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A Computational Framework and Pipeline Architecture for Sustainable Online Consumer Behavior

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Abstract

This study proposes a design-oriented computational framework and pipeline architecture for e-commerce systems to address the gap between pro-environmental attitudes and sustainable purchase behaviors. Despite growing availability of green personal care products (GPCP) on e-commerce platforms, consumer engagement remains limited. Prior studies often overlook this niche, focusing instead on broader green product categories or offline retail contexts. This study also addresses the gap by examining how pro-environmental and consumption values shape consumer behavior for GPCPs in digital commerce, and then translates the validated determinants into a computational design. A quantitative design guided by the Value–Attitude–Behavior framework was employed. Data were collected from 302 consumers who purchased GPCPs online in the past six months. Constructs were measured using validated scales and analyzed through Partial Least Squares Structural Equation Modelling (PLS-SEM). The empirically significant determinants were then mapped into a multi-stage pipeline architecture to demonstrate how behavioral factors can be operationalized within e-commerce systems. The findings indicate that emotional value, functional quality value, and perceived environmental knowledge significantly shape positive consumer attitudes toward GPCPs in e-commerce settings. Green purchase attitudes were strongly predictive of purchase intentions ($\beta = 0.781$, $p < 0.000$), which subsequently influenced actual purchase behavior ($\beta = 0.726$, $p < 0.000$). These empirically validated determinants inform the computational pipeline, where values act as inputs, attitudes and intentions as intermediate system states, and behaviors as measurable outcomes. Theoretically, this study advances the Value–Attitude–Behavior framework by confirming the distinct and context-dependent roles of emotional and functional quality values, as well as environmental knowledge, in shaping sustainable consumer attitudes in digital contexts. Practically, by integrating these behavioral insights into a pipeline design, the study contributes a computational framework that links consumer psychology with system architecture.

Keywords: *Pipeline Architecture, Sustainable Online Purchasing, Green Personal Care Products, sdg12, Consumption Values, Pro-Environmental Values*

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I. INTRODUCTION

Computational systems architected to influence, measure, and reinforce sustainable choices are becoming increasingly important as sustainability challenges intensify. Rising environmental problems like climate change, resource depletion, and pollution create both behavioural and design challenges for digital commerce platforms. This shift has shaped consumer behaviour, as individuals are more aware of the environmental impact of their purchasing choices and prefer eco-friendly alternatives [1]. However, a gap remains between consumers' stated environmental attitudes and their actual purchases [2]. This discrepancy is visible across product categories, including personal care, where eco-friendly products are growing rapidly, especially in digital marketplaces. E-commerce systems must reduce this gap by using structured data flows, layered interfaces, and behaviour-informed pipeline architectures.

While prior studies have extensively examined the role of personal values in shaping sustainable consumption, much of the existing literature has focused on offline or general retail contexts, with limited attention paid to product-specific behaviour within digital environments. This omission is striking because the sector carries

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distinctive characteristics that set it apart from the broader green industry [3]. Unlike general green products, personal care items are applied directly to the body, raising concerns about safety and ingredient transparency [4]. At the same time, aesthetic and sensory dimensions (like texture, scent, even packaging appeal) intersect with ethical considerations, producing a complex impact of drivers that are not easily reduced to environmental concern alone. So, the drivers of online green personal care purchases may differ substantially from other segments, making focused study on this category necessary. By viewing these behavioural drivers as inputs and outputs in a computational pipeline, values can be turned into measurable signals, and interventions can be organized as modular layers within the system.

On a practical level, personal care products occupy a distinctive place in everyday routines. Dodson et al. (2021), for instance, reported that women typically use a median of 8 personal care items each day, while some incorporate as many as 30 into their regimen [5]. More recent work suggests that men are also increasingly demanding the green cosmetics market, noting a steady rise in demand [6]. These trends show the importance to study the GPCP purchases, especially on e-commerce platforms where the absence of physical interaction introduces unique decision-making constraints [7]. Computational approaches such as pipeline architectures, SEM-based system design, and algorithmic feedback loops enable the monitoring of how values shape actual purchase behaviour.

Prior green-consumption models, such as the Theory of Planned Behaviour (TPB), the Norm Activation Model (NAM), and the Value–Belief–Norm (VBN) theory, have offered valuable insights into sustainable consumer choices. These frameworks explain attitudinal, normative, and value-based drivers of behaviour. However, they remain largely descriptive and are rarely connected to system-level implementation.

In parallel, existing sustainability and e-commerce architectures have largely concentrated on optimizing technical or operational dimensions rather than addressing the underlying drivers of sustainable consumer behaviour. Recommender-system architectures have improved prediction through collaborative filtering, content-based methods, and hybrid techniques. For instance, sustainability-oriented designs have introduced digital nudges to promote greener product selection [8], while others have optimized algorithmic efficiency to reduce the energy and carbon footprint of recommender training [9]. Blockchain-based solutions have also been proposed to ensure traceability and verification of green claims [10]. Yet, these architectures remain limited to surface-level optimization, such as recommending greener items, improving transparency, or lowering technical costs. However, they fail to address the deeper issue of why consumers often struggle to translate pro-environmental attitudes into actual purchases.

By contrast, the pipeline proposed in this study is novel in three key ways. First, it operationalizes the Value–Attitude–Behavior (VAB) framework by mapping values, attitudes, and intentions into modular layers that can guide e-commerce system design. Second, it focuses only on empirically significant determinants, making the pipeline more parsimonious and practically implementable than broader models or architectures that rely on weak predictors. Third, it is tailored specifically to GPCPs, a category often overlooked in sustainability research but uniquely important due to its intimate, health-related, and emotional dimensions. Together, these contributions distinguish the proposed pipeline from existing sustainability and e-commerce architectures and position it as a blueprint for behaviourally intelligent system design.

The study is guided by two primary objectives:

To empirically examine how consumption and pro-environmental values shape sustainable online consumer behaviour through the Value–Attitude–Behaviour framework, using SEM analysis.

To propose a computational pipeline architecture that operationalizes these behavioural determinants into system components.

To achieve these aims, the structure of the paper is arranged as follows. Section 2 introduces the theoretical foundation and formulates research hypotheses. Section 3 details the methodological approach used to examine proposed relationships. Section 4 reports the results of the empirical investigation, while Section 5 discusses these findings in relation to prior studies, outlines limitations, and suggests directions for future research. Lastly, Section 6 concludes the study by summarizing its main contributions.

II. Theoretical Framework and Hypotheses

A. *The Pipeline Concept in Digital Consumer Behaviour*

In computational system design, a pipeline is a sequence of stages where inputs are encoded, transformed, and evaluated into outputs. Each stage performs a specific function, passing its results forward to the next stage, ensuring both modularity and transparency in how data and interactions are processed. In the context of sustainable e-commerce, the pipeline provides a formal architecture for translating abstract constructs such as values, attitudes, and intentions into observable digital signals that can be monitored, modelled, and optimized.

This study first seeks to identify the relationships between consumer values and green purchasing behavior in e-commerce platforms, and then to translate these relationships into a structured pipeline design. Framing digital commerce as a pipeline allows behavioral theories to be built into system design. Values can become encoded inputs, for instance through sustainability surveys, clickstream metadata indicating preference for organic products, or eco-label interactions such as consumers filtering for “Fair Trade” certifications. Attitudes are represented as evaluative states, which can be inferred from engagement patterns (e.g., time spent comparing carbon-neutral products versus conventional alternatives) or micro-surveys embedded post-purchase to gauge perceptions of brand responsibility. Intentions serve as commitment nodes, visible through low-friction trial actions such as adding an item to a Wishlist on Amazon, subscribing to a “back-in-stock” notification, or opting into a free trial of a digital service like Premium versions. Behaviors then constitute the measurable outputs, most directly observable in completed purchases, repeat subscriptions (e.g., auto-replenishment of household items on

Instacart), or participation in loyalty programs that reflect sustained commitment.

Beyond behavioral mapping, recent research has also applied computational and AI-based methods to sustainable consumption. Machine learning classifiers and clustering algorithms have been used to predict green purchase propensities and segment consumers by sustainability preferences [11, 12]. Computational approaches, including reinforcement learning (RL) are also being utilized to encourage sustainable consumption behaviors. In particular, Huynh et al. (2022) demonstrate how RL can optimize marketing interventions for sustainable products through personalization and behavioral modeling, leading to improved adoption outcomes [13]. Natural language processing techniques have been applied to analyze consumer reviews of eco-friendly products, revealing insights into sustainability perceptions and product design optimization [14]. Explainable AI has also been employed to advance sustainable growth by enhancing trust, transparency, and data-driven decision-making in business contexts [15]. While these approaches demonstrate the technical feasibility of embedding sustainability into digital commerce pipelines, they tend to remain isolated focusing on prediction, personalization, or verification in silos. The present study extends this line of work by embedding such computational capacities within a Value–Attitude–Behavior framework, where psychological determinants are mapped directly onto pipeline stages for systematic implementation.

The pipeline structure also enables modular intervention: platform designers can insert various nudges at specific stages. This aligns with dual-process theories of persuasion, which argue that interventions are most effective when targeted at the right processing stage- peripheral cues at early stages, central arguments when attitudes are being formed, and commitment devices when intentions are being consolidated.

B. Green Consumer Behaviour in the E-Commerce Context

Digital commerce platforms can be conceptualized as information-processing systems, in which consumer behavior emerges from data flows, interaction signals, and algorithms. In this context, understanding green consumer behaviour requires not only behavioural insights but also system design strategies that reduce information asymmetries.

