

Article

AI-Assisted Greenwashing Detection and Rational Green Food Purchase Intention in Online Shopping: A Hybrid PLS-SEM and ANN Approach

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Abstract

Artificial intelligence (AI) is increasingly used to help consumers detect greenwashing in online food markets, yet how AI-use motivations relate to rational green food consumption intention (RCI) remains unclear. Integrating information processing theory, the consumer decision-making process model, and the theory of planned behavior, this study examines how risk avoidance (RA), performance expectations (PE), and health benefits (HB) are associated with RCI through subjective norm (SN) and perceived behavioral control (PBC). Based on 619 valid responses from a cross-sectional online survey, the data were analyzed using partial least squares structural equation modeling (PLS-SEM) and artificial neural network (ANN). The PLS-SEM results show that PE, RA, SN, and PBC are significantly associated with RCI, whereas HB has no significant direct association. SN is strongly associated with PBC, and the SN–PBC sequential mediation path is supported for RA, PE, and HB. The RA–PBC–RCI path is not supported, indicating that risk awareness does not automatically translate into perceived control. The ANN results identify PE as the strongest nonlinear predictor, followed by RA, while HB shows the weakest predictive importance. The findings advance AI-mediated sustainable consumption research and provide intention-level evidence for responsible online green food purchasing.

Keywords: greenwashing; green food; artificial intelligence; sustainable consumption; online shopping; theory of planned behavior; SDG 12



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1. Introduction

The global market for green food is expanding quickly [1]. Because food safety and sustainability are key quality dimensions, products with fewer chemical residues are gaining wider acceptance worldwide [2]. Data show that 72% of consumers are actively pursuing a healthier and greener lifestyle [3]. However, this trend has also made the food industry particularly susceptible to greenwashing behaviors [4], which are closely linked to the 500% growth rate of veganism and the surge in demand for green food [5]. To build favorable brand and product images, some firms selectively disclose environmental information, exaggerate sustainability performance, or use misleading ecological claims to obtain price premiums [6]. Greenwashing therefore refers to misleading claims, symbols,

labels, images, or narratives that create an impression of environmental responsibility without sufficient substantive support [7].

Greenwashing is increasingly visible in the food industry [8]. It may appear at the company or product level [9] and is commonly expressed as claim greenwashing, which relies on false or ambiguous written statements, or execution greenwashing, which uses natural visual elements inconsistent with actual product performance [10,11]. Such practices are encouraged by the high cost of genuine green transition and the premium attached to green products [6,12]. They weaken green purchase intention, yet ordinary consumers often find them difficult to identify [13].

The online channel is a particularly important context for green food consumption and greenwashing risk. Global online grocery sales have grown substantially, with green and organic food among the fastest-expanding categories [14]. Unlike offline consumers, who can inspect packaging, evaluate handling conditions, and ask staff for guidance, online shoppers rely mainly on digital labels, product descriptions, images, and user reviews [15]. This information asymmetry makes misleading eco-labels, vague sustainability statements, and deceptive visual packaging easier to deploy and harder to scrutinize [16]. At the same time, food choices are embedded in family care, cultural memory, local identity, and shared understandings of safe and responsible food [17]. Food heritage research further shows that traditional knowledge is transmitted through communities and can support social, cultural, and sustainability goals [18,19]. In online shopping, however, such embodied cues are weakened and replaced by platform descriptions, algorithmic recommendations, and visual marketing. This shift increases the need for AI-assisted information processing to support rational, greenwashing-resistant decisions.

Prior research has mainly examined firm-level responses, including third-party certification [20] and AI demand forecasting systems [21]. However, digital innovation has also reshaped how consumers search for, evaluate, and act on product information [22]. Generative AI may transform consumers from passive receivers of green information into active evaluators of greenwashing [23,24]. In online food markets, AI can flag false green claims and provide healthier buying advice [25,26], although algorithmic opacity, data quality, and potential misuse may still limit practical effectiveness.

A clear research gap remains. Existing studies largely define greenwashing, describe its forms, or examine its firm- and institution-level drivers [27,28]. Food-related studies are fewer, and few investigate how greenwashing affects consumer purchasing decisions [29]. Boncinelli et al. [30] examined food choices through market-share simulations, while AI-related greenwashing research has largely adopted a corporate perspective, such as developing algorithms to predict demand and consumer preferences [21,31]. Little is known about how consumers' motivations to use AI applications shape rational green food consumption intention (RCI) in online settings, especially when the goal is to resist greenwashing.

Because food accounts for a substantial share of living expenses [30], this context deserves closer analysis. This study integrates information processing theory (IPT) and the theory of planned behavior (TPB) [32,33]. IPT explains how consumers process AI-mediated product information, whereas TPB explains how such information becomes behavioral intention through social-cognitive mechanisms. However, both frameworks require contextual adaptation: IPT may overstate rational individual processing, while TPB faces the intention-behavior gap and variability in the roles of attitude, SN, and PBC. Recent and meta-analytic studies show that decision-making under information overload depends on decision aids, algorithmic recommendations, and context-specific control beliefs, and that TPB paths differ across food and pro-environmental contexts [34,35]. Accordingly, this study identifies SN and PBC as mediating constructs through which

AI-use motivations influence RCI. Consequently, the objective of this study is to address the following research questions.

RQ1: How do motivations for using AI-assisted greenwashing detection tools influence consumers' rational online green food consumption intention?

RQ2: How do subjective norms and perceived behavioral control mediate the relationship between AI-use motivations and rational online green food consumption intention?

RQ3: Which factors are most important in predicting consumers' rational online green food consumption intention?

By answering these questions, the study contributes to research on AI-mediated consumer decision-making and provides empirical evidence for sustainable, evidence-based, and greenwashing-resistant consumption aligned with SDG 12.

2. Literature Review and Hypothesis

This study develops an integrative framework combining IPT [32], the classical consumer buying behavior model [36,37], and TPB [33] in the context of AI-mediated green consumption.

2.1. Critical Synthesis of Theoretical Foundations and the Decision-Making Process for Purchasing Green Food Online

The classical consumer buying behavior model describes decision-making as problem recognition, information search, evaluation of alternatives, purchase decision, and post-purchase evaluation [36,37]. In online green food purchases, this process is more flexible and flatter, which increases both opportunities and risks in evaluating green claims [38]. Figure 1 shows how internal and external factors shape attitudes and lifestyles, generate needs, and influence consumers' responses to suspicious green claims. AI applications enter this cycle as decision aids that help consumers process product attributes and environmental performance. The model therefore links previous greenwashing experiences, current choices, and emerging demands, showing that resistance to misleading green information is iterative.

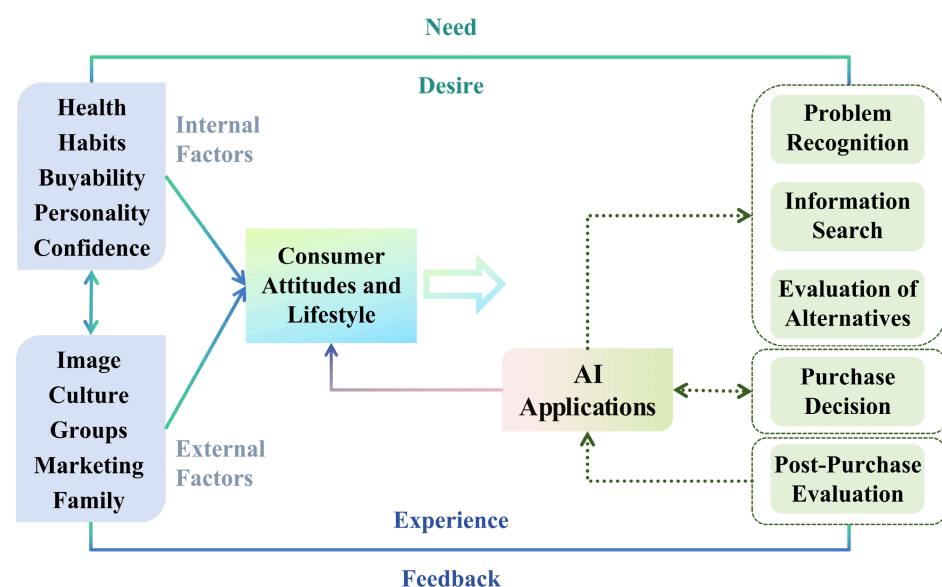


Figure 1. The decision-making process for purchasing green food online.

