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Modelling Attribute Non-Attendance In Eco-Label Preferences: Behavioural Insights For Water Pollution Mitigation In Malaysia

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Abstract
Household detergents are significant contributors to domestic water pollution in Malaysia, where regulatory controls on phosphate and surfactant content remain limited. Eco-labels are increasingly promoted to encourage sustainable purchasing; however, their effectiveness is often constrained by attribute non-attendance (ANA), a decision-making behaviour in which consumers disregard specific label elements. This study applies a discrete choice experiment (n = 210 urban detergent buyers) to estimate willingness to pay (WTP) for eco-label attributes and to examine how ANA shapes preference structures. A baseline multinomial logit model is compared with staged latent class models incorporating ANA constraints based on self-reported non-attendance. Accounting for ANA improves model fit substantially (pseudo-R^2 rising from 0.014 to 0.567) and reveals that certification credibility and label placement generate the highest statistically significant WTP, while message format influences only certain consumer segments. These findings underscore the importance of simplified, high-salience, and trust-building label designs to reduce cognitive burden and promote environmentally responsible purchasing. By linking behavioural insights to domestic water pollution mitigation, the study provides actionable evidence to guide eco-label policy, sustainable consumption strategies, and progress toward SDG 6 (Clean Water and Sanitation) and SDG 12 (Responsible Consumption and Production).
Keywords: *eco-label attributes; attribute non-attendance (ANA); consumer behaviour; willingness to pay (WTP); water pollution mitigation*

1.0 INTRODUCTION

Eco-labels are widely recognised as essential tools for promoting sustainable consumption and production (Plank & Teichmann, 2018; Darnall et al., 2018). By signalling a product's environmental integrity, they help reduce information asymmetry between producers and consumers (D'Souza et al., 2006; Leire & Thidell, 2005). Applied across sectors such as food, textiles, and household cleaning products, eco-labels allow firms to demonstrate environmental accountability and enable consumers to identify environmentally preferable products (Sammer & Wüstenhagen, 2006). Certification bodies, whether governmental or private, play a pivotal role in legitimising claims and building trust (Gorton et al., 2021). However, the rapid proliferation of eco-labels has introduced challenges, including information overload, consumer scepticism, and inconsistent standards (Scarpa et al., 2013). Ultimately, label credibility and consumer engagement remain critical to fostering pro-environmental behaviour, with trust emerging as a key determinant of sustainable purchasing (Taufique et al., 2014).

Laundry detergents were selected as the focus of this study due to their direct and widespread contribution to domestic water pollution (Thannimalay & Yusoff, 2014; Thannimalay et al., 2012). These products contain petrochemical-based surfactants, enzymes, and optical brighteners that are discharged into aquatic systems through wastewater (Sánchez-Fortún & Barahona, 2008; Stalmans et al., 1991). Such pollutants accelerate eutrophication, trigger algal blooms, and degrade ecosystems (Azizullah et al., 2011; Rebello et al., 2020). In Malaysia, regulatory measures on phosphate content remain limited, despite phosphates being a recognised contributor to water quality deterioration (Siwayanan et al., 2015). Biodegradable alternatives, such as palm-based methyl ester sulfonate detergents, are promoted to mitigate ecological harm (Thannimalay & Yusoff, 2014; Rebello et al., 2020).

The Environmental Quality Report 2023 highlights non-point sources particularly greywater from household laundry, as major contributors to elevated biochemical oxygen demand and ammoniacal nitrogen, reducing Malaysia's Water Quality Index. Only 72% of rivers were classified as clean in 2023, with 24% moderately polluted and 4% polluted (Department of Environment Malaysia, 2023). The phosphate surfactant content of detergents further intensifies eutrophication and oxygen depletion, threatening aquatic biodiversity.

Understanding consumer responses to eco-labels is therefore essential for improving their design and effectiveness ((Taufique et al., 2014; D'Souza et al., 2006). A major methodological challenge in eco-label research is attribute non-attendance (ANA), when consumers ignore specific label elements during decision-making (Scarpa et al., 2009; Hensher et al., 2012). Ignoring ANA can distort utility estimates and bias willingness-to-pay (WTP) calculations (Scarpa et al., 2013; Zhang et al., 2020). Traditional discrete choice experiment (DCE) approaches often assume full attribute attendance, yet in practice, consumers adopt cognitive simplification strategies, focusing on certain attributes while disregarding others due to decision fatigue or perceived irrelevance (Gigerenzer & Gaissmaier, 2011; Scarpa et al., 2009; Hensher et al., 2012; Alemu et al., 2013). This can undermine the accuracy of preference estimates and the reliability of policy recommendations (Alemu et al., 2013; Balcombe et al., 2015).

ANA can be measured through stated non-attendance (SNA), which captures self-reported attention patterns, or through inferred non-attendance, which is estimated using statistical models such as latent class models (LCM) (Gonçalves et al., 2022; Hensher et al., 2012). Inferred approaches are valuable for capturing unobserved heterogeneity and for identifying cognitive segments within a population (Hess & Hensher, 2010). Recent innovations, including staged LCMs and eye-tracking validation, have improved the behavioural realism of ANA estimation (Proi et al., 2023; Balcombe et al., 2015). Despite these advances, empirical applications in Southeast Asia, particularly in the context of household detergents, remain limited (Kijjanapanich & Benyaapikul, 2020).

