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Generative AI-Enabled Precision Recommendation for Green Products: Mechanisms of Consumer Cognitive Fluency and Low-Carbon Purchase Decisions

Kai Si [1,†], Cenpeng Wang [2,*,†], Sizheng Wei [3,*] and Yafei Lan [4,*]

[1] Business School, Xuzhou University of Technology, Xuzhou 221018, China; sk@xzit.edu.cn
[2] Centre for Gaming and Tourism Studies, Macao Polytechnic University, Macao 999078, China
[3] School of Finance, Xuzhou University of Technology, Xuzhou 221018, China
[4] Business Department, Semyung University, Jecheon 27136, Republic of Korea
* Correspondence: p2425235@mpu.edu.mo (C.W.); wei4zheng@xzit.edu.cn (S.W.); 2023638806@semyung.ac.kr (Y.L.)
† These authors contributed equally to this work.

Abstract

To address the information-processing burden faced by consumers in green consumption markets due to complex carbon footprint labels, opaque certification standards, and vague descriptions of environmental benefits, this study proposes a generative artificial intelligence (GenAI)-based precision recommendation mechanism for green products. The mechanism aims to enhance cognitive fluency and promote low-carbon purchase decisions. An experimental system, termed Eco-GenRec, is developed by integrating large language models (LLMs), multimodal generation, and retrieval-augmented generation (RAG) techniques to enable personalized presentation of green product information. Based on inferred user cognitive styles, the system transforms product information into chart-based representations for analytical users or emotionally framed scenario narratives for intuitive users. This study is conducted on a web-based simulated shopping platform and employs a fully randomized design. A total of 1000 participants are randomly assigned to either a standardized information display group (control group) or an Eco-GenRec-generated display group (experimental group). Participants are drawn from diverse socioeconomic backgrounds and cover a wide age range. The sample exhibits substantial demographic diversity, which enhances the representativeness of the findings. Cognitive fluency and low-carbon purchase conversion rates are measured as the primary outcomes. The results show that the Eco-GenRec group achieves a significantly higher cognitive fluency score (M = 5.68, SD = 0.89) than the control group (M = 4.60, SD = 1.01). This represents an increase of 23.4% ($t = 18.34$, $p < 0.001$, effect size $d = 1.17$). In addition, the low-carbon purchase conversion rate in the experimental group (36.3%) is significantly higher than that in the control group (17.6%). The absolute increase of 18.7% is statistically significant ($\chi^2 = 70.28$, $p < 0.001$, effect size Cramér's V = 0.265). Under conditions of high cognitive-style matching, the conversion rate improvement reaches 27.2%. Mechanism analysis shows that cognitive fluency mediates the relationship between GenAI-based recommendations and purchase intention. By transforming abstract environmental parameters into intuitive and easily interpretable content, artificial intelligence reduces information-processing burden and activates positive affect and trust among consumers. Overall, this study empirically validates the effectiveness of GenAI in green product recommendation. It provides a practical pathway for addressing the "comprehension barrier" in green consumption and extends the theoretical boundaries of research on cognitive fluency and low-carbon decision-making.

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1. Introduction

In green consumption markets, despite rising environmental awareness, factors such as the higher prices of green products and their limited availability may lead consumers to exhibit a pattern of "high stated concern but low actual purchase behavior" [1–3]. Green products form a heterogeneous category. They include certified eco-friendly items, such as organic or fair-trade products, and also cover goods with reduced carbon footprints, high-energy-efficiency appliances, and other products that differ in symbolic or functional attributes. The existence of this "intention–behavior" gap is driven by a set of complex and interrelated factors [4,5]. Existing studies have offered multiple explanatory perspectives. For example, Yang et al. (2021) [6] indicated that the widespread price premium associated with green products constituted a major barrier, as high consumer price sensitivity might suppress actual purchasing. In addition, limited coverage of offline retail channels and restricted online accessibility of green products have been shown to reduce both purchase convenience and purchase intention [7–9].

Where does the problem lie? In-depth analysis indicates that the core issue often does not stem from price or product quality, but from information comprehensibility [10]. Consumers are currently confronted with complex carbon footprint labels, highly specialized environmental certifications, and vague descriptions of environmental benefits. Such information is overly technical and causes confusion and fatigue among ordinary consumers. During decision-making, consumers frequently abandon purchases because they cannot clearly understand or interpret these labels [11]. These information elements not only require professional knowledge to decode, but also tend to induce cognitive overload due to their technicality, fragmentation, and uncertainty [12]. As a result, consumers experience "comprehension fatigue" in the decision-making process, which ultimately leads to choice avoidance or delayed decisions [13]. Existing mainstream e-commerce recommendation systems, whether based on collaborative filtering or content matching, primarily focus on solving the problem of "what to recommend" in terms of product exposure [14]. They fail to address the deeper cognitive barrier of "how to understand," and therefore cannot effectively bridge the gap between green consumption intention and actual behavior [15].

Recent breakthroughs in generative artificial intelligence (GenAI) provide new possibilities for addressing this challenge [16–18]. GenAI technologies, represented by large language models (LLMs) and multimodal generation, exhibit strong capabilities in content understanding, reconstruction, and creation [19–21]. They can function as real-time "information translators" and "narrative architects" [22,23]. These technologies dynamically transform standardized and technical product parameters and environmental data into personalized narratives and visualizations that align with individuals' cognitive habits and knowledge backgrounds. This process goes beyond superficial optimization of information presentation and represents a fundamental shift in the information-processing paradigm [24–26]. In addition to generating textual explanations, GenAI can create images and charts to present information in a more intuitive manner [27,28]. In this way, complex environmental information becomes easier to understand, substantially reducing cognitive burden and increasing the likelihood of purchase decisions. Although GenAI shows substantial promise in the green consumption domain, it also faces challenges such as model hallucinations and data bias. For example, LLMs may generate inaccurate or misleading environmental information, which can undermine consumer trust. Therefore, when applying GenAI, measures are required to ensure the accuracy and objectivity of the information provided.

In this context, beyond traditional factors such as price and availability, the comprehensibility of information represents an independent and critical influence. It directly shapes consumers' cognitive decision-making and can amplify or reduce the impact of other barriers. This study focuses on products with verifiable and quantifiable environmental attributes, such as carbon emissions and energy efficiency ratings. These attributes are typically communicated through technical labels or certifications. Based on this, a central research question is posed: how can GenAI shift green product recommendations from the traditional "what to recommend" problem to the "how to recommend" problem, emphasizing cognitive adaptation? To address this question, this study develops and validates Eco-GenRec, a generative AI–based precision recommendation system. Unlike conventional systems that only predict user preferences, Eco-GenRec acts as a "cognitive translator." It dynamically converts standardized product parameters into personalized narratives and visual presentations that align with users' cognitive preferences. This approach actively improves the user's information-processing experience, enhances cognitive fluency, and ultimately promotes low-carbon purchasing decisions.

This study makes three main contributions. First, it theoretically proposes and empirically tests the full mediating role of cognitive fluency between generative AI recommendations and low-carbon purchase decisions. The results show that perceived understandability, rather than algorithmic accuracy, drives consumer behavior. Second, it identifies and validates the moderating role of cognitive style, clarifying the psychological conditions necessary for precise personalization and extending personalization from behavioral to cognitive dimensions. Third, it demonstrates that multimodal content generated by generative AI can provide immediate and concrete visual feedback. This reduces consumers' perceived psychological distance to environmental benefits and heightens their sense of urgency to act. Overall, these findings offer a novel theoretical framework and practical guidance for designing next-generation intelligent systems that encourage sustainable consumption.

2. Related Work Review

Research on green consumption has long indicated a pronounced "cognitive gap" between consumers' pro-environmental attitudes and their actual purchasing behavior. This gap does not primarily arise from weak environmental motivation, but from comprehension barriers caused by excessive information-processing burdens. Wang et al. (2023) [29] pointed out that most carbon footprint labels contained multidimensional parameters that required consumers to independently infer meanings and convert implicit values, thereby constituting a typical high–cognitive-threshold information structure. Similarly, Velaoras et al. (2025) [30] emphasized in their study of green certification systems that, although such systems aimed to be objective and standardized, their highly technical and jargon-based presentation made it difficult for consumers to quickly extract key benefit cues relevant to their own decisions. Together, these studies revealed that green information itself was not inherently incomprehensible; rather, its presentation failed to adequately consider consumers' limited information-processing capacity. However, Ho-dac and Mulder-Nijkamp (2025) [31] noted a clear limitation in existing improvement strategies.

Most prior efforts focused on parameter standardization and procedural normalization within labeling systems. Few studies examined how to reduce consumers' comprehension burden. In particular, the role of information presentation mechanisms remained largely unexplored. The comprehension barriers faced by consumers are not merely a cognitive limitation; they also reflect information asymmetry in the green product market. Producers possess specialized technical knowledge about environmental impacts, whereas consumers typically lack this expertise. This gap often results in unverifiable or vague "eco-claims." Such asymmetry fosters distrust and cognitive dissonance, as consumers struggle to align their pro-environmental attitudes with credible product choices. Effectively reducing this asymmetry requires providing reliable signals that translate proprietary technical data into information that consumers can understand and trust.