This process can be further explained through rational choice theory and IPT. IPT clarifies how consumers acquire, encode, compare, and use information under uncertainty and cognitive load [32]. This is relevant to online green food shopping, where consumers

evaluate sustainability labels, product descriptions, reviews, certification signals, visual cues, and AI-generated recommendations. However, IPT should not be read as a purely rational and individualistic model. Information processing is bounded by limited attention, affective cues, platform design, and sociocultural routines; decision aids may also create over-reliance or choice overload when information is excessive or frequently updated [39,40]. Thus, AI-assisted greenwashing detection tools are conceptualized as external cognitive aids whose value depends on whether they reduce information asymmetry. This framing also incorporates food heritage and community norms because claims about safe, authentic, or responsible food are interpreted through local identity and transmitted knowledge [17,19].

TPB complements IPT by explaining how processed information becomes intention. Its value lies in linking cognition to social expectation and perceived control, but it also has limitations. Meta-analytic evidence shows that TPB predicts intention more consistently than actual behavior and that attitude, SN, and PBC vary in strength across domains, measures, and food contexts [41,42]. Pro-environmental and sustainable food meta-analyses further show that normative, moral, and control-related mechanisms are context-dependent rather than universally ordered [43]. Therefore, this study adapts TPB to AI-assisted greenwashing detection, where social expectations about responsible food consumption and perceived control over digital verification are especially salient.

2.2. Greenwashing, AI Application Usage Motivation, and Rational Green Food Consumption Intention

Based on the consumer decision-making process model and IPT, this study examines how AI helps identify greenwashing in online green food consumption [32]. Greenwashing is understood as misleading communication that exaggerates, fabricates, or selectively presents environmental attributes to make products or firms appear more sustainable than they actually are [44]. In the food industry, this concept is closely linked to consumers' health concerns, trust in labels, perceived authenticity, and willingness to pay for green premiums. Recent systematic review evidence also shows that food greenwashing is associated with unclear labels, unsupported environmental claims, and insufficient transparency, all of which undermine consumer trust and informed decision-making [4].

In the current information-overloaded environment, consumers face the dual challenges of screening effective information and identifying greenwashing behaviors, and AI-based recommendation systems may also suppress the willingness to engage in green consumption due to the reduced need for impression management [25]. In this study, AI application usage motivation refers to consumers' cognitive appraisal of why they use AI-assisted tools to support greenwashing detection and online green food decision-making. Three dimensions are examined: risk avoidance, performance expectations, and health benefits. These constructs are not simply listed as technical features of AI; rather, they are theoretically grounded in IPT because they describe how consumers evaluate the informational utility of AI tools under uncertainty, information overload, and potential deception.

Risk avoidance (RA) is consumers' perceived ability to avoid buying greenwashing food in online green food purchases [45]. RA reflects risk perception, coping ability, and emotional response [46] and acts as a key inhibitor in the decision process [47]. Greenwashing is widespread in ads, labels, and public relations [26] and introduces functional, financial, psychological, physical, social, and time-related risks [48]. Information asymmetry makes these risks hard to assess and the value of green premiums hard to judge [49,50]. AI can reduce the risk of encountering greenwashing in online green food purchases by enhancing traceability and the transparency of information disclosure [51]. Thus, RA captures the protective motivation to use AI as a risk-reduction tool when consumers face uncertainty about the authenticity of green food claims.

Performance expectations (PE) refer to consumers' belief about the effectiveness of AI in identifying greenwashing behaviors and their ability to enhance the efficiency of online green-food purchases [52,53]. Research shows that expectation gaps significantly influence consumers' perception of food quality and their purchase intention [54]. The information about green food is complex and difficult to verify [55]. Although most consumers are willing to pay a premium, they lack the ability to verify [56]. Offline buyers can judge store environments and handling standards. Online buyers rely mainly on labels, package claims, and reviews [15]. Misleading green packaging is a common greenwashing tactic, which exacerbates information asymmetry [57]. Against this backdrop, the advantage of AI-assisted decision-making lies in providing personalized recommendations and abundant information through continuous learning, thus improving the accuracy of identification [58]. Its powerful data processing capabilities help identify corporate-level greenwashing and alleviate the trust gap caused by information asymmetry [31]. Therefore, PE captures consumers' expectation that AI can improve the accuracy, speed, and efficiency of greenwashing detection.

Health benefits (HB) refer to consumers' expected health gains from AI-assisted online green food purchases [59]. As nutrition knowledge and environmental awareness rise, consumers prefer natural, high-quality, and trustworthy foods [60]. However, companies may falsely promote the health attributes of green food through greenwashing [61], which may even harm consumers' health. This makes it necessary for consumers to have more reliable decision-support tools. When consumers use AI to purchase green food online, they can avoid greenwashing food while learning about the advantages and health benefits of the food [62]. AI-driven personalized nutrition can tailor green food advice to individual differences such as genetic traits and metabolic status [63]. Furthermore, combined with bioinformatics technology, AI can deeply analyze the molecular mechanisms of nutrition and health, providing a scientific basis for consumer decision-making [21]. These functions significantly enhance consumers' feasibility assessment of choosing healthy green food [64]. Thus, HB captures a health-oriented motivation to use AI for distinguishing genuine health-related value from misleading or exaggerated green claims.

These three motivations are conceptually upstream of subjective norm and perceived behavioral control. RA, PE, and HB explain why consumers engage with AI tools, whereas SN and PBC explain how such engagement is translated into rational purchase intention through social pressure and perceived control.

2.3. Rational Consumption Intention

Rational consumption intention (RCI) reflects consumers' decision-making tendency in green food purchase decisions based on comprehensive evaluation rather than single green propaganda [65]. It is important to distinguish RCI from standard green purchase intention. Standard green purchase intention captures a general willingness to buy green products, often driven by emotional responses to green branding or promotional claims. RCI captures the additional dimension of decision rationality that distinguishes informed from uninformed green consumption, specifically emphasizing whether the decision process is grounded in evidence-based, multi-criteria evaluation that actively resists greenwashing influence. This concept emphasizes maximizing consumer interests through optimal choices [66]. The core is to balance environmental demands, sustainable expectations, and personal needs [67].

This distinction is central to the study. Consumers may strongly intend to buy green food while still being vulnerable to vague labels, natural imagery, or unsupported health and sustainability claims. RCI instead emphasizes verification, comparison, critical judgment, and refusal to pay green premiums when claims lack credibility. Recent empirical

studies have operationalized comparable evidence-based or greenwashing-resistant decision constructs rather than only generic green purchase intention. Sun et al. [68] measured greenwashing perception and showed its negative effect through perceived betrayal; Ng et al. [69] operationalized multiple perceived values and motivational regulations in green purchase intention; Fuchs and Brusa [70] experimentally measured consumers' ability to distinguish honest green products from greenwashed products; and Zhang et al. [71] examined rational consumption intention in a digital community context. These studies support treating RCI as an evaluative intention grounded in credibility assessment, value comparison, and resistance to deceptive cues. Food-specific evidence also shows that choices depend on packaging-greenness evaluation [30], perceived deception and value assessment [6], and risk perception, trust, and environmental-information evaluation ability [13]. RCI is derived from TRA and aligns with sustainable consumption goals [72]. Because irrational green consumption often stems from misjudging greenwashed food [73], correct identification can support more rational behavior and sustainable values [74,75]. Therefore, the following hypotheses are proposed.

H1a: *Risk avoidance positively influences online rational green food consumption intention.*

H1b: *Performance expectations positively influence online rational green food consumption intention.*

H1c: *Health benefits positively influence online rational green food consumption intention.*

2.4. Subjective Norm, Perceived Behavioral Control, and the Exclusion of Attitude

Existing research indicates that in consumer decision-making, consumers often prefer algorithmic recommendations to human advice [25]. However, green food consumption is characterized by unique psychological benefits, making the influence mechanism of AI applications in this field yet to be clarified. The Theory of Planned Behavior (TPB) is an important framework for explaining human decision-making [33]. It extends TRA by adding perceived behavioral control, which improves explanation of behaviors that are not fully voluntary [76,77].

