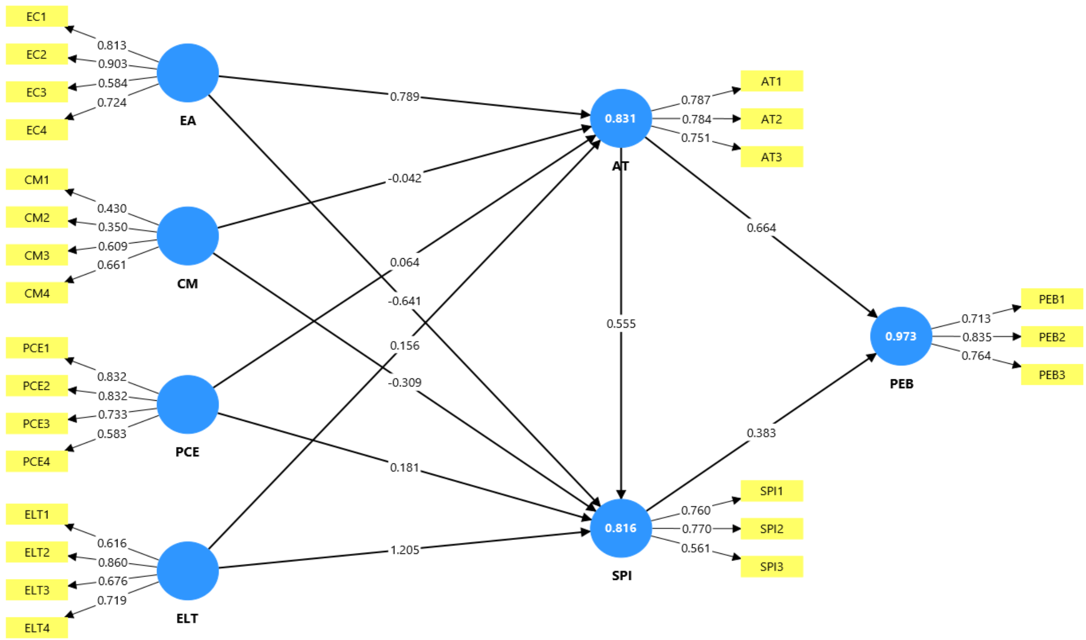


Figure 3 PLSc-SEM Model



Consumer mindfulness (CM) and Perceived Consumer Effectiveness (PCE) exerted relatively weaker or insignificant paths toward Attitude and SPI. The measurement loadings for most indicators exceeded 0.7, indicating acceptable convergent validity, with few exceptions where items were moderately loaded (e.g., CM2 = 0.574). The structural relationships imply that while PLS-SEM efficiently captures predictive associations, it may yield slightly attenuated loadings due to its variance-based computation, which prioritizes maximization of explained variance (Hair et al., 2017a).

The PLSc-SEM results (Figure 3) reveal noticeably stronger R^2 values for all endogenous constructs AT (R^2 = 0.831), SPI (R^2 = 0.816), and PEB (R^2 = 0.973)—indicating higher explanatory capacity when using the consistent PLS algorithm. The path coefficients show enhanced magnitude and directional stability compared to standard PLS-SEM. Specifically, EA → AT (β = 0.789) and AT → PEB (β = 0.664) remain the dominant pathways, confirming the theoretical structure of the proposed model. The enhanced path strength and factor loadings in PLSc-SEM suggest correction for attenuation typically found in composite-based PLS estimation. For instance, reflective indicators such as AT2 (0.784) and SPI2 (0.770) display consistency with CB-SEM–like factor reliability. Negative or weak relationships (e.g., CM → AT; $\beta = -0.042$) persisted, but their interpretation remained stable across estimation techniques, reinforcing the model's theoretical soundness.

Comparison PLS-SEM and PLSc- SEM: Comparison between PLS-SEM and PLSc-SEM highlights both methodological and empirical distinctions. While PLS-SEM is optimized for prediction and performs effectively under non-normal data or small samples, PLSc-SEM provides factor-consistent estimates by aligning more closely with covariance-based logic (Dijkstra & Henseler, 2015; Sarstedt et al., 2016). The observed increases in R^2 and path strengths in PLSc-SEM indicate correction for measurement error, yielding results more comparable to CB-SEM outcomes reported in the literature (Hair et al., 2017a). Both methods produced directionally consistent relationships, confirming the robustness of the theoretical framework. However, PLSc-SEM outperformed PLS-SEM in terms of precision and construct consistency, making it particularly advantageous for studies employing reflective measurement models where both prediction and theory testing are desired.