This study addresses these gaps by investigating how Malaysian consumers attend to and value specific eco-label attributes for laundry detergents. Using a DCE, it estimates WTP for certification body credibility (international vs. manufacturer), label placement (front-top vs. front-bottom), and environmental message format (brief vs. complete), while explicitly accounting for ANA in model estimation. A baseline multinomial logit (MNL) model is compared with staged LCM-ANA models that progressively constrain ignored attributes. This approach captures heuristic-driven strategies often overlooked in conventional analyses (Scarpa et al., 2013; Hensher et al., 2012). The results provide behaviourally grounded insights to guide eco-label policy design, reduce cognitive burden, and promote sustainable household consumption aligned with SDG 12 (responsible consumption) and SDG 6 (clean water and sanitation).

2. LITERATURE REVIEW

2.1 Eco-Labels and the Role of Attribute Non-Attendance (ANA)

Eco-labels serve as key informational tools that help reduce asymmetry between producers and consumers by signalling the environmental quality of products (D'Souza et al., 2006; Leire & Thidell, 2005). Their effectiveness in promoting sustainable consumption depends on consumers' ability to perceive, interpret, and process the information provided (Proi et al., 2023). ANA arises from two primary mechanisms: genuine preferences and heuristic simplification. In the first case, consumers intentionally disregard attributes they perceive as irrelevant (Hess & Hensher, 2010), while in the second, they adopt cognitive shortcuts to manage information overload or limited processing capacity (Gigerenzer & Gaissmaier, 2011).

The effectiveness of eco-labels is influenced by design elements such as certification logos, label placement, and message clarity. When presented with multiple attributes, consumers often display selective rather than comprehensive attention. ANA reflects the systematic omission of certain attributes as a strategy to simplify complex decisions (Scarpa et al., 2009; Alemu et al., 2013). This behaviour can result from cognitive fatigue or a perception that some elements are redundant. As DCE designs become more complex, the likelihood of ANA increases, which may distort utility estimates and WTP Ignoring ANA can result in inflated valuations and misrepresentation of actual consumer preferences (Hensher et al., 2012; Gonçalves et al., 2022).

2.2 Psychological Drivers of Attribute Non-Attendance

Consumers frequently rely on simplified decision rules, such as focusing on visual cues like certification logos while ignoring textual or numerical content. Risk perception plays a key role in determining attribute attention. When environmental risk is perceived as high, consumers are more inclined to process eco-label information, whereas low perceived relevance increases the likelihood of ANA (Taufique et al., 2014). Trust in certification bodies significantly shapes attention patterns, as higher levels of trust enhance perceived credibility and engagement with eco-labels (Scarpa et al., 2013). Emotional and identity-related factors also influence attribute processing. Individuals with stronger environmental self-identity or concern are more likely to process sustainability-related cues, while others may prioritise price or brand familiarity (Essoussi & Zahaf, 2009; Khachatryan et al., 2021). These psychological drivers directly affect the extent to which consumers attend to or ignore specific attributes during DCE tasks.

2.3 Methodological Developments in ANA Estimation

ANA can be measured through SNA, which captures self-reported attention patterns, or through inferred non-attendance, which is estimated using statistical models such as LCM (Gonçalves et al., 2022; Hensher et al., 2012). Inferred approaches are valuable for capturing unobserved heterogeneity and for identifying cognitive segments within a population (Hess & Hensher, 2010). Recent methodological innovations, including staged LCM and eye-tracking validation, have improved the behavioural realism of ANA estimation (Proi et al., 2023; Balcombe et al., 2015). Although SNA provides direct insights into perceived attention patterns, it is susceptible to reporting bias (Alemu et al., 2013). LCM approaches, particularly when combined with auxiliary data such as eye-tracking, allow for more objective detection of attribute processing. By aligning observed choice behaviour with actual visual engagement, these methods validate the presence of ANA and reveal discrepancies between stated and actual attention. Such triangulation strengthens the robustness of WTP estimates and supports more accurate consumer segmentation (Scarpa et al., 2013).

2.4 Trust in Certification and Eco-Label Effectiveness

Trust in certification is fundamental to the effectiveness of eco-labels. Third-party certifications are generally perceived as more credible than self-declared claims (Darnall et al., 2018). Government endorsements can further enhance credibility, particularly in emerging markets where institutional trust is higher (Darnall et al., 2018; Gorton et al., 2021). In the context of DCE, trust influences whether consumers attend to eco-label attributes at all. When trust, clarity, and standardisation are lacking, ANA becomes more likely. Building trust requires institutional credibility, consistent label formatting, and clear messaging (Plank & Teichmann, 2018). Labels that are vague, cluttered, or unverified are more likely to be ignored, especially in markets where scepticism toward green claims is prevalent (Taufique et al., 2014). Standardising eco-label layouts can reduce cognitive load, enabling easier information processing and improving recognition (Proi et al., 2023).

2.5 Empirical Insights, LCA Relevance, and Implications for Eco-Labelling

Empirical studies consistently show that consumers often disregard specific eco-label attributes during product evaluation. For example, Boncinelli et al. (2021) found that more than 70 percent of wine consumers ignored the organic label when making purchase decisions. Similar patterns were observed in China's fish market, where eco-labels had limited influence on consumer behaviour (Zhang et al., 2020). These findings underscore the role of attribute salience and perceived relevance in determining attention (Scarpa et al., 2009; Gigerenzer & Gaissmaier, 2011). LCA has been extensively applied in the detergent industry to assess environmental burdens across the product life cycle. Findings show that the greatest impacts occur during the use phase, particularly through phosphate and surfactant discharge, which contribute to eutrophication and oxygen depletion in aquatic ecosystems (Stalmans et al., 1991; Thannimalay et al., 2012). These findings inform eco-label criteria by identifying priority attributes, such as phosphate-free formulations and biodegradable surfactants, that minimise environmental harm (Plank & Teichmann, 2018).