Psychological research on cognitive fluency provides an important theoretical lens for addressing these issues. Cognitive fluency refers to the subjective ease individuals experience during information processing. Recent theoretical developments further distinguish it into two related but mechanism-distinct dimensions: perceptual fluency and conceptual fluency [32–34]. Perceptual fluency refers to the clarity and readability of information presentation, whereas conceptual fluency refers to the ease with which information is understood [35]. Perceptual fluency primarily influences consumers' first impressions and attentional engagement, while conceptual fluency shapes their understanding and evaluation of product attributes [36]. In green consumption contexts, clear and legible eco-labels and intuitive icon designs directly enhance perceptual fluency [37]. High conceptual fluency, by contrast, enables consumers to more easily grasp the specific meaning, benefits, and causal logic of a product's environmental attributes. This facilitates deeper, attribute-based evaluation and judgment [38].

In green consumption decision-making, these two forms of fluency jointly shape consumers' cognitive and affective pathways, although through different mechanisms. Perceptual fluency functions as a "cognitive gateway" that attracts attention and generates favorable affect by reducing visual interference and initial cognitive load. Conceptual fluency, in contrast, serves as a "bridge to understanding" that helps consumers construct purchase rationales by concretizing and contextualizing environmental value, thereby directly influencing attitudes and behavioral intentions [39,40]. Hertwig et al. (2008) [41] argued that cognitive fluency reflects the subjective ease with which individuals process information, and that it directly influences judgment speed, credibility assessments, and emotional responses, thereby exerting a strong heuristic effect on decision-making. In the context of green consumption, the role of cognitive fluency is particularly salient. Moreover, Lee (2024) [42] demonstrated that visualized and concrete presentations effectively reduce the psychological distance of environmental issues, transforming abstract future benefits into perceivable motivations for immediate action. Although these studies underscored the importance of information presentation, existing applications primarily relied on linguistic simplification or static text–image formats, and paid limited attention to differences in consumers' cognitive styles.

With advances in artificial intelligence technologies, particularly in recommendation systems and generative models, researchers have begun to explore how AI can enhance consumers' comprehension efficiency at the content level. Martins et al. (2020) [43] pointed out that traditional AI recommendation systems mainly relied on collaborative filtering or content matching to predict user preferences. Their core logic focuses on solving the product exposure problem of "what to recommend," but they struggle to effectively handle the complexity and technical nature of green product information. Such systems lack the ability to deeply analyze structured environmental labels, such as "carbon footprint" and "life cycle assessment." They also fail to translate vague descriptions of "environmental benefits" into values that consumers can directly perceive and evaluate [44,45]. The emergence of GenAI provides a new pathway to address these challenges [46]. GenAI, particularly LLMs, can leverage natural language processing and knowledge graph techniques to dynamically transform professional and complex environmental parameters into personalized content that aligns with consumers' cognitive habits and is easy to understand [47].

For example, Oprea and Bâra (2025) [48] emphasized that the advent of LLMs enabled recommendation content to be dynamically rewritten through generative approaches, thereby achieving semantic-level adaptive expression. At the same time, Jiang et al. (2025) [49] showed that retrieval-augmented generation (RAG) combined knowledge retrieval with generative models to improve factual accuracy and content consistency. Therefore, the strong natural language understanding and generation capabilities of GenAI, together with its potential for dynamic content adaptation and integration with external knowledge bases, make it particularly suitable for addressing "information comprehension barriers" in green consumption contexts [50–52]. It goes beyond the traditional role of recommendation systems as mere information filters and enables a cognitive reconstruction of green product information itself. This capability provides a technological foundation for fundamentally enhancing consumers' perceptual fluency and conceptual fluency.

However, empirical research that applies these technologies to real green consumption scenarios remains limited. Although current GenAI-based recommendation studies emphasize content generation capabilities, they provide insufficient discussion of the mechanisms through which cognitive style influences content comprehension. Existing evidence suggests that visual information enhances understanding, yet systematic evidence is still lacking on how multimodal generative content specifically reshapes the psychological processing of green information. The Eco-GenRec generative green recommendation system proposed in this study aims to move beyond the traditional recommendation logic that focuses solely on content matching, and instead prioritizes the generation of cognitively friendly content. Cognitive fluency is treated as a key psychological mechanism influencing low-carbon purchase decisions. Through experimental validation of the interactive effects among personalized generative content, cognitive style matching, and psychological distance reduction, this study seeks to fill the theoretical and empirical gaps in the literature concerning how reducing comprehension burden can promote green purchasing decisions.

Green consumption can encompass a variety of pro-environmental actions, yet purchasing behavior represents a direct and consequential decision point. Therefore, this study explicitly treats purchase decisions as the dependent variable. It measures these decisions through both behavioral intention and actual conversion behavior, aiming to address the specific attitude–behavior gap that arises at the point of transaction. The overall research framework is illustrated in Figure 1.

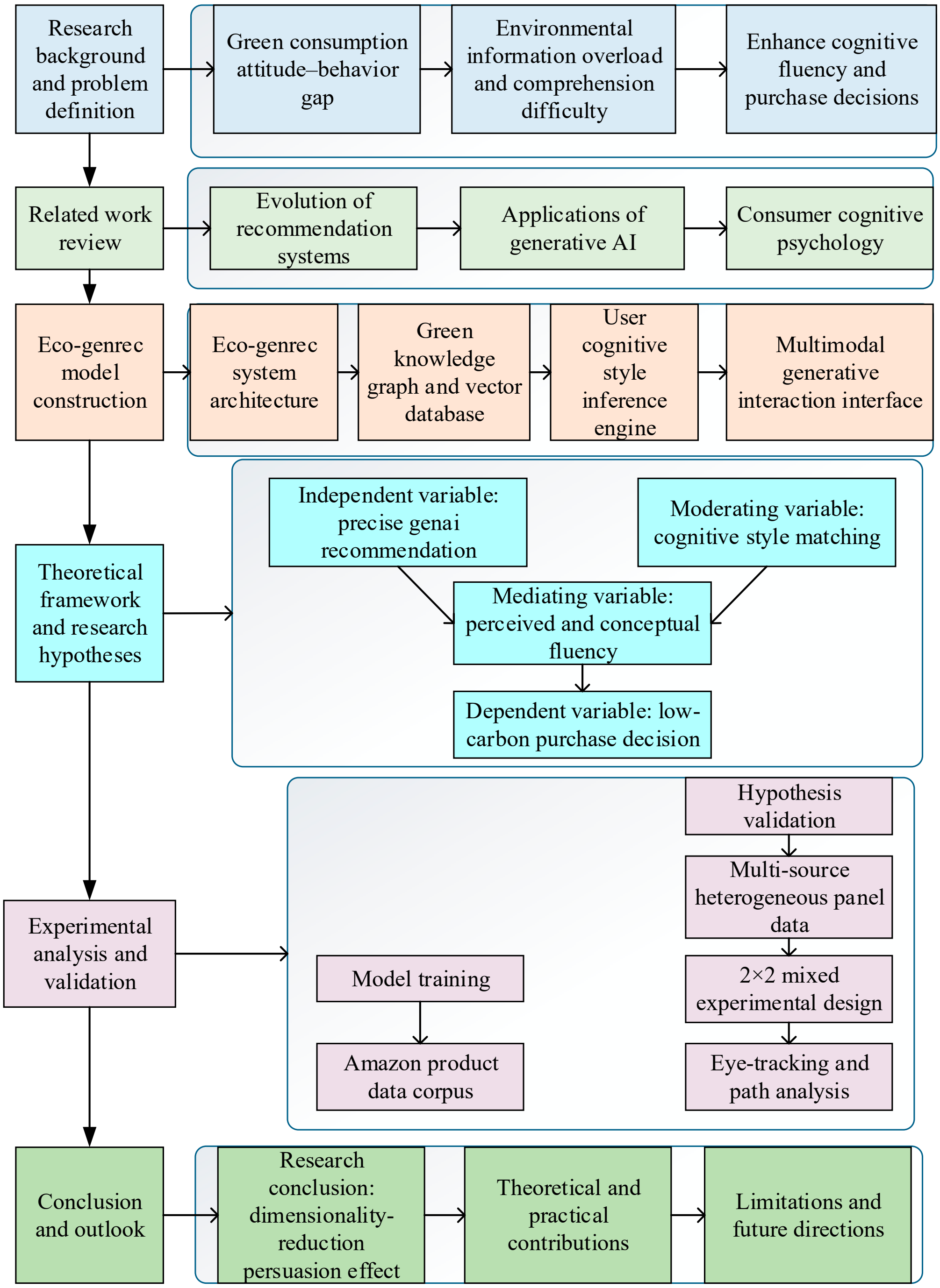


Figure 1. Overall research framework.