This study adapts TPB by retaining SN and PBC while excluding attitude. This does not deny the relevance of attitude. Rather, it follows meta-analytic evidence showing that TPB components are not equally stable across contexts. Armitage and Conner [41] showed that PBC explains additional variance beyond TRA variables and that behavior prediction is weaker when objective behavioral measures are used. McDermott et al. [78] found heterogeneous TPB associations in discrete food-choice studies, while Scalco et al. [42] reported that attitude is important in organic food consumption but is followed by SN and PBC, with limited evidence on the intention-behavior link. Pro-environmental and sustainable food evidence likewise indicates that normative, moral, and control factors vary by behavior and cultural setting [43]. These findings justify a parsimonious, context-sensitive TPB specification rather than mechanical inclusion of all original constructs.

Theoretically, the evaluative function normally captured by attitude is already represented upstream by IPT-derived motivations: RA reflects evaluation of greenwashing risk, PE reflects evaluation of AI performance, and HB reflects health-related evaluation of food outcomes. Adding a general attitude toward green food would risk conceptual redundancy, because the dependent variable is not ordinary green purchase intention but rational, verification-oriented intention. The exclusion of attitude is therefore a theory-driven modeling decision to isolate the social-normative and control pathways through which AI-use motivations become RCI, not a claim that attitude is irrelevant to green consumption.

Multiple studies have confirmed that SN and PBC are key predictors of consumption intention [79,80]. Based on these findings, this study selects SN and PBC as direct variables

and core mediating variables to investigate the formation mechanism of rational online green food consumption under AI assistance.

Subjective norm (SN) is perceived social pressure from important others or groups about adopting a behavior [33]. In green food consumption, SN refers to expectations to reject greenwashed products and make rational online choices [81]. When AI tools support decisions, views of key people or groups may shape rational consumption intention [82,83]. Ajzen distinguishes injunctive norms, or expectations about how one should act, and descriptive norms, or the visible behavior of important others [84,85]. This distinction is important in green behavior [86], and studies show a positive relationship between SN, especially injunctive norms, and green food purchase intention [82,87]. Food-heritage studies further show that food choices carry local identity, cultural memory, and intergenerational knowledge [18] while sustainable consumption research shows that community values and cultural norms shape responsible consumption [72,88]. In online environments, family members, peers, and online communities may become normative filters that encourage consumers to verify green claims with AI and avoid misleading food products. Therefore, the following hypothesis is proposed.

H2a: *Subjective norm mediates the positive relationship between risk avoidance and online rational green food consumption intention.*

H2b: *Subjective norm mediates the positive relationship between performance expectations and online rational green food consumption intention.*

H2c: *Subjective norm mediates the positive relationship between health benefits and online rational green food consumption intention.*

H2d: *Subjective norm positively influences online rational green food consumption intention.*

Perceived behavioral control (PBC) is the belief about how easy or hard it is to carry out greenwashing-resistant and rational online green food behaviors [33]. PBC depends on control beliefs and resources such as time, money, skills, and access to information [89–91]. In greenwashing contexts, PBC shows strong regression effects [92], and green consumption studies also find that PBC predicts purchase intention [93]. For online green food shopping, PBC is especially important because consumers lack direct sensory access to products and must evaluate claims through digital information. AI-assisted tools can increase control by providing verification cues, comparison information, and decision support. This mechanism clarifies H3a. RA involves recognizing potential losses and seeking coping resources [46,47]. When consumers seek to avoid deceptive green food, they are more likely to learn and use AI functions such as traceability checks, claim comparison, and credibility alerts. These actions transform perceived vulnerability into stronger control beliefs, thereby increasing PBC and supporting rational choices. The following hypothesis is advanced.

H3a: *Perceived behavioral control mediates the positive relationship between risk avoidance and online rational green food consumption intention.*

H3b: *Perceived behavioral control mediates the positive relationship between performance expectations and online rational green food consumption intention.*

H3c: *Perceived behavioral control mediates the positive relationship between health benefits and online rational green food consumption intention.*

H3d: *Perceived behavioral control positively influences online rational green food consumption intention.*

2.5. Sequential Mediating Effects

TPB can integrate AI-use motivations with behavioral intentions in green food consumption [94,95]. In the proposed chained mediation structure, AI-use motivations influence RCI through SN and PBC. This sequence is theoretically reasonable because social expectations may first increase attention to responsible, greenwashing-resistant consumption, whereas PBC determines whether consumers believe they can actually perform such behavior online. Consumers who perceive stronger social pressure to avoid greenwashing may become more motivated to use AI tools and, through AI-supported verification, feel more capable of making rational choices. Therefore, the following hypothesis regarding chained mediation effects is proposed.

H4a: *Subjective norm and perceived behavioral control sequentially mediate the relationship between risk avoidance and online rational green food consumption intention.*

H4b: *Subjective norm and perceived behavioral control sequentially mediate the relationship between performance expectations and online rational green food consumption intention.*

H4c: *Subjective norm and perceived behavioral control sequentially mediate the relationship between health benefits and online rational green food consumption intention.*

By integrating these perspectives, the proposed model explains how AI-assisted evaluations of green food influence purchase decisions. Figure 2 summarizes the hypothesized relationships among multidimensional AI perceptions, SN, PBC, and RCI. It transforms the general decision sequence in Figure 1 into a testable psychological framework based on IPT and TPB, clarifying how AI-assisted evaluations are associated with green food purchase motivation and support sustainable food consumption.

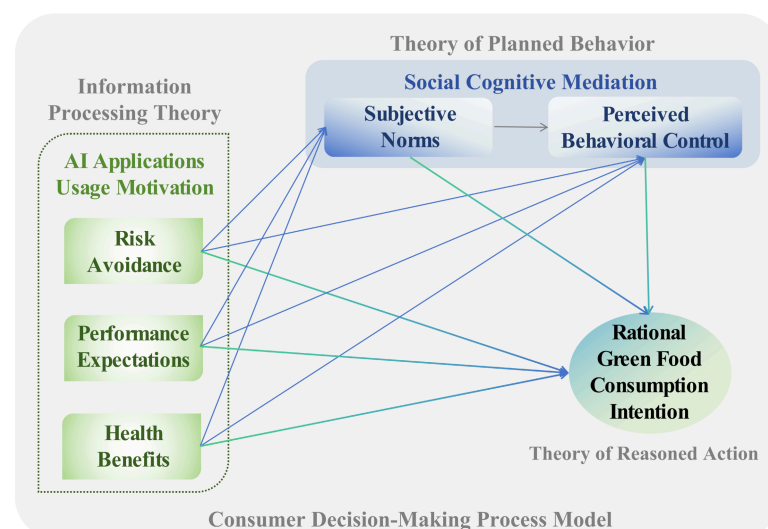


Figure 2. Research model for rejecting greenwashing consumption with AI assistance.

3. Research Design and Methods

3.1. Measurement Items

Constructs were measured with items validated in prior studies, as listed in Table 1. Six constructs were included. All items used a 5-point Likert scale from 1, strongly disagree, to 5, strongly agree. The instrument was reviewed by five food consumption experts and

five AI software developers to assess content relevance and measurement quality. The questionnaire was also pilot tested by collecting responses from 60 consumers. The results of the pilot survey were not included in the total sample size. Based on the pilot results, the wording and structure of the questionnaire were refined to improve its clarity, relevance, and consistency.

Table 1. Measurement items.

