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When and how AI personalization drives sustainable purchases: The roles of relevance, privacy, and transparency in eco-friendly advertising

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ABSTRACT

AI-driven personalization uses algorithmic tailoring to deliver content aligned with consumers' preferences. Although prior research suggests that personalized sustainability messages can influence green behavior by enhancing perceived message relevance, the literature has not systematically examined how this relevance pathway is disrupted by privacy concerns or repaired by AI transparency disclosures. Drawing on the Elaboration Likelihood Model, Self-Congruity Theory, and Privacy Calculus Theory, this research conceptualizes perceived message relevance as the key mechanism through which AI-driven personalization promotes sustainable purchase intention. Across two studies, a scenario-based experiment and a time-lagged field survey in China, this research demonstrates that the effect of AI personalization on sustainable purchase intention is mediated by perceived relevance and conditionally moderated by privacy concern and AI transparency. Specifically, privacy concern weakens, and AI transparency strengthens, the personalization–relevance pathway. The findings are robust across experimental and real-world e-commerce contexts and clarify when AI personalization is likely to succeed or fail in motivating sustainable behavior. In particular, relevance emerges as a persuasion route that depends on the presence of ethical and transparent personalization cues. Managerial implications for designing privacy-respectful, transparency-rich personalization strategies in green advertising are presented.

1. Introduction

The use of AI-driven personalization in digital marketing is expanding rapidly, reflecting firms' growing reliance on algorithmic systems to deliver content that is more relevant, persuasive, and tailored to individual consumers (Aguirre et al., 2015; Bleier and Eisenbeiss, 2015). Global investment in AI-enabled customer engagement is projected to exceed USD 632 billion by 2028 (FutureCIO, 2024), while the global green economy is expected to surpass USD 14 trillion by 2030 (Climate Crisis 247, 2025). These transformations intersect around a critical challenge: although nearly two-thirds of consumers express environmental concern, fewer than one-quarter consistently act on these concerns when making purchases (White et al., 2019). Personalization has been advanced as a means of narrowing this "attitude–behavior gap" by enhancing the self-relevance of sustainability messages and strengthening alignment with consumers' values (Theocharis and Tsekouropoulos, 2025). Yet this promise is tempered by intensifying concerns about data surveillance, algorithmic opacity, and manipulation (Lee et al., 2025). Recent surveys reveal that almost 70 % of consumers regard AI-driven personalization as a privacy risk (Fazlioglu, 2024), and emerging studies show that perceived intrusion can diminish persuasion even when targeting appears accurate (Yeo et al., 2025; Kim et al., 2024). This tension, between enhanced relevance and perceived intrusion, creates both a strategic dilemma for practitioners and an unresolved theoretical puzzle for researchers (Sundar, 2020).

The dilemma is acute in green advertising, where persuasion depends on both personal relevance and collective motives such as altruism and environmental responsibility (Leonidou and Skarmeas, 2017; White et al., 2019). Unlike conventional appeals, eco-messages face heightened skepticism and concerns about greenwashing (Schmuck et al., 2018; Munir and Mohan, 2022). As a result, AI-driven personalization in this domain must meet a stricter threshold: it must simultaneously enhance message relevance and establish the authenticity of prosocial intent. When these conditions are not met, even strong environmental concern may fail to translate into purchase behavior. Credibility signals, such as third-party eco-labels and clear transparency

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disclosures, are therefore critical, as they validate altruistic appeals, shift attributions away from manipulation, and reduce suspicion (Wang and Qiu, 2024; Sanchez-Chaparro et al., 2024; Wulf and Seizov, 2024). Accordingly, personalization in green advertising requires both psychological congruence and ethical legitimacy to be persuasive.

Prior research identifies perceived message relevance as the central route through which personalization shapes consumer responses (Aguirre et al., 2015; Bleier and Eisenbeiss, 2015; Alhelaly et al., 2025). Consistent with the Elaboration Likelihood Model (Petty and Cacioppo, 2012), relevance motivates deeper processing, and value-congruent messages in green contexts have been shown to promote pro-environmental behavior (Schmuck et al., 2018). Yet several gaps remain unresolved. First, although the ELM specifies both central and peripheral routes, prior research has disproportionately emphasized heuristic cues such as eco-labels, algorithmic badges, or brand credibility, often explaining personalization outcomes through shortcuts rather than systematic elaboration (Sundar, 2020; Veeramani et al., 2025). By contrast, limited attention has been given to isolating perceived message relevance as the central mediator, particularly in sustainability advertising.

Second, privacy concerns have often been modeled as a direct inhibitor of personalization effectiveness (Malhotra et al., 2004). Emerging findings suggest, however, that it directly weakens the relevance–persuasion pathway itself, reducing acceptance of messages that would otherwise be congruent (Alhelaly et al., 2025; Kim et al., 2024). Third, while transparency disclosures are theorized to restore trust, little is known about whether they also strengthen perceived relevance by clarifying why personalization fits the consumer (Wulf and Seizov, 2024). This mechanism is particularly important in green advertising, where credibility thresholds are elevated and claims are scrutinized for authenticity (Schmuck et al., 2018). Fourth, empirical evidence on AI-driven personalization remains concentrated in Western contexts. Far fewer studies have examined markets such as China, where consumers frequently encounter personalization within super-app ecosystems (e.g., WeChat, Taobao) and operate under distinct cultural expectations and regulatory environments (Lee, 2025; Li et al., 2025). Whether the relevance–privacy–transparency dynamics observed in Western markets generalize to, or diverge within, China is not yet clear. Finally, many studies assume a direct effect of personalization on purchase intention; less attention has been given to when and why this effect attenuates, especially in green advertising, where credibility and ethical legitimacy are central. Accordingly, the present study focuses on the relevance-based (central) pathway linking AI personalization to sustainable purchase intention, while acknowledging that heuristic and peripheral cues represent complementary avenues for future research.

Building on these gaps, this study investigates how AI-driven personalization influences sustainable purchase decisions by treating perceived message relevance as the central pathway and privacy concern and AI transparency as boundary conditions. Drawing on the Elaboration Likelihood Model (Petty and Cacioppo, 2012), Self-Congruity Theory (Sirgy, 1982), and Privacy Calculus Theory (Culnan and Armstrong, 1999), we develop a conditional-process framework that links persuasion, identity, and trust in green advertising. The ELM highlights how personalization enhances relevance and motivates deeper processing, Self-Congruity explains why relevance matters through alignment with environmental identity, and Privacy Calculus accounts for the trade-offs consumers make between personalization benefits and perceived risks. Within this framework, we examine whether personalization increases sustainable purchase intention via message relevance, whether privacy concern weakens this relevance mechanism, and whether transparency disclosure restores legitimacy by clarifying how data are used (Malhotra et al., 2004; Wulf and Seizov, 2024; Veeramani et al., 2025). To test these propositions, we conduct two complementary studies: a scenario-based experiment in China that isolates causal effects and a three-wave field survey of e-commerce consumers that validates the model in real-world settings.

Finally, this investigation makes several contributions. Theoretically, it demonstrates how ethical and trust-related cues reshape the effectiveness of personalization in green advertising, adding nuance to persuasion research by explaining why personalization alone does not directly predict purchase intention. Methodologically, it introduces rare longitudinal evidence from China's AI-intensive marketplace, addressing calls for greater contextual diversity in AI and consumer behavior research (Yin et al., 2025). Practically, it offers guidance for marketers seeking to design personalization strategies that enhance relevance while safeguarding privacy and legitimacy, and for policymakers striving to create governance frameworks that support explainable, trust-preserving AI. Collectively, these contributions refine theory, broaden empirical foundations, and provide a roadmap for narrowing the sustainability attitude–behavior gap without compromising consumer autonomy.

2. Theoretical background and research hypotheses

2.1. Underpinning theories

2.1.1. Persuasion and identity foundations: ELM and Self-Congruity Theory

The Elaboration Likelihood Model (ELM) explains attitude change through two cognitive routes: a central route, characterized by systematic processing based on message relevance, and a peripheral route, where individuals rely on surface heuristics when motivation or ability is limited (Petty and Cacioppo, 1986, 2012). Within this study, AI-driven personalization functions as the design lever that heightens perceived message relevance, thereby engaging the central processing route that shapes sustainable purchase intention when sustainability claims are viewed as personally diagnostic (Aguirre et al., 2015; Bleier and Eisenbeiss, 2015; Schmuck et al., 2018). The Self-Congruity Theory complements this perspective by explaining why the central-route mechanism is particularly influential in sustainability contexts: when messages align with consumers' environmental and moral self-concepts, the resulting congruity intensifies cognitive importance, facilitating value-driven evaluation and intention formation (Sirgy, 1982; White et al., 2019; Essiz and Senyuz, 2024). Because green appeals explicitly invoke altruistic and collective motives alongside self-interest, our tests situate personalization effects within eco-specific credibility thresholds rather than generic advertising contexts.