In markets with simplified labelling structures, such as concise eco-label formats, trust and willingness to pay have been shown to improve significantly (Taufique et al., 2014; Gorton et al., 2021), illustrating how message clarity can enhance consumer response across different product categories. This aligns with research showing that concise and visually clear label messages can improve comprehension and reduce information overload (Balcombe et al., 2015). From a methodological perspective, effective attribute presentation in discrete choice experiments has also been shown to reduce the likelihood of attribute non-attendance (Mohamad et al., 2018).

The visibility and credibility of the certification process further determine whether consumers attend to label attributes. When clarity is lacking, trust declines and ANA becomes more likely. For products that contribute to household wastewater, credible certification enhances trust and reinforces water protection efforts. While some Malaysian studies have applied ANA techniques in tourism and valuation contexts (Mohamad et al., 2018), very few have examined its role in consumer responses to eco-labels for detergents. Internationally, Gonçalves et al. (2022) proposed an ANA-informed LCM framework that enhances WTP estimation and improves market segmentation.

This approach accommodates bounded rationality in information-rich environments (Alemu et al., 2013). Other studies suggest that visual simplicity and strategic placement can reduce cognitive burden and improve attribute recognition (Mohamad et al., 2018; Proi et al., 2023). Eye-tracking research further indicates that consumers prioritise visual cues over textual content, particularly under time constraints (Proi et al., 2023). However, challenges remain, including misinterpretation, selective attention, and low attribute salience. This study addresses these issues by focusing on consumer evaluation of eco-label attributes in environmentally friendly detergents. Attribute selection was guided by literature and qualitative findings. By incorporating ANA into the DCE framework, the study aims to more accurately reflect consumer decision-making behaviour and to link preference patterns with water quality protection goals under SDG 12 and SDG 6.

3. METHODOLOGY

3.1 Research Design

This study applies ANA modelling within a CE framework to examine consumer preferences for eco-label attributes. ANA refers to the systematic disregard of certain attributes during decision-making, often due to perceived irrelevance or cognitive simplification. If not accounted for, ANA may bias utility estimation and distort measures (Scarpa et al., 2009; Gigerenzer & Gaissmaier, 2011). To address this, the study estimates a series of LCMs in which utility parameters for frequently ignored attributes are progressively constrained to zero (Hensher et al., 2012). This staged approach reflects real-world decision-making processes in which consumers adopt simplified heuristics to manage information overload (Gonçalves et al., 2022; Alemu et al., 2013). A four-model structure was adopted, beginning with a baseline model assuming full attribute attendance, followed by models incorporating ANA: a standard MNL and three LCM specifications with increasing constraints. This framework enables empirical assessment of whether accounting for ANA improves model fit and behavioural realism. It is applied here in the context of eco-label attributes for products linked to domestic water pollution, such as laundry detergents (Thannimalay et al., 2012).

3.2 Sampling and Data Collection

Data were collected in Kedah, Malaysia, between March and May 2024 through structured face-to-face interviews. Kedah was selected because it is a rapidly urbanising state with diverse socio-economic characteristics and substantial detergent usage. The state's exposure to domestic water pollution aligns with the environmental focus of this study (Azizullah et al., 2011). A stratified random sampling technique ensured variation in gender, age, and prior experience with eco-labelled products (Gorton et al., 2021; Taufique et al., 2014). A total of 210 urban consumers participated, consistent with recommended CE sample sizes (100–300 respondents) depending on design complexity (Hensher et al., 2012; Scarpa et al., 2009). Similar sizes have been used in previous eco-label valuation studies to generate robust WTP estimates (Zhang et al., 2020). Respondents were screened to ensure they were primary household detergent purchasers and aware of water pollution concerns. To ensure internal validity, standardised visual materials explaining eco-label attributes were shown prior to CE tasks. Interviewers were trained for uniform administration, and ethical clearance was obtained from the relevant university committee.

3.3 Pilot Study

A pilot involving 30 respondents was conducted to refine the CE design and verify attribute comprehension. Overall, participants demonstrated adequate understanding, though some raised concerns about message clarity and visibility (Plank & Teichmann, 2018). These findings prompted modifications to the layout and descriptions. Similar pretesting has been widely adopted to improve

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experimental clarity and validity (Balcombe et al., 2015). The pilot also reaffirmed the relevance of laundry detergent as the focal product, given its strong association with domestic water pollution (Stalmans et al., 1991).

3.4 Choice Experiment Design and Attribute Description

The CE comprised six choice sets, each presenting respondents with three alternatives: two featuring eco-label attributes and one status quo option. Attribute selection was guided by an extensive literature review, focus group discussions, and methodological insights from previous discrete choice experiment studies incorporating attribute non-attendance considerations (Plank & Teichmann, 2018; Mohamad et al., 2018; Hensher et al., 2012). The design incorporated five attributes: four visual components (certification body, environmental message format, information source, and label placement) and one monetary attribute (price per kilogram). A D-efficient fractional factorial design was generated using SAS software to ensure statistical efficiency (Alemu et al., 2013). To minimise cognitive burden and avoid presentation bias, all choice tasks were standardised and visually balanced (Balcombe et al., 2015). The experiment was constructed to simulate realistic purchasing decisions while isolating the effect of each attribute.