3. Eco-GenRec Model Construction

The construction of the Eco-GenRec system aims to translate the theoretical potential of GenAI into an operational and verifiable experimental framework. This framework is designed to empirically test the core hypothesis that enhancing cognitive fluency promotes green consumption. The entire system operates through three tightly integrated and dynamically coordinated core layers. Together, these layers form a precise pipeline that transforms large-scale data into personalized cognitive experiences.

3.1. Core System Architecture and Dynamic Workflow

The core of the Eco-GenRec system is a three-layer dynamic architecture, whose workflow follows a progressive logic from data preparation, to user understanding, and ultimately to experience generation. This architecture ensures that the output of each stage serves as both the input and the constraint of the subsequent stage, thereby enabling a seamless integration of scientific facts with individual cognitive preferences. Figure 2 illustrates the overall architecture of the Eco-GenRec system. It integrates cognitive fluency theory with GenAI technologies and aims to enhance users' cognitive fluency through personalized information presentation.

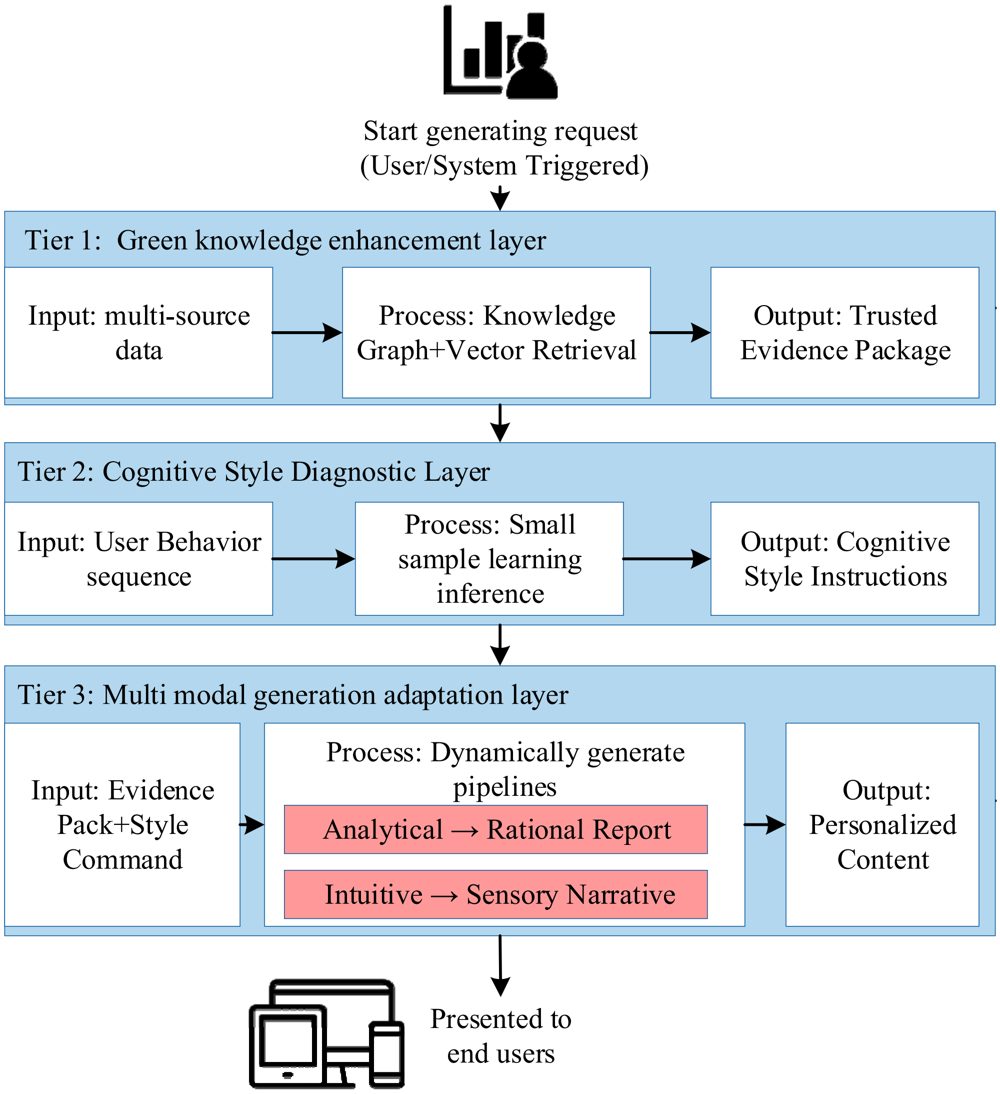


Figure 2. Structure of the Eco-GenRec model. Arrows indicate information flow; red blocks represent the analytical and intuitive generation pathways.

In Figure 2, to ensure the reproducibility and clarity of the technical implementation, the core system components are specified as follows. The LLMs employed is GPT-3.5-Turbo, which contains approximately 175 billion parameters and is selected for its strong performance in instruction following and textual coherence. The diffusion model is based on Stable Diffusion. The multimodal generation module utilizes Stable Diffusion 2.1, which is pre-trained on the LAION-5B dataset, to generate vivid visual scenes from textual descriptions. The RAG module adopts a top-k retrieval strategy. It selects the five knowledge snippets with the highest similarity to the query (k = 5) and applies a cosine similarity threshold of 0.8. Knowledge snippets below this threshold are filtered out during retrieval from the proprietary green product knowledge graph. This threshold is empirically determined to balance information relevance and factual accuracy. It also effectively suppresses the tendency of LLMs to generate inaccurate or fabricated content in this specialized domain.

To further reduce the risk of misinformation and enhance the credibility of generated content, the Eco-GenRec system implements a multi-level "fact-anchoring" strategy. A cosine similarity threshold of 0.8 was optimized through preliminary experiments. On a validation set containing both accurate knowledge fragments and plausible but incorrect "distractor" information, this threshold achieved a precision above 0.95 while maintaining a recall greater than 0.85. This effectively filters out irrelevant or low-confidence information before it reaches the generative model. Next, explicit system prompt instructions require the LLMs to generate content strictly based on the provided "trusted evidence package," preventing the introduction of external knowledge or unsupported inferences. The prompt template includes directives such as, "Do not generate claims if they are not explicitly supported by the evidence." Each output sentence containing environmental claims (e.g., "reduce carbon footprint by 30%") can be traced back to the specific knowledge fragments in the supporting evidence package. This traceability enables manual fact-checking and audit of the system's outputs.

The system hub is built on a dual-engine architecture that integrates a green knowledge graph with a high-dimensional vector database. The knowledge graph and the vector database are unified through a shared knowledge representation framework. Conflict detection and resolution mechanisms are implemented to prevent knowledge inconsistencies. Redundant information is evaluated using metrics such as information entropy and mutual information, and highly redundant content is removed.

The knowledge graph defines, in a structured and rigorous manner, the entities, attributes, and relationships among products, materials, certification standards, and environmental indicators, such as carbon emissions and water footprints. This structure enables logical reasoning and causal tracing. For example, the graph explicitly records the relationship between "Product A adopts Technology B" and "Technology B is certified to achieve an average energy saving of C%."

In parallel, the vector database transforms unstructured expert knowledge into high-dimensional vectors using natural language processing techniques and stores them accordingly. Such knowledge sources include environmental science literature, reports from authoritative certification bodies, and professional life cycle assessment summaries. To ensure the timeliness and authority of its factual basis, the knowledge core of the system incorporates two key design features. First, it establishes a reliability hierarchy within the knowledge graph. Data from official standards and peer-reviewed databases are prioritized over general corporate sustainability reports. In cases of conflicting information, sources with higher priority are adopted. Second, for critical and frequently updated quantitative metrics—such as regional grid carbon emission factors—the system architecture includes interfaces for real-time queries to authoritative external databases. Although this functionality is not enabled in the current experimental prototype, the design specification indicates that in future deployments, verification checks or data updates can be triggered whenever cached data exceed a preset time threshold or show significant discrepancies with authoritative real-time values.

This design allows the system to efficiently retrieve professional statements and data fragments that are semantically most relevant to a given product. During content generation, the system simultaneously queries the knowledge graph and the vector database. The graph provides structured logical chains and precise numerical values, while the vector database supplies supporting professional textual evidence. These outputs are integrated into a unified "credible evidence package," which is used as a mandatory input for the generation process. This mechanism strictly constrains the generative scope of the LLMs and ensures that every environmental claim and data comparison is grounded in authoritative and traceable facts.

The middle layer represents the real-time cognitive style diagnosis and inference engine, which functions as the system's "personalization brain." Its task is to rapidly and accurately infer users' information processing preferences, namely their cognitive styles, at the early stage of user–platform interaction. Unlike traditional recommender systems that rely on delayed and coarse-grained purchase histories, this engine focuses on analyzing users' real-time and fine-grained interaction texts and browsing behavior sequences. The core of the diagnostic engine is a pre-trained language model that is fine-tuned through few-shot learning using an annotated dataset comprising 100 users. Each user provides 5–10 browsing records along with responses to a cognitive style questionnaire. The annotation process is conducted independently by two domain experts, and Cohen's Kappa coefficient is calculated to ensure inter-annotator reliability. When users begin browsing a small number of benchmark product pages, the system already captures multiple signals. These signals include whether search keywords emphasize technical parameters, such as energy efficiency ratings, or usage scenarios; whether users spend more time examining data charts or are quickly attracted by scenario-based images and narrative descriptions; and what patterns emerge from mouse clicks and scrolling trajectories.