Eco-claims, unlike conventional product appeals, are credence-based, requiring consumers to infer authenticity through both personal values and institutional signals such as eco-labels and audits. These features heighten skepticism and conditional trust, making the credibility of cues a prerequisite for persuasion (Leonidou and Skarmeas, 2017; Schmuck et al., 2018). Within AI interfaces, machine heuristics—the tendency to perceive algorithmic outputs as objective and efficient—can also shape acceptance without elaboration or, conversely, elicit concern when perceived as intrusive (Sundar and Kim, 2019; Sundar, 2020). Consistent with Sundar's account, we acknowledge machine-heuristic influences as plausible peripheral routes in AI advertising; however, our design purposefully minimizes such cues to isolate the theoretically primary relevance mechanism. To isolate the theoretically relevant mechanism, the study explicitly focuses on the central route, controlling or omitting peripheral affordances such as brand badges or algorithmic icons in Study 1. Study 2 acknowledges that naturalistic platforms incorporate peripheral signals, yet it treats them as background conditions while foregrounding the personalization → relevance → intention pathway as the primary explanatory process for narrowing the green attitude–behavior gap.

2.1.2. Risk–benefit evaluation: Privacy Calculus Theory and transparency

The Privacy Calculus Theory conceptualizes consumer evaluation of AI-based personalization as a trade-off between perceived benefits, such as usefulness, fit, and convenience, and perceived risks, including surveillance and data misuse. Within this framework, privacy concerns represent a context-sensitive appraisal that fluctuates with the salience of design and data-handling cues, rather than a fixed trait (Culnan and Armstrong, 1999; Malhotra et al., 2004). In AI-mediated advertising, heightened perceptions of privacy risk redirect attention from message content to data governance, thereby reducing perceived relevance and weakening persuasion, even when targeting accuracy is objectively high (Bleier and Eisenbeiss, 2015; Yeo et al., 2025; Alhelaly et al., 2025). Conversely, AI transparency disclosure, defined as reason-giving and plain-language disclosure explaining why a message fits and how user data inform personalization, restores perceived fairness, control, and diagnosticity, enabling consumers to remain focused on message utility and mitigating psychological reactance (Shin and Park, 2019; Krafft et al., 2021; Wulf and Seizov, 2024; Wang and Qiu, 2024).

Sustainability messaging is inherently legitimacy-dependent, requiring consumers to reconcile moral motives with skepticism arising from concerns about greenwashing (Schmuck et al., 2018; Munir and Mohan, 2022). In such contexts, privacy risk and transparency are not secondary message cues, but rather governance boundary conditions that determine whether algorithmic personalization is perceived as authentic, prosocial, or manipulative. The theoretical integration adopted here assigns non-redundant roles: ELM specifies how personalization fosters deep processing through relevance; Self-Congruity explains why identity-consistent relevance is central in green persuasion; and Privacy Calculus identifies when governance appraisals enable or constrain that process. Our contribution is to model privacy concern as a boundary on the *entire* indirect pathway (personalization → relevance → intention) and to specify transparency as the complementary enabler that restores this central-route mechanism in green advertising. Peripheral and machine-heuristic influences are acknowledged as contextual scope conditions, while the central route remains the most theoretically appropriate explanatory mechanism for credence-laden, prosocial green decisions.

2.2. AI-driven personalization and sustainable purchase intention

AI-driven personalization is the automated tailoring of marketing messages using predictive algorithms that adjust content in real time to individual behavioral and contextual data (Jayapal, 2025; Chandra et al., 2022). By increasing perceived personal relevance, personalization can motivate consumers to process messages more deeply and strengthen behavioral intentions (Aguirre et al., 2015; Schmuck et al., 2018). In sustainability advertising, this mechanism is particularly important because consumers often express pro-environmental values yet fail to act consistently, the so-called attitude–behavior gap.

When environmental messages are personalized, they become more concrete and self-relevant, encouraging deliberate evaluation and favorable responses (Aguirre et al., 2015; Schmuck et al., 2018). Alignment with environmental identity further reinforces authenticity and intention, as consumers perceive the appeal as consistent with their values (White et al., 2019; Essiz and Senyuz, 2024). Personalization thus transforms abstract ecological benefits into tangible outcomes (e.g., highlighting household energy savings), which increases perceptions of fit and mobilizes values into purchase behavior (Cenizo, 2025; Chandra et al., 2022; Yeo et al., 2025).

Despite enduring credibility concerns in green advertising, higher levels of personalization are expected to raise sustainable purchase likelihood, as they channel attention to message substance and enhance perceived authenticity. Yet, robust evidence of this direct link remains sparse, especially in data-intensive markets like China. In these contexts, consumers are embedded within highly integrated digital commerce environments, where personalized content is pervasive and entwined with both social and retail channels (Cenizo, 2025). These settings differ markedly from Western norms in terms of trust formation and regulatory expectations, underscoring the importance of analyzing personalization's effect on sustainability behaviors in such unique digital ecosystems (Yin et al., 2025; Lee et al., 2025). Consistent with the theoretical rationale above, we posit that:

H1. Higher levels of AI-driven personalization in eco-friendly product ads are positively associated with consumer sustainable purchase intention.

2.3. Mediating role of perceived relevance

Perceived relevance refers to a recipient's judgment that a message aligns with their personal circumstances, interests, or self-concept, thereby shifting message processing from cursory scanning to more effortful evaluation (Jung, 2017; Chen et al., 2025; Yeo et al., 2025). Personalized appeals enhance this judgment by signaling diagnostic fit (i.e., "this is for me"), and higher perceived relevance, in turn, has been shown to strengthen purchase intention (Yeo et al., 2025; An and Ngo, 2025). Compared with static segmentation, AI-enabled personalization continuously recalibrates content fit based on behavioral and contextual inputs, reinforcing the perception that the message is personally meaningful (Teepapal, 2025). In sustainability-related product categories, many consumers endorse environmental values but hesitate to purchase when claims appear generic or distant (White et al., 2019; Schmuck et al., 2018). Tailoring strategies help overcome this barrier by translating abstract ecological benefits into concrete, self-relevant outcomes (e.g., energy savings from short, cold washing cycles), which enhances perceptions of authenticity and mobilizes values into action (Fens et al., 2022; Foroughi et al., 2025). Because green appeals often emphasize altruistic and collective benefits, consumers apply higher credibility thresholds; framing that highlights personal relevance is therefore pivotal for persuasion (Schmuck et al., 2018).

Although prior studies show that personalization can shape consumer intention (e.g., An and Ngo, 2025; Yeo et al., 2025), few have specified perceived relevance as the central mechanism in green advertising. Much prior work emphasizes peripheral cues like eco-labels or credibility signals (Sundar and Kim, 2019; Schmuck et al., 2018), overlooking how relevance drives persuasion under higher scrutiny in sustainability contexts (White et al., 2019). Recent findings also indicate that this pathway depends on perceptions of legitimacy: transparent and respectful data use sustains attention on message merits, while opaque or intrusive practices weaken the translation of relevance into intention (Sanchez-Chaparro et al., 2024; Wulf and Seizov, 2024; Chen et al., 2025). This underexplored conditionality clarifies when the central route holds in AI-personalized eco-ads. Therefore, we hypothesize that:

H2. Perceived relevance of the sustainable message mediates the relationship between AI-driven personalization and sustainable purchase intention.

2.4. Moderating role of privacy concern

Privacy concern, the belief that algorithmic data collection and use threaten one's autonomy, control, or security, has become increasingly central as firms expand AI-driven targeting (Chen et al., 2025; Li et al., 2025). In principle, personalization enhances perceived fit and, with it, perceived relevance; individuals devote greater cognitive effort to messages that feel "for me," thereby increasing the likelihood of intention change (An and Ngo, 2025; Yeo et al., 2025). Yet this favorable trajectory remains fragile. When privacy concern is salient, the same cues that signal fit may be reinterpreted as evidence of surveillance or manipulation, diverting attention from message merits and undermining the relevance pathway (Sanchez-Chaparro et al., 2024; Alhelaly et al., 2025).

This dynamic reflects how individuals weigh the benefits of tailored information against perceived risks of exposure: when risks dominate, attention to message merits declines, and elaboration gives way to defensive processing. Two boundary conditions intensify this effect. First, data sensitivity matters: inferences drawn from location, cross-device tracking, or long-run browsing histories provoke resistance among privacy-sensitive individuals, weakening attention to core claims and the sense of fit (Kim et al., 2024). Second, perceived opacity matters: when systems are seen as “black boxes,” people report lower control and stronger reactance, further undermining relevance gains (Li et al., 2025).