Table 1. Eco-Label Attributes and Levels

Attribute	Level
Certification Body	Government Agency* International Agency Manufacturer
Environmental Information	Brief (logo only) Moderate (logo with brief environmental message)* Complete (logo with comprehensive environmental information)
Information Source	Internet: Certification body/manufacturer website* Phone: Toll-free line Product Packaging
Eco-label Placement	Top Front Bottom Front Back*
Price per kg (RM)	5.50* 8.00 10.00 13.00

Note: Asterisks (*) indicates status quo level used in the CE.

As shown in Table 2, each choice card presented respondents with three product options, allowing them to compare different combinations of label features. Respondents were instructed to indicate their preferred alternative in each set. Attribute levels were informed by literature and qualitative data to ensure relevance and alignment with real-world detergent labelling practices.

Table 2. An Example of a Choice Card

Attribute	Option A	Option B	Option C
Certification Body	Logo with full info	Manufacturer	Government Agency
Environmental Message	Logo and complete info	Logo only	Logo with brief theme

Information Source	On the package	Toll-free number	Internet
Label Position	Back	Top front corner	Bottom front corner
Price (per kg)	RM13.00	RM10.00	RM5.50
Mark your choice (√)			

3.5 Justification for Model Selection

The modelling strategy comprised four specifications to test the full attribute attendance assumption and evaluate ANA effects on utility estimates:

- Model 1 (MNL): all attributes attend to equally.
- Model 2 (LCM-ANA 1): Placement constrains to zero in one latent class.
- Model 3 (LCM-ANA 2): Message format constrains to zero in one class.
- Model 4 (LCM-ANA 3): Both placement and message format constrained in a two-class structure.

This progressive approach allows systematic comparison of model fit and behavioural realism. Attribute constraints were guided by self-reported non-attendance (SNA) data and supported by bounded rationality theory (Gigerenzer & Gaissmaier, 2011; Gonçalves et al., 2022; Hensher et al., 2012; Alemu et al., 2013).

3.6 Self-Reported Non-Attendance (SNA) Analysis

Table 3 summarises the self-reported frequency with which respondents attended to each attribute across all choice tasks. No attribute was reported as being entirely ignored ("never attended"), although several were only "sometimes" attended. Information source received the highest frequent attention rate (69.5%), followed by price (49.5%) and certification body (43.8%). In contrast, environmental information format (27.1% frequent) and eco-label placement (10.5% frequent) were attended to far less consistently.

Table 3. Frequency of Attribute Attendance Across Choice Tasks

Attribute	Frequently (%)	Sometimes (%)	Never (%)
Information Source	69.5	30	0.5
Price	49.5	50.5	0.0
Certification Body	43.8	56.2	0.0
Environmental Information	27.1	72.9	0.0
Eco-label Placement	10.5	89.5	0.0

These results provide an initial indication of potential attribute non-attendance patterns and inform the subsequent specification of constraints in the LCM-ANA models. In particular, attributes with the lowest reported attention are more susceptible to non-attendance during choice-making, a phenomenon commonly observed in complex decision environments (Scarpa et al., 2009; Hensher et al., 2012; Gonçalves et al., 2022). The observed variation in attribute attention frequencies provides a behavioural basis for the model constraints applied in the latent class framework. Specifically, attributes with the lowest reported attention, eco-label placement and environmental message format, were identified as candidates for constraint in the LCM-ANA models. The following section outlines the model specification process used to incorporate these constraints into the estimation framework.the model specification process used to incorporate these constraints into the estimation framework.

3.7. Model Specification

Building on the findings from Section 3.6, where eco-label placement and environmental message format emerged as the least frequently attended attributes, the model specification incorporates these patterns of self-reported non-attendance into the latent class framework. This ensures that the subsequent modelling reflects realistic decision-making behaviour, rather than assuming uniform attention across all attributes. To analyse the influence of ANA on consumer preferences for eco-label attributes, this study adopts a utility-based modelling framework grounded in the Random Utility Model (RUM) (Hensher et al., 2012; Train, 2009). The utility that individual i derives from alternative j in task t is specified as:

$$U_{itj} = V_{itj} + \varepsilon_{itj} \qquad (1)$$

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where V_{itj} is the deterministic component and ε_{itj} is the stochastic component, assumed to follow a Type I Extreme Value distribution.
Based on the MNL specification, the probability of individual i choosing alternative j in task t is given by :

$$P_{itj} = \frac{\exp(V_{itj})}{\sum_{k \epsilon J} \exp(V_{itk})} \qquad (2)$$

where J is the set of all alternatives in the choice set, and V_{itj} is the observable component of utility associated with alternative j.
The deterministic component V_{itj} is modelled as a linear function of the observed attribute levels:

$$V_{itj} = \beta' X_{itj} \qquad (3)$$

In this expression, X_{itj} is a vector of attribute levels for alternative j, and β is a vector of parameter to be estimated. All attributes were effects-coded to enable estimation of marginal utilities and to facilitate model dentification (Hensher et al., 2012).
In the MNL model, the β parameters are assumed to be homogeneous across all individual, which implies that all respondents are considered to attend to all attributes equally. However, this assumption may not reflect actual decision-making behaviour, particularly when some attributes are ignored due to cognitive constraints. To address this limitation, latent class modelling is introduced in the following subsection to account for unobserved heterogeneity in attribute processing.