These multimodal behavioral sequences are fed into the diagnostic model in real time. The model is pre-trained on a limited set of labeled data and is capable of decoding user preferences from sparse behavioral cues. It dynamically positions users along a cognitive style spectrum ranging from analytical to intuitive. Analytical users prefer rational data, logical reasoning, and systematic comparisons, whereas intuitive users are more responsive to emotional narratives, vivid experiences, and affective resonance. This real-time diagnostic outcome serves as the key instruction that drives content format switching at the upper layer.

The top layer receives both the "credible evidence package" from the bottom layer and the "cognitive style instruction" from the middle layer. It then invokes advanced generative AI models to produce fully differentiated content for the same green product. The core of this layer consists of two parallel generation pipelines, which are dynamically activated by an intelligent scheduler based on the diagnosed cognitive style. Content generation relies on LLMs and diffusion models to deliver tailored multimodal outputs.

When the system interacts with analytical users, it activates the "rational report" generation pipeline. The LLMs uses the rigorous data contained in the evidence package as its foundation and adopts logical argumentation as its organizing principle to generate a concise report with a clear structure and detailed quantitative information. This report may include precise comparative charts of emission reductions relative to conventional products in the same category, as well as visual decompositions of environmental impacts across different stages of the product life cycle. In contrast, when processing intuitive users, the system switches to an "affective narrative" mode. The LLMs transforms the same evidence package into a vivid and emotionally engaging story script that depicts concrete environmental improvement scenarios resulting from product use. Based on this script, the diffusion model generates corresponding expressive and immersive visual images. For example, it may illustrate a warmer household atmosphere and a clearer sky outside the window after the adoption of an energy-efficient appliance. The accompanying textual content is rich in metaphor and empathy, aiming to directly engage users' emotions and imagination.

To illustrate this generative mechanism, this study uses the core environmental attribute of an "A-rated energy efficiency air purifier" as an example: a full lifecycle carbon footprint reduction of 30%. Table 1 shows how the system generates differentiated content for users with distinct cognitive styles.

Table 1. Core examples of personalized content generation.

Original Input (From Evidence Package)	Analytical User Output (Rational Report Pipeline)	Intuitive User Output (Narrative-Emotional Pipeline)
Full lifecycle carbon footprint: 150 kg CO_2-eq, a 30% reduction compared with the category average (215 kg CO_2-eq).	Quantitative advantage: Based on lifecycle assessment, the product's carbon footprint (150 kg CO_2-eq) is significantly lower than the industry benchmark (215 kg CO_2-eq). Direct carbon reduction: Choosing this product equates to avoiding 65 kg of carbon emissions, roughly equivalent to planting seven trees over a 10-year growth period.	Immersive scenario narrative: Turning it on is like opening a window to a forest in your home. It protects your family's breathing health while quietly reducing the burden on distant blue skies. Every kilogram of carbon you save makes next weekend's outdoor sunshine a little clearer.
No original visual content	Generated infographic: a clear bar chart comparing "this product" with the industry average, highlighting the "−30%" difference.	Generated scene image: a diffusion model produces a warm home scene—sunlight streaming through windows onto a clean room, with lush greenery and clear blue skies outside.

This example demonstrates that Eco-GenRec does not merely filter information. Instead, it reconstructs the content according to cognitive style: analytical users receive verifiable quantitative evidence and structured comparisons, whereas intuitive users are presented with narratives and imagery that elicit emotional resonance. This tailored content reconstruction constitutes the system's core mechanism for enhancing cognitive fluency.

3.2. Model Training and Adaptive Adjustment Strategy

To ensure that the Eco-GenRec system operates effectively, its core components are systematically trained. The entire process focuses on two key objectives. The first objective is to enable the system to internalize professional knowledge related to green products. The second objective is to ensure that it accurately interprets users' cognitive preferences. To this end, a stepwise training strategy is adopted. The training process begins with data preparation. A large-scale e-commerce corpus, such as Amazon Product Data, serves as the primary data source for constructing the training dataset. These data include not only basic product information and environmental certifications, but also a substantial volume of real user reviews. Such reviews play a critical role in understanding how consumers think, evaluate, and express their perceptions.

The first training stage focuses on the core component of the system, namely the LLMs. Using the prepared domain-specific data, a general-purpose base model undergoes domain-adaptive fine-tuning. This fine-tuning process pursues two explicit goals. On the one hand, it enables the model to internalize specialized knowledge and to describe the environmental attributes of green products using accurate and standardized language, such as correctly explaining the calculation and implications of carbon footprints. On the other hand, it equips the model with style recognition capabilities, allowing it to automatically distinguish analytically oriented expressions from intuitive and affective expressions in user reviews. Figure 3 illustrates the process of domain-adaptive training, which is designed to enable LLMs to better understand the specialized knowledge of green products as well as users' emotional expressions.

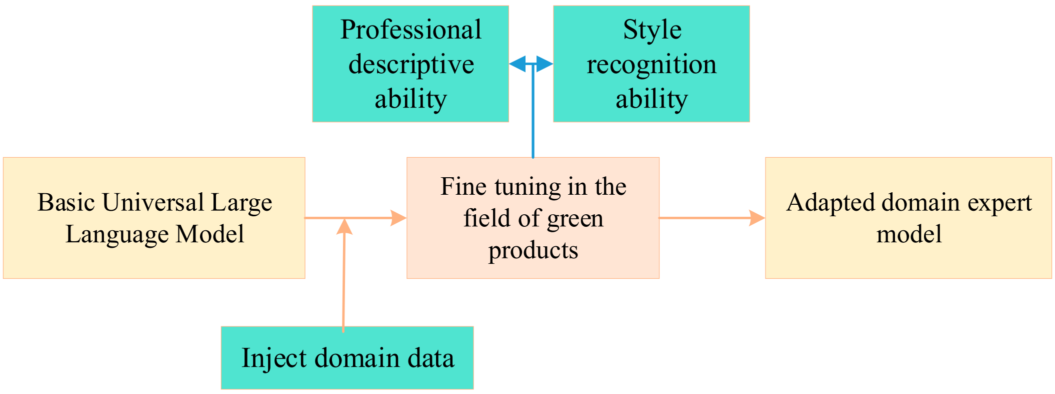


Figure 3. Schematic illustration of domain-adaptive training for the LLMs. Arrows indicate training and data flow directions; different colors are used to distinguish model components and capability modules.

Subsequently, the cognitive style diagnosis model responsible for real-time user classification is trained. This model is required to infer users' cognitive preferences at an early stage of system interaction, relying only on limited behavioral data such as browsing, clicking, and commenting activities. A few-shot learning approach is adopted for this purpose. First, a small sample of user behavioral data is collected during the experiment, and participants are asked to complete a standardized cognitive style questionnaire. This procedure yields paired annotations linking behavioral patterns to cognitive styles. After fine-tuning the diagnosis model with these labeled data, the model learns to identify key patterns from sparse behavioral cues and to make reliable inferences for new users. Finally, the trained generative model, the cognitive style diagnosis model, and the knowledge retrieval module that provides accurate factual inputs are integrated into a stable and efficient online system.

4. Theoretical Framework and Research Hypotheses

4.1. Theoretical Model and Variable Definitions

By integrating information processing theory and psychological distance theory [53–55], this study proposes a chained mediation–moderation model in which cognitive fluency serves as the core mediating mechanism, while cognitive style matching and psychological distance act as key boundary conditions. The conceptual framework is illustrated in Figure 4. The central logic of the model is as follows. The primary value of the generative AI–based personalized recommendations provided by the Eco-GenRec system does not lie in directly persuading consumers. Instead, the system exerts its influence by actively adapting to and optimizing consumers' information processing experiences. It translates and reconstructs professional and complex green product information into content formats that align with users' individual cognitive preferences and are easier to understand. This fundamental transformation of information presentation aims to minimize users' comprehension burden and, in turn, enhance cognitive fluency. The smooth and positive psychological experience derived from ease of processing constitutes the internal psychological engine that fosters favorable attitudes and trust toward green products and ultimately shapes consumers' purchase intentions.

The effectiveness of this core mechanism is moderated by two important contextual factors. The impact of personalized content depends on a "matching threshold." The enhancement of cognitive fluency reaches its maximum only when the style of the generated content closely aligns with the user's inherent cognitive style. In addition, a fluent understanding experience must overcome the inherent sense of distance associated with environmental benefits in order to translate into urgent purchase actions. Vivid and concrete multimodal content created by generative AI, such as images and scenario simulations, effectively reduces the psychological distance between green benefits and consumers. This process makes future and global impacts feel immediate and tangible, thereby catalyzing purchase decisions.