In sustainability advertising, legitimacy thresholds are structurally higher because appeals characteristically invoke altruistic and collective outcomes and are judged against a backdrop of skepticism about corporate environmental claims. Under these conditions, privacy concern operates as a particularly diagnostic factor: when audiences infer that an eco-appeal is assembled from sensitive or opaque data, a message that otherwise appears well matched can be discounted as opportunistic or greenwashed. This weakens trust, compresses perceived relevance, and reduces downstream purchase intentions (Schmuck et al., 2018; White et al., 2019). Therefore, we propose:

H3. Privacy concern moderates the relationship between AI-driven personalization and perceived relevance, such that the positive effect is weaker for consumers with high privacy concern.

2.5. Moderating role of AI transparency disclosure

AI transparency disclosure refers to providing clear and comprehensible information about how consumer data informs the tailoring of a message (Wulf and Seizov, 2024). By making data use intelligible, disclosure enhances perceptions of control and fairness, shifts attribution from covert surveillance to diagnostic alignment, and sustains the sense that a message genuinely fits the recipient (Hosseini Tabaghdehi and Ayaz, 2025). When such explanations are absent or overly complex, recipients focus on data practices rather than message content, discounting even accurate tailoring (Shin and Park, 2019; Lim and Kim, 2025). In this way, disclosure preserves the central relevance-based pathway by ensuring that attention remains on message merits and that elaboration is directed toward evaluating informational value.

This mechanism is especially critical in sustainability advertising, where credibility thresholds are elevated and audiences are vigilant for signs of manipulation or greenwashing. Short “why you are seeing this” explanations legitimize the tailoring process, encouraging recipients to interpret personalization as authentic and cooperative rather than extractive (Sanchez-Chaparro et al., 2024; Schmuck et al., 2018). Such explanations also reinforce identity alignment by clarifying why a message is relevant, thereby strengthening the perception that the appeal is consistent with one’s pro-environmental goals and increasing the likelihood that relevance translates into intention (Jin, 2025).

Most prior work examines transparency as a direct driver of trust or acceptance (Shin and Park, 2019; Wulf and Seizov, 2024; Wang and Qiu, 2024), but rarely as a moderator of the relationship between personalization and relevance. This gap is important in AI-personalized green advertising, where plain-language disclosures are both practical and consequential. Recognizing transparency as a boundary condition clarifies not only how personalization works, through perceptions of fairness, authenticity, and perceived control, but also where it matters most, namely in high-skepticism, ethics-salient contexts. Accordingly, we hypothesize:

H4. AI transparency disclosure moderates the relationship between AI-driven personalization and perceived relevance, such that the positive effect is stronger when AI transparency disclosure is high.

2.6. The role of privacy concerns in mediating paths

AI-enabled personalization is designed to enhance perceived fit, prompting recipients to transition from cursory scanning to deeper evaluation and, ultimately, stronger purchase intentions (Aguirre et al., 2015; Chandra et al., 2022). This process, however, depends on how individuals appraise the data practices that produced the fit. When data use is perceived as safe and controllable, attention remains on the informational value of the message, allowing perceived relevance to translate into intention (Colucci et al., 2025). Conversely, when data practices are viewed as risky or opaque, attention shifts from message merits to privacy concerns, increasing skepticism and weakening the relevance pathway (Zaman, 2025; Chen et al., 2025; Bleier and Eisenbeiss, 2015). Recent meta-analytic evidence confirms that perceived intrusiveness consistently reduces personalization effectiveness (e.g., Yeo et al., 2025), and field as well as lab studies show that loss-of-control cues, such as cross-device or location tracking, undermine persuasion by disrupting systematic evaluation (Xu et al., 2025). Neurocognitive research further indicates that privacy-invasive cues trigger heightened threat monitoring and reduced elaboration, patterns incompatible with the relevance-based route that personalization seeks to activate (Kokolakis, 2017). These dynamics are particularly salient in sustainability advertising, where eco-claims are judged under heightened legitimacy thresholds. When consumers perceive that an appeal relies on sensitive or opaque data, they often discount the alignment as engineered rather than authentic, weakening its impact on purchase intention (Schmuck et al., 2018; White et al., 2019). Evidence shows that hyper-personalized ads based on sensitive signals are especially penalized by privacy-sensitive audiences (Bleier and Eisenbeiss, 2015).

Prior research has largely modeled privacy concern as a direct inhibitor of advertising effectiveness or as a first-stage moderator dampening the personalization-fit link (Bleier et al., 2019; Kim et al., 2024). Less attention has been given to privacy concerns as a boundary on the *entire indirect pathway*, limiting both the recognition of relevance and the legitimacy of translating that relevance into intention (Shin and Park, 2019; Yeo et al., 2025). This omission is critical in AI-personalized sustainability appeals, where credibility thresholds are high and consumers remain alert to manipulation risks such as greenwashing (Munir and Mohan, 2022; Mansoor et al., 2025). By clarifying how risk appraisals disrupt mediation at multiple stages, this study addresses an important theoretical gap. Accordingly, we hypothesize:

H5. The indirect effect of AI-driven personalization on sustainable purchase intention through perceived relevance is weaker when privacy concerns are high.

2.7. The role of AI transparency disclosure in mediating paths

Transparent disclosures help preserve the central, relevance-based route of persuasion. When consumers are informed about why a message is tailored to them and how their inputs influenced the offer, they attribute personalization to identifiable reasons rather than opaque surveillance, keeping their attention focused on the message’s merits and encouraging effortful evaluation that supports their intention (Petty and Cacioppo, 2012; Krafft et al., 2021; Shin and Park, 2019). In sustainability appeals, such reasons-based clarity also sustains authenticity, as alignment with a pro-environmental self-view is perceived as genuine rather than contrived, thereby reinforcing persuasion under heightened scrutiny of legitimacy (White et al., 2019; Schmuck et al., 2018). Moreover, by signaling procedural fairness and user agency, disclosure shifts appraisal from data opacity to informational value, dampening suspicion that would otherwise displace relevance with defensive processing (Culnan and Armstrong, 1999; Wulf and Seizov, 2024).

Prior work largely models transparency as a main-effect booster of trust or fairness or as a generic safeguard against manipulation. Rarely is transparency theorized and tested as a second-stage condition that strengthens the indirect pathway from personalization to purchase intention via perceived relevance, precisely where central processing must hold in green advertising. This omission is consequential: without understanding why the ad fits, perceived relevance remains fragile and easily overshadowed by privacy-based suspicions, particularly in eco-claims where credibility thresholds are high (Yeo et al., 2025; Sanchez-Chaparro et al., 2024; Schmuck et al., 2018). To address this gap, we specify three reinforcing channels by which disclosure can amplify relevance-based persuasion. First, disclosure increases diagnosticity, which strengthens perceived relevance (Krafft et al., 2021; Shin and Park, 2019). Second, it enhances the authenticity of self-alignment, helping perceived relevance translate into purchase intention (Jin, 2025; White et al., 2019). Third, it conveys fairness and agency, which keeps cognitive focus on message merits (Culnan and Armstrong, 1999; Wulf and Seizov, 2024). Drawing from these insights, we suggest that:

H6. The indirect effect of AI-driven personalization on sustainable purchase intention through perceived relevance is stronger when AI transparency disclosure is high.

3. Method

3.1. Overview of the studies

Fig. 1 illustrates the two-study design. Study 1 employed a scenario-based experiment to test the direct effect of AI-driven personalization on sustainable purchase intention (H1), the mediating role of perceived message relevance (H2), and the moderating roles of privacy concern and AI transparency disclosure (H3–H4). Participants were randomly assigned to high- or low-personalization ad conditions, following guidelines for realistic and orthogonal manipulations with checks (Aguinis and Bradley, 2014). Study 2 extended the inquiry to the field using a three-wave survey of online shoppers in first-tier Chinese cities (e.g., Shanghai, Beijing). Wave 1 measured exposure to AI-personalized sustainability ads and relevance; Wave 2, two weeks later, assessed privacy concern and AI transparency disclosure; Wave 3, another two weeks later, measured sustainable purchase intention and online shopping frequency (control). The time lags reduced common-method bias and established temporal order (Podsakoff et al., 2003). All scales were adapted from established research on personalization, privacy calculus, and sustainability advertising, and were translated using Brislin's (1980) back-translation procedure. Ethics approval and informed consent were obtained. Hypotheses H1–H6 were tested with PROCESS Macro v4.0 (Hayes, 2017) to estimate direct, mediating, moderating, and conditional process effects.

4. Study 1

4.1. Sampling and procedure (study 1)

To establish causal evidence for the effects of AI-driven personalization on perceived message relevance and sustainable purchase intention, we conducted a controlled, scenario-based experiment using face-to-face and self-administered questionnaires. This mode afforded tight experimental control and ensured full engagement with the scenario regardless of prior familiarity with digital advertising (Aguinis and Bradley, 2014). The sample was drawn from second-tier cities in Eastern China (e.g., Hangzhou, Ningbo), economically vibrant regions with rapid e-commerce growth that differ from heavily studied first-tier centers. Studying second-tier markets illuminates how digital innovations diffuse beyond early adopters (Akter and Wamba, 2016; Yin et al., 2025).