Green consumer behaviour is often described as a key driver in steering markets toward more sustainable practices [16]. Within this broader movement, the personal care industry appears to have significant growth in the range of eco-conscious alternatives. Consumers seem increasingly drawn to products framed as safe, ethically produced, and environmentally responsible

Simultaneously, the rise of digital retail has complicated this landscape. E-commerce offers convenience, greater variety, wider accessibility, and efficiency of purchase without physical constraints. This makes it a primary channel for GPCPs. Yet these features also introduce a set of difficulties. Sustainable decision-making may be undermined when buyers cannot handle items directly or scrutinise packaging in person. As McLoughlin et al. (2024) observed, the absence of tactile inspection limits verification of quality, authenticity, and ecological claims. By contrast, Traditional retail settings allow for sensory evaluation and face-to-face consultation, both of which can reinforce consumer trust [17]. In digital spaces, however, assessments are mediated by textual descriptions, symbolic branding, and the often-uneven authority of third-party reviews [18]. Designing e-commerce pipelines allows proxies to be filtered, weighted, and presented to reduce cognitive burden and support sustainable decision-making.

E-commerce environments are not neutral spaces; they are shaped by persistent information asymmetry. Consumers frequently encounter overlapping or even contradictory sustainability claims, but the means of verifying these claims are often limited or opaque [19]. In such contexts, factors like perceived value, trust, and a certain level of digital literacy appear to play an outsized role in guiding green purchasing behaviour. From a system-design standpoint, these challenges can be addressed by encoding values, attitudes, and trust-building mechanisms into digital pipelines that structure consumer interactions, algorithmic nudges, and feedback loops. Online platforms, can be harnessed to promote sustainable products through curated digital interactions that highlight ecological benefits or by embedding green values into the broader shopping experience [20]. Yet digital mediation can also magnify barriers. The absence of physical cues, coupled with the sheer volume of information, may foster uncertainty, scepticism, or decision fatigue. Framing consumer uncertainty in computational terms allows these frictions to be treated as data-processing bottlenecks, addressable through system-level interventions.

C. The Value–Attitude–Behaviour (VAB) Framework

The VAB framework can be treated as a layered processing model where values act as system inputs, attitudes as intermediate states, intentions as commitment nodes, and behaviour as measurable outputs. This makes it naturally suited for implementation within a digital pipeline architecture. It was first articulated in the field of psychology and sociology [21]. At its core, the model suggests that individuals' underlying values influence their attitudes, which then guide intentions and, eventually, observable behaviours. Consumer researchers have found this structure useful, particularly when trying to make sense of decision-making processes that appear fragmented or inconsistent at first glance.

In green consumption, the framework is especially useful for investigating how ecological values and beliefs might translate into favourable orientations toward sustainable products and services [22-24]. Attitudes and intentions mediate this gap by highlighting where interventions may be targeted. When integrated into a computational architecture, VAB determinants can be logged as structured signals (clicks, hovers, micro-surveys), processed as intermediate states (attitudes and intentions), and linked causally to outcomes (purchases). This allows both explanatory modelling and real-time adaptive interventions.

This study adopts the Value–Attitude–Behaviour (VAB) theory because it aligns more effectively with data-driven models in digital commerce. Compared with other behavioral theories such as the TPB, NAM, or VBN theory, VAB offers a more parsimonious and computationally compatible structure for digital commerce. Constructs like subjective norms, perceived control, or moral obligation are valuable in offline contexts but are challenging to infer from online behavioral data. By contrast, values and attitudes can be proxied through measurable signals such as eco-label interactions, product-quality checks, or engagement with sustainability content. These online traces reveal consumers' underlying priorities and can be systematically captured within the platform. This makes the sequential flow of values → attitudes → intentions → behaviour particularly well suited for integration into pipeline architectures, where abstract psychological constructs must be translated into observable system states.

D. Consumption Values

Consumption values represent the benefits or utilities that people seek when making consumption decisions. This study focuses on four consumption values to examine their impact on e-commerce platforms. These are functional quality value (FQV), functional price value (FPV), emotional value (EMV) and social value (SCV).

FPV refers to how consumers judge the value they receive from the price paid. This shows how cost-effective they find a product or service. This value strongly affects brand loyalty and purchase intent, as buyers compare prices with perceived benefits [25]. High prices are often seen as a main barrier in green product settings [26, 27]. But consumers may find green products worth the higher cost if they see additional benefits related to health, environmental or ethics [28]. For GPCPs, this trade-off becomes especially significant as these items are compared to widely available non-green alternatives. Higher prices may be more acceptable to consumers who value non-toxic ingredients, ethical sourcing, and skin safety. Also, perceived price value in online settings might become a decisive factor because price comparisons are immediate and product experience is limited. When consumers believe the price aligns with perceived benefits, they are more likely to complete the purchase. Therefore:

H1: "Functional Price Value has a significant relationship with Green Purchase Attitude."

On the other hand, FQV pertains to the consumer's perception of the quality and performance of a product or service. It encompasses attributes such as reliability, quality, and effectiveness [29]. Functional value is especially critical in green product consumption because eco-friendly alternatives are sometimes perceived as less effective than conventional products [30]. For GPCPs, functional quality is even more essential due to the intimate and health-related nature of their use. Consumers consider factors like effectiveness, skin compatibility, and ingredient transparency, all of which strongly influence trust and satisfaction [4, 31, 32] . In online contexts, where consumers cannot physically evaluate products-functional value becomes a decisive factor. Digital shoppers rely heavily on descriptions, third-party certifications, and user reviews to assess performance [33], making functional quality perception central to their decision-making. Therefore:

H2: "Functional Quality Value has a significant relationship with Green Purchase Attitude."

SCV refers to the benefits a product provides by improving consumers' social standing or self-perception within their social context [30]. In the context of green consumption, it plays a role when consumers believe that buying eco-friendly products signals responsibility, awareness, or prestige [34]. For GPCPs, this signalling effect may be even more significant, as personal grooming choices such as using organic shampoos or cruelty-free cosmetics are often associated with ethical self-expression and visible lifestyle choices. In digital settings, social value becomes stronger through social media, peer sharing and influencer support. Consumers may choose GPCPs not just for personal use, but to earn social approval, match with identity-based groups, and shape their online image. Therefore:

H3: "Social Value has a significant relationship with Green Purchase Attitude."

EMV refers to the affective states that a product can evoke, feelings such as pride, pleasure, or even a more subdued sense of satisfaction [35]. In the context of green consumption, this affective dimension often appears to stem from the alignment between purchases and ethical or environmental commitments [36]. In particular, GPCPs seem capable of generating strong emotional responses. This may be because they intersect with aspects of self-identity, body image, and modes of self-expression in ways that utilitarian green products for example, energy-efficient appliances rarely do [37]. In other words, GPCPs are not simply consumed for their functional properties; they are entangled with lifestyle aspirations and broader wellness narratives. In digital retail environments, the affective pull of these products may be heightened. Influencer marketing, visual brand storytelling, and other forms of digitally mediated persuasion can amplify emotional resonance, sometimes blurring the line between personal expression and commercial promotion [38]. For these reasons, it seems plausible that EMV plays a particularly salient role in shaping consumer responses to online GPCPs. Therefore,

H4: "Emotional Value has a significant relationship with Green Purchase Attitude."

E. Pro-Environmental Values

Pro-environmental values show a consumer's intent to lower their environmental impact, protect natural resources and support ethical brands. These values often lead to a higher chance of buying GPCPs. Following earlier studies, this research uses three key dimensions to measure pro-environmental values: Environmental Concern (ENC), perceived environmental knowledge (PEK) and perceived consumer effectiveness (PCE) [39].

ENC refers to the extent to which a person understands environmental problems and feels responsible to act against them. It shows both awareness of environmental damage and readiness to take steps that reduce harm [40]. It is a core component of pro-environmental values and is strongly linked to green consumer behaviour [40, 41] . For GPCPs, this concern can lead consumers to choose items that are cruelty-free, ethically sourced, or packed in biodegradable materials. Such choices help them express their environmental values through daily grooming habits. Even online, where sensory engagement is limited, these consumers pay attention to eco-labels, certifications, and sustainability claims. Therefore:

H5: "Environmental Concern has a significant relationship with Green Purchase Attitude."

PEK is the extent to which a consumer believes they know about environmental issues, sustainable practices, and the impact of their own consumption. It differs from actual or objective knowledge, which is based on factual accuracy. Perceived knowledge, even if not completely accurate, can strongly influence attitudes and behaviours toward sustainability [42]. It plays a foundational role in shaping pro-environmental attitudes and behaviour. As people who feel more knowledgeable are more likely to notice green products and make sustainable choices [43]. For GPCPs, this knowledge helps consumers judge ingredients, understand production impacts, and interpret sustainability certification. In online shopping such knowledge becomes critical as physical checks are not possible. It helps consumers trust credible green claims, lowers uncertainty and increases their willingness to buy. Therefore:

H6: "Perceived Environmental Knowledge has a significant relationship with Green Purchase Attitude."