Category	Source		Measurement Items
Risk Avoidance (RA)	Hasan et al. [96] Hakim et al. [97]	RA1	The AI application helps me avoid risks associated with greenwashing food products in online shopping.
		RA2	The AI application helps me mitigate uncertainties when purchasing green food products online.
		RA3	The AI application helps me prevent potential losses caused by greenwashing food products in online shopping.
		RA4	The AI application alleviates my anxiety about encountering greenwashing food products during online shopping.
		RA5	The AI application helps me avoid spending money on food products that falsely claim to be green.
AI Usage Motivation (AI UM)	Performance Expectations (PE)	PE1	I can rely on the AI application whenever I need to identify greenwashing food products in online shopping.
		PE2	The AI application's identification of greenwashing food products saves me time when purchasing green food online.
		PE3	The AI application assists me in quickly distinguishing between greenwashing food products and authentic green food during online purchases.
		PE4	The AI application helps me locate authentic green food products that match my sustainability criteria during online shopping.
		PE5	The AI application significantly enhances my shopping efficiency when purchasing green food products online.
	Health Benefits (HB)	HB1	The AI application reinforces my confidence in the health benefits when purchasing green food products online.
		HB2	The AI application helps me select green food products that fit my health needs during online purchases.
		HB3	The AI application improves my ability to recognize misleading health claims associated with greenwashing food products.
		HB4	The AI application helps me plan green food purchases that fit my health goals during online shopping.
		HB5	The AI application supports my confidence in assessing the health benefits of unfamiliar green food products during online purchases.

Table 1. Cont.

Category	Source	Measurement Items
Theory of Planned Behavior (TPB)	Subjective Norm (SN) Carfora et al. [100]	SN1 People who are important to me believe I should identify greenwashing food products during online shopping.
		SN2 People important to me would expect me to make rational green food consumption choices during online purchases.
		SN3 People important to me expect me to distinguish greenwashing food products during online shopping.
		SN4 I perceive social pressure to avoid purchasing greenwashing food products during online shopping.
		SN5 People who are important to me see avoiding greenwashing food products when shopping online as part of being a responsible consumer.
		SN6 People important to me expect me to use the AI application to identify greenwashing food products.
	Perceived Behavioral Control (PBC) Carfora et al. [100]	PBC1 I can usually identify greenwashing claims even when they are presented persuasively in online marketing.
		PBC2 I feel strong personal control over my green food purchasing decisions during online shopping.
		PBC3 Even when others share opinions or reviews, I am able to follow my own judgment when buying green food products online.
		PBC4 I am confident in my ability to identify greenwashing food products during online shopping.
		PBC5 I am confident I can avoid purchasing greenwashing food products when buying online.
		PBC6 I have acquired the competency to utilize the AI application for identifying greenwashing food products.
Rational Consumption Intention (RCI)	Xu et al. [65]	RCI1 I systematically evaluate the authenticity of sustainability claims before purchasing green food products online.
		RCI2 I prioritize value for money by selecting green food products that offer genuine environmental or health benefits within my budget.
		RCI3 I consciously avoid purchasing greenwashing food products during online shopping.
		RCI4 I conduct comprehensive evaluations of negative information regarding greenwashing food products and refuse to pay green premiums during online purchases.
		RCI5 I intend to make rational online purchases of green food products consistently.
		RCI6 I intend to apply critical thinking so that my online green food purchases are ethically and environmentally sound.
		RCI7 I intend to make every effort to purchase green food products rationally online.

3.2. Data Collection

Data were collected through Credamo (<https://www.credamo.com/>), a general-purpose online survey platform. Credamo distributed the questionnaire to its registered

online panel members. A screening procedure was applied before the formal questionnaire. Eligible participants had to be at least 18 years old and must have purchased green food online at least three times during the previous three months. This criterion was used to ensure that respondents had sufficient familiarity with online green food shopping and were able to evaluate AI-assisted greenwashing detection in a meaningful consumption context.

A total of 800 questionnaires were initially collected, and 619 valid responses were retained after data screening. The 181 excluded questionnaires met at least one of the following pre-specified exclusion criteria: failure to satisfy the eligibility requirements; incomplete questionnaire submission; failure of attention-check or logic-check items; unrealistically short completion time, indicating insufficient engagement with the questionnaire; repeated responses from the same participant or device record; and patterned responses such as straight-lining across major scale items. These exclusion rules were applied to improve data quality. However, because the survey was conducted through an online panel rather than probability sampling, the possibility of self-selection bias cannot be fully eliminated. Therefore, the sample should be interpreted as representing digitally active online green food consumers rather than the entire population of food shoppers.

Participation was voluntary. All participants gave informed consent before starting the survey. The study used a self-administered online questionnaire, and all respondents completed the same procedure individually. Participants first read the study information and consent statement, then completed the eligibility screening questions, viewed the standardized scenario materials, and finally answered the measurement items and demographic questions. Respondents could withdraw at any point before submission. The research team did not retain personally identifiable information, and the data were analyzed only in aggregated form.

Before completing the questionnaire, all participants were exposed to a standardized scenario comprising two components: (1) a brief instructional video demonstrating how AI tools support green food information search and greenwashing detection in online shopping [101,102], and (2) written reference materials introducing greenwashing definitions and case examples adapted from [103], as detailed in Table 2. This design ensured a consistent baseline understanding of AI-assisted greenwashing detection across respondents, complementing rather than replacing real-world experience, given the eligibility requirement of at least three prior online green food purchases.

Table 2. Greenwashing techniques: definitions and examples.

Technique	Definition	Example
Hidden tradeoff	Focusing on a narrow set of positive attributes when more significant negative impacts go unmentioned	Emphasizes that it can replace certain unhealthy foods, but is itself harmful to health
No proof	Claims made with no supporting/verifiable evidence	Listed relevant green data but not verified
Vague	Claims so broadly defined or general that they are misunderstood or rendered meaningless	Even “all-natural” products may still contain unhealthy additives and are not necessarily “green”
Irrelevant	Truthful claims that are unimportant or unhelpful to the consumer	Claiming that a certain additive is not used in the production process, when in fact this additive is prohibited in the food industry
Lesser of two evils	Statements about the product may be true, but they use vocabulary and descriptions that consumers are unfamiliar with	Food additive labels use names or terms unfamiliar to consumers

Table 2. *Cont.*

Technique	Definition	Example
Fibbing/lying	Making claims that are false	Many foods claim to be certified organic, but in reality they are not
False	Utilizing ecolabels that look like independent, third-party verifications but are either controlled by the company itself or that originate from questionable sources	Use labels issued by relevant stakeholders in the food industry or register descriptions of food quality such as “natural” and “organic” as trademarks and print them on packaging

This study used a cross-sectional survey rather than experience sampling, which collects repeated in situ responses during or shortly after actual behavior. Because the present aim was to test a standardized theory-driven structural model, a one-time survey with controlled scenario exposure was more appropriate. Future research may use experience sampling to capture actual online purchasing processes.

3.3. Profile of Respondents

Among the 619 valid respondents, females had a slightly higher proportion (54.0%) compared to males (46%). The age distribution was concentrated among the younger groups who tend to be more familiar with e-commerce. 59% of the respondents were aged between 18 and 39, while only 22% were 50 years old or above. This indicates that the research results will mainly reflect the behavioral characteristics of digital-active adults. Still, it should be noted that this age structure may limit the generalizability of findings to older or less digitally literate consumer groups.

Regarding education, 59% of the respondents had at least a bachelor’s degree, and another 22% were current university students. This educational concentration may have enhanced respondents’ capacity to process AI-generated information and critically evaluate green claims. This educational concentration may have increased respondents’ ability to process AI-generated information prompts and critically evaluate green claims. However, it also limits the extent to which the findings can be generalized to online food shoppers with lower educational attainment or weaker familiarity with digital decision-support tools. Therefore, the results are most applicable to relatively young, educated, and digitally active online green food consumers.

Regarding consumption patterns, two thirds of respondents allocated 10 to 40 percent of household budgets to food, indicating its importance in total spending. 71% directed 20 to 60 percent of food budgets to products labeled green, showing strong engagement with sustainable choices. AI adoption was high. A total of 53% used AI tools in at least 41% of shopping activities, and 21% used AI in 61 to 80% of purchases. This variation supports tests of how AI-assisted greenwashing detection is associated with TPB pathways and rational online green food consumption.