A total of 350 paper questionnaires were distributed via trained research assistants in community centers, local markets, and educational institutions; 305 were returned. After screening out five cases (due to incomplete responses or failed attention checks), the final sample consisted of 300 participants. Eligible participants were aged 18 or above. We did not screen based on online purchasing history because the scenario standardized exposure to AI personalization, consistent with advertising experiments that prioritize realism and comprehension (Aguirre et al., 2015; Schmuck et al., 2018).

Participants viewed one static, brand-neutral product card for an eco-friendly laundry detergent that mirrored a common e-commerce layout (single product image, brief claim, price, and a "Buy Now" call-to-action). No brand name, third-party seals, or AI/privacy icons were shown to minimize peripheral cues. In the low-personalization condition, the card presented a neutral headline (e.g., "Eco-friendly laundry detergent"), bottle copy reading "Plant-based laundry detergent • Cold-wash efficacy • Biodegradable formula," a price of "¥29.90/1.0 L," and the "Buy Now" button, with no personal data cues. In the high-personalization condition, the card was identical except for a single top strip referencing the participant's given name, district-level location, and a generic prior-purchase cue (e.g., "Hi Li Wei, popular in Xuhui. People like you recently bought eco detergent."). Holding all other elements constant, we isolated personalization intensity while controlling for brand, design, and heuristic signals. Reference mock-ups of both versions are provided in the Appendix (Figures A1 and A2).

Immediately after exposure, respondents completed a structured questionnaire including a personalization manipulation check ("I feel this advertisement was tailored specifically for me") and a three-item realism check adapted from Baek and Morimoto (2012). All measures were double-translated using Brislin's (1980) back-translation procedure. Research assistants provided neutral clarifications as needed. Attention-check items and minimum-time flags were used during data entry; Harman's single-factor test indicated common-method variance was not a concern (Podsakoff et al., 2003). All participants provided

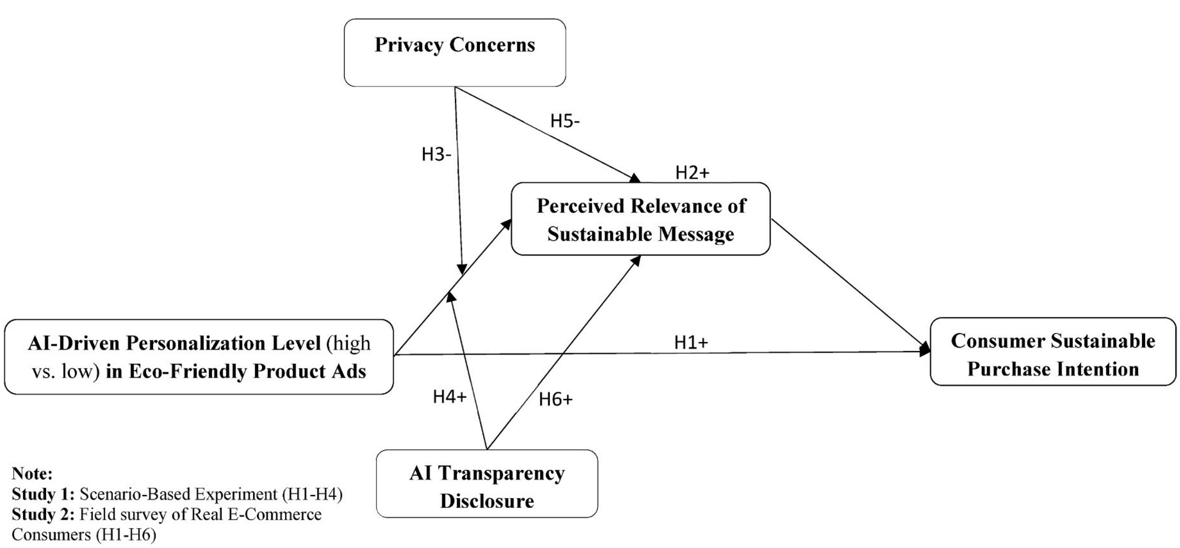

Fig. 1. Theoretical framework.

informed consent and received a modest token consistent with local norms.

4.2. Measures (study 1)

All constructs were measured using validated multi-item scales adapted to AI-driven personalization in green advertising. Unless otherwise specified, items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). All items were translated into Mandarin Chinese and back-translated to ensure linguistic equivalence (Brislin, 1980). The independent variable, AI personalization level, was operationalized as an experimental manipulation. Participants were randomly assigned to either a high- or low-personalization version of an eco-friendly detergent advertisement, which differed only in the presence of personal data cues (Aguirre et al., 2015). A single-item manipulation check was used to verify perceived tailoring ("I feel this advertisement was tailored specifically for me"). Perceived message relevance, the proposed mediator, was defined as the extent to which participants found the advertisement personally meaningful (Aguirre et al., 2015; Bleier and Eisenbeiss, 2015; Yeo et al., 2025). It was measured with four items (e.g., "The information in this ad is relevant to me"), which demonstrated good reliability (α = .897). The dependent variable, sustainable purchase intention, was measured using three items adapted from Chen and Chang (2012) and Schmuck et al. (2018) (e.g., "I would consider buying this eco-friendly product"), with a reliability coefficient of α = .875. The first moderator, privacy concern, was assessed using three items that reflected discomfort with online data collection (Malhotra et al., 2004; Chen et al., 2025; e.g., "I worry about my personal information being collected online"), and demonstrated strong reliability (α = .860). The second moderator, AI transparency disclosure, was measured with three items evaluating the clarity of company explanations of data use (Shin, 2021; Sundar and Kim, 2019; Wulf and Seizov, 2024; e.g., "The company explains clearly how AI is used to personalize ads"), which also showed good reliability (α = .832). Finally, scenario plausibility was assessed using a three-item realism check adapted from Baek and Morimoto (2012), confirming that the advertisement was perceived as realistic (α = .700). An instructional manipulation check was also embedded to identify inattentive respondents (Oppenheimer et al., 2009).

Control Variables: We initially considered gender, age, and education as controls (Bleier and Eisenbeiss, 2015; Malhotra et al., 2004). As shown in Table 1, none of these demographics significantly correlated with perceived relevance or purchase intention (ps > .05), so we omitted them from the main models to avoid over-control (Becker et al., 2016). Results are unchanged when all demographics are included (robustness available on request).

4.3. Results

4.3.1. Measurement, manipulation, realism, and validity checks

Prior to hypothesis testing, we assessed manipulation, realism, reliability, and validity. Realism checks confirmed that participants perceived the scenario as believable, with all items scoring significantly above the neutral midpoint of 3.00: "similar to what I might see online" ($M = 4.32$, t (299) = 22.89, $p < .001$), "the product seems believable" ($M = 4.29$, t (299) = 23.44, $p < .001$), and "the situation could happen to me" ($M = 3.96$, t (299) = 13.41, $p < .001$). A personalization check showed that participants in the high-personalization condition reported significantly higher perceived personalization than those in the low condition (t (298) = 5.09, $p < .001$), confirming the success of the manipulation (Aguinis and Bradley, 2014).

The measurement model exhibited strong reliability and validity. Cronbach's α and CR values for all constructs exceeded .80, and AVE values were above .50, supporting convergent validity (Hair et al., 2019). Discriminant validity was established using the Fornell–Larcker criterion, as the square root of each construct's AVE exceeded inter-construct correlations (Fornell and Larcker, 1981). Correlations were in expected directions, with AI-driven personalization positively associated with perceived relevance ($r = .198$, $p < .001$) and purchase intention ($r = .138$, $p < .001$). Among demographics, only education correlated with relevance ($r = -.239$, $p < .001$), so it was retained as a covariate (Becker et al., 2016). The CFA results further supported construct validity, with excellent model fit indices (χ^2/df = 1.287, RMSEA = .031, CFI = .993, TLI = .990, GFI = .964, AGFI = .942). These results confirm robust reliability, convergent and discriminant validity, and appropriate manipulations for subsequent hypothesis testing (Podsakoff et al., 2003).

4.3.2. Hypotheses testing

Table 2 reports tests of the direct, mediating, and moderating paths estimated with PROCESS v4.0 using 5000 bootstrap resamples (Hayes, 2017). The direct effect of AI-driven personalization on sustainable purchase intention was positive but nonsignificant, β = .132, SE = .153, t = .868, 95 % CI [–.168, .432]; thus, H1 was not supported. Consistent with H2, AI-driven personalization significantly increased perceived message relevance, β = .344, SE = .152, t = 2.27, p < .05, 95 % CI [.045, .642], and perceived relevance significantly predicted purchase intention, β = .297, SE = .058, t = 5.13, p < .001, 95 % CI [.183, .411]. The indirect effect of personalization on purchase intention via perceived relevance was significant (indirect effect = .102, 95 % CI [.023, .196]), indicating full mediation in line with the Elaboration Likelihood Model (Petty and Cacioppo, 1986).