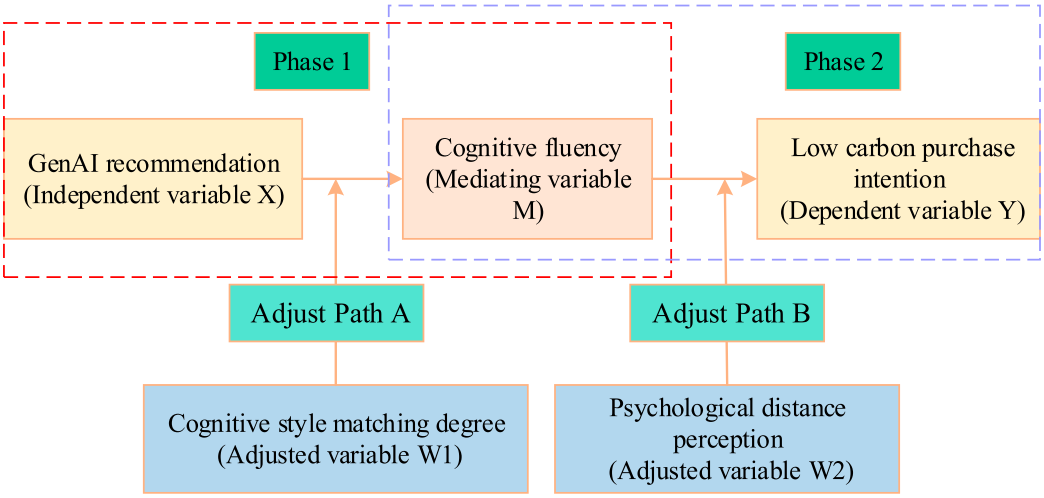


Figure 4. Structure of the chained mediation–moderation model. Arrows indicate causal paths; different colors and dashed boxes distinguish phases and variable types.

In this model, the independent variable is recommendation type, which includes personalized content generated by the Eco-GenRec system and traditional standardized product pages. The mediating variable is cognitive fluency, which is measured through two subdimensions: perceptual fluency and conceptual fluency. These dimensions capture the clarity of external information presentation and the ease of understanding internal meaning, respectively. The dependent variable is low-carbon purchase decision, which is jointly assessed using post-experiment purchase intention scores and actual purchase conversion behavior recorded on the simulated experimental platform. The moderating variables include cognitive style matching and perceived psychological distance.

4.2. Development of Research Hypotheses

Based on the proposed model, this study advances the following three core hypotheses:

H1. *Compared with traditional standardized information, GenAI-generated personalized narratives and visual content that match users' cognitive styles significantly enhance both perceptual fluency and conceptual fluency. This enhancement reaches its peak when the presentation style of the recommended content precisely matches the user's cognitive style. Cognitive style matching refers to the degree of alignment between the style of content generated by GenAI and the user's cognitive style. This alignment is quantified by calculating the cosine similarity between the content style vector and the user's cognitive style vector. A higher cosine similarity indicates a higher degree of matching. Users with a cosine similarity greater than 0.7 are defined as high-matching users, while those with a similarity of 0.7 or below are defined as low-matching users.*

H2. *Cognitive fluency mediates the relationship between GenAI-based recommendations and low-carbon purchase intention. Users primarily choose green products recommended by GenAI because the AI-generated content creates a sense of ease in understanding, rather than because the recommendation algorithm itself is inherently more accurate.*

H3. *Multimodal content generated by GenAI positively influences the pathway from cognitive fluency to low-carbon purchase intention by modulating psychological distance. According to Construal Level Theory, individuals' responses to events depend on perceived psychological distance, which—across temporal, spatial, social, and probabilistic dimensions—determines whether events are mentally represented in a concrete or abstract manner [56–58]. Objects or outcomes perceived as psychologically closer are more likely to be seen as concrete, real, and urgent, making them easier to accept and act upon [59].*

The Eco-GenRec system leverages GenAI to generate concrete and vivid multimodal content, such as images, scene simulations, and narratives, effectively reducing the psychological distance between green benefits and individual consumers. This strengthens the positive impact of cognitive fluency on purchase intention.

Specifically, in terms of temporal and spatial distance, the system can transform abstract, distant outcomes—such as "reducing 10 kg of carbon emissions"—into localized, near-term visual scenarios, making long-term benefits feel immediate and tangible. At the social distance level, GenAI generates narrative scenes featuring individuals or communities that share similar identities or values with the user, enhancing social recognition and belonging related to environmental behaviors, thereby reducing the sense of "others' business" [60–62]. For probabilistic distance, the system integrates authoritative data, such as information retrieved via RAG, to produce clear causal diagrams or comparative visualizations. This reduces users' doubts about the actual effectiveness of green products and increases the perceived credibility of their environmental commitments.

5. Experimental Design and Validation

5.1. Experimental Platform and Procedure Design

This study designs and implements a controlled experiment based on a simulated online shopping context. The experiment is conducted on a self-developed web-based simulated shopping platform. To control for social desirability bias, the experimental instructions emphasized that the purpose of the study was to explore the impact of information presentation on purchase decisions, rather than to evaluate participants' environmental awareness. Additionally, to minimize discrepancies between the simulated environment and real-world settings, the platform adopted the interface style of mainstream e-commerce websites and featured actual green products, while replicating the shopping process as realistically as possible. The platform replicates the interfaces of mainstream e-commerce websites and features real green products across 20 categories, including home appliances, personal care products, and food items. This design ensures high ecological validity of the experimental setting. At the beginning of the experiment, all participants enter a five-minute baseline phase. During this phase, participants are required to browse five preselected benchmark products. In this process, the system activates the cognitive style diagnostic engine in the background. It infers users' cognitive style tendencies by continuously capturing eye-tracking trajectories, such as fixation distributions between data charts and scenario images. The system also records interaction patterns, including whether users preferentially click parameter tabs or user-generated images, as well as any brief comments they input.

To ensure the reliability and validity of these behavioral measurement tools, rigorous psychometric validation is conducted. For reliability, the internal consistency of the behavioral indicators is assessed. Regarding eye-tracking metrics, Cronbach's alpha is calculated for the proportion of total fixation time that users allocate to analytic versus intuitive content areas across multiple trials, yielding $\alpha = 0.86$, which indicates excellent internal consistency. For interaction behavior sequences, such as the stability of consecutive click patterns, test–retest reliability is assessed, resulting in a correlation of r = 0.79, demonstrating stable and reliable measurement. For validity, content validity is ensured through expert evaluation. Three experts in cognitive psychology assess the predefined "analytic" and "intuitive" behavioral pattern labels, and the inter-expert agreement (Kendall's W) reaches 0.92, indicating that the behavioral indicators effectively represent the target constructs. Criterion-related validity is verified by correlating the behavioral classification results with questionnaire scores. A significant positive correlation is observed (r = 0.75, $p < 0.001$), confirming a high level of consistency between behavioral inferences and classic paper-and-pencil tests, thereby demonstrating strong convergent validity.

Participants are recruited through a professional online research panel. To ensure diversity and representativeness across key demographic dimensions—such as age, gender, education, and region—a quota sampling method is employed, with quotas set to approximate the proportions of the target consumer population. A total of 1000 valid participants are recruited. Upon entering the study, participants are randomly assigned to one of two groups using a fully randomized allocation procedure. A statistical power analysis conducted using G*Power (version 3.1.9.7) indicates that, with $\alpha = 0.05$ and power = 0.8, a sample size of 800 is required to detect a medium effect size (f = 0.25). The sample size of 1000 in this study satisfies the requirements for adequate statistical power. The control group consists of 500 users who consistently view standardized product detail pages with a fixed information structure. The experimental group consists of another 500 users who experience personalized content interfaces generated in real time by the Eco-GenRec system, based on their inferred cognitive styles. In the core task phase, all participants complete eight independent simulated purchase decision scenarios. The platform comprehensively records all interface interactions, browsing paths, and decision outcomes, thereby generating detailed interaction logs.

5.2. Data Collection and Analysis

The experiment systematically collects multi-source, heterogeneous longitudinal panel data. The first dimension is full-process behavioral panel data, which continuously records each user's clickstream sequences, page dwell time measured in milliseconds, and final purchase conversion behavior with precise timestamps. The second dimension consists of pre-test and post-test questionnaire data. At key stages before and after the experiment, validated seven-point Likert scales are used to measure users' psychological state variables. These variables include perceptual and conceptual cognitive fluency as mediators, perceived psychological distance as a moderator, and low-carbon purchase intention as the dependent variable. The effective response rate reaches 98.2%. The third dimension comprises generated content data. For users in the experimental group, the system automatically stores each personalized content instance generated for them and annotates it with the corresponding cognitive style label. These data support subsequent analyses of the relationships between content characteristics and outcomes. In addition, all interaction events are assigned millisecond-level timestamps, which allow analysis of the relationship between deliberation time and decision outcomes.