PCE refers to an individual's belief that their personal actions can help solve environmental problems. It is a critical factor in understanding consumer behaviour particularly in the context of sustainability [44]. It reflects a sense of individual responsibility and self-efficacy in driving environmental change. Prior studies consistently found that individuals with high PCE are more likely to engage in green behaviours, including ethical consumption, waste reduction and green purchase [45]. In online settings, where consumers cannot physically inspect products or verify the authenticity of green claims, trust becomes a major barrier. Consumers often rely on internal beliefs such as PCE, to justify sustainable purchasing decisions. This reliance is especially relevant in the context of GPCPs which involve health-sensitive and ethically charged factors like ingredient safety, animal testing and biodegradability. When external cues are limited, people who strongly believe that their purchases matter are more likely to buy GPCPs online. Therefore:

H7: "Perceived Consumer Effectiveness has a significant relationship with Green Purchase Attitude."

The overall system can be conceptualized as a pipeline in which encoded values are processed through evaluative nodes (attitudes), commitment nodes (intentions), and behavioural outputs (purchases). In this formulation, mediators such as GPA and GPI serve as intermediate processing layers, enabling both prediction and intervention. Overall, Consumption values focus on personal benefits like usefulness, emotional satisfaction and social recognition. Whereas pro-environmental values address broader ethical concerns of sustainability and responsibility. Consumers support eco-friendly products in attitude but often do not purchase them [46]. Connecting these two value domains is key to reducing the value–action gap. Understanding this link is important for building effective digital marketing and policy measures that encourage sustainable consumption. Fig. 1 provides the conceptual model proposed by the study.

Digital marketplaces create challenges such as limited product tangibility and overwhelming information, which can affect how values turn into green purchase behaviour (GPB). To explain this process, the present model uses green purchase attitude (GPA) and green purchase intention (GPI) as mediators, in line with theories like the Theory of Planned Behaviour [39]. These mediators help explain how personal values are internalized into behavioural motivation and, ultimately, online purchase actions. Therefore, the following hypotheses were developed:

H8: "Green Purchase Attitude has a significant relationship with Green Purchase Intention."

H9: "Green Purchase Intention has a significant relationship with Green Purchase Behaviour".

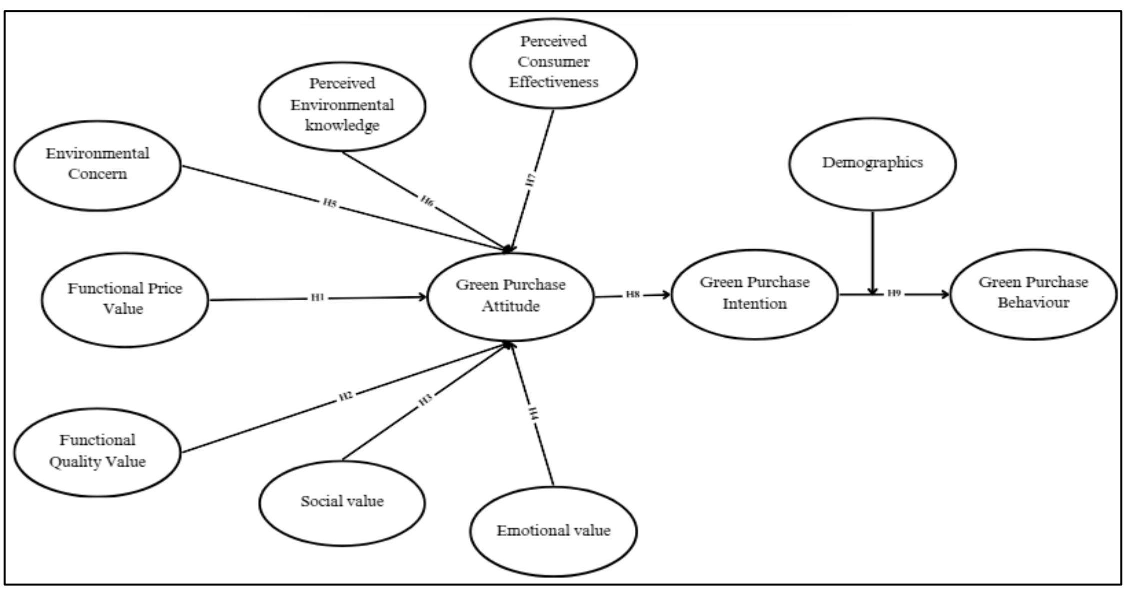

Fig. 1. Conceptual model (Author)

III. METHODOLOGY

A. Research Design

The study relied on a quantitative design to explore how consumer values might influence the adoption of GPCPs through e-commerce channels. Data were gathered using a structured questionnaire, which provided a relatively standardized way of capturing consumer responses. For the analysis, Structural Equation Modelling (SEM) was employed. This method has been widely recommended when dealing with complex causal frameworks, particularly those that involve multiple latent constructs and interrelated pathways [48]. Although other techniques were possible, SEM appeared especially useful here because it allows for simultaneous testing of measurement and structural relationships.

B. Sampling Strategy and Participants

The sampling process was purposive, reflecting the need to reach participants with prior experience purchasing GPCPs online. To achieve this, screening questions were embedded within the survey to filter out ineligible respondents. In terms of sample size, the study drew on the "10-times rule" proposed by Hair et al. (2014), which suggests a minimum of 200 cases given the 10 latent variables and 9 hypothesised paths in the model [48]. The study also used power analysis to validate sample size adequacy. Power analysis determines the minimum number of cases required to detect a specified effect size with a given statistical power (commonly 0.80) at a significance level of 0.05. Using G*Power 3.1.9.7, the analysis indicated that a sample of at least 262 respondents would be sufficient for the structural model. With 302 valid responses retained, the sample size of this study comfortably exceeds both the 10-times rule and the power analysis threshold, ensuring robustness for hypothesis testing. In terms of geographic distribution, all respondents were based in India, with both urban (65.23%) and rural (34.76%) representation across several states. Recruitment channels included emails, professional networks, and social media groups (e.g., WhatsApp, LinkedIn, Instagram), with an emphasis on communities likely to include environmentally conscious consumers. Questionnaire also included screening questions ensuring access to participants who had demonstrable experience with online GPCP purchases, while also capturing diversity in socio-demographic characteristics. After data cleaning procedures such as removing incomplete or inconsistent responses, 302 relevant responses cases were retained.

C. Instrument Development

The questionnaire was structured into distinct sections, beginning with demographic information and then moving into the main research constructs. Demographic items included gender, age, education, and income, providing context for consumer behaviour. Measures of pro-environmental values drew on three constructs PCE, ENC, and PEK each represented by three items adapted from earlier work [49, 50] . The decision to rely on these constructs reflects their repeated use in prior sustainability research. In terms of consumption values, the study adopted four dimensions commonly discussed in consumer behaviour research: FPV, FQV, EMV, and SCV. Each was measured with three items, drawing from validated scales in existing literature [51, 52] . Finally, the behavioural side of the framework was operationalised through GPA, GPI, and GPB. These were measured with five items each, adapted from several studies that have sought to connect attitudinal measures to actual consumer practices [51-56] . Though it does not necessarily capture the full breadth of "green" value orientations, slight modifications were made to fit in the context of study.

D. Validity and Reliability Procedures

To strengthen the credibility of the instrument, a multi-stage validation process was followed. In the first stage, six scholars with expertise in marketing and consumer behaviour reviewed the questionnaire. Their assessment focused on face and content validity, and several items were revised in response to concerns about clarity and nuance. This expert review is often treated as routine, but it arguably provides only a partial safeguard, as consensus among reviewers does not guarantee conceptual precision.

A second stage involved a pilot test with 50 participants, which served two purposes: to evaluate the intelligibility of the items and to flag potential issues in wording or structure. Although pilots cannot replicate full study conditions, they help identify ambiguities researchers may overlook. Finally, a preliminary SEM analysis was carried out using the pilot data. This step helped assess the fit of the measurement model and provided early evidence of reliability and construct validity. While the pilot results were encouraging, it should be noted that findings based on such a small sample may not always be stable; nonetheless, they offered a degree of reassurance before moving forward with the full-scale survey.

E. Data Analysis

The data were analysed using Structural Equation Modelling (SEM), a method well-suited for handling complex relationships between latent constructs. The analysis proceeded in two stages. First, the measurement model was tested through Confirmatory Factor Analysis (CFA). Reliability was gauged using Cronbach's alpha alongside composite reliability, while convergent validity was examined through factor loadings and the average variance extracted (AVE). Discriminant validity was also checked, with the goal of ensuring that the constructs were sufficiently distinct from one another.

In the second stage, the structural model was tested to evaluate the hypothesised paths. Model fit was assessed using indices commonly cited in SEM research. Path coefficients were examined for statistical significance and the explained variance (R^2) of the endogenous constructs was reported as an indicator of predictive strength. This procedure examined how consumer values shape GPCP adoption in online marketplaces.

IV. RESULTS

A. Descriptive Statistics and Sample Characteristics

Table I summarizes the demographic profile of the 302 respondents. The sample comprised a slightly higher proportion of females (55.96%) compared to males (44.03%). A significant majority resided in urban areas (65.23%), while 34.76% were from rural locations. In terms of educational attainment, most participants held either a postgraduate (48.01%) or graduate degree (41.72%). The age distribution skewed towards younger individuals, with 65.23% aged between 18–27 years and 26.49% between 28–43 years. Respondents above 44 years constituted less than 10% of the total sample. Regarding annual income, a majority (56.29%) reported earnings up to ₹2,50,000, while 25.16% earned between ₹2,50,000–₹5,00,000. Higher income brackets were less represented.