For H3, the interaction of personalization × privacy concern on relevance was negative and significant, interaction = −.805, SE = .165, t = −4.897, 95 % CI [−1.129, −.482], $\Delta R^2 = .065$, p < .001. Conditional

Table 1
Construct reliability, validity, descriptive statistics, and correlations (study 1).

	1	2	3	4	5	6	7	8	Mean	SD	CR	AVE	MSV	α
1. AI Transparency disclosure	**.814**	.069	−.071	.039	.135*	.011	−.146*	.059	4.198	.845	.851	.663	.013	.832
2. Purchase Intention	–	**.844**	.323**	.041	.138*	−.045	.003	−.177**	2.073	1.067	.880	.712	.130	.875
3. Perceived Relevance	–	–	**.827**	.313**	.198**	−.038	−.073	−.239**	2.028	1.046	.896	.683	.132	.897
4. Privacy Concerns	–	–	–	**.830**	−.116*	.010	.000	−.124*	1.844	.954	.865	.684	.132	.860
5. AI-Driven Personalization (0 = Low; 1 = High)	–	–	–	–	1	−.025	−.012	−.327**	.790	.407	.851	.663	.013	–
6. Gender [a]	–	–	–	–	–	1	.000	−.007	1.413	.524	–	–	–	–
7. Age [b]	–	–	–	–	–	–	1	.041	2.463	1.280	–	–	–	–
8. Education [c]	–	–	–	–	–	–	–	1	2.656	1.343	–	–	–	–

Notes: n = 300; SD: Standard deviation; AVE: "Average Variance Extracted"; α = Cronbach's alpha; MSV: "Maximum Shared Variance"; CR: "Composite Reliability"; significance: *p < .01; **P < .05. Bold data: square root of AVE; Model Fit: CMIN/DF = 1.287; GFI = .964; AGFI = .942; CFI = .993; TLI = .990; RMSEA = .031.

[a] **Gender**: 1 = Male; 2 = Female; 3 = Prefer not to say.

[b] **Age**: 1 = 18–24 years; 2 = 25–34 years; 3 = 35–44 years; 4 = 45–54 years; 5 = 55 years or older.

[c] **Education Level**: 1 = High school diploma; 2 = Associate degree; 3 = Bachelor's degree; 4 = Master's degree; 5 = Doctorate degree.

Table 2
Results of the direct, mediating, and moderating analyses (study 1).

Antecedents	Perceived Relevance of Sustainable Message					Consumer Sustainable Purchase Intention				
	β	SE	t-value	LLCI	ULCI	β	SE	t-value	LLCI	ULCI
AI-Driven Personalization	.344*	.152	2.269	.045	.642	.132	.058	.868	−.168	.433
Perceived Relevance of Sustainable Message	–	–	–	–	–	.297***	.058	5.129	.183	.411
Education	.152**	.046	3.305	.242	.062	.072	.046	.125	−.164	.020
	Effect	SE		LLCI	ULCI	–	–	–	–	–
Total Effect	.235	.158		−.076	.545	–	–	–	–	–
Direct Effect	.132	.153		−.168	.432	–	–	–	–	–
Indirect Effect	.102	.044		.023	.196	–	–	–	–	–
Interaction: (AI-Driven Personalization X Privacy Concerns)	−.805**	.165	−4.897	−1.129	−.482	–	–	–	–	–
-1SD	.959***	.174	5.506	.616	1.302	–	–	–	–	–
Mean	.279*	.138	2.020	.007	.551	–	–	–	–	–
+1SD	−.489*	.230	−2.132	−.942	−.038	–	–	–	–	–
Interaction: (AI-Driven Personalization X AI Transparency)	.500*	.229	2.182	.049	.951	–	–	–	–	–
-1SD	.025	.278	.092	.574	.523	–	–	–	–	–
Mean	.397**	.153	2.603	.097	.697	–	–	–	–	–
+1SD	.798***	.203	3.943	.400	1.197	–	–	–	–	–
ΔR^2	.015*									–

Notes: n = 300; Statistical significance at *p < .05, **p < .001, ***p < .0001; ULCI: Upper-level confidence intervals at 95 %, LLCI: Lower-level confidence intervals at 95 %; ΔR^2 = Delta R-squared; Bootstrap Samples = 5000.

effects showed that personalization's effect on relevance was negative at high privacy concern (+1 SD: effect = −.489, 95 % CI [–.942, −.038]) and positive at low privacy concern (−1 SD: effect = .959, 95 % CI [.616, 1.302]) (Fig. 2a), consistent with privacy-calculus accounts (Culnan and Armstrong, 1999). For H4, the interaction of personalization × AI transparency on relevance was positive and significant, interaction = .500, SE = .229, t = 2.18, 95 % CI [.049, .951], ΔR^2 = .015, p < .05. Personalization had a stronger positive effect on relevance when transparency was high (+1 SD: effect = .798, 95 % CI [.400, 1.197]) than when transparency was low (−1 SD: effect = .025, 95 % CI [–.574, .523]) (Fig. 2b), aligning with evidence that transparency buffers privacy risk and enhances persuasion (Krafft et al., 2021).

5. Study 2

5.1. Sampling and procedure

To complement the controlled experiment in Study 1, Study 2 used a field-based, three-wave (time-lagged) survey of online shoppers in China's first-tier cities (e.g., Shanghai, Beijing), where AI-enabled personalization and sustainability marketing are highly developed (Yin et al., 2025). Participants were recruited through Sojump, a verified panel provider that serves experienced e-commerce users (e.g., JD.com, Tmall). Quota sampling was conducted in accordance with national internet-user benchmarks for age and gender (Cnnic, 2021). Eligibility required adults (18+) who had made multiple online purchases in the prior three months and reported purchasing household cleaning products (e.g., eco-friendly detergents).

Unlike Study 1, which presented a randomized, static, unbranded product card, Study 2 did not administer a researcher-controlled stimulus and did not reuse the mock-up from Study 1. Instead, the focal predictor indexes respondents' naturally occurring, in-situ encounters with platform-personalized advertising during the immediate recall window. A brief illustration at T1 was shown only to standardize construct interpretation; it contained no brand identifiers or call-to-action, was not re-shown at T2 or T3, and was not treated as persuasive input. To maintain construct, focus, and support accurate recall, at each wave, respondents wrote a one-sentence note documenting any recent encounters with platform-personalized eco-detergent ads within the prior 7–14 days; this served solely as a procedural aid to attention and recall. Three waves were administered two weeks apart (approximately one month total: T1 → T2 → T3). This horizon aligns with evidence that advertising effects are short-lived due to memory and persuasion decay (Hanssens et al., 2001; Tellis, 2003; Vakratsas and Ambler, 1999), as well as with media-response models showing the rapid depreciation of advertising goodwill (Naik and Raman, 2003;

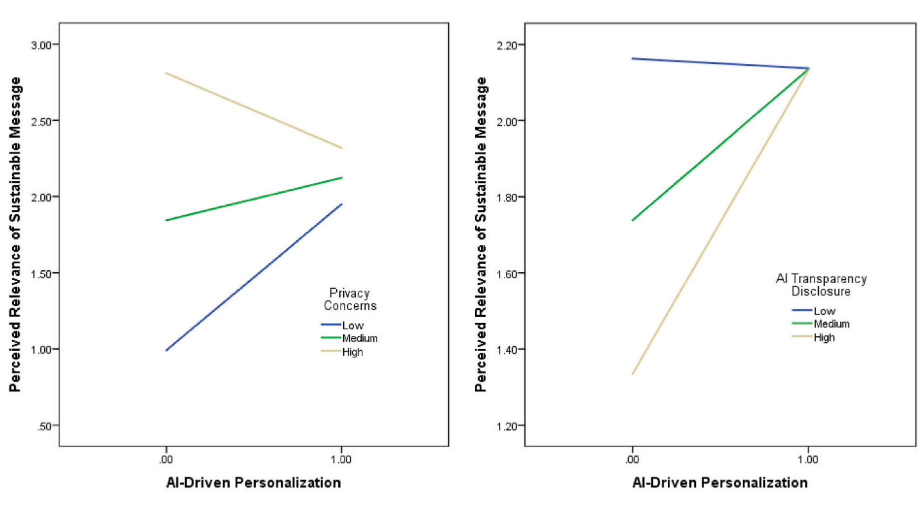

Fig. 2. Moderating effects of privacy concerns & AI transparency disclosure (study 1).