Independent-samples *t*-tests are conducted to directly compare mean differences between the experimental group and the control group on key outcome variables, in order to examine the presence of the main effect of GenAI-based personalized recommendations. To test the core mediation mechanism proposed in H2, the PROCESS macro developed by Hayes is used for mediation analysis. The indirect effects of cognitive fluency between recommendation type and purchase intention are estimated using the bootstrap method with confidence intervals. For the moderation effects involved in H1 and H3, hierarchical regression analyses are conducted. Interaction terms between recommendation type and cognitive style matching, as well as between cognitive fluency and psychological distance, are introduced to test the significance of the moderating effects. Finally, cognitive fluency scores obtained from questionnaires are correlated with behavioral indicators of fluency, such as shorter decision times and fewer page revisits observed in the behavioral data.

5.3. Hypothesis Testing Results and Discussion

5.3.1. Descriptive Statistics and Validity Tests

Figures 5–7 show that the sample exhibits reasonable distributions across key demographic variables, including gender, age, and education level. No significant differences are observed between the experimental group and the control group on any of these variables (all $p > 0.05$), indicating successful random assignment and strong group comparability. The core psychological construct scales used in this study demonstrate robust psychometric properties. All Cronbach's alpha coefficients exceed 0.85, indicating excellent internal consistency reliability.

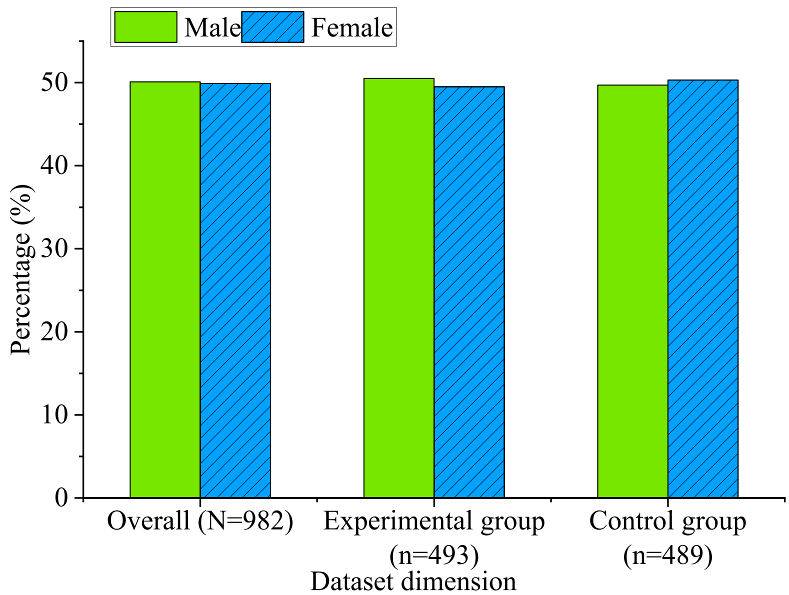


Figure 5. Distribution of participants by gender.

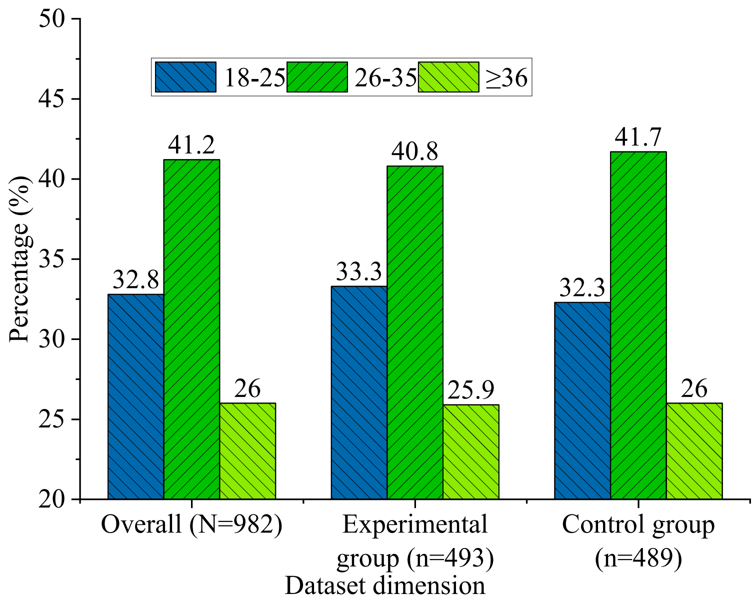


Figure 6. Distribution of participants by age.

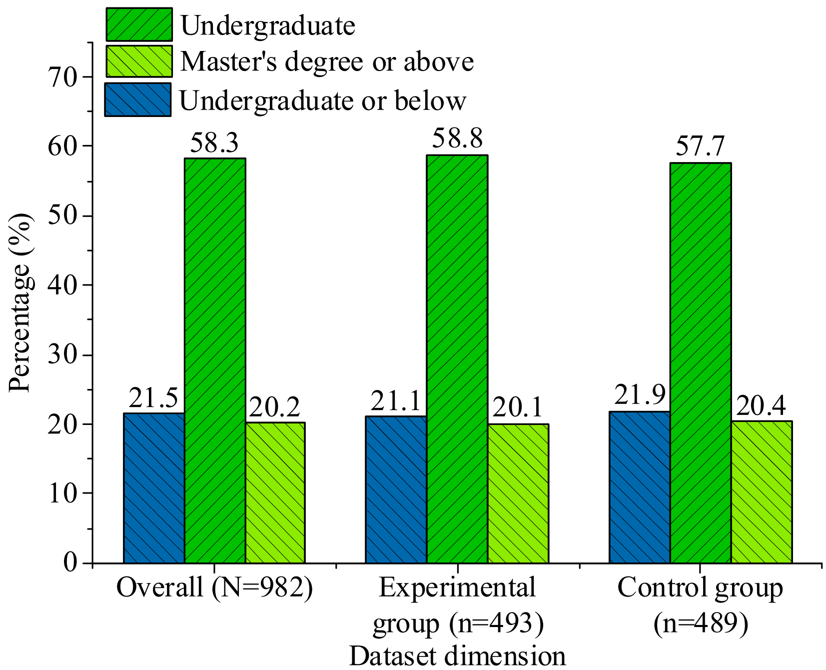
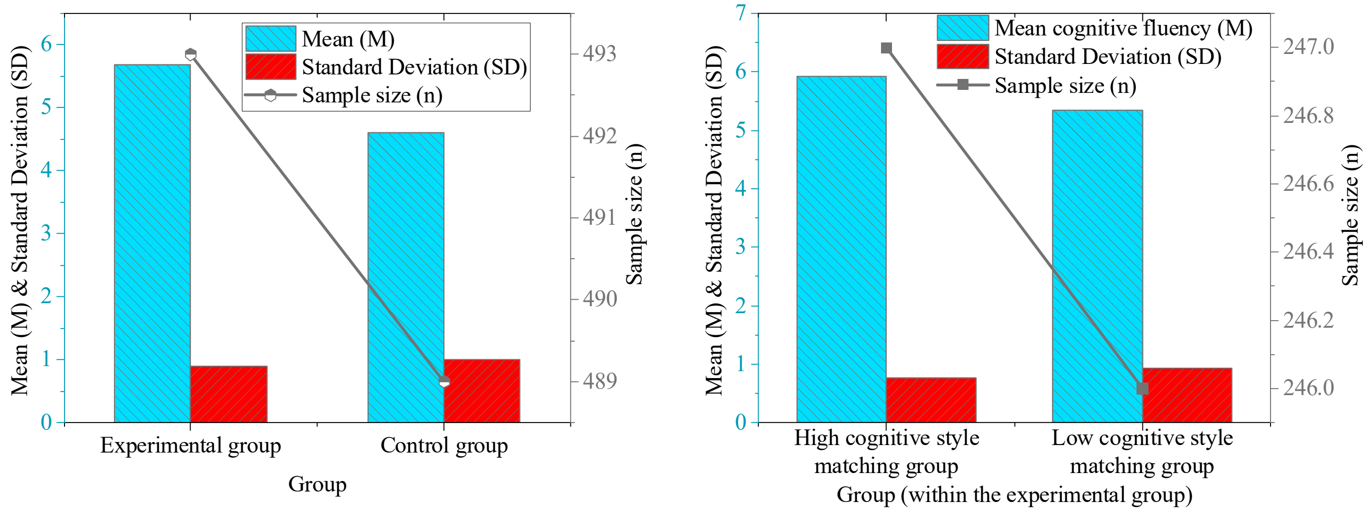


Figure 7. Distribution of participants by educational level.