3.4. Data Analysis Methods

This study used partial least squares structural equation modeling (PLS-SEM) because it is suitable for theory-driven models involving multiple latent constructs, indicators, and mediation paths. Given the complexity of the proposed model, PLS-SEM allows the measurement model and structural associations to be evaluated simultaneously. SmartPLS 4.1.1.2 was used to estimate the measurement and structural models. Artificial neural network (ANN) analysis was then conducted in SPSS 30.0 to examine nonlinear predictive patterns [104]. While PLS-SEM is appropriate for testing hypothesized linear associations, ANN can capture complex nonlinear relationships among predictors [105–107]. Because

ANN has limited interpretability and operates as a “black box” [108], it was used as a supplementary predictive procedure rather than as a substitute for hypothesis testing.

4. Data Analysis Results

This analysis first comprehensively evaluated the structural model. Subsequently, the two-stage PLS-SEM-ANN analysis technique was adopted to evaluate the collected data [109]. Finally, all the analysis results were summarized.

4.1. Measurement Model

Firstly, to assess whether common method bias (CMB) constitutes a substantive threat to the research findings, this study employed confirmatory factor analysis (CFA) to compare the fit of a single-factor model against the theoretically specified multi-factor model. The single-factor model showed poor fit ($\chi^2/\text{df} = 23.839$, RMSEA = 0.192, GFI = 0.341, AGFI = 0.256, SRMR = 0.165, NFI = 0.311, TLI = 0.276, CFI = 0.319), indicating that the covariance structure of the measurement items cannot be adequately explained by a single latent factor. In contrast, the theoretically specified multi-factor model demonstrated good fit ($\chi^2/\text{df} = 4.053$, RMSEA = 0.070, GFI = 0.867, AGFI = 0.845, SRMR = 0.040, NFI = 0.886, TLI = 0.903, CFI = 0.912). The multi-factor model also yielded substantially lower AIC and BIC values than the single-factor model (AIC = 2241.054 vs. 12,699.070; BIC = 2608.587 vs. 13,000.182). As a supplementary check, Harman’s single-factor test indicated that the first unrotated factor accounted for 31.186% of the total explained variance (74.895%), well below the conventional threshold. Taken together, the variance in measurement items is primarily explained by the theoretical constructs rather than dominated by a single method factor.

Secondly, Table 3 shows the structural validity and reliability of the measurement data collection tool. This tool assesses the internal consistency of the items and whether they measure the expected phenomenon structure [110]. Cronbach’s α coefficients range from 0.895 (RA; PE) to 0.953 (SN), which is higher than the traditional standard of 0.70. The composite reliability ranges from 0.898 to 0.955, which further confirms that each indicator can consistently reflect its corresponding construct. In the measurement of convergent validity, the average variance extracted (AVE) of each construct is at least 0.704 (RA, PE, RCI) and at most 0.809 (SN), all well above the threshold of 0.50. This provides a solid foundation for subsequent structural model estimation and hypothesis testing.

Table 3. Construct validity and reliability.

Variable	Cronbach’s Alpha	CR (rho_a)	AVE
Risk Avoidance (RA)	0.895	0.901	0.705
Performance Expectations (PE)	0.895	0.898	0.705
Health Benefits (HB)	0.940	0.943	0.805
Subjective Norm (SN)	0.953	0.955	0.809
Perceived Behavioral Control (PBC)	0.928	0.930	0.735
Rational Consumption Intention (RCI)	0.930	0.933	0.704

Thirdly, discriminant validity was strongly supported by measuring the heterotrait-monotrait (HTMT) ratio (Table 4). Inter-construct HTMT values range from 0.233 for HB–SN to 0.417 for PBC–SN, all below the conservative 0.85 threshold [111]. These low values show that each construct relates more to its own indicators than to others, which lowers risks of redundancy and multicollinearity.

Table 4. The heterotrait-monotrait (HTMT) ratio.

	HB	PBC	PE	RCI	RA	SN
HB	-					
PBC	0.246	-				
PE	0.323	0.384	-			
RCI	0.251	0.365	0.361	-		
RA	0.339	0.244	0.369	0.331	-	
SN	0.233	0.417	0.326	0.334	0.294	-

Fourthly, the Fornell–Larcker matrix confirmed discriminant validity for all latent constructs as shown in Table 5. The square roots of AVE ranged from 0.839 for RA and RCI to 0.899 for SN and exceeded every related inter-construct correlation in the same rows and columns. This shows that each latent variable shared more variance with its own indicators than with other constructs. The Fornell–Larcker criterion was met and the result reinforced earlier HTMT evidence of adequate discriminant validity in the measurement model.

Table 5. The Fornell–Larcker matrix.

	HB	PBC	PE	RCI	RA	SN
HB	0.897					
PBC	0.231	0.858				
PE	0.302	0.352	0.84			
RCI	0.237	0.34	0.338	0.839		
RA	0.314	0.227	0.332	0.304	0.839	
SN	0.224	0.397	0.308	0.316	0.275	0.899

Finally, the R^2 results indicate modest but theoretically meaningful explanatory power for the three endogenous variables. Adjusted R^2 is approximately 0.22 for PBC and RCI, while adjusted R^2 for SN is lower at 0.133. These values suggest that the model captures part of the social-cognitive mechanism underlying rational online green food consumption, but also leaves a substantial proportion of variance unexplained. This limitation is particularly important for SN, because normative pressure in online food consumption may also depend on variables not included in the present model, such as online community norms, social identity, cultural collectivism, family food culture, peer communication, platform trust, and influencer-based recommendation environments. All three endogenous constructs show positive Q^2 values between 0.126 and 0.153, indicating predictive relevance. However, these results should be interpreted as evidence of acceptable model relevance rather than strong explanatory completeness.

4.2. PLS-SEM Path Testing

Bootstrapping with 5000 subsamples tested the hypotheses and evaluated all proposed relationships. Effect size diagnostics using f^2 showed a clear hierarchy of structural effects, as reported in Table 6. The strongest path was from SN to PBC with $f^2 = 0.099$, approaching but below a medium effect. This suggests that subjective norms are meaningfully associated with perceived control in AI-assisted greenwashing detection, although the effect remains modest. PE had small but meaningful effects on PBC with $f^2 = 0.050$ and on SN with $f^2 = 0.048$, indicating that confidence in AI performance raises both perceived control and normative recognition. PBC has a small effect on RCI ($f^2 = 0.031$), while RA has a small effect on SN ($f^2 = 0.028$). All other associations have small effects ($f^2 \leq 0.011$). Overall, the effect-size pattern indicates that performance-related beliefs, subjective norms, and

perceived behavioral control are the most relevant predictors in the current model, whereas risk and health-related motivations show weaker or more indirect associations.

Table 6. Test for direct effects.

Hypothesis	Direct Effect Path	f ²	β	SE	t	p	Lower	Upper	VIF	Result
--	RA $\rightarrow$ SN	0.028	0.170	0.042	4.026	<0.001	0.085	0.249	1.192	Supported
--	RA $\rightarrow$ PBC	0.002	0.045	0.041	1.101	0.271	−0.040	0.123	1.225	Not Supported
H1a	RA $\rightarrow$ RCI	0.024	0.150	0.042	3.543	<0.001	0.064	0.233	1.228	Supported
--	PE $\rightarrow$ SN	0.048	0.220	0.045	4.871	<0.001	0.128	0.306	1.182	Supported
--	PE $\rightarrow$ PBC	0.050	0.220	0.048	4.595	<0.001	0.123	0.310	1.238	Supported
H1b	PE $\rightarrow$ RCI	0.026	0.162	0.045	3.622	<0.001	0.070	0.249	1.300	Supported
--	HB $\rightarrow$ SN	0.011	0.104	0.037	2.781	0.005	0.031	0.176	1.167	Supported
--	HB $\rightarrow$ PBC	0.008	0.083	0.039	2.153	0.031	0.003	0.156	1.179	Supported
H1c	HB $\rightarrow$ RCI	0.005	0.068	0.043	1.576	0.115	−0.015	0.154	1.188	Not Supported
--	SN $\rightarrow$ PBC	0.099	0.298	0.046	6.415	<0.001	0.204	0.386	1.160	Supported
H2d	SN $\rightarrow$ RCI	0.020	0.139	0.041	3.410	0.001	0.060	0.220	1.274	Supported
H3d	PBC $\rightarrow$ RCI	0.031	0.178	0.046	3.830	<0.001	0.090	0.270	1.290	Supported

Furthermore, the assessment of direct effects in Table 6 and Figure 3 confirmed the direct relationships of the variables and clarified the relative strengths of the driving factors for rational green food consumption from the perspective of rejecting greenwashing. All variance inflation factors were far below 1.30, eliminating the problem of multicollinearity. SN served as a key lever as it significantly enhanced PBC ($\beta = 0.298$, $p < 0.001$) and independently increased RCI ($\beta = 0.139$, $p = 0.001$). Therefore, H2d was supported. The impact of PBC on rational consumption intention remained significant ($\beta = 0.178$, $p < 0.001$), confirming the role of personal beliefs. Thus, H3d was supported.