Tellis, 2003). Accordingly, each wave anchors measurement to the immediately preceding 7–14 days to capture proximal, everyday platform exposures; the design does not presume durability from a single ad exposure across the month. Temporal alignment—two-week spacing combined with 7–14-day reference windows—separates constructs across waves while limiting recall bias in high-velocity digital contexts (Lewis and Reiley, 2014; Vakratsas and Ambler, 1999).

An a priori power analysis indicated that 350 respondents would provide 80 % power to detect small to medium conditional effects (Faul et al., 2009; Hayes, 2017). Invitations totaled 440; valid responses were 428 at T1 (97.3 %), 417 at T2 (97.4 % retention), and 412 at T3 (98.8 % retention). After excluding seven incomplete or inattentive cases, the final sample consisted of 405 respondents, consistent with best practices for multi-wave survey research and indicative of high panel stability (Podsakoff et al., 2003). Constructs were staggered across waves to enhance temporal separation and reduce common-method bias (MacKenzie and Podsakoff, 2012; Podsakoff et al., 2003). At T1, respondents reported their naturally occurring exposure to AI-driven personalization and rated the perceived message relevance. A single neutral, brand-free illustration was shown to standardize construct interpretation, contained no brand identifiers or calls-to-action, and was not analyzed as an exposure (e.g., Bleier and Eisenbeiss, 2015). At T2, we assessed privacy concern and perceived AI transparency, following guidance to separate predictors and moderators temporally to mitigate spurious interactions (Siemsen et al., 2010). At T3, we measured sustainable purchase intention along with demographics and online shopping frequency. Data-quality safeguards included attention checks, IP duplication filters, and minimum completion time thresholds. A Harman single-factor test indicated no dominant common-method variance, and procedural remedies supported construct validity across waves (MacKenzie and Podsakoff, 2012).

5.2. Measures (study 2)

In Study 2, the same core constructs used in the scenario-based experiment (Study 1) were measured using validated multi-item scales to ensure conceptual consistency and allow meaningful cross-study comparisons in a real-world e-commerce context. All measures used validated scales and Brislin back-translation (Brislin, 1980). At Time 1, AI-driven personalization (T1) captured respondents' perceived experience that eco-detergent ads on Chinese shopping sites were tailored to them by platform algorithms, with emphasis on content fit (e.g., non-toxic formula, cold-wash efficacy, biodegradable packaging). Three items adapted from Aguirre et al. (2015) and Bleier and Eisenbeiss (2015) demonstrated good reliability (α = .865). Perceived message relevance (T1), the proposed mediator, was measured with four items adapted from Aguirre et al. (2015), Bleier and Eisenbeiss (2015), and Yeo et al. (2025), showing high reliability (α = .921).

At Time 2, privacy concern was assessed with a three-item scale adapted from Malhotra et al. (2004) and Chen et al. (2025) (α = .851), and Perceived AI transparency disclosure was measured using three items adapted from Shin (2021), Sundar and Kim (2019), and Wulf and Seizov (2024), who provide validated constructs for perceived explainability and system transparency in human–AI interactions (α = .818). Finally, at Time 3, sustainable purchase intention was captured using a three-item scale adapted from Chen and Chang (2012) and Schmuck et al. (2018) (α = .871). To reduce common method bias and strengthen temporal ordering, these constructs were measured at separate time points following established recommendations (Podsakoff et al., 2003).

Control variables: We initially included gender, age, education, and online shopping frequency as covariates, given their potential to influence responses to personalization and privacy (Bleier and Eisenbeiss, 2015; Alhelaly et al., 2025). As reported in Table 3, only education correlated with perceived relevance at p < .01; gender, age, and shopping frequency were not significantly associated with the mediator or the dependent variable and were therefore excluded from the focal models to preserve degrees of freedom and avoid suppressor effects (Becker et al., 2016). Education was retained as a covariate in all analyses of Study 2.

5.3. Results (study 2)

5.3.1. Descriptive statistics, reliability, and validity

Before testing hypotheses, the psychometric properties of the Study 2 measurement model were assessed (Fornell and Larcker, 1981). As shown in Table 3, all Study 2 constructs demonstrated adequate internal consistency, with CR values above .70 (Nunnally and Bernstein, 1994). AVE values exceeded .50, supporting convergent validity (Hair et al., 2019), and discriminant validity was confirmed because the square roots of AVEs were greater than inter-construct correlations and each AVE exceeded the maximum shared variance (Fornell and Larcker, 1981). Descriptive statistics from Study 2 indicated moderate agreement levels and sufficient variance for hypothesis testing (e.g., AI-driven Personalization: $M = 3.55$, $SD = 1.29$; Perceived Relevance: $M = 3.72$, $SD = 1.14$). Correlations were consistent with theoretical expectations, showing positive associations between AI Transparency and Purchase Intention ($r = .246$, $p < .01$) and between AI-driven Personalization and Perceived Relevance ($r = .420$, $p < .01$) (Aguirre et al., 2015; Bleier and Eisenbeiss, 2015). Privacy Concerns correlated modestly with Perceived Relevance ($r = .205$, $p < .05$), aligning with research on privacy as a boundary condition (Alhelaly et al., 2025). The Study 2 measurement model demonstrated acceptable fit (CMIN/DF = 2.546, CFI = .965, RMSEA = .060), confirming reliability, convergent and discriminant validity, and suitability for subsequent hypothesis testing.

Table 3
Construct reliability, validity, descriptive statistics, and correlations (study 2).

	CR	AVE	MSV	Mean	SD	1	2	3	4	5	6	7	8	9
1. AI Transparency disclosure	.829	.622	.118	3.009	1.323	**.788**	(.818)	–	–	–	–	–	–	–
2. AI-Driven Personalization	.869	.690	.188	3.551	1.290	.309**	**.831**	(.865)	–	–	–	–	–	–
3. Purchase Intention	.875	.702	.279	3.734	1.172	.246**	.360**	**.838**	(.871)	–	–	–	–	–
4. Perceived Relevance	.930	.770	.279	3.704	1.240	.161**	.420**	.473**	**.877**	(.921)	–	–	–	–
5. Privacy Concerns	.866	.687	.045	4.187	.927	−.060	−.176**	.072	.205**	**.829**	(.858)	–	–	–
6. Gender [a]	–	–	–	1.400	.514	−.015	.000	.021	.022	−.001	–	–	–	–
7. Age [b]	–	–	–	2.450	1.272	.032	.015	−.003	.067	.022	.023	–	–	–
8. Education [c]	–	–	–	2.603	1.212	.023	.119*	.147**	.180**	.098*	−.006	.055	–	–
9. Frequency of Online Shopping [d]	–	–	–	1.765	1.049	.071	.093	.033	.046	.027	−.053	.133**	.014	–

Notes: n = 405; significance: *p < .01; **P < .05. **Bold data**: square root of AVE; Values in parentheses are Cronbach's alpha coefficients.
[a] **Gender**: 1 = Male; 2 = Female; 3 = Prefer not to say.
[b] **Age**: 1 = 18–24 years; 2 = 25–34 years; 3 = 35–44 years; 4 = 45–54 years; 5 = 55 years or older.
[c] **Education Level**: 1 = High school diploma; 2 = Associate degree; 3 = Bachelor's degree; 4 = Master's degree; 5 = Doctorate degree.
[d] **Frequency of Online Shopping**; 1 = Rarely (Less than once a month); 2 = Occasionally (1–2 times a month); 3 = Regularly (3–5 times a month); 4 = Frequently (More than 5 times a month).

5.3.2. Hypothesis testing

The direct, mediating, and conditional indirect effects were tested using PROCESS v4.0 (Hayes, 2017) with 5000 bootstrap resamples. As shown in Table 4, AI-driven personalization positively predicted sustainable purchase intention ($\beta = .316$, SE $= .042$, $t = 7.454$, $p < .001$), supporting H1. Perceived relevance also predicted purchase intention ($\beta = .361$, SE $= .045$, $t = 7.981$, $p < .001$), and mediated the effect of personalization (indirect effect = .140, SE = .027, LLCI = .091, ULCI = .195), with the direct effect remaining significant ($\beta = .175$, SE = .043, LLCI = .090, ULCI = .260), confirming partial mediation (H2). For H3, privacy concern moderated the personalization–relevance link ($\beta = -.113$, SE $= .043$, $t = -2.614$, $p < .01$, $\Delta R^2 = .014$), weakening the effect under high concern ($\beta = .289$) compared to low concern ($\beta = .486$). For H4, AI transparency strengthened the personalization–relevance effect ($\beta = .122$, SE $= .036$, $t = 3.411$, $p < .001$, $\Delta R^2 = .024$), with stronger effects at high transparency ($\beta = .607$) versus low transparency ($\beta = .284$). Finally, conditional indirect effects supported H5 and H6: the relevance pathway weakened under high privacy concern (index = .044, SE = .016, LLCI = .017, ULCI = .078) and strengthened under high transparency (index = −.040, SE = .019, LLCI = −.081, ULCI = −.006) (see Fig. 3a and b) (see Table 5).