5.3.2. Hypothesis Testing

The three core hypotheses proposed in this study are tested sequentially. The test results for Hypothesis 1 are presented in Figure 8. An independent-samples *t*-test for H1 shows that the experimental group reports a significantly higher overall cognitive fluency score (M = 5.68, SD = 0.89) than the control group (M = 4.60, SD = 1.01). The difference is highly statistically significant, $t(980) = 18.34$, $p < 0.001$, with a large effect size ($d = 1.17$). This result confirms the main effect of GenAI in improving information comprehension. To examine the moderating role of cognitive style matching in the effect of GenAI on cognitive fluency, the experimental group ($n = 493$) is divided into high- and low-matching subgroups based on the median matching score. These subgroups are then compared with the control group. One-way ANOVA results indicate that users with high matching report significantly higher cognitive fluency (M = 5.92, SD = 0.76) than users with low matching (M = 5.35, SD = 0.94), $F(1, 491) = 64.73$, $p < 0.001$. More importantly, the improvement relative to the control group is substantially larger for high-matching users ($\Delta M = 1.32$) than for low-matching users ($\Delta M = 0.75$). The between-group difference is statistically significant, $F(1, 498) = 24.56$, $p < 0.001$. These findings clearly indicate that cognitive style matching positively moderates the effect of GenAI on cognitive fluency. Hypothesis H1 is therefore fully supported.

The test results for Hypothesis 2 are reported in Table 2. The total effect of GenAI-based recommendations on purchase intention is 0.41 ($p < 0.001$). After introducing cognitive fluency as a mediator, the direct effect decreases to 0.07 and becomes non-significant, as the 95% confidence interval includes zero. In contrast, the indirect effect through cognitive fluency is 0.34, with a 95% confidence interval of [0.26, 0.43], which does not include zero, indicating that the mediating effect is significant. The mediation effect accounts for 82.9% of the total effect. These results provide strong support for H2. They indicate that GenAI enhances purchase intention primarily by increasing users' cognitive fluency. Cognitive fluency thus plays a full mediating role.



(**a**) (**b**)

Figure 8. Results for Hypothesis 1: (**a**) comparison of cognitive fluency scores between the experimental and control groups; (**b**) within-group comparison of cognitive fluency scores in the experimental group.

Table 2. Mediation analysis of cognitive fluency.

Path	Effect (β)	SE	95% Confidence Interval	*p*-Value	Conclusion
Total effect (X → Y)	0.41 ***	0.04	[0.33, 0.49]	<0.001	Significant
Direct effect (X → Y)	0.07	0.05	[−0.02, 0.16]	0.121	Not significant
Indirect effect (X → M → Y)	0.34 ***	0.04	[0.26, 0.43]	-	Significant
Proportion mediated	82.9%				

Note: X = Recommendation type (experimental group = 1, control group = 0); M = Cognitive fluency; Y = Low-carbon purchase intention. *** $p < 0.001$.

Hierarchical regression results are reported in Table 3. After controlling for the main effects, the interaction between cognitive fluency and psychological distance significantly predicts purchase intention (β = −0.19, $p < 0.01$). The inclusion of the interaction term leads to a significant increase in explained variance ($\Delta R^2 = 0.03$, $p < 0.01$). The index of moderated mediation is −0.07, and its bootstrap 95% confidence interval is [−0.13, −0.02]. The interval does not include zero, which confirms the significance of the moderation effect. These results support Hypothesis H3.

Table 3. Moderated mediation analysis.

Predictor	Model 1: Purchase Intention (Y)	Model 2: Purchase Intention (Y)
Step 1: Independent and Mediating Variables		
Cognitive fluency (M)	0.38 ***	0.36 ***
Step 2: Moderating Variable		
Psychological distance (W)	−0.22 ***	−0.20 ***
Step 3: Interaction Term		
M × W		−0.19 **
R^2	0.31	0.34
ΔR^2		0.03 **
Moderation index		−0.07 *

Note: All variables are standardized; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.3.3. Exploratory Analysis: Demographic Heterogeneity

To further investigate the boundary conditions of the cognitive style matching effect, this study conducted an exploratory subgroup analysis on the experimental group data (n = 500). It focused on two key demographic variables: age and education level. The goal was to examine whether the enhancement effect of "high matching" over "low matching" on cognitive fluency and purchase conversion differed across these subgroups. Age was divided into a "young group" (≤30 years, n = 266) and a "middle-aged group" (>30 years, n = 234). Education level was classified as "higher education" (bachelor's degree or above, n = 328) and "medium or lower education" (associate degree or below, n = 172). The results are summarized in Table 4.

Table 4. Subgroup Analysis of Cognitive Style Matching Effects: Cognitive Fluency and Purchase Conversion.

Demographic Subgroup	Matching Level	Cognitive Fluency (M, SD)	Purchase Conversion	Within-Group Effect Size (Cohen's d/Cramér's V)	Difference vs. Control (Δ)
Overall (Experimental)	High (n = 247)	5.92 (0.76)	44.8%	d = 1.55/V = 0.295	Fluency Δ = +1.32; Conversion Δ = +27.2%
	Low (n = 253)	5.35 (0.94)	28.1%	d = 0.83/V = 0.110	Fluency Δ = +0.75; Conversion Δ = +10.5%
Young (≤30)	High (n = 138)	6.05 (0.71)	49.3%	d = 1.70/V = 0.332	Fluency Δ = +1.45; Conversion Δ = +31.7%
	Low (n = 128)	5.40 (0.92)	29.7%	d = 0.87/V = 0.125	Fluency Δ = +0.80; Conversion Δ = +12.1%
Middle-aged (>30)	High (n = 109)	5.76 (0.78)	39.4%	d = 1.32/V = 0.243	Fluency Δ = +1.16; Conversion Δ = +21.8%
	Low (n = 125)	5.31 (0.95)	26.4%	d = 0.79/V = 0.093	Fluency Δ = +0.71; Conversion Δ = +8.8%
Higher education	High (n = 168)	5.98 (0.73)	46.4%	d = 1.63/V = 0.308	Fluency Δ = +1.38; Conversion Δ = +28.8%
	Low (n = 160)	5.33 (0.90)	28.1%	d = 0.85/V = 0.115	Fluency Δ = +0.73; Conversion Δ = +10.5%
Medium or lower education	High (n = 79)	5.78 (0.82)	41.8%	d = 1.33/V = 0.259	Fluency Δ = +1.18; Conversion Δ = +24.2%
	Low (n = 93)	5.38 (1.02)	28.0%	d = 0.82/V = 0.103	—

Note: Cohen's d compares cognitive fluency between high- and low-matching participants within each subgroup. Cramér's V compares purchase conversion differences. All within-group comparisons are statistically significant (p < 0.01).

The analysis indicates that the enhancement effect of cognitive style matching exhibits notable demographic heterogeneity. Specifically, the young group benefits most from high matching. Their high-matching participants achieve the highest cognitive fluency mean (M = 6.05) and the largest increase in purchase conversion (Δ = +31.7%), which exceeds that of the middle-aged group (Δ = +21.8%). A logistic regression with purchase behavior as the dependent variable, and matching level (high/low) and age group (young/middle-aged) as independent variables, shows a significant interaction effect (B = 0.42, p < 0.05). This indicates that cognitive style matching has a stronger effect on purchase behavior among younger users.

For education level, high-matching participants in the higher education group show the highest cognitive fluency (M = 5.98) and conversion increase (Δ = +28.8%). Although the absolute difference compared with the medium-or-lower education group (Δ = +24.2%) is smaller than for the age subgroups, the interaction term between matching level and education level is not statistically significant (p = 0.12). This suggests that cognitive style matching is generally effective across educational levels, but the effect tends to be more pronounced among higher-educated participants. Overall, these exploratory analyses reveal that while cognitive style matching positively influences all user groups, the effect is significantly moderated by age, with the strongest impact observed in younger participants. Education level shows a similar trend, though the moderation effect is less robust statistically.

5.3.4. Behavioral Conversion Results

The experimental results for actual purchase behavior are illustrated in Figure 9. The findings demonstrate a pronounced effect of generative AI recommendations on green consumption. To test the statistical significance of the difference in conversion rates between groups, a chi-square test is conducted. The analysis shows that the purchase conversion rate in the experimental group (36.3%) is significantly higher than that in the control group (17.6%), $\chi^2 = 70.28$, $p < 0.001$, with an effect size of Cramér's V = 0.265. This difference corresponds to an absolute increase of 18.7% and a relative increase of 106.3%. These results confirm that GenAI-based precision recommendations effectively promote actual consumer purchase behavior. The behavioral conversion effect is further amplified within the subgroup of users with a high degree of cognitive style matching. The conversion rate in this subgroup reaches 44.8%. This result corresponds to an absolute increase of 27.2 percentage points relative to the control group baseline. The relative increase reaches 154.5%. These results confirm that generative AI recommendations can substantially improve conversion rates. They also reveal the heterogeneity and conditional nature of this effect. When AI-generated content achieves a high level of alignment with users' cognitive styles, its capacity to stimulate consumption increases markedly.