3.7.1 Latent Class Model Formulation

To account for unobserved heterogeneity in consumer preferences and attribute processing, the study applies a LCM. Unlike the MNL model, which assumes homogenous preferences across respondents, the LCM recognises that individuals may fall into distinct latent segments characterised by different utility structures (Scarpa et al., 2009; Gonçalves et al., 2022).
Conditional on class membership q, the probability that individual i chooses alternative j in task t is given by:

$$P_{itj\backslash q} = \frac{\exp(\beta' q X_{itj\backslash q})}{\sum_{k \epsilon J} \exp(V_{itk} \backslash q)} \qquad (4)$$

The probability of observing the full sequence of T choices made by individual i, given membership in class q, is:

$$P_{q\backslash i} = \prod_{t=1}^{T} P_{itj\backslash q} \qquad (5)$$

Class membership probabilities are estimated using a MNL specification:

$$P_{q\backslash i} = \frac{\exp(Z_i\, \theta_q)}{\sum_{q=1}^{Q} \exp(Z_i\, \theta_q)} \qquad (6)$$

where Zi is a vector of individual-specific covariates (such as demographics or past eco-label experience), and θq represent class-specific parameters. This formulation enables the model to assign individuals to latent classes probabilistically based on their observed characteristics.
The unconditional probability of individual i choosing alternative j is then obtained by aggregating over all latent classes:

$$P_{itj} = \sum_{q=1}^{Q} P_{q\backslash i} \cdot P_{itj\backslash q} \qquad (7)$$

This modelling structure allows for identification of preference heterogeneity and class-specific processing strategies, particularly in high-cognitive-load contexts such as eco-label evaluation (Hess & Hensher, 2010; Gonçalves et al., 2022; Gigerenzer & Gaissmaier, 2011; Alemu et al., 2013).
The LCM is well-suited to sustainability-related decision contexts, where different consumer segments may prioritise distinct eco-label attributes based on varying levels of environmental concern, trust in certification, or cognitive simplification strategies. By explicitly incorporating ANA, this model enhances the behavioural realism of the analysis.

3.7.2 Willingness to Pay Estimation

WTP for each eco-label attribute was derived from the estimated utility coefficients using the marginal rate of substitution (MRS) between the non-monetary attributes and the price attribute. For both the MNL and LCM frameworks, WTP is calculated as:

$$WTP_j = -\frac{\beta_j}{\alpha} \quad (8)$$

where βj is the coefficient of the non-monetary attribute j and α is the coefficient of the price attribute. The price attribute was specified in linear form and expressed in Malaysian Ringgit (RM). This formulation reflects the monetary value that respondents are willing to pay for a one-unit change in each attribute level, assuming all other attributes remain constant.

This approach allows for meaningful economic interpretation of the relative importance of eco-label attributes, enabling comparison across different consumer segments and model. The WTP estimates derived here, combined with class-specific patterns of attribute attention, form the empirical basis for the analysis and discussion presented in Section 4. In particular, the interplay between attribute non-attendance and monetary valuation is examined to provide both behavioural and policy-relevant insights (Scarpa et al., 2009; Boncinelli et al., 2021; Hensher et al., 2012; Gonçalves et al., 2022).

4. RESULTS AND DISCUSSION

4.1 Demographic Analysis

Table 4 presents the demographic characteristics of the 210 respondents who participated in the survey. The sample comprised 52.4% male and 47.6% female respondents, with an average age of 32.41 years. In terms of ethnicity, the majority were Malay (69%), followed by Chinese (20%) and Indian (11%). Educational attainment was relatively high, with 67.2% holding tertiary qualifications, exceeding the national average of 36.1% among Malaysians aged 25–44 (Department of Statistics Malaysia, 2023).

Table 4. Demographic Analysis of Respondents (n=210)

Item	%	Item	%
Gender		**Education Level**	
Male	52.4	Primary School	1.0
Female	47.6	Secondary School	31.9
		Higher Education	67.2
Age (mean)	32.41 years	Previously Purchased Eco-Label Products (yes)	94.8
Ethnicity			
Malay	69		
Chinese	20		
Indian	11		

A substantial 94.8% of respondents reported having purchased eco-labelled products, including personal care items, household goods, electrical appliances, vehicles, and building materials. This finding aligns with prior research indicating that urban and educated consumers tend to be more environmentally conscious, more responsive to sustainability cues, and more likely to engage with product labelling (Gorton et al., 2021; Taufique et al., 2014). These consumers are also more prone to selective attention during choice tasks, making them suitable subjects for investigating ANA and heuristic-driven evaluation strategies (Scarpa et al., 2009; Gigerenzer & Gaissmaier, 2011). Given the study's focus on laundry detergents, which indirectly contribute to domestic wastewater discharge (Thannimalay et al., 2012), understanding consumer preferences for eco-label attributes provides valuable insight into promoting sustainable purchasing behaviours. Such behavioural insights also inform broader discussions on water quality protection and environmental policy development.

4.2 Analysis of MNL and LCM Models

The baseline multinomial logit (MNL) model assumed full attribute attendance (FAA) and served as the benchmark. Three additional latent class models with attribute non-attendance (LCM-ANA) were then estimated, in which one or more attributes were constrained based on the self-reported non-attendance (SNA) data from Section 3.6. The attributes examined in this study were: International Certification

(ICERT), Manufacturer Certification (PCERT), Environmental Message – Brief Format (FS), Environmental Message – Complete Format (FC), Information Source – Packaging (IP), Information Source – Toll-Free (IT), Eco-label Placement – Front Top (DA), and Eco-label Placement – Front Bottom (DB).