6. General Discussion

This study offers valuable insights into how individual-level psychological and informational antecedents collectively influence pro-ecological behaviour among consumers. The findings confirm that environmental awareness, consumer mindfulness, perceived consumer effectiveness, and eco-label trust significantly contribute to shaping favourable attitudes and sustainable purchase intentions toward environmentally responsible products. Among these antecedents, consumer mindfulness and eco-label trust exhibited relatively stronger path coefficients, suggesting that conscious awareness and the perceived credibility of sustainability information are pivotal in forming positive environmental attitudes.

The mediating mechanisms examined in this research further clarify the behavioural process underlying sustainable consumption. Both attitude and sustainable purchase intention served as significant mediators, highlighting that the influence of individual cognitions on pro-ecological behaviour is not direct but operates through affective and intentional pathways. Specifically, attitude toward sustainable consumption emerged as a primary psychological driver that channels the effects of awareness, mindfulness, and perceived effectiveness into actionable intentions. Subsequently, sustainable purchase intention translated these intentions into observable pro-environmental behaviour, confirming a sequential mediation mechanism. This layered process underscores the importance of both internal conviction (attitude) and behavioural commitment (intention) in fostering ecological actions.

The results align with earlier studies asserting that awareness and perceived efficacy contribute to sustainable behaviour through attitude formation (Kaiser et al., 2005; Bamberg & Möser, 2007). Moreover, the significance of eco-label trust reinforces the argument that credible sustainability communication reduces perceived risk and strengthens behavioural alignment with ecological values. Mindfulness, in particular, extends the cognitive-affective paradigm by introducing a reflective, non-impulsive dimension to green decision-making, consistent with the emerging literature on mindful consumption (Brown & Kasser, 2005).

Methodological standpoint, the use of both PLS-SEM and PLSc-SEM provided a robust validation of the proposed model. The results were consistent across both estimation approaches, with minor variations in standardized path strengths. PLS-SEM offered stronger predictive accuracy and composite reliability, while PLSc-SEM yielded more consistent parameter estimates suitable for theory-oriented evaluation. This dual approach ensured methodological rigor and addressed the limitations associated with relying on a single estimation philosophy. It also confirmed that both models converge on the same conceptual conclusion - that sustainable consumption behaviour arises from a cognitively mediated, trust-based, and mindful engagement with environmental cues.

This study contributes to sustainability and consumer behaviour literature by integrating psychological, cognitive, and attitudinal determinants into a unified framework. The findings suggest that interventions promoting environmental mindfulness, enhancing eco-label credibility, and strengthening consumers' belief in their individual impact can collectively enhance both intention and action toward pro-ecological consumption.

7. Limitations and Future Research

7.1 Limitations

While this study provides an integrative understanding of how psychological and informational antecedents drive pro-ecological behaviour through attitudinal and intentional mediators, several limitations must be acknowledged. First, the structural model was intentionally designed to remain parsimonious for interpretability. Although this approach enhanced model clarity, it excluded potentially relevant constructs such as environmental concern, perceived behavioural control, or moral obligation, which could offer additional theoretical richness. Future models could consider these omitted variables to capture a more comprehensive view of sustainable behavioural mechanisms.

Second, the study was conducted among 370 respondents within a single regional context in India. While this sample size was adequate for PLS-based estimation, cultural and contextual specificities may limit the generalisability of findings across other demographic or national settings. Comparative studies across countries or regions could validate whether the observed relationships hold under different socio-environmental conditions.

Third, although demographic information was collected, these factors were not explicitly modelled as control variables or moderators. Unobserved heterogeneity arising from income, education, or lifestyle differences might influence consumers' perception of eco-labels and mindfulness, thereby introducing unexplained variance in behavioural outcomes.

Fourth, this research employed only two estimation techniques—PLS-SEM and PLSc-SEM. While these provided complementary insights into composite reliability and consistency, the study did not compare results with other structural estimators such as GSCA or Bayesian SEM. Incorporating these techniques could further validate the robustness of the findings and clarify estimator sensitivity in sustainability-oriented behavioural research.