TABLE I. DEMOGRAPHIC CHARACTERISTICS OF THE RESPONDENTS

Demographic variables	Frequency	Percent
Gender		
Female	169	55.96
Male	133	44.03
Region		
Rural	105	34.76
Urban	197	65.23
Qualifications		
Secondary	9	2.98
Higher Secondary	11	3.64
Doctoral	11	3.64
Graduate	126	41.72
Postgraduate	145	48.01
Age		
18- 27 years	197	65.23
28- 43 years	80	26.49
44- 59 years	18	5.96
60 and above	7	2.31
Annual Income		
0 to Rs. 2,50,000	170	56.29
Between Rs. 2,50,000- 5,00,000	76	25.16
Between Rs. 5,00,000- 7,50,000	29	9.6
Between Rs. 7,50,000- 10,00,000	4	1.32
Between Rs. 10,00,000- 12,50,000	5	1.65
Between Rs. 12,50,000- 15,00,000	4	1.32
Above Rs. 15,00,000	14	4.63

Although the survey was broadly distributed across multiple channels, a purposive sampling strategy was applied, and respondents without prior experience purchasing GPCPs online were excluded. As a result, the final sample was predominantly younger, urban, and more educated a demographic segment that is also the most active in online green personal care product consumption.

B. Measurement Model Evaluation

Reliability and validity of the constructs were first assessed and the results are shown in Tables II and VI. As shown in Table VI, all constructs exceeded the recommended thresholds for internal consistency, with Cronbach's alpha values exceeding the recommended threshold of 0.70 [57]. AVE values for all constructs were above the 0.50 threshold [58], indicating adequate convergent validity. Factor loadings were above 0.70 for all items except one (PCE2), which was subsequently removed to improve construct validity. The constructs show strong reliability and validity.

To test the potential influence of common method bias, Harman's single-factor test was conducted as an initial diagnostic. The unrotated factor solution revealed that the first factor accounted for less than 40% of the total variance, which is less than the threshold value of 50% [59]. Variance Inflation Factor values were also examined to detect any issues related to multicollinearity among the indicators. Its values ranged from 1.00 to 3.81, all below the conservative threshold of 5 [57]. This means the indicators are free from multicollinearity concerns.

TABLE II. FORNELL-LARCKER CRITERION

	EMV	ENC	FPV	FQV	GPA	GPB	GPI	PCE	PEK	SCV
EMV	0.884									
ENC	0.549	0.843								
FPV	0.599	0.333	0.889							
FQV	0.695	0.401	0.675	0.862						
GPA	0.598	0.436	0.501	0.569	0.903					
GPB	0.674	0.558	0.544	0.611	0.591	0.827				
GPI	0.701	0.512	0.506	0.564	0.781	0.726	0.866			
PCE	-0.147	-0.079	-0.352	-0.14	-0.184	-0.261	-0.177	0.909		
PEK	0.58	0.587	0.446	0.571	0.532	0.637	0.522	-0.219	0.817	
SCV	0.633	0.374	0.649	0.581	0.486	0.543	0.514	-0.427	0.47	0.863

The Fornell-Larcker criterion was used to evaluate discriminant validity (Table II). Based on this criterion, a construct's square root of Average Variance Extracted (AVE) must exceed its largest correlation with any other construct [58]. The diagonal elements represent the square roots of AVE and the off-diagonal elements represent inter-construct correlations. As shown in the Table III, all diagonal values exceed the corresponding off-diagonal correlations in their respective rows and columns. The findings confirm discriminant validity, as each construct is conceptually and empirically distinct.

C. Structural Paths and Hypotheses Tests

The structural model was evaluated using bootstrapping with 5,000 resamples to assess the significance of hypothesized relationships. Table III presents the standardized path coefficients, associated t-statistics, and p-values. Among the antecedents of Green Product Attitude (GPA), Functional Quality Value (FQV) ($\beta = 0.174$, $t = 2.294$, $p = 0.022$), Perceived Environmental Knowledge (PEK) ($\beta = 0.177$, $t = 2.262$, $p = 0.024$), and Emotional Value (EMV) ($\beta = 0.241$, $t = 2.747$, $p = 0.006$) has shown a significant influence. Conversely, Environmental Concern (ENC) ($\beta = 0.079$, $p = 0.228$), Perceived Consumer Effectiveness (PCE) ($\beta = -0.025$, $p = 0.618$), Social Value (SCV) ($\beta = 0.047$, $p = 0.524$), and Functional Price Value (FPV) ($\beta = 0.096$, $p = 0.232$) did not demonstrate significant effects on GPA. Fig. 2 presents the structural model.

In the outcome model, Green Product Attitude showed a strong positive effect on Green Purchase Intention ($\beta = 0.781$, $t = 25.019$, $p < 0.001$), which in turn significantly influenced Green Purchase Behavior ($\beta = 0.726$, $t = 23.125$, $p < 0.001$). The results confirmed the central role of attitude and intention in purchase outcomes.

TABLE III. PATH COEFFICIENTS

	Original sample	Sample mean	Standard deviation	T statistics	P values
EMV -> GPA	0.241	0.237	0.088	2.747	0.006
FPV -> GPA	0.096	0.092	0.080	1.196	0.232
FQV -> GPA	0.174	0.177	0.076	2.294	0.022
GPA -> GPI	0.781	0.781	0.031	25.019	0.000
GPI -> GPB	0.726	0.726	0.031	23.125	0.000
PCE -> GPA	-0.025	-0.028	0.050	0.498	0.618
ENC -> GPA	0.079	0.082	0.065	1.207	0.228
PEK -> GPA	0.177	0.176	0.078	2.262	0.024
SCV -> GPA	0.047	0.050	0.073	0.637	0.524

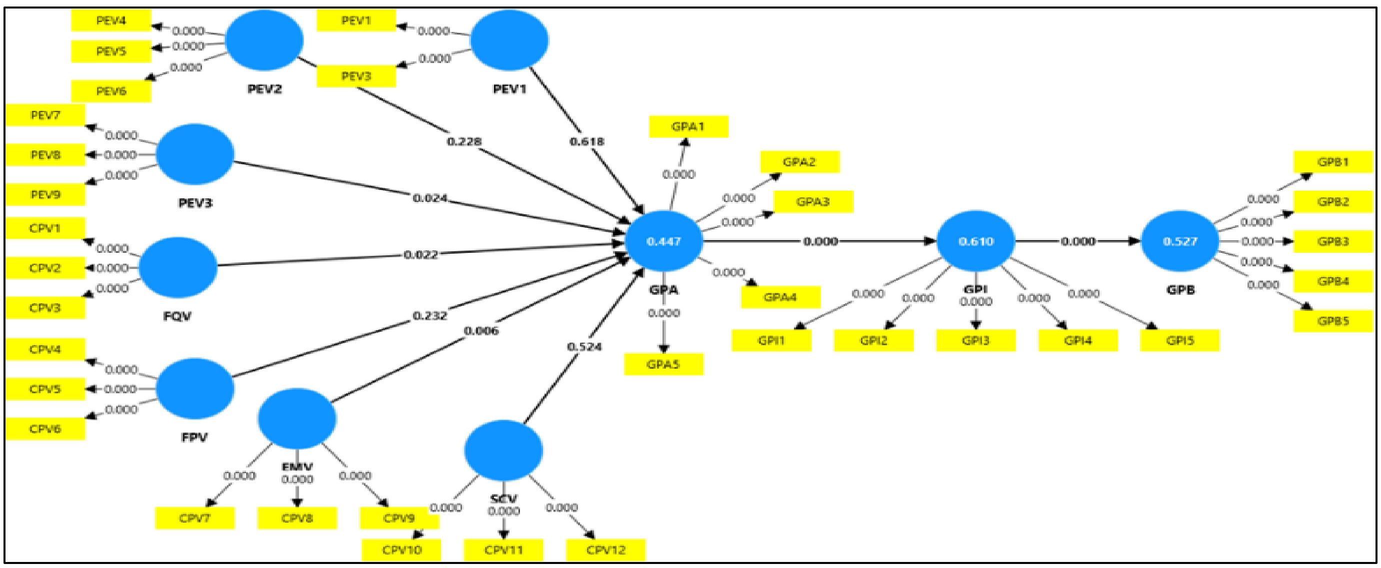

Fig. 2. Structural Model (Author)

Note: Numbers on paths represent standardized path coefficients (β). Values in grey adjacent to paths are p-values. Circles show latent constructs; rectangles represent observed indicators. R^2 values are reported inside endogenous constructs (GPA, GPI, GPB) and indicate the proportion of variance explained

Overall, these findings offer partial empirical support for the proposed model. While selected consumption values including functional and emotional significantly shape green product attitudes, from pro-environmental values, PEK demonstrates direct effects in this context. Additionally, GPA significantly predicted GPI, which in turn significantly influenced GPB. These findings support the value-attitude-behaviour framework, highlighting the mediating role of attitude and intention in translating values into sustainable behaviour.

Table IV presents the coefficients of determination (R2). The model explains 44.7% of the variance in Green Product Attitude (GPA), 61.0% in Green Purchase Intention (GPI), and 52.7% in Green Purchase Behaviour (GPB). Adjusted R^2 values confirmed model stability. The predictors explain a substantial share of variance in the outcomes. In particular, the explanatory power is highest for GPI ($R^2 = 0.610$), followed by GPB ($R^2 = 0.527$), supporting the mediating role of intention in the value-attitude-behaviour sequence.