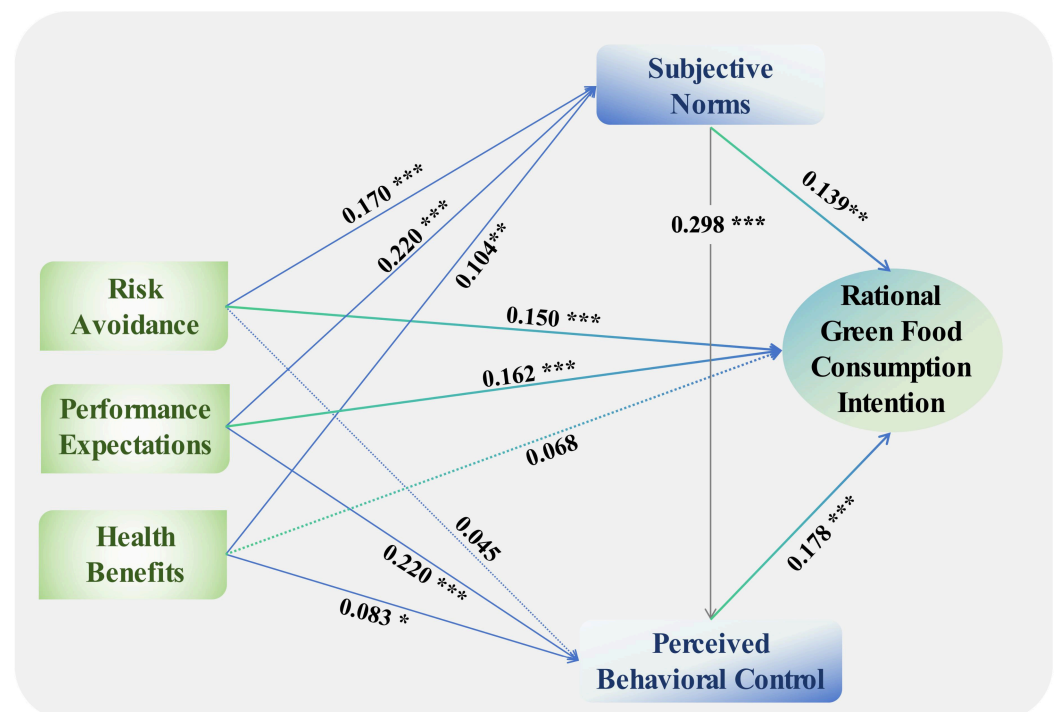


Figure 3. PLS-SEM testing results. Note: * indicates $p < 0.05$; ** indicates $p < 0.01$; *** indicates $p < 0.001$; the dotted line represents the insignificant path.

Among the AI-related factors, PE showed the strongest overall pattern of associations. It was positively associated with PBC and SN (both $\beta = 0.220$, both $p < 0.001$) and was also

directly associated with RCI ($\beta = 0.162, p < 0.001$). Therefore, H1b was supported. RA positively predicted SN ($\beta = 0.170, p < 0.001$) and RCI ($\beta = 0.150, p < 0.001$), supporting H1a. However, RA was not significantly associated with PBC ($\beta = 0.045, p = 0.271$). HB showed small positive associations with PBC ($\beta = 0.083, p = 0.031$) and SN ($\beta = 0.104, p = 0.005$), but its direct association with RCI was not significant ($\beta = 0.068, p = 0.115$). Therefore, H1c was not supported. This result means that HB should not be described as a direct predictor of RCI. Instead, its role is indirect and limited, operating through social and control-related mechanisms.

Meanwhile, the mediation analysis in Table 7 confirms that the SN mechanism is the main pathway through which technology perception is transformed into rational AI-assisted green food purchasing behavior. All three H2 paths are significant. Specifically, RA ($\beta = 0.024, p = 0.008$), PE ($\beta = 0.031, p = 0.004$), and HB ($\beta = 0.014, p = 0.042$) all indirectly influence consumption intention through SN, highlighting the crucial role of social recognition in transforming AI usage perceptions into purchase motivation. PBC mediates the link between PE and intention ($\beta = 0.039, p = 0.004$), thus supporting H3b. In addition, PBC also weakly mediates the relationship between HB and intention ($\beta = 0.015, p = 0.050$), thereby supporting H3c. In contrast, the indirect path from RA to intention through PBC is not significant ($\beta = 0.008, p = 0.312$), so H3a is not supported.

Table 7. Test for mediating effects.

Hypothesis	Indirect Effect Path	β	SE	t	p	Lower	Upper	Result
H2a	RA $\rightarrow$ SN $\rightarrow$ RCI	0.024	0.009	2.65	0.008	0.009	0.045	Supported
H2b	PE $\rightarrow$ SN $\rightarrow$ RCI	0.031	0.011	2.85	0.004	0.013	0.056	Supported
H2c	HB $\rightarrow$ SN $\rightarrow$ RCI	0.014	0.007	2.034	0.042	0.004	0.033	Supported
H3a	RA $\rightarrow$ PBC $\rightarrow$ RCI	0.008	0.008	1.012	0.312	−0.006	0.026	Not Supported
H3b	PE $\rightarrow$ PBC $\rightarrow$ RCI	0.039	0.013	2.896	0.004	0.017	0.072	Supported
H3c	HB $\rightarrow$ PBC $\rightarrow$ RCI	0.015	0.008	1.872	0.050	0.002	0.034	Supported
--	RA $\rightarrow$ SN $\rightarrow$ PBC	0.051	0.015	3.323	0.001	0.025	0.085	Supported
--	PE $\rightarrow$ SN $\rightarrow$ PBC	0.066	0.016	4.073	<0.001	0.038	0.101	Supported
--	HB $\rightarrow$ SN $\rightarrow$ PBC	0.031	0.012	2.545	0.011	0.01	0.059	Supported
--	SN $\rightarrow$ PBC $\rightarrow$ RCI	0.053	0.016	3.343	0.001	0.028	0.09	Supported
H4a	RA $\rightarrow$ SN $\rightarrow$ PBC $\rightarrow$ RCI	0.009	0.003	2.569	0.010	0.004	0.019	Supported
H4b	PE $\rightarrow$ SN $\rightarrow$ PBC $\rightarrow$ RCI	0.012	0.004	2.784	0.005	0.006	0.023	Supported
H4c	HB $\rightarrow$ SN $\rightarrow$ PBC $\rightarrow$ RCI	0.005	0.003	2.186	0.029	0.002	0.013	Supported

The mediation results further show that SN transmits the impacts of these technology perceptions to PBC, which in turn further influences intention. Specifically, the paths through which AI perception motives influence PBC via SN are all significant. The standardized effect of RA is 0.051 ($p = 0.001$), that of PE is 0.066 ($p < 0.001$), and that of HB is 0.031 ($p = 0.011$). Further, SN has a significant indirect effect on RCI through PBC ($\beta = 0.053, p = 0.001$). These paths help explain 22% of the variation in PBC (adjusted $R^2 = 0.220$) and 21% of the variation in intention (adjusted $R^2 = 0.214$), highlighting the crucial position of PBC in the extended TPB chain.