6. Discussion

The purpose of this study was twofold: (i) to establish that perceived message relevance, privacy concern, and AI transparency are empirically distinct constructs, and (ii) to assess whether AI-driven personalization directly influences sustainable purchase intention across different contexts (Fig. 4). In Study 1, the direct effect was not significant, consistent with evidence that personalization often loses persuasive strength in controlled or abstract settings without brand or contextual cues (Bleier and Eisenbeiss, 2015; Schmuck et al., 2018). In Study 2, the effect was positive and significant, in line with prior work showing that personalization is more effective in real-world e-commerce environments where consumers are accustomed to algorithmic recommendations (Lewis and Reiley, 2014; Yeo et al., 2025). Taken together, these results indicate that personalization's direct influence is contingent on ecological realism and consumer familiarity with digital shopping contexts.

Consistent evidence across both studies supported H2, showing that perceived message relevance functions as the central route of persuasion in line with the ELM (Petty and Cacioppo, 2012). Personalization significantly increased relevance, and relevance in turn predicted sustainable purchase intention, confirming that personalization motivates pro-environmental behavior only when it makes sustainability claims feel personally meaningful. Yet, as our results for H3 and H4 indicate, this central pathway is not stable. Privacy concern weakened the personalization–relevance link, consistent with updated privacy calculus research (Zaman, 2025; Tian et al., 2024), whereas AI transparency disclosure strengthened it, in line with recent work on algorithmic explainability and fairness (Shin and Park, 2019; Wulf and Seizov, 2024). These findings highlight that personalization's effectiveness is governed not only by the cognitive route it activates but also by legitimacy cues that either constrain or enable that route.

The moderated-mediation results for H5 and H6 provide further support for this governed central-route perspective. Specifically, the indirect effect of personalization on purchase intention through relevance was weaker when privacy concern was high, showing that even when relevance is perceived, consumers do not translate it into behavioral intention if they suspect surveillance or data misuse. Conversely, the indirect effect was stronger when AI transparency was high, demonstrating that disclosure restores legitimacy and sustains the translation of relevance into intention. In other words, personalization enhances persuasion only when relevance is both experienced and legitimized. This echoes Self-Congruity Theory (Sirgy, 1982; Kressmann et al., 2006), which suggests that alignment with one's environmental self-concept produces favorable evaluations, but extends it by showing that such alignment must also be perceived as ethically justified in order to translate into sustainable purchase behavior.

These dynamics can be illustrated by the Stitch Fix analogy (Davenport, 2021). Just as recommendations require explanation to be perceived as appropriate, AI personalization succeeds only when the basis of fit is made clear. Without such explanation, even relevant eco-claims may appear intrusive rather than meaningful (Milne and Bahl, 2010). This underscores that personalization is persuasive only when transparency clarifies why the ad is relevant, sustaining central processing and strengthening the relevance–intention pathway (Krafft et al., 2021; Wulf and Seizov, 2024; Shin and Park, 2019).

6.1. Theoretical implications

This study advances theory on AI-driven personalization in sustainability advertising and offers a focused contribution to eco-friendly ads. First, we reconceptualize personalization as a conditional, relevance-mediated process rather than a uniformly direct driver of persuasion. Prior work often treats tailoring as inherently effective (e.g., Yeo et al.,

Table 4
Results of the direct, mediating, and moderating analyses (study 2).

Antecedents	Perceived Relevance of Sustainable Message					Consumer Sustainable Purchase Intention				
	β	SE	t-value	LLCI	ULCI	β	SE	t-value	LLCI	ULCI
AI-Driven Personalization	.388***	.043	8.953	.303	.474	.316***	.042	7.454	.232	.399
Perceived Relevance of Sustainable Message	–	–	–	–	–	.361***	.045	7.981	.272	.450
Education	.135**	.046	2.913	.044	.225	.054	.042	1.274	−.029	.137
Interaction: (AI-Driven Personalization X Privacy Concerns)	−.113**	.043	−2.614	−.198	−.028	–	–	–	–	–
-1SD	.486***	.059	8.203	.369	.602	–	–	–	–	–
Mean	.381***	.043	8.777	.296	.466	–	–	–	–	–
+1SD	.289***	.056	5.186	.180	.399	–	–	–	–	–
ΔR^2	.014**									–
Interaction: (AI-Driven Personalization X AI Transparency)	.122**	.036	3.411	.052	.193	–	–	–	–	–
-1SD	.284***	.055	5.120	.175	.393	–	–	–	–	–
Mean	.445***	.048	9.345	.351	.539	–	–	–	–	–
+1SD	.607***	.077	7.863	.455	.758	–	–	–	–	–
ΔR^2	.024**									–
	Effect	**SE**		**LLCI**	**ULCI**	–	–	–	–	–
Total Effect	.316	.042		.232	.399	–	–	–	–	–
Direct Effect	.175	.043		.090	.260	–	–	–	–	–
Indirect Effect	.140	.027		.091	.195	–	–	–	–	–

Notes: n = 405; Statistical significance at *p < .05, **p < .001, ***p < .0001; ULCI: Upper-level confidence intervals at 95 %, LLCI: Lower-level confidence intervals at 95 %; R, R-squared (R^2); ΔR^2 = Delta R-squared; Bootstrap Samples = 5000.

Table 5
Moderated mediation of privacy concerns & AI transparency disclosure (study 2).

Path	Moderators	Indirect Effect	SE	ΔR^2	LLCI	ULCI
Effects of AI-Driven Personalization on Consumer Sustainable Purchase Intention via Perceived Relevance of Sustainable Message	Privacy Concerns at -1SD	.171	.035	.014***	.106	.246
	Privacy Concerns at Mean	.133	.026		.085	.188
	Privacy Concerns at +1SD	.100	.026		.051	.155
Effects of AI-Driven Personalization on Consumer Sustainable Purchase Intention via Perceived Relevance of Sustainable Message	AI Transparency at -1SD	.096	.027	.024***		
	AI Transparency at Mean	.155	.029		.101	.213
	AI Transparency at +1SD	.214	.042		.135	.301
		Index	**SE**		**LLCI**	**ULCI**
Index of Moderated Mediation for AI Transparency		.044	.016		.017	.078
Index of Moderated Mediation for Privacy Concerns		−.040	.019		−.081	−.006

n = 405; ULCI: Upper-level confidence intervals at 95 %, LLCI: Lower-level confidence intervals at 95 %; ΔR^2 = Delta R-squared; Bootstrap Samples = 5000.

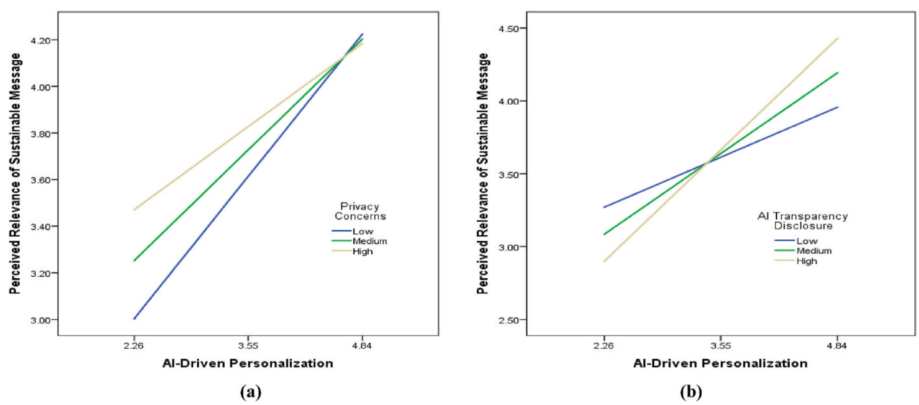

Fig. 3. Moderating effects of privacy concerns & AI transparency disclosure (study 2).