TABLE IV. COEFFICIENT OF DETERMINATION (R^2)

	R-square	R-square adjusted
GPA	0.447	0.434
GPB	0.527	0.525
GPI	0.61	0.609

In addition to explanatory power, model fit was assessed using the Standardized Root Mean Square Residual (SRMR). The SRMR value for the saturated model was 0.059, which is below the recommended threshold of 0.08, indicating an adequate measurement model fit. The SRMR for the estimated model was 0.110, indicating a slightly weaker structural fit, with values between 0.08 and 0.10 generally considered to reflect a mediocre fit [60]. However, as PLS-SEM prioritizes predictive accuracy over absolute model fit, and given the satisfactory R^2 values obtained, the model was retained due to its strong theoretical foundation and empirical adequacy.

V. Discussion

A. Interpretation of Significant Relationships

The results can be interpreted both behaviourally and as signals for system design. Significant predictors can be treated as high-priority modules within a digital pipeline. The analysis revealed three statistically significant paths within the proposed model: Functional Quality Value → Green Product Attitude, Emotional Value → Green Product Attitude, perceived environmental knowledge → Green Product Attitude, and the sequential mediation pathway of Green Product Attitude → Green Purchase Intention → Green Purchase Behaviour. The findings provide critical insights into sustainable decision-making in the e-commerce context.

The results suggest that FQV has a measurable effect on GPA ($\beta = 0.174$, $t = 2.294$, $p = 0.022$). In other words, consumers appear to weigh the perceived effectiveness of a product alongside its environmental claims, though this emphasis is not entirely surprising. For GPCPs in particular, attributes tied to performance, safety, and reliability often emerge as decisive factors in shaping evaluations [4, 61]. A moisturizer that feels ineffective or a shampoo that fails to deliver basic quality expectations may undermine the appeal of its eco-friendly positioning. Conversely, when products are framed as beneficial for health or skin, consumer attitudes often lean more positively [62].

At the same time, this does not mean that consumers automatically privilege functionality over sustainability; rather, many expect eco-friendly options to deliver both. There is an implicit demand that environmental responsibility should not come at the expense of efficacy. A tension that marketers must navigate carefully. Credibility can be enhanced through signals such as clinical validations, third-party certifications, or even the seemingly mundane reassurance of user testimonials. Such strategies may help consumers reconcile quality concerns with sustainability commitments. In this sense, functional value reinforces confidence not just in what the product does, but also in whether its green claims can be believed.

Similarly, the analysis indicates that EMV exerted a notable influence on GPA ($\beta = 0.241$, $t = 2.747$, $p = 0.006$). This finding points to the increasingly recognized role of affective responses in how consumers interpret and evaluate environmentally friendly products, though the strength of this relationship may vary across contexts. In online settings where buyers cannot physically inspect goods, emotional cues seem to take on added weight. A feeling of personal satisfaction, or even the perception of contributing to broader environmental goals, can become a powerful motivator. Prior work shows that green products emphasizing natural ingredients, ethical sourcing, or cruelty-free practices effectively elicit emotional responses [63, 64]. At the same time, these responses are not purely about immediate gratification; some consumers may also see environmentally conscious purchasing as tied to identity, pride, or moral consistency [37, 65] . Taken together, the results suggest that e-retailers might benefit from foregrounding emotional appeals in their messaging, for instance by highlighting alignment with personal values or the “feel-good” dimension of sustainable consumption..

PEK exerted a moderate effect on GPI ($\beta = 0.177$, $t = 2.262$, $p = 0.024$). In practical terms, consumers who believe they understand environmental issues are more inclined to view GPCPs positively. This does not necessarily mean that objective knowledge drives behaviour; rather, the perception of being informed seems to matter as much, if not more. Prior studies have pointed out that environmental knowledge often influences consumer decision-making indirectly by shaping attitudes first, which are then filtered into intentions and eventual behaviour [66, 67].

Online marketplace complicates this dynamic. In contexts where product claims cannot easily be verified, consumers often lean on their own perceived expertise to judge whether labels such as “organic,” “biodegradable,” or “cruelty-free” should be trusted. Some may also be aware of broader concerns about health and environmental impact, which, as Kaur et al. (2024) suggest, can reinforce a preference for eco-friendly alternatives [68]. This highlights the role of consumer education: Certifications, impact facts, and ingredient details can bolster credibility and attitudes.

The paths from attitude to intention and intention to behaviour were strongly supported ($\beta = 0.726$, $t = 23.125$, $p = 0.000$). This corroborates the VAB hierarchy [69-71] . The sequence confirms that positive evaluations of GPCPs translate into stronger purchase intentions, which in turn lead to actual buying behaviour. The high explanatory power of intention ($R^2 = 0.615$) and behaviour ($R^2 = 0.593$) further confirms the importance of intention as a psychological mechanism that helps translate green product attitudes into actual purchase behaviour, particularly in digital contexts. This strong link between attitude, intention and behaviour reflects classical behavioural theories (e.g., the Theory of Reasoned Action and TPB). This assert that intention is the most immediate predictor of behaviour [47]. In the case of GPCPs, once a consumer forms a purchase intention driven by positive attitudes, emotional value, and perceived knowledge, they are likely to act on it, especially in an e-commerce setting where friction to purchase is low (e.g., fast checkout, product recommendations, promotions).

Overall, online green purchases are driven more by practical factors like how useful the product is, how well it performs, and consumer’s perceived knowledge, and emotions than by abstract ideals. These factors appear to exert a greater influence on behavioural outcomes than ideologically rooted values such as environmental concern or ethical commitment. Thus, while consumers may express pro-environmental attitudes, their actual purchasing behaviour within digital environments is more strongly shaped by functional value perceptions and emotions than by abstract ecological ideals.

While this study deliberately focused on GPCPs because of their unique intersection of safety, ingredient transparency, and daily-use intimacy, some of the mechanisms identified are not entirely confined to this sector. For example, the importance of functional quality value reflects a broader expectation that green products whether in personal care, household goods, or food should not compromise on performance. Likewise, emotional value and perceived environmental knowledge are likely to influence sustainable choices across categories, even if the strength of these drivers varies by context. Thus, although GPCPs warrant independent study, our findings also suggest potential points of convergence that future cross-category research could explore to test external validity.

B. Non-Significant Effects and Possible Explanations

Several hypothesized relationships were not supported by the data. SCV, ENC, PCE, and FPV do not demonstrate statistically significant effects on green product attitude.

The hypothesized relationship between FPV and GPA was not supported ($\beta = 0.096$, $t = 1.196$, $p = 0.232$). This indicates that consumers' perception of whether a GPCP offers good value for its price does not significantly shape their attitude toward purchasing it. While favourable price assessments were expected to encourage positive purchase attitudes, the data suggest otherwise. Instead, consumer attitudes appear more strongly influenced by perceived product quality. This diverges from prior studies where price value emerged as a significant predictor of sustainable consumption, particularly in categories where cost differences are more salient [26,27]. One explanation is that in online GPCP markets, prices are relatively transparent and easily compared across sellers, reducing the role of perceived price value as a differentiating factor. In the context of GPCPs, consumers may prioritize attributes such as social support, safety, and environmental impact over affordability. However, financial scarcity can shift priorities toward affordability, thereby reducing the likelihood of choosing green options [72]. Instead, higher prices may even be associated with superior quality, ethical practices, or safer ingredients [73]. Consequently, brands in this space should avoid competing primarily on price and instead focus on communicating product quality, emotional benefits, and sustainability commitments

The hypothesized relationship between SCV and GPA is not supported ($\beta = 0.047$, $t = 0.637$, $p = 0.524$). This indicates that, in the online context, social approval or the opinions of others do not significantly shape consumers' attitudes toward GPCPs. A likely explanation is that personal care routines are private and individualized, making them less visible to others and therefore less influenced by social recognition. As a result, their adoption tends to be driven more by personal comfort and perceived benefits [74]. Moreover, personal care needs, such as skin type, hair texture, and sensitivity vary greatly between individuals, further reinforcing the personalized nature of product choices [75]. As a result, consumers may not rely heavily on peer recommendations or influencer endorsements, perceiving them as less relevant or trustworthy for their specific needs. This weakens the impact of social proof, a key component of social value. Prior studies in offline or more publicly visible product categories have reported significant effects of social value on sustainable consumption (e.g., [34]). Our result diverges from this evidence, suggesting that the inherently private and individualized nature of GPCPs, combined with the less observable nature of online shopping, diminishes the signalling power of social value. This finding implies that social value cannot be assumed to drive green purchase attitudes unless visibility is actively created, for example, through eco-badges, community features, or public sharing options that make sustainable choices more observable. Consequently, marketing strategies for GPCPs should move beyond reliance on social proof. Instead, brands should focus on transparent ingredient communication, emphasizing safety, effectiveness, and suitability for different skin and hair types. Clear, trustworthy information empowers consumers to make informed choices and builds confidence in the product's value, especially when personal relevance matters more than social validation.

The hypothesized relationship between ENC and GPA is not supported ($\beta = 0.079$, $t = 1.207$, $p = 0.228$). This result diverges from previous research showing a positive connection between the variables [76, 77], but aligns with Chu's (2020) findings in similar context of skincare products [78]. A possible explanation lies in the well-documented attitude–behaviour gap, where expressed concern does not always lead to corresponding actions. In the digital shopping environment, consumers may prioritize immediate, tangible factors such as product trustworthiness, or brand familiarity over broader environmental ideals. Furthermore, uncertainty about the authenticity of green claims can reduce the effectiveness of concern-based messaging [79]. Consequently, marketers should link environmental issues directly to product-level impacts and present information in a way that feels credible, emotionally engaging, and directly relevant to the consumer's personal needs. More broadly, this divergence suggests that in online retail contexts, environmental concern may function more as a background value than as a direct predictor of green purchase attitudes. To activate it effectively, platforms need to translate abstract concern into verifiable product attributes such as certified eco-labels, transparent supply-chain disclosures, or quantified environmental benefits, that make concern tangible at the point of decision.