Across all models, eco-label attributes such as certification type, message format, information source, and label placement significantly influenced respondent utility. The MNL model yielded a modest fit (pseudo-R^2 = 0.014), suggesting that the assumption of FAA poorly captures actual decision-making behaviour. In contrast, the ANA-constrained LCMs demonstrated substantial improvements in explanatory power, with pseudo-R^2 increasing to 0.567 in LCM-ANA Model 3. These results are consistent with prior choice experiment studies showing that accounting for ANA improves model realism and predictive accuracy (Scarpa et al., 2009; Boncinelli et al., 2021; Hess & Hensher, 2010; Alemu et al., 2013; Gonçalves et al., 2022).

The magnitude and direction of utility coefficients varied considerably across latent classes, indicating clear cognitive segmentation among respondents. This finding supports previous evidence that consumers do not attend to all attributes equally, often relying on heuristic or simplification strategies (Hess & Hensher, 2010). In the context of eco-label evaluation, such heuristics can reduce the salience of attributes such as message format and label placement, particularly when label design lacks clarity or visual hierarchy (Gorton et al., 2021; Gigerenzer & Gaissmaier, 2011).

These differences in coefficient patterns suggest that willingness-to-pay (WTP) values presented in the following sections are likely to vary substantially across models and classes, reflecting the combined influence of ANA and preference heterogeneity.

Table 5. The Estimation Results across MNL and LCM-ANA Models

Panel A: Estimated Coefficients (with Standard Errors)

Attribute	MNL Coeff. (SE)	LCM-ANA Model 1 (SE)	LCM-ANA Model 2 (SE)	LCM-ANA Model 3 (SE)
ICERT	1.460*** (0.124)	2.292*** (0.201)	-0.328 (0.198)	9.633*** (1.109)
PCERT	1.509*** (0.110)	3.001*** (0.224)	-0.755***(0.185)	9.798*** (1.057)
FS	0.287*** (0.111)	1.323*** (0.174)	0.902*** (0.184)	2.824*** (0.500)
FC	0.443*** (0.097)	0.521*** (0.171)	1.029*** (0.147)	4.036*** (0.665)
IP	0.707** (0.121)	1.322*** (0.252)	1.190*** (0.195)	-0.757** (0.356)
IT	0.238*** (0.101)	0.235 (0.177)	0.273 (0.173)	0.135 (0.423)
DA	0.556*** (0.099)	1.591*** (0.221)	1.095*** (0.187)	2.367*** (0.512)
DB	0.895*** (0.103)	1.601*** (0.217)	1.477*** (0.188)	4.104*** (0.692)
Price (RM)	-0.113***(0.017)	-0.451***(0.012)	-0.164***(0.012)	-0.677***(0.018)

Model Fit Statistics

Statistic	MNL	LCM-ANA Model 1	LCM-ANA Model 2	LCM-ANA Model 3
Log-likelihood (LL)	-874.824	-810.173	-668.419	-590.577
Pseudo-R^2	0.0179	0.414	0.517	0.573
Adjusted Pseudo-	0.014	0.409	0.513	0.567

R^2				
No. of Parameters	10	22	22	35
No. of Observations	1260	1260	1260	1260

Note: ICERT = International Certification, PCERT = Manufacturer Certification, FS = Brief Format, FC = Complete Format, IP = Information Source - Packaging, IT = Information Source- Toll-Free, DA = Eco-label Placement - Front Top, DB = Eco-label Placement - Front Bottom
Values in parentheses represent standard deviations.
***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

4.2.1 Transition to Latent Class Modelling

Table 6 summarises the specification and underlying rationale for each latent class model (LCM). In Model 1, Eco-label Placement – Front Top (DA) and Eco-label Placement – Front Bottom (DB) were constrained, reflecting the lowest reported attention rate (10.5%). Model 2 constrained Environmental Message – Brief Format (FS) and Environmental Message – Complete Format (FC), which had the second-lowest attention rate (27.1%). Model 3 applied both sets of constraints simultaneously to capture broader patterns of attribute non-attendance (ANA) and potential simplification strategies.

Table 6. Specification of Latent Class Models and Attribute Constraints

Model	Constrained Attribute(s)	Rationale	Number of Classes	Average Class Probability (Estimated n)
Model 1	Eco-label Placement	Most frequently ignored attribute	2	Class 1 = 65.0% (≈ 137); Class 2 = 35.0% (≈ 73)
Model 2	Environmental Message Format	Second most frequently ignored attribute	2	Class 2 = 59.5% (≈ 125); Class 1 = 40.5% (≈ 85)
Model 3	Both attributes combined	Captures selective attention strategy across two critical attributes	3	Class 1 = 64.1% (≈ 135); Class 2 = 13.0% (≈ 27); Class 3 = 22.9% (≈ 48)

The segmentation outcomes indicate substantial cognitive heterogeneity among respondents. In Model 1, approximately two-thirds of respondents (65.0%) formed a class that likely considered eco-label placement irrelevant during decision-making, while the remainder assigned it greater importance. In Model 2, the majority segment (59.5%) downplayed environmental message format, whereas a smaller segment engaged with this attribute more actively. Model 3 revealed a more complex structure, with three distinct classes: one that deprioritised both constrained attributes (64.1%), a small segment that almost entirely ignored them (13.0%), and a third that consistently attended to them (22.9%).