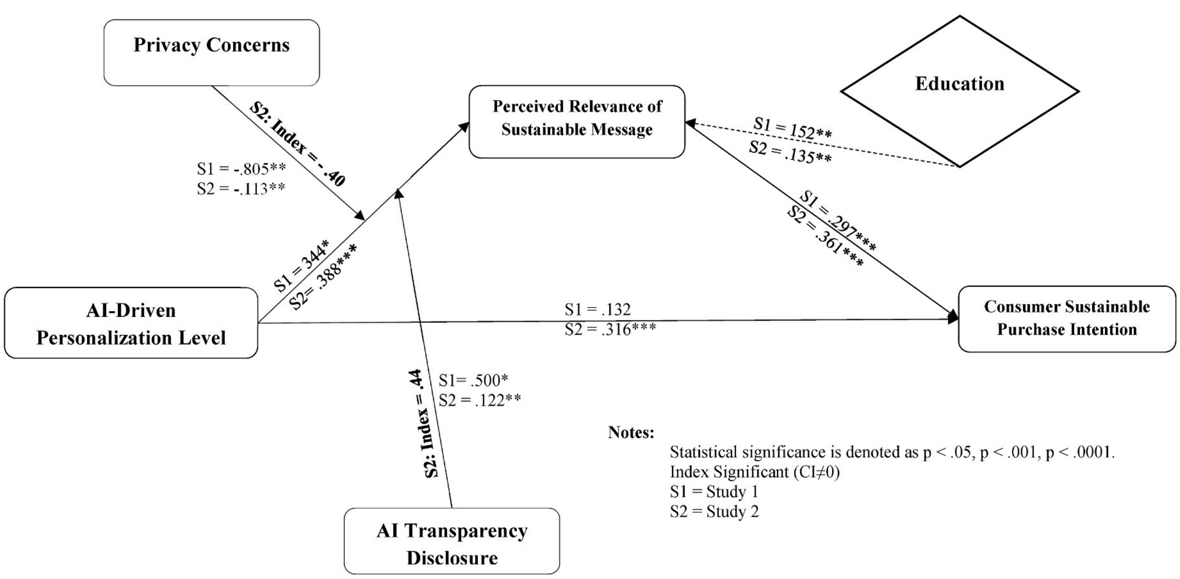

Fig. 4. Integrated model of hypothesized and tested relationships (study 1 & 2).

2025; Aguirre et al., 2015). Our account positions perceived message relevance as the core cognitive route by which AI tailoring can influence sustainable purchase intention, while clarifying that this route is governed by moderators—it strengthens under enabling conditions and weakens under risk appraisals. This refines central-route theorizing by showing that relevance is necessary but not sufficient and is sensitive to the context in which it is formed.

Second, we extend self-congruity explanations to eco-advertising by linking identity alignment to authenticated relevance. Sustainability appeals work when tailored benefits feel personally meaningful and consistent with self-views (e.g., White et al., 2019; Schmuck et al., 2018). We add that alignment is more persuasive when the basis of fit is legible and legitimate, helping translate pro-environmental attitudes into purchase intentions in categories such as household cleaning, where greenwashing concerns are salient (Sanchez-Chaparro et al., 2024; Munir and Mohan, 2022). Third, we advance privacy calculus by theorizing privacy concern as a moderator of the entire indirect path from personalization to intention. Rather than a purely direct inhibitor, privacy concern is conceptualized as a constraining moderator that shifts attention from message merits to data handling, eroding the relevance-based route and curtailing intention (Malhotra et al., 2004; Bleier et al., 2019). This "path-level" view specifies when the cognitive benefits of personalization are neutralized by risk appraisals.

Fourth, we position AI transparency disclosure as an enabling moderator that strengthens relevance-based persuasion. Short, plain-language disclosures increase diagnosticity ("why this ad fits me") and perceived fairness/agency, thereby encouraging effortful evaluation of substantive sustainability claims (Krafft et al., 2021; Shin and Park, 2019; Wulf and Seizov, 2024). Conceptually, transparency strengthens the central route by clarifying why a message is relevant to the individual, thereby increasing diagnosticity, perceived fairness, and agency. This directs attention to message content and supports effortful evaluation of sustainability claims (Krafft et al., 2021; Shin and Park, 2019; Wulf and Seizov, 2024).

Fifth, we contribute to green advertising scholarship by specifying when personalization helps close the attitude–behavior gap. Tailored eco-ads are more likely to move beyond value endorsement to purchase intention when relevance is both felt (fit with needs and identity) and seen as legitimate (transparent data use), offering a mechanism to overcome credibility thresholds that often hinder green claims (Schmuck et al., 2018; White et al., 2019; Mnzava, 2025). Sixth, we articulate a "governed central-route" perspective for AI-personalized eco-ads. In this view, AI transparency disclosure and privacy concern act as complementary moderators that, respectively, enable or constrain the conversion of AI-generated fit into perceived relevance and, ultimately, sustainable purchase intention. This framing integrates the three lenses: central processing (route to persuasion), self-congruent meaning (why relevance resonates), and privacy calculus (when risk appraisals derail the route).

Finally, this study adds contextual breadth by examining AI-driven personalization in China's data-intensive marketplace. By testing the framework with Chinese online consumers, it extends evidence beyond Western settings and supports external validity in platform ecosystems characterized by super-apps and frequent personalization (Lee, 2025; Li et al., 2025). Collectively, these contributions (a) specify personalization's effect as relevance-mediated and condition-dependent, (b) show how authenticated fit links identity and persuasion in eco-ads, (c) recast privacy concern as a path-level moderator, (d) explain why transparency strengthens the relevance mechanism by enhancing clarity and fairness, and (e) situate these dynamics in sustainability contexts where credibility is pivotal.

6.2. Practical implications

This study offers several implications for managers, policymakers, and industry bodies seeking to align AI-enabled personalization with sustainability goals. First, for managers, the results emphasize that personalization should be used only when environmental claims are credible, verifiable, and clearly linked to consumer needs. Diagnostic signals, such as product category preferences or local environmental concerns, are more effective than intrusive, identity-sensitive data because they allow consumers to focus on the substantive merits of the message. Providing substantiating evidence, such as lifecycle disclosures, further strengthens consumer engagement by reinforcing the authenticity of sustainability claims (Sanchez-Chaparro et al., 2024; White et al., 2019).

Second, for privacy and compliance leaders, findings confirm that high privacy concern can disrupt the personalization–relevance pathway. To counter this, firms should institutionalize privacy-respectful design by limiting the use of sensitive signals, adopting shorter data retention periods, and making opt-out mechanisms accessible. Evaluating the incremental contribution of each data element ensures that personalization remains effective without undermining consumer trust (Bleier et al., 2019; Wulf and Seizov, 2024). Third, for platform and product teams, transparency should be a core feature of user experience. Clear, concise explanations of how data are used to tailor sustainability messages enable consumers to evaluate the ad on its informational value rather than its data practices. Well-designed disclosures reinforce perceptions of fairness and control, supporting sustained elaboration on message content (Krafft et al., 2021; Shin and Park, 2019; Wulf and Seizov, 2024).

Fourth, for sustainability and brand leaders, the study underscores the need for governance processes that preserve credibility in eco-advertising. Documented substantiation of claims, pretesting messages with privacy-sensitive audiences, and coordinated reviews between marketing, privacy, and UX teams help ensure that AI-personalized sustainability messages are both relevant and legitimate (Schmuck et al., 2018; Munir and Mohan, 2022). Fifth, for regulators and industry bodies, results indicate that AI-driven personalization in green advertising succeeds only when transparency and privacy safeguards are enforced. Regulatory standards should therefore require disclosures that specify how inputs shape targeting, not merely that data are used. Outcomes-based audits focusing on consumer comprehension and trust, alongside formal compliance, will ensure personalization contributes to sustainability objectives without eroding autonomy (Wulf and Seizov, 2024; Krafft et al., 2021).

Finally, for consumer advocacy groups and NGOs, the findings highlight opportunities to play a proactive role in building consumer literacy about AI-driven personalization. By developing independent tools, educational campaigns, and watchdog reports, these organizations can help consumers critically evaluate personalized sustainability claims, reducing suspicion and enabling more informed central-route processing. Such initiatives can also pressure firms to adopt clearer disclosures and verifiable sustainability standards, strengthening both accountability and consumer trust (Yeo et al., 2025).

6.3. Limitations and directions for future research

Like any empirical investigation, this research has limitations that open important avenues for further study. First, the study deliberately excluded additional cues (e.g., eco-labels, brand signals, AI badges) to preserve parsimony and isolate the role of message relevance as the central processing route. While this clarified the mechanism of personalization through relevance, future research should compare conditions in which relevance cues are presented alone versus jointly with supporting informational evidence (e.g., third-party certifications, lifecycle facts) to determine how multiple diagnostic signals reinforce elaboration in sustainability advertising.

Second, both studies were conducted in China's e-commerce context—an AI-intensive setting that is appropriate for the research questions. However, cultural norms, institutional governance, and regulatory frameworks vary across markets. Future work should therefore conduct cross-national replications, comparative panels, and institutional analyses to examine whether relevance–privacy–transparency dynamics generalize or diverge globally. Third, our treatment of persuasion routes prioritized central processing and intentionally minimized peripheral affordances (e.g., brand badges, algorithmic icons). This design choice enhances internal validity but may understate the role of peripheral and "machine-heuristic" pathways (i.e., inferences of algorithmic authority) in AI advertising (Sundar, 2020). Subsequent experiments should orthogonally manipulate machine-heuristic cues alongside relevance to assess dual-route interplay in green contexts.

Fourth, the Study 1 stimulus focused on an eco-friendly household product and used an unbranded, static mock-up to isolate personalization. Although appropriate for causal inference, this may not capture responses in higher-involvement or sensitivity categories (e.g., health, finance) or contexts where brand equity strongly shapes trust. Future research