The hypothesized relationship between PCE and GPA is not supported ($\beta = -0.025$, $t = 0.498$, $p = 0.618$). This suggests that consumers' belief in their ability to make a positive environmental impact through their purchases does not significantly influence their attitude toward buying GPCPs online. This diverges from prior research that often identifies PCE as a strong predictor of pro-environmental attitudes in offline settings [45]. A likely explanation is that such products are typically associated with self-care, aesthetics, and health, leading consumers to prioritize personal benefits over collective environmental impact. Their routine and low-involvement nature may also reduce the perceived significance of individual actions. In online shopping specifically, the influence may be weakened as consumers may struggle to verify the credibility of sustainability claims [80]. These findings suggest that in online GPCP contexts, PCE is unlikely to shape attitudes unless platforms make the impact of individual purchases transparent and personally meaningful for example, by quantifying outcomes ("this order saves X litres of water") or by linking consumers to collective achievements (e.g., community carbon offsets).

Collectively, these results suggest that cognitive and ideological drivers alone may not be sufficient. More robust informational strategies, supported by credible certification, product transparency, emotional appeals and real-world efficacy, may be needed. These can help turn environmental values into positive attitudes and action.

VI. Pipeline Architecture for Sustainable Online Consumer Behaviour

The empirical analysis in this study confirmed that FQV, EMV, and PEK significantly shape GPA, which in turn predicts GPI and, ultimately, GPB. Non-significant predictors (FPV, SCV, ENC, and PCE) were excluded from the pipeline equations because of parsimony and computational efficiency. While these findings advance the theoretical understanding of consumer decision-making, their practical application requires a computational instantiation that can be embedded within digital commerce platforms. To this end, we propose a multi-stage pipeline architecture that formalizes the Value–Attitude–Behavior (VAB) framework and the SEM results into a modular system design. The SEM findings were used to derive equations (1–4), which then served as the basis for proposing the pipeline architecture for sustainable online consumer behavior. In the equations (1-4), u denotes the index for an individual consumer, as each model operates at the consumer level. Parameter α (alpha) represents the intercept or constant term, capturing the baseline value of the dependent variable (such as GPA or GPI) when predictors are absent. The coefficients β (beta) quantifies the influence of predictor variables, indicating how much the dependent variable changes with a one-unit increase in the predictor, holding other factors constant.

Similarly, γ (gamma) represents the coefficient for control variables (C_u) in the GPI equation, reflecting the effect of external or contextual factors such as incentives, trials, or platform-specific interventions. The term ϵ (epsilon) denotes the error component that accounts for unexplained variation or noise in consumer responses. In the augmented model, κ (kappa) is introduced as a reduced-form coefficient, which consolidates constants and indirect effects when multiple equations are combined. Collectively, these parameters provide a structured way to quantify how consumer values, attitudes, and contextual mechanisms shape intentions and sustainable purchasing behaviors.

Each stage of the pipeline corresponds to a theoretical construct validated in this study, operationalized as an observable system component or intervention layer. This architecture enables e-commerce systems to measure, influence, and reinforce sustainable choices in a structured and transparent manner. Fig. 3 illustrates the overall pipeline.

Stage 0: Data Instrumentation (Foundations)

To construct event streams, to capture proxies of GPA, GPI, and GPB. GPA proxies include product detail page (PDP) dwell time, ingredient-info expansions, and short surveys designed to assess user attitudes and perceptions. GPI proxies include add-to-cart, wishlist, and subscription trial actions. GPB proxies include conversions and repeat purchases within a defined window. These signals are stored in a fused clickstream + survey dataset, enabling causal and path analyses aligned with the SEM structure.

Stage 1: FQV Encoding Layer

Structured quality representations such as clinical claims, dermatological test results, and verified certifications are encoded as metadata objects linked to product entities. Interactive UI affordances (e.g., badges, expandable quality panels) expose these signals to consumers. In the pipeline model, this relationship is captured by Equation (1), where FQV serves as a positive predictor of Green Purchase Attitude (GPA).

$$GPA\_u = \alpha_1 + \beta_1 \, FQV\_u + \epsilon_1 u, \; \beta_1 > 0 \qquad (1)$$

Stage 2: EMV Encoding Layer

Self-congruent narrative embeddings are generated within the UI by combining personal benefits with environmental alignment. Affective reinforcement mechanisms (e.g., encouraging messages post-add-to-cart) deliver feedback loops. In Equation (2), EMV is modeled as a positive predictor of GPA."

$$GPA\_u = \alpha_2 + \beta_2 \, EMV\_u + \epsilon_2 u, \; \beta_2 > 0 \qquad (2)$$

Stage 3: PEK Augmentation Layer

Micro-learning interventions such as hover-tooltips, label decoders, or short explainers can be deployed to increase knowledge accessibility. These modules can be coupled with interactive tasks linked to loyalty rewards. In Equation (3), PEK is modeled as a positive predictor of GPA.

$$GPA\_u = \alpha_3 + \beta_3 \, PEK\_u + \epsilon_3 u, \; \beta_3 > 0 \qquad (3)$$

Stage 4: Intention Induction Layer

Green purchase attitudes (GPA) are translated into purchase intentions (GPI) via low-friction commitment mechanisms, including sample-size trials and one-click subscriptions with deferred opt-out. This attitudinal influence is formalized in Equation (4), where GPA positively predicts GPI, alongside contextual control factors (C_u) such as platform incentives or trial offers.

$$GPI\_u = \alpha_4 + \beta_4 \, GPA\_u + \gamma \, C\_u + \epsilon_4 u, \; \beta_4, \gamma > 0 \qquad (4)$$

Notably, SEM results showed that these predictors accounted for 44.7% of the variance in GPA, 61.0% in GPI, and 52.7% in GPB. These R^2 benchmarks provide evidence that the reduced-form pipeline equations have substantial predictive strength in explaining consumer behavior.

Stage 5: Behavior Reinforcement Layer

To close the gap between GPI and GPB, post-purchase reinforcement mechanisms can be implemented. These include onboarding prompts, product-use nudges, and structured review solicitation. Review feedback loops feed directly into FQV encoding by enriching product metadata with user-reported efficacy.

Stage 6: A/B Testing and Path Modeling

An experimentation module evaluates the impact of interventions on GPA, GPI, and GPB. Lightweight path models replicate the SEM mediation structure in live settings, testing whether system interventions improve explained variance (R^2) across behavioral outcomes.

Stage 7: Governance and Trust Enforcement

A centralized claim verification registry ensures that all quality and knowledge claims are supported by credible sources. Review integrity filters mitigate noise, fraud, or manipulation which could undermine trust in FQV signals.

A. Metrics & Evaluation

Construct-level proxies: FQV = interaction with proof panels, review filters, certification hovers, EMV = completion of narrative components, positive affect feedback taps, PEK = micro-learning completion, label hover frequency.

Outcome metrics: GPA = micro-survey scores, GPI = commitment actions, GPB = conversion, repeat purchase. Evaluation criterion: improvement in explained variance (R^2) across constructs, aligned with study benchmarks (GPA: 44.7%, GPI: 61.0%, GPB: 52.7%).

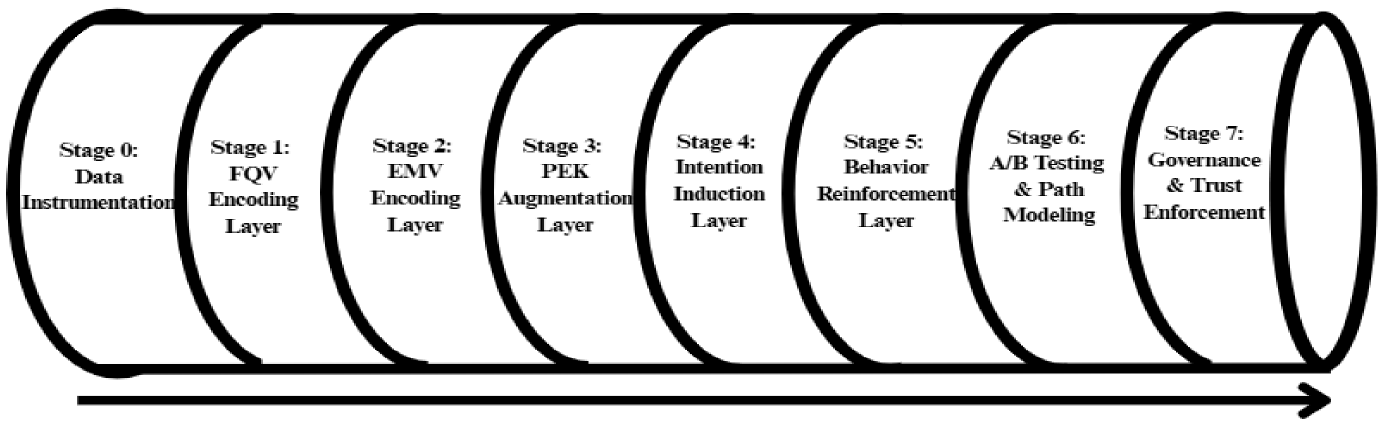

Fig. 3. Proposed pipeline architecture for sustainable online consumer behaviour (Author)

Overall, this pipeline operationalizes psychological constructs into computational modules within an e-commerce system. Each layer implements a causal intervention aligned with significant SEM predictors (FQV, EMV, PEK) and is validated through online experimentation and path modeling. The design adheres to evidence-driven feature prioritization, excluding non-significant determinants (FPV, SCV, ENC, PCE), thus maximizing system efficiency in driving sustainable online consumption.