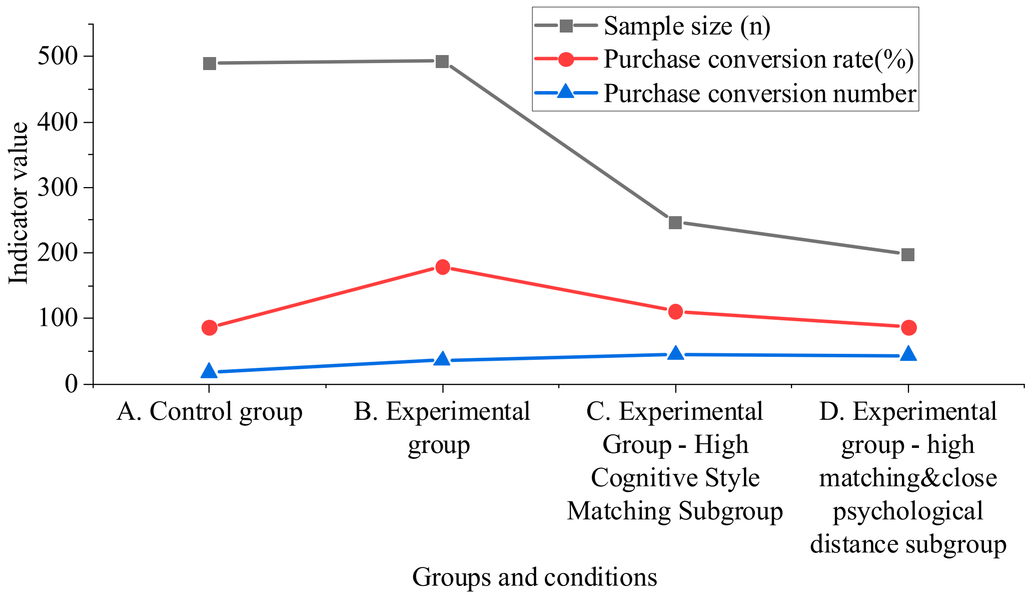


Figure 9. Conversion rates of low-carbon product purchases under different experimental conditions.

5.4. Comprehensive Discussion and Practical Implications

5.4.1. Theoretical Dialog with Existing Research

The findings of this study extend and deepen the empirical application of cognitive fluency theory at the intersection of green consumption and artificial intelligence. Consistent with earlier research on how information presentation affects consumer judgment, the results support the view that processing fluency serves as a key mechanism. For example, Puente-Díaz (2023) [63] shows that easily processed information triggers positive metacognitive experiences, which in turn influence judgment and decision-making. Traditional studies typically manipulate fluency by altering superficial features, such as font style or contrast, yet the effects of these approaches are limited. A major contribution of this study is the demonstration that generative AI–driven personalized content reconstruction can fundamentally enhance processing fluency at both semantic and structural levels. The effect sizes achieved far exceed those obtained by conventional methods, such as visual optimization or information simplification. This confirms that fluency improvements are not solely due to physical presentation features but arise from a deep alignment between information structure and individual cognitive architecture [64].

Furthermore, this research offers a new perspective on strategies to promote green consumption. Prior studies have documented the effectiveness of external interventions, such as social norm signals, group identity appeals, or economic incentives. However, such strategies may trigger psychological resistance or "backfire effects." More critically, Geng and Bingyu (2024) [65] highlight that a core barrier for consumers facing green products is high perceived risk and uncertainty, particularly regarding the credibility and validity of environmental claims. The findings suggest that reducing the cognitive burden associated with understanding environmental benefits directly and effectively stimulates purchase intentions. When consumers encounter complex or unfamiliar eco-attributes, enhancing the processability and comprehensibility of information provides a foundational intervention pathway that may bypass psychological resistance. This aligns with growing calls in the literature to focus on consumer cognition in sustainable consumption research [66].

Exploratory analyses also reveal demographic boundary conditions for the cognitive style matching effect. The enhancement effect is more pronounced among younger and highly educated consumers. This may be because these groups are more receptive to personalized, technology-driven interactions, or because their cognitive styles are more plastic or pronounced, which amplifies the fluency gained from tailored content. These insights suggest that future applications of such recommendation mechanisms should consider the structural characteristics of target user groups to achieve more precise personalization.

5.4.2. Practical Implications and Managerial Applications

The findings provide actionable insights for e-commerce, environmental communication, and AI product development. For e-commerce platforms and green product retailers, the results support integrating cognitive style adaptation as a core feature of their marketing technology stack. Platforms can develop intelligent content generation tools that allow merchants to input standardized environmental product parameters. The system then automatically generates personalized display content tailored to different user types—for instance, concise data reports and comparative charts for analytical users, and immersive narrative scenarios with accompanying images for intuitive users. This capability not only lowers the technical threshold and cost of producing high-quality green communication content but also enhances users' cognitive fluency. Improved fluency directly translates into higher click-through rates, conversion rates, and customer satisfaction for green products. Consequently, platforms can achieve substantial commercial benefits while simultaneously promoting environmental value.

For environmental certification bodies, standards organizations, and public policy agencies, this study offers an innovative technological solution to the long-standing "cognitive gap" in green product information. Complex data, such as carbon footprint labels or life cycle assessment results, often fail to influence consumer decisions because they are difficult for the general public to interpret. Certification bodies could explore AI-based public services or API interfaces that provide "intelligent label interpretation," thereby enhancing the communicative effectiveness of their certifications. Policymakers could build on these insights to encourage or require user-centered, dynamic information presentation in green product standards or corporate environmental disclosure guidelines. Such measures could promote transparency and efficiency in the green consumption market at a systemic level.

For AI researchers and product developers, this study highlights the critical role of real-time adaptive personalization in behavior-intervention applications. In other domains that involve complex decision-making—such as health, finance, or education—future intervention systems inspired by Eco-GenRec should go beyond traditional user profiling based on historical behavior. Instead, they should construct interactive models capable of dynamically responding to users' cognitive states and processing preferences. This approach requires algorithms not only to determine what to recommend but also to decide how and why to present recommendations in a particular form at a specific moment.

6. Conclusions

6.1. Research Contributions

This study makes significant contributions to the intersection of green consumption, cognitive psychology, and artificial intelligence through the design and validation of the Eco-GenRec system. First, it extends the application of cognitive fluency theory in digital interaction contexts. Prior research mainly manipulated surface information features to affect perceptual fluency or simplified text to influence conceptual fluency. The findings demonstrate that generative AI can reconstruct information at both semantic and structural levels in a personalized manner. This approach simultaneously enhances perceptual and conceptual fluency, shifting from passive, static presentation optimization to active, dynamic cognitive adaptation.

Second, the study offers a novel information-processing perspective on the attitude–behavior gap in green consumption. Previous work primarily focused on external factors such as motivational conflicts, social norms, or economic costs. In contrast, this study identifies the processability of information itself as an independent and critical internal barrier. By empirically establishing the full mediating role of cognitive fluency, it shows that reducing consumers' cognitive burden directly promotes green purchase intentions. This shifts the focus from persuading consumers to empowering their understanding and provides a complementary cognitive-process perspective for addressing challenges in sustainable consumption.

Finally, this study introduces a new paradigm—cognitive alignment—into personalized recommendation theory. Traditional systems emphasize behavioral alignment. By demonstrating the moderating role of cognitive style, this study proposes cognitive alignment as a framework in which system effectiveness depends not only on what is recommended but also on how information is presented to align with users' mental models. This provides a theoretical foundation for next-generation recommendation systems, evolving them from "preference prediction engines" to "cognitive communication partners."

6.2. Limitations and Future Directions

This study has several limitations, which also point to directions for future research. First, practical and ethical challenges remain in technology deployment. While enhancing system reliability and personalization through RAG, strict source filtering, and real-time diagnostics, real-world applications face greater complexity. These include AI "hallucinations," data biases, and user privacy concerns. Future deployments should integrate stronger fact-checking mechanisms and lightweight, privacy-compliant diagnostic models, such as federated learning, to balance effectiveness with ethical compliance.

Second, the ecological validity and long-term effects require further investigation. The controlled experiment ensures internal validity but does not capture long-term dynamics in real e-commerce contexts, such as user adaptation or fatigue with personalized content.

Future research should conduct longitudinal field studies on live platforms to examine impacts on retention, repurchase behavior, and customer lifetime value. Dynamic content update strategies could help sustain engagement over time. Third, the cross-cultural generalizability of the findings is limited. The training data and sample reflect a specific market context. Consumers in other cultural settings may differ in their understanding of green values, information-processing preferences, and trust in certification systems. Future studies should replicate and compare findings across diverse cultural regions and explore culturally adaptive fine-tuning to enhance global applicability. Despite these limitations, this study provides key theoretical validation and an initial technical framework for developing next-generation, cognition-driven systems that promote sustainable consumption.

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Institutional Review Board Statement: The study was conducted in accordance with the guidelines of the Declaration of Helsinki and approved by the Medical Ethics Committee (Science and Education Section) of Nanjing Normal University (Approval number: NNU202508105; date of approval: 27 August 2025).

Informed Consent Statement: Written informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available upon request from the corresponding authors.

Conflicts of Interest: The authors declare no conflicts of interest.

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