In addition, the chained mediation test clarifies how AI-use motivation constructs shape rational green food purchase intention in an AI environment through social and control mechanisms. In H4, the chained mediation effects through the combined action of SN and PBC are all significant but of a small magnitude. Specifically, among the antecedents, AI-perceived PE shows the largest chained effect (H4b, $\beta = 0.012$), followed by RA (H4a, $\beta = 0.009$) and HB (H4c, $\beta = 0.005$). These findings suggest that confidence in the technical efficacy of AI is the strongest trigger of the normative-control pathway, whereas risk avoidance and health benefits play weaker downstream roles.

4.3. ANN Results

The ANN was implemented as a multilayer perceptron with one hidden layer. The number of hidden nodes was automatically determined by SPSS 30.0 via internal cross-validation. A hyperbolic tangent activation function was applied in the hidden layer and an identity function in the output layer. Training was stopped when the relative change in the training error fell below 0.0001 across consecutive epochs or the maximum number of iterations was reached. The ANN input variables were the latent variable scores derived from PLS-SEM for PE, RA, PBC, SN, and HB, with RCI as the output. Using latent variable scores ensures consistency with the theoretical constructs estimated in the structural model.

This analysis validated the model using ANN and compared its performance with the SEM results. The ANN employed 10-fold cross-validation [112], using approximately 90% of the data in each fold for training and 10% for testing (Table 8). Because absolute SSE depends on the number of observations in each fold, it should not be directly compared between training and testing samples. Mathematically, RMSE is defined as the square root of SSE divided by the number of observations. Therefore, the much smaller testing SSE reflects the smaller testing fold size rather than lower prediction error. To avoid confusion, Table 8 reports SSE per observation as a normalized indicator, while RMSE is retained as the main comparative measure. Across the ten folds, the average training RMSE was 0.146 (SD = 0.006), and the average testing RMSE was also 0.146 (SD = 0.008). The mean per-observation SSE was also comparable between the training and testing folds, indicating no meaningful generalization gap. These results suggest that the ANN captured nonlinear predictive patterns without clear evidence of overfitting.

Table 8. Root mean square error (RMSE) values (Inputs: PE\RA\PBC\SN\HB; Output: RCI).

Neural Network	Training			Testing		
	Samples	SSE/n	RMSE	Samples	SSE/n	RMSE
ANN1	555	0.0192	0.139	64	0.0199	0.141
ANN2	550	0.0220	0.148	69	0.0192	0.139
ANN3	556	0.0203	0.143	63	0.0198	0.141
ANN4	551	0.0207	0.144	68	0.0265	0.163
ANN5	568	0.0205	0.143	51	0.0200	0.142
ANN6	562	0.0212	0.146	57	0.0242	0.156
ANN7	550	0.0224	0.150	69	0.0200	0.142
ANN8	568	0.0234	0.153	51	0.0210	0.145
ANN9	557	0.0247	0.157	62	0.0216	0.147
ANN10	559	0.0200	0.142	60	0.0214	0.146
MEAN		0.0214	0.146		0.0214	0.146
SD		0.0017	0.006		0.0023	0.008

The sensitivity analysis of the neural network model was used to estimate standardized importance scores and to assess the relative contribution of each predictor to RCI. As shown in Table 9, PE exhibits the highest average relative importance (0.297; 29.7%), followed by RA (0.228; 22.8%). PBC and SN form a middle tier, with average relative importance values of 0.189 (18.9%) and 0.163 (16.3%), respectively, while HB exhibits the lowest importance (0.124; 12.4%). In terms of normalized relative importance, PE reaches the highest value (100.0%). RA, PBC, SN, and HB score 78.0%, 65.2%, 55.9%, and 43.0%, respectively. These results indicate that PE is the strongest nonlinear predictor of RCI, followed by RA, whereas HB remains the weakest predictor.

Table 9. Sensitivity analysis (Inputs: PE\RA\PBC\SN\HB; Output: RCI).

Neural Network	PE	RA	PBC	SN	HB
ANN1	0.265	0.237	0.171	0.181	0.146
ANN2	0.338	0.221	0.173	0.203	0.065
ANN3	0.304	0.223	0.171	0.184	0.118
ANN4	0.291	0.254	0.190	0.155	0.110
ANN5	0.367	0.211	0.170	0.136	0.118
ANN6	0.304	0.249	0.196	0.149	0.101
ANN7	0.317	0.219	0.157	0.146	0.162
ANN8	0.264	0.191	0.255	0.182	0.108
ANN9	0.253	0.230	0.220	0.151	0.146
ANN10	0.262	0.242	0.186	0.145	0.165
Average RI	0.297	0.228	0.189	0.163	0.124
Normalised RI	100.0%	78.0%	65.2%	55.9%	43.0%

Table 10 compares evidence from SEM and ANN and supports a robust assessment of the drivers of rational online green food consumption through rejection of greenwashing. The two analysis methods tend to be consistent in the importance hierarchy, but there are slight differences. ANN identifies PE as the strongest predictor of RCI, whereas linear SEM ranks PBC first. This pattern shows that confidence in AI performance is central to resisting greenwashing and promoting rational purchases. In ANN, RA ranks above PBC and SN, while in PLS-SEM its direct path coefficient is smaller. This difference suggests that risk-related responses may involve nonlinear or threshold-like patterns that are not fully captured by linear path estimates. PBC ranks third in the ANN but first in PLS-SEM, indicating that perceived behavioral control has a strong linear effect while also retaining substantial nonlinear predictive importance. SN holds a similar position in both models, which confirms its secondary role. HB is marginal in both analyses and appears limited unless it strengthens social or control beliefs. Taken together, the importance weights show that performance-based confidence is central. They also point to nonlinear effects of risk perception and the need for reliable AI support.

Table 10. SEM and ANN results comparison.

SEM Path	β (PLS-SEM)	ANN Normalised Importance	PLS-SEM Rank	ANN Rank	Remark
PBC $\rightarrow$ RCI	0.178 ***	65.2%	1	3	PBC is the strongest linear driver but carries less weight in the non-linear ANN.
PE $\rightarrow$ RCI	0.162 ***	100.0%	2	1	PE is the dominant predictor in the ANN and a close second in SEM, confirming its centrality.
RA $\rightarrow$ RCI	0.150 ***	78.0%	3	2	RA gains additional salience in the ANN, suggesting threshold or interaction effects.
SN $\rightarrow$ RCI	0.139 **	55.9%	4	4	SN holds a consistent mid-tier position across methods.
HB $\rightarrow$ RCI	0.068 (n.s.)	43.0%	5	5	HB remains the weakest predictor in both analyses.

Note: Ranks are based on the absolute magnitude of the standardized path coefficients; ** indicates $p < 0.01$; *** indicates $p < 0.001$; n.s. indicates $p \geq 0.05$.

5. Discussion

This study examined how AI-assisted tools are associated with consumers' ability to identify and resist greenwashing when purchasing green food online (Table 11). By

combining PLS-SEM and ANN, the analysis captured both theory-driven linear associations and data-driven nonlinear predictive patterns. The findings should be interpreted as correlational evidence from a cross-sectional self-report design rather than as proof of causal effects.

Table 11. Summary of hypothesis testing.