Final Single (Augmented) Equation

After substituting GPA into GPI and grouping terms, the augmented equation becomes as follows:

$$GPI_u = (\gamma + \delta\alpha) + \delta\beta_1 \cdot FQV_u + \delta\beta_2 \cdot EMV_u + \delta\beta_3 \cdot PEK_u + (\delta\varepsilon_u + \xi_u) \quad (5)$$

Here, δ is defined as β_4, the path coefficient from GPA to GPI. This allows GPA predictors to be substituted directly into the GPI equation.

We can define reduced-form coefficients and a composite error term as follows:

$\kappa_0 = \gamma + \delta\alpha$ (absorbs constants + commitment effect)
$\kappa_1 = \delta\beta_1$, $\kappa_2 = \delta\beta_2$, $\kappa_3 = \delta\beta_3$
$\eta_u = \delta\epsilon_u + \xi_u$ (composite error term)

Thus, the final estimable regression model is:

$$GPI_u = \kappa_0 + \kappa_1 \cdot FQV_u + \kappa_2 \cdot EMV_u + \kappa_3 \cdot PEK_u + \eta_u \quad (6)$$

B. Practical Application in E-commerce Systems

The proposed pipeline is technically implementable within standard e-commerce infrastructures because it leverages existing data flows and modular system components. At the data layer, most platforms already capture the key behavioral proxies required for the model: clickstream logs, product-detail-page dwell time, ingredient information expansions, add-to-cart and wish list events, subscription activations, and repeat purchases. These events can be fused into a unified dataset (clickstream + survey signals) that feeds into the pipeline as the foundation for modeling attitudes, intentions, and behaviors.

The first operational stage functional quality value (FQV) encoding can be realized by structuring product metadata such as clinical claims, dermatological test results, and verified ingredient lists as machine-readable attributes within the product database. These metadata objects can be exposed at the interface level through badges, expandable proof panels, or certification icons, while also serving as features in recommender engines and ranking algorithms. Similarly, emotional value (EMV) encoding can be handled by embedding narrative-driven content into the user interface, supported by vectorized testimonial corpora or natural language generation pipelines. Reinforcement triggers can be added at interaction points (e.g., after an item is added to cart, a pop-up confirmation communicates the environmental or ethical value of the action).

The knowledge augmentation layer (PEK) can be operationalized using micro-frontends that deliver eco-label decoders, hover-tooltips, or interactive quizzes. Engagement events such as tooltip hovers or quiz completions are logged and ingested back into the system as features that approximate perceived knowledge. Attitudinal states (GPA) are then transitioned into intentions (GPI) through existing low-friction mechanisms like wishlists, “subscribe and save” options, pre-orders, or free-sample trials. Each of these nodes can be monitored by backend flags that track state transitions in line with the VAB sequence.

To close the loop, behavior reinforcement modules can be integrated into customer relationship management (CRM) systems, email automation, and push notification workflows. These deliver personalized onboarding tips, replenishment reminders, or structured review requests, with user-generated reviews flowing back into the metadata layer to enrich quality signals. A/B testing engines such as Optimizely, Google Optimize, or in-house experimentation frameworks can be used to validate the causal impact of each intervention, measuring improvements in explained variance (R^2) across attitudes, intentions, and behaviors. Finally, governance and trust mechanisms can be built on claim-verification registries, either centralized APIs or blockchain-based provenance systems, while review fraud detection models ensure the integrity of consumer feedback.

Taken together, this design can be deployed as a modular middleware service that sits between the data layer, application/UI layer, and experimentation layer of an e-commerce platform. By treating psychological determinants as programmable modules encoded as structured data, interface elements, or backend processes, the pipeline provides a practical, scalable, and evidence-driven approach that can be layered into existing commerce architectures without requiring disruptive system redesign.

C. Theoretical Implications

The findings add to theoretical understanding of green consumer behaviour within the domain of GPCPs. First, the study reinforces the VAB hierarchy by demonstrating that functional quality, emotional value, and perceived environmental knowledge significantly shape GPA, which in turn influence purchase intentions and ultimately behaviour. This sequential mediation underscores the attitudinal mechanisms through which consumption values are translated into action, supporting the relevance of behavioural theories such as the Theory of Reasoned Action and Theory of Planned Behaviour in digital consumption contexts. Importantly, the study also extends the application of Consumption Value Theory [81] to the sustainable e-commerce domain.

By extending Consumption Value Theory into a pipeline design framework, the study bridges behavioural science with systems modelling. The significant influence of functional and emotional values on consumer attitudes demonstrates that these consumption values are central to green decision-making. The effect remains important even without in-store interaction. Second, the results highlight a shift in the salience of values, where practical and affective considerations rather than ideological or social factors emerge as primary drivers of green purchase attitudes online. This diverges from earlier studies emphasizing SCV and ENC, indicating that the digital nature of the marketplace alters the cognitive weighting of influencing variables. Third, the study challenges the presumed centrality of constructs like PCE and FPV, suggesting that their impact may be more context-dependent and less influential at the attitudinal stage than previously theorized. These insights call for a refinement of green consumer behaviour models, especially for low-involvement product categories in e-commerce settings. For computer science, this provides evidence that system architectures for sustainable commerce must prioritize encoding verifiable quality, embedding affective reinforcement, and augmenting knowledge rather than generic environmental signalling.

D. Managerial Implications

From a practical standpoint, the results translate directly into system requirements for pipeline-based e-commerce architectures. From a practical standpoint, the strong impact of FQV on consumer attitudes underscores the need for platforms to encode structured product-quality metadata (e.g., dermatological testing, clinical claims) as machine-readable objects, surfaced through trustworthy interface components. Highlighting these signals strengthens trust and drives favorable attitudes.

Second, the importance of EMV indicates that systems should include affective encoding layers that deliver emotionally resonant interactions. Platforms can implement narrative embeddings, reinforcement messages, and testimonial-driven storytelling to deepen engagement. These affective modules transform psychological value into measurable digital signals, increasing the likelihood of attitude formation and intention activation.

Third, the effect of PEK underscores the necessity of knowledge-augmentation layers within digital pipelines. Micro-learning interventions, interactive eco-label decoders, and credibility-enhancing educational content can be embedded as dynamic UI features. Such modules reduce uncertainty and increase product trust in ways consistent with the SEM findings.

Non-significant predictors such as SCV, FPV, ENC, and PCE did not emerge as statistically significant in this study, but they still carry practical relevance in specific contexts. For example, SCV may become more salient in communities where sustainable consumption is visible to peers; platforms could experiment with eco-badges, public sharing features, or influencer tie-ins to activate this value. FPV might matter more in price-sensitive segments, where promotions, bundles, or loyalty rewards can lower perceived financial barriers. ENC, though not directly predictive, can still be mobilized by translating abstract concerns into tangible product-level attributes such as biodegradable packaging or cruelty-free certifications. Similarly, PCE could be reinforced by linking purchases to measurable outcomes (e.g., “this order prevents X grams of plastic waste”), making individual contributions feel concrete and personally meaningful. Taken together, these insights suggest that managers should focus primarily on quality, emotional engagement, and knowledge-building, while selectively activating non-significant values in contexts where they are likely to matter.

Beyond system-level design, the findings also hold broader strategic implications for business managers seeking to operationalize sustainability in e-commerce contexts. Managers can leverage the validated determinants (functional quality, emotional value, and perceived knowledge) in multiple ways. These factors can serve as actionable levers for shaping brand strategy, improving CRM, and guiding market segmentation. For instance, integrating verified sustainability data into CRM systems may enable more personalized engagement with green-oriented consumers, while AI-driven analytics could help identify clusters of users more responsive to functional or emotional cues. The pipeline's measurable attitudinal and behavioral stages offer a foundation for developing sustainability-oriented key performance indicators (KPIs), allowing firms to monitor progress toward responsible consumption goals. Moreover, leadership teams may consider investing in training and incentive programs for vendors and employees to ensure credible sustainability communication, thereby strengthening brand trust, loyalty, and differentiation in competitive online marketplaces.

E. Policy Implications

From a policy standpoint, the proposed computational pipeline offers actionable insights for advancing Sustainable Development Goal 12 (Responsible Consumption and Production). Policymakers can apply such frameworks to monitor and evaluate sustainable consumption behaviors on digital platforms through data-driven mechanisms. Encouraging standardized eco-certification databases, interoperable sustainability APIs, and transparent data governance structures can enhance consumer trust and accountability in online markets. Furthermore, regulations promoting explainable and ethically aligned AI systems can help prevent algorithmic bias, misinformation, and greenwashing in e-commerce. Public–private partnerships could also leverage these computational insights to design educational initiatives that enhance digital literacy and empower consumers to make informed sustainable choices. Collectively, these measures can align market incentives with environmental policy objectives, fostering more responsible consumption ecosystems in digital economies.

To further clarify how the proposed computational pipeline differs from and extends previous research, Table V summarizes the study's positioning in relation to prior literature across key dimensions of theory, modeling approach, and system design.