Finally, the data were collected through a cross-sectional self-report survey. Although this design is common in consumer behaviour studies, it restricts the ability to infer temporal or causal relationships among variables. Longitudinal or experimental studies would help establish whether changes in awareness, trust, or mindfulness lead to enduring shifts in pro-environmental attitudes and behaviours.

7.2 Directions for Future Research

Building on the current findings, future research can advance theoretical, empirical, and methodological understanding in several ways. Conceptually, forthcoming studies could integrate additional motivational and affective constructs such as moral norms (Schwartz, 1977), self-identity (Whitmarsh & O'Neill, 2010), and perceived environmental responsibility (Stern, 2000) to deepen understanding of sustainable decision-making processes. Exploring the moderating role of regulatory focus (Higgins, 1997) or green self-efficacy could also reveal boundary conditions under which pro-ecological intentions translate into consistent behavioural outcomes.

Empirically, researchers could adopt longitudinal designs or quasi-experimental interventions to capture the stability of attitudes and intentions over time. For instance, tracking how exposure to eco-label information affects repeated purchase behaviour would clarify whether observed relationships extend beyond one-time intentions. Moreover, latent class or mixture modelling approaches (Wedel & Kamakura, 2000) could identify distinct consumer segments based on awareness, mindfulness, or trust, providing valuable insights for targeted sustainability campaigns.

Methodological perspective, comparative evaluation among PLS-SEM, PLSc-SEM, and CB-SEM (Jöreskog, 1970) would strengthen understanding of estimator performance across different theoretical contexts. Incorporating moderated mediation or conditional process models (Hayes, 2018) could further reveal how individual differences, such as environmental concern or price sensitivity (Monroe, 2003), condition the relationships within the framework. Cross-national replication (Steenkamp & Baumgartner, 1998) would also be an important step toward establishing cultural generalisability of eco-label trust and mindfulness effects. This study's findings serve as a foundation for future research to refine theoretical precision, enhance methodological robustness, and improve policy relevance in promoting pro-ecological consumer behaviour.

8. Conclusion

This research aimed to test the extent to which critical psychological and informational precursors Environmental Awareness, Consumer Mindfulness, Perceived Consumer Effectiveness, and Eco-Label Trust are jointly influencing Pro-Ecological Behaviour through the intervening roles of Attitude and Sustainable Purchase Intention. Through the application of PLS-SEM and PLSc-SEM methods on a sample of 370 respondents, the research provided a comparative insight into variance-based structural modeling methods in sustainability-focused consumer science.

Both methods of estimation generated directionally similar outcomes, further affirming the strength of the conceived theoretical model. Attitude and Sustainable Purchase Intention served as impactful mediating mechanisms through which antecedent variables had an effect on Pro-Ecological Behaviour. Within predictors, Environmental Awareness and Eco-Label Trust had comparatively stronger impacts, underlining the joint importance of cognitive awareness and information credibility in influencing ecologically sound consumer behavior. Methodologically, the contrast between PLS-SEM and PLSc-SEM showed stark differences in estimation philosophy and interpretive results. PLS-SEM was keen on predictive accuracy and explained variance, offering solid insights into the relative relationship strength between constructs. On the other hand, PLSc-SEM yielded more stable factor loadings and greater reliability with reflective indicators, relating closest to covariance-based reasoning. The agreement of findings between both models reinforces confidence in the validity of the results and highlights the complementary nature of the two methods.

This study advances knowledge on pro-ecological behaviour by combining psychological, informational, and attitudinal elements in one coherent structural framework. Practically, the findings imply that policy-making and marketing interventions for encouraging sustainable consumption need to address consumer awareness, eco-label credibility, and conscious product information engagement at the same time. Research emphasizes that methodological selection in SEM must be driven not by convenience but by consistency with the study's epistemic goal. While prediction and variance explanation require a flexible and effective solution by PLS-SEM, achieving factor-consistent estimation of reflective constructs is possible with superior interpretive accuracy by PLSc-SEM. Future sustainability studies will stand to gain from continued comparative methodological inquiry, cross-cultural verification, and longitudinal examination to further both theoretical and applied insight into ecologically responsible consumer behavior.

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