	Path	Key Statistic	Result
DIRECT EFFECTS			
H1a	RA → RCI	$\beta = 0.150, p < 0.001$	Supported
H1b	PE → RCI	$\beta = 0.162, p < 0.001$	Supported
H1c	HB → RCI	$\beta = 0.068, p = 0.115$	Not supported
H2d	SN → RCI	$\beta = 0.139, p = 0.001$	Supported
H3d	PBC → RCI	$\beta = 0.178, p < 0.001$	Supported
SN MEDIATION			
H2a	RA → SN → RCI	$\beta = 0.024, p = 0.008$	Supported
H2b	PE → SN → RCI	$\beta = 0.031, p = 0.004$	Supported
H2c	HB → SN → RCI	$\beta = 0.014, p = 0.042$	Supported
PBC MEDIATION			
H3a	RA → PBC → RCI	$\beta = 0.008, p = 0.312$	Not supported
H3b	PE → PBC → RCI	$\beta = 0.039, p = 0.004$	Supported
H3c	HB → PBC → RCI	$\beta = 0.015, p = 0.050$	Supported
SEQUENTIAL MEDIATION (SN–PBC)			
H4a	RA → SN → PBC → RCI	$\beta = 0.009, p = 0.010$	Supported
H4b	PE → SN → PBC → RCI	$\beta = 0.012, p = 0.005$	Supported
H4c	HB → SN → PBC → RCI	$\beta = 0.005, p = 0.029$	Supported

Performance expectations (PE) showed the most consistent pattern across PLS-SEM and ANN. In PLS-SEM, PE was associated with RCI, SN, and PBC. It also showed significant indirect associations through SN, PBC, and the SN–PBC chain. In the ANN analysis, PE had the highest normalized importance (100%). These results suggest that perceived AI performance is not merely a convenience belief. It is linked to consumers' confidence that digital tools can make green claims more diagnosable and easier to verify. This interpretation is consistent with previous research on AI-assisted decision-making and information processing [113–115]. However, the small f^2 values indicate that PE should be understood as an important but not sufficient condition for rational green food consumption. Its practical relevance depends on whether AI systems provide transparent and usable verification evidence.

Subsequently, in the linear analysis, the direct effect of risk avoidance (RA) on RCI is second only to that of PE, and it has a significant indirect impact by enhancing the subjective norm (SN) and sequential SN–PBC (subjective norm–perceived behavioral control), which is consistent with the conclusion of Carvalho et al. [116]. The ANN analysis further identifies RA as the second largest non-linear influencing factor. This means that when RA exceeds a specific threshold, the consumers' dependence on AI verification tools rises sharply. This indicates that if consumers overestimate the regulatory reliability of green manufacturers, they may inadvertently maintain a market equilibrium with greenwashing [50]. However, RA does not directly affect PBC, suggesting that awareness of greenwashing risk does not automatically translate into a stronger sense of behavioral control.

This non-significant pathway can be understood through risk-coping theory, but the explanation should be treated cautiously. Prior risk research suggests that threat awareness and coping appraisal are not identical: perceiving risk may heighten concern, but it does not necessarily increase perceived capability unless consumers also have sufficient self-efficacy, response efficacy, or usable decision resources. In the present model, RA may capture

the recognition of potential loss more than the perceived competence to manage that loss. Therefore, the model does not provide a fully satisfactory explanation for why RA fails to translate into PBC. Future studies should include AI literacy, response efficacy, digital self-efficacy, trust in AI verification, and perceived diagnosticity to explain this missing link more directly.

In contrast, the perceived health benefits (HB) have a relatively limited but not negligible motivational effect. Although HB has weak positive effects on SN and PBC, its direct impact on RCI is not significant, ranking last in both analytical methods. However, the mediation results show that HB can still influence RCI indirectly through PBC, although this effect is weak and only marginally significant. Thus, HB should be interpreted as an indirect and relatively weak predictor, not as a direct determinant of rational consumption intention. This finding differs from Shimul [117] and suggests that under greenwashing risk, health appeals alone are not persuasive. Health considerations appear to become behaviorally relevant only when reinforced through social recognition and perceived control, rather than operating as an independent motivational force. Verified health claims should be paired with social proof or AI-based visual explanations to strengthen persuasion.

The SN–PBC pathway also requires a more nuanced interpretation. SN showed the strongest direct association with PBC, while PBC had the strongest direct PLS-SEM association with RCI. This pattern suggests that normative expectations may operate not only as social pressure but also as a source of practical confidence. In online green food shopping, family expectations, peer discussions, and community evaluations may provide cues about which claims should be checked and which AI-assisted verification practices are socially legitimate. This interpretation extends Ham et al. [118] and Sun et al. [68] by showing that SN may be linked to RCI partly through perceived control. Nevertheless, the effect sizes remain small to modest, suggesting that social norms and perceived control are relevant but incomplete mechanisms. Platform trust, online community identity, cultural collectivism, and family food culture may further explain why some consumers convert social expectations into a stronger sense of control.

At the same time, the adjusted R^2 values indicate that the model is not comprehensive. The relatively low adjusted R^2 for SN (0.133) suggests that AI-use motivations alone cannot fully explain normative pressure. Online community norms, social identity, cultural collectivism, family food culture, platform trust, and influencer credibility may also shape whether consumers perceive greenwashing avoidance as socially expected. These omitted factors are particularly relevant in online food shopping, where decisions are embedded in both digital platforms and shared cultural meanings.

The ANN results further complement the PLS-SEM findings. PE was the strongest nonlinear predictor, while RA was more salient in ANN than in the linear model. This suggests that consumers' reliance on AI may increase disproportionately when perceived AI usefulness or greenwashing risk reaches a certain level. However, these nonlinear patterns should not be interpreted as causal mechanisms. They only indicate predictive relationships that may involve thresholds or interactions. Overall, the findings suggest that practical recommendations should be tied to the relative strength of PE, SN, PBC, and HB, as discussed in the conclusion.

6. Conclusions

This study examines how AI-assisted tools help consumers identify and resist greenwashing and support rational online purchases of green food. Drawing on information processing theory, the consumer decision-making process model, and the theory of planned behavior, the analysis links motivations to use AI with social cognitive mechanisms involving subjective norms and perceived behavioral control.

The findings contribute to information processing theory (IPT) and the theory of planned behavior (TPB) in two ways. First, subjective norm (SN) was strongly associated with perceived behavioral control (PBC) ($\beta = 0.298$, $f^2 = 0.099$), suggesting that social expectations may strengthen consumers' perceived control in AI-assisted greenwashing detection. Second, performance expectations (PE) showed the strongest nonlinear importance in the artificial neural network (ANN) analysis and significant paths to rational consumption intention (RCI), SN, and PBC, indicating that perceived AI performance is central to evidence-based green food evaluation. In contrast, health benefits (HB) were not directly associated with RCI ($\beta = 0.068$, $p = 0.115$), but only showed weak indirect associations through SN and PBC. This suggests that health-related claims require social recognition and verifiable decision support before they become relevant to rational consumption intention.

The practical implications should be interpreted according to the relative strength of the results. Because PE ranked first in ANN importance and was significantly associated with RCI ($\beta = 0.162$), AI platforms should improve the transparency and diagnostic clarity of greenwashing detection, such as claim-level evidence, confidence scores, and data-source explanations. Because SN showed the strongest structural association with PBC ($\beta = 0.298$; $f^2 = 0.099$), regulators and platforms should strengthen credible social and institutional signals, such as verified labels, expert-endorsed certificates, and AI-readable certification markers. Because PBC was the strongest direct partial least squares structural equation modeling (PLS-SEM) predictor of RCI ($\beta = 0.178$), AI tools should provide actionable verification functions, including certification lookup, claim comparison, and source-quality checks. Because HB was not directly significant and ranked lowest in ANN importance, health claims should not be used as standalone persuasion but should be supported by verifiable evidence.

The link to SDG 12 should also be stated cautiously. The findings provide intention-level evidence that AI-assisted verification may support more responsible consumer decision-making. However, most observed f^2 values were below 0.05, and the study measured purchase intention rather than actual sustainable behavior or environmental outcomes. Therefore, the results indicate potential relevance to SDG 12 rather than direct evidence of SDG 12 impact. Future research should use field experiments, purchase records, or platform A/B tests to estimate whether AI-assisted greenwashing detection reduces greenwashed-product purchases or increases verified green-food choices.

Several limitations remain. First, the cross-sectional self-report design does not support causal inference and may be affected by social desirability and scenario priming. Second, the sample was concentrated among younger, educated, and digitally active consumers, limiting generalizability. Third, the model explains only part of the variance, especially for SN, suggesting that future research should include online community norms, social identity, cultural collectivism, platform trust, and family food culture. Fourth, algorithmic opacity and data bias may cause AI tools to reproduce greenwashing rather than correct it. Future studies should use longitudinal, field experimental, experience-sampling, or behavioral-purchase data to test whether these intention-level associations translate into actual sustainable consumption.

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