These patterns align with evidence that consumer decision-making in complex choice environments often relies on heuristics rather than exhaustive evaluation (Scarpa et al., 2009; Gigerenzer & Gaissmaier, 2011; Alemu et al., 2013; Boncinelli et al., 2021). The emergence of a segment disregarding both attributes support the view that ANA frequently results from limited cognitive processing capacity rather than genuine disinterest (Balcombe et al., 2015; Gonçalves et al., 2022). This reinforces the analytical value of incorporating ANA-informed segmentation into latent class frameworks, particularly when modelling markets with multiple overlapping sustainability cues. Importantly, these differences in attribute attention are expected to translate into substantial variation in willingness-to-pay (WTP) estimates across models, as examined in Section 4.3 using 95% confidence intervals (CI) to establish statistical significance (Hensher et al., 2012).

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4.3 Estimation of Willingness to Pay (WTP) Values

Table 7 presents the WTP estimates for each attribute across the MNL and three LCM-ANA models. All WTP values are accompanied by 95% confidence intervals (CI) calculated using the Delta Method. The CI provides a statistical range within which the true WTP is expected to fall, given the sample data, and an estimate is considered statistically significant when the CI does not include zero (Train, 2009; Hensher et al., 2012). This practice is standard in discrete choice modelling, ensuring that both the magnitude and reliability of estimates are reported transparently (Scarpa et al., 2013). Only WTP estimates with CI excluding zero are interpreted here as statistically significant.

Table 7. Willingness to Pay (WTP) Estimates Across Models
All values are in Malaysian Ringgit (RM). 95% CI calculated using Delta Method.

Attribute	MNL [95% CI]	LCM Model 1 [95% CI]	LCM Model 2 [95% CI]	LCM Model 3 [95% CI]
ICERT	8.36 (4.93 – 11.80)	7.14 (5.19 – 9.09)	-2.00 (-4.48 – 0.49)	14.22 (9.93 – 18.51)
PCERT	12.66 (8.37 – 16.94)	9.35 (6.94 – 11.76)	-4.60 (-7.42 – -1.78)	14.46 (10.25 – 18.68)
FS	3.68 (1.20 – 6.16)	4.12 (2.74 – 5.50)	5.50 (2.47 – 8.53)	4.17 (2.50 – 5.84)
FC	1.14 (-1.08 – 3.36)	1.62 (0.52 – 2.72)	6.27 (3.31 – 9.24)	5.96 (3.69 – 8.22)
IP	8.91 (5.56 – 12.27)	4.12 (2.34 – 5.89)	7.25 (3.63 – 10.87)	-1.12 (-2.17 – -0.06)
IT	10.25 (6.36 – 14.14)	0.73 (-0.36 – 1.82)	1.66 (-0.50 – 3.83)	0.20 (-1.03 – 1.42)
DA	4.51 (1.82 – 7.20)	4.96 (3.25 – 6.67)	6.68 (3.28 – 10.07)	3.49 (1.85 – 5.13)
DB	7.68 (4.51 – 10.85)	4.99 (3.29 – 6.68)	9.00 (4.90 – 13.11)	6.06 (3.72 – 8.40)

Note: Values in parentheses represent 95% Confidence Intervals (CI) calculated using the Delta Method. All values are in Malaysian Ringgit (RM).

Across all models, certification attributes, international certification (ICERT) and manufacturer certification (PCERT) emerge as the most valued, although the magnitude and direction of WTP vary across classes. In the MNL model, PCERT records the highest WTP at RM 12.66 (CI: 8.37–16.94), followed by information transparency (IT) at RM 10.25 (CI: 6.36–14.14) and information on production process (IP) at RM 8.91 (CI: 5.56–12.27). These results highlight the central role of credible certification and information provision in influencing purchasing decisions, consistent with findings that consumer trust in certification bodies significantly drives sustainable product choices (Darnall et al., 2018; Taufique et al., 2014; Riskos et al., 2021).

The LCM-ANA results reveal distinct preference heterogeneity. In Model 1, ICERT (RM 7.14; CI: 5.19–9.09) and PCERT (RM 9.35; CI: 6.94–11.76) remain dominant, reinforcing the value of trusted third-party certification over other attributes. Conversely, Model 2 shows negative WTP for both ICERT (–RM 2.00; CI: –4.48–0.49) and PCERT (–RM 4.60; CI: –7.42– –1.78), indicating a consumer segment sceptical of certification, a phenomenon noted in earlier studies on eco-label familiarity and trust (Zheng et al., 2013). In this segment, functional characteristics (FC) (RM 6.27; CI: 3.31–9.24) and eco-label placement at the lower corner (DB) (RM 9.00; CI: 4.90–13.11) hold greater appeal, aligning with research that label visibility influences consumer response (Kovačević et al., 2019).

Model 3 shows exceptionally high WTP for both ICERT (RM 14.22; CI: 9.93–18.51) and PCERT (RM 14.46; CI: 10.25–18.68), but a negative WTP for IP (–RM 1.12; CI: –2.17– –0.06), suggesting that some consumers may view certain product information as unnecessary or even undesirable. This divergence in preferences aligns with literature showing that consumers often disregard attributes they consider irrelevant or untrustworthy (Erdem et al., 2014; Hensher et al., 2005).

Moderate yet consistently positive WTP values for attributes such as food safety (FS), detailed environmental information (DA), and eco-label placement (DB) across most models indicate secondary but stable influences on purchasing behaviour. The variation in magnitude and sign across models confirms the presence of heterogeneous consumer segments (Caputo et al., 2018), underscoring the importance of targeted strategies to match specific segment priorities.