TABLE V. POSITIONING THE PROPOSED COMPUTATIONAL PIPELINE IN RELATION TO PRIOR LITERATURE

Aspect	Literature Findings	Current Study Findings (Novelty / Differences)
Behavioural constructs & Theory Use	Many studies use Value–Attitude–Behaviour (VAB) or Theory of Planned Behaviour (TPB) to relate values → attitudes → intention, often via surveys/SEM [82, 83].	This study embeds the VAB chain into a computational pipeline architecture, mapping values → attitudes → intentions → behaviour as operational modules/signals rather than abstract constructs.
Predictive / System Design vs Descriptive Modelling	Literature is often descriptive or predictive (e.g., identifying which values correlate with green purchase, what affects intention) but rarely builds full system pipelines [84].	This study builds a multi-stage pipeline that translates behavioural determinants into computational design (signal inputs, modular layers, output behaviours), moving beyond correlational analysis.
Category-specific Tailoring	Research on green consumption often focuses on broad categories, but product-specific contexts such as personal care highlight more specific implications [3].	This study is specifically tailored to green personal care products, capturing emotional and functional quality drivers unique to this category.
Parsimony/ Empirical Feature Selection	Several studies include multiple predictors, though only some consistently emerge as significant [4].	This study includes only empirically significant predictors (functional quality value, emotional value, perceived environmental knowledge), making the pipeline leaner and more implementable.
Bridging Consumer Psychology + Computational Implementation	Some works propose tools (e.g., environmental-impact ratings) or experiments (nudges), but there are limited examples of full pipelines integrating psychological theory into system modules [85].	This study directly bridges psychological constructs with system design, mapping theory into computational modules as programmable, testable components for e-commerce platforms.

F. Limitations and Future Research

The study offers meaningful insights into green consumer behaviour within the e-commerce context. However, it has some limitations. First, the data were collected using a cross-sectional design. This restricts the ability to infer causality between variables. Cross-sectional data provide only a snapshot at a single point in time and therefore cannot capture how these constructs evolve over time, nor can it confirm the temporal ordering of the pathways. Second, the sample was geographically limited, potentially constraining the generalizability of the findings to broader or more diverse populations. Third, the study relied on self-reported data, which may have been affected by social desirability bias or gaps between stated and actual behaviour. Additionally, the exclusive focus on GPCPs limits the applicability of results to other product categories with different involvement levels or purchase motivations. Finally, although the survey was circulated broadly, purposive sampling and the exclusion of respondents without prior online GPCP purchase experience resulted in a sample skewed toward younger, urban, and more educated consumers. While appropriate for ensuring data relevance, this demographic concentration may restrict external validity. Future studies should test the framework with more diverse populations to enhance generalizability.

Future research could build on the current findings by exploring value–behaviour relationships across multiple green product categories, such as household goods, apparel, or food, to identify whether predictors vary by product type or perceived risk. Longitudinal studies may also offer a deeper understanding of how values and attitudes evolve over time and in response to repeated exposure or satisfaction with green products. In addition, qualitative investigations could enrich the quantitative results by capturing nuanced consumer perceptions, emotional drivers, and trust dynamics in online green shopping contexts. Finally, future work could assess the influence of digital marketing elements such as eco-label visibility, platform credibility, and product presentation on consumer trust and purchase behaviour in sustainability-driven segments.

VII. CONCLUSION

This study approached consumer behaviour not only as a psychological process but also as a computational system design problem, where values, attitudes, and behaviours can be represented as data inputs, processing nodes, and measurable outputs. Focusing on green personal care products (GPCPs) in the e-commerce context, it validated the Value–Attitude–Behaviour (VAB) framework and confirmed that functional quality value, emotional value, and perceived environmental knowledge significantly shape attitudes, which in turn influence purchase intentions and behaviours.

The originality of this work lies in translating these validated behavioural determinants into a multi-stage computational pipeline architecture. Unlike existing digital consumer models that emphasize descriptive analytics, recommendation engines, or predictive tools detached from psychological theory, the proposed framework operationalizes values, attitudes, and intentions as programmable system components. It prioritizes only empirically significant predictors, ensuring a parsimonious and efficient design, and tailors the architecture to the unique drivers of GPCPs-a product category often overlooked in digital sustainability research.

By bridging consumer psychology and computer science, this study advances both theory and practice. This contribution is distinct from prior work in two ways. Theoretically, unlike existing green-consumption models, which are primarily descriptive and offer little guidance for system implementation, our pipeline extends the VAB framework into a computational instantiation suitable for digital commerce. Practically, it offers a blueprint for e-commerce platforms to implement evidence-driven modules that encode product quality signals, embed emotional reinforcement, and augment consumer knowledge. This dual contribution distinguishes the study from prior research, positioning the pipeline as both a theoretical innovation and a practical pathway for fostering sustainable online consumption.

Future research should extend this work by testing the pipeline across other product categories, geographic contexts, and digital environments. Longitudinal and experimental designs could further refine the architecture and examine how adaptive pipelines, powered by real-time data and reinforcement learning, can optimize sustainability outcomes at scale. In doing so, researchers and practitioners can continue to advance the integration of behavioural science with system design for a more sustainable digital marketplace.

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APPENDIX

TABLE VI. MEASURES, ITEM LOADINGS, AND RELIABILITY

Variables/Items	Item Source	Factor Loadings	VIF	Cronbach 's alpha	(rho_a)	(rho_c)	AVE
Function Quality value				0.827	0.844	0.896	0.743
"The green personal care product has an acceptable standard of quality."	[51]	0.851	1.848				
"The green personal care product would perform consistently."	[52]	0.916	2.454				
"The green personal care product is well made."	[52]	0.815	1.806				
Function Price value				0.868	0.873	0.919	0.791
"The green personal care product is reasonably priced."	[51]	0.879	2.282				
"The green personal care product offers value for money."	[52]	0.91	2.526				
"The green personal care product is a good product for the price."	[52]	0.88	2.113				
Emotional value				0.86	0.879	0.914	0.781
"Buying the green personal care product instead of conventional products would feel like making a good personal contribution to something better."	[51]	0.906	2.613				
"Buying the green personal care product instead of conventional products would feel like the morally right thing."	[51]	0.923	2.81				
"Buying the green personal care product instead of conventional products would make me feel like a better person."	[51]	0.82	1.78				
Social value				0.828	0.831	0.897	0.745
"I feel buying the green personal care products would give its owner social approval."	[51]	0.911	2.547				
"Purchasing green personal care products helps me to feel acceptable to others."	[51]	0.85	2.008				
"Purchasing green personal care products enable me to impress others."	[51]	0.826	1.709				
Perceived consumer effectiveness				0.791	0.819	0.904	0.826
"It is worthless for an individual consumer to do anything about environment"	[49]	0.929	1.647				
"Whenever I buy products, I try to consider how my use of them will affect the environment and other consumers."	[49]						
"Because a lone individual cannot have any effect on environment or the over-exploitation of natural resources, it does not make any difference what I do"	[49]	0.887	1.372				
Environmental Concern				0.797	0.802	0.88	0.711
"I am worried about the worsening quality of the environment"	[50]	0.828	1.63				
"I often think about how the environmental quality can be improved"	[50]	0.874	1.512				
"Environment Protection is my major concern"	[50]	0.826	1.229				
Perceived Environmental Knowledge				0.752	0.758	0.858	0.668
"I feel I am quite knowledgeable about environmental issues"	[50]	0.858	-				
"I know how to select products and packages that reduce the amount of landfill waste".	[50]	0.796	1.628				
"I understand the environmental labels and symbols on product package (like- 100% organic, or vegan or cruelty free)"	[50]	0.796	1.352				
Green Purchase attitude				0.943	0.944	0.957	0.815
"I think Buying eco-friendly personal care products from an online platform is a good idea."	[51]	0.899	3.469				
"I have a favourable attitude towards the purchasing of eco-friendly personal care products from an online platform."	[51]	0.903	3.709				
"I feel that online shopping for eco-friendly personal care products is something I would like to do. [It's desirable]"	[51]	0.911	3.93				

"I think Buying eco-friendly personal care products from an online platform is a smart decision."	[51]	0.909	3.814				
"I think Buying eco-friendly personal care products from an online platform would be pleasant [enjoyable]."	[51]	0.892	3.182				
Green Purchase Intention				0.916	0.921	0.938	0.75
"I intend to purchase green personal care products in the near future from e-commerce platforms."	[53]	0.88	2.199				
"I will make an effort to buy green personal care products from e-commerce platforms in the near future."	[53]	0.911	2.486				
"I intend to buy green personal care products instead of conventional products in my future online shopping."	[53]	0.879	2.286				
"I would consider switching to green personal care products in future."	[53]	0.803	1				
"I would consider buying green personal care products if I happen to see them in an e-commerce platform."	[56]	0.855	1.638				
Green Purchase Behaviour				0.884	0.891	0.915	0.684
"When buying on e-commerce, I have green purchasing behaviour for my daily needs' products."	[54]	0.851	2.334				
"When buying on e-commerce, I have already switched to buy green personal care products."	[53,54]	0.862	2.773				
"When buying on e-commerce, I often buy green personal care products instead of conventional products if the quality is comparable"	[53]	0.832	2.108				
"When buying on e-commerce, I often buy green personal care products even if they are more expensive than nongreen ones."	[53]	0.84	2.378				
"When buying on e-commerce, I pay attention that the personal care products are sustainable"	[55]	0.744	1.774				