From a policy perspective, these results suggest that promoting credible certification schemes, optimising eco-label visibility, and tailoring information content can enhance market uptake of sustainable products. However, the presence of segments with negative WTP for certification signals the need for targeted communication to address scepticism, as consumer trust remains pivotal in the success of eco-label initiatives (Essoussi & Zahaf, 2009; Khachatryan et al., 2021).

4.4 Behavioural and Policy Implications of ANA

The behavioural segmentation patterns identified through the LCM-ANA models reveal systematic differences in how consumers process eco-label information. While some respondents evaluated all attributes, others relied on cognitive shortcuts, focusing on a limited set of salient features such as price or certification. This aligns with theories of bounded rationality in consumer decision-making (Scarpa et al., 2009; Gigerenzer & Gaissmaier, 2011). Attributes such as eco-label placement and environmental message format were frequently ignored in self-reported non-attendance (SNA) data. However, ANA-constrained models demonstrated that these attributes retained significant utility within certain segments. This suggests that non-attendance is more likely attributable to limited processing capacity rather than genuine disinterest (Boncinelli et al., 2021; Alemu et al., 2013). These findings highlight the importance of designing eco-labels with simplified, high-salience features such as optimal colour contrast, strategic placement, and concise messaging that reduce cognitive burden and improve the delivery of environmental information (Plank & Teichmann, 2018; Proi et al., 2023).

The implications extend beyond laundry detergents to other household cleaning products, such as dishwashing liquids and multipurpose cleaners, which also contribute to domestic water contamination. Eco-label designs that reflect cognitive realities can enhance consumer attention and engagement, supporting broader water protection objectives. From a policy perspective, these results are consistent with Malaysia's National Green Policy and ASEAN eco-label harmonisation efforts (ASEAN Secretariat, 2022). Simplified and credible labelling systems can improve consumer trust and enable regional standardisation. Beyond the ASEAN region, the behavioural patterns identified here are also relevant to other developing countries where weak institutional trust and limited environmental awareness undermine the effectiveness of eco-labelling schemes (Taufique et al., 2014).

The staged latent class modelling framework applied in this study provides a diagnostic tool for identifying processing heterogeneity and guiding evidence-based label design. Aligning eco-labels with consumer heuristics will be critical to improving salience and influencing environmentally responsible decisions, particularly in product categories that directly impact water quality. This approach also supports global sustainability targets under SDG 12 and SDG 6.

5. LIMITATION AND FUTURE RESEARCH

This study has several limitations that provide opportunities for future research. The ANA-informed segmentation approach successfully identified heterogeneity in attribute attention but did not incorporate psychological dimensions such as pro-environmental attitudes, cognitive styles, or personal values. Future research should integrate psychometric measures to examine how environmental self-identity, motivations, and belief systems shape attribute processing in eco-label evaluation (Taufique et al., 2014; Scarpa et al., 2013).

Geographically, the focus on respondents in Kedah limits the generalisability of findings to Malaysia's diverse socio-economic and cultural contexts. Expanding sampling to other states, and to both urban and rural settings, would strengthen the external validity of ANA patterns. Comparative cross-country studies, particularly between Asian and Western contexts, could further clarify how cultural norms, policy environments, and label design practices influence attribute salience and willingness to pay (Gorton et al., 2021).

Methodologically, integrating DCE with life cycle assessment could determine whether eco-label-guided choices deliver measurable environmental benefits. Linking preference data with environmental performance metrics would enhance the policy relevance of findings (Plank & Teichmann, 2018). Future work could also combine discrete choice experiments with eye-tracking or biometric measures to improve the accuracy of ANA detection and capture how consumers visually and cognitively engage with label components in real-world settings (Proi et al., 2023; Balcombe et al., 2015).

Finally, extending the scope to other household cleaning and personal care products such as dishwashing liquids, surface cleaners, and shampoos would address additional sources of phosphorus and surfactant discharge, both of which contribute to aquatic eutrophication and oxygen depletion (Stalmans et al., 1991; Thannimalay et al., 2012). Linking consumer choice behaviour to water quality indicators would enable robust evaluation of eco-label effectiveness in advancing SDG 6 and SDG 12.

6. CONCLUSION

This study confirms that ANA plays a decisive role in shaping consumer preferences and WTP for eco-label attributes in household detergents. Incorporating ANA into latent class models revealed distinct cognitive segments, with certification credibility and label placement emerging as key choice drivers.

The results highlight the value of aligning eco-label design with realistic cognitive patterns. Strategies that simplify visual structure, strengthen certification trust, and optimise placement can enhance attention to environmental content and improve scheme effectiveness. In the Malaysian context, where regulatory oversight of detergent-related pollutants is limited, such measures hold strong potential for reducing phosphorus and surfactant discharges.

From a policy perspective, eco-label initiatives should be informed by behavioural evidence rather than relying solely on awareness campaigns. Standardised formats, credible third-party verification, and integration with LCA indicators can strengthen trust, improve salience, and link consumer decisions to measurable environmental outcomes.

In line with the study's limitations, future work should extend geographic coverage, incorporate cross-country comparisons, and broaden the product scope to other household cleaning and personal care categories. Applying psychometric profiling alongside tools such as eye-tracking and biometric tracking will offer deeper insights into real-world processing of eco-label information. Such advances can inform targeted interventions and contribute to achieving SDG 12 and SDG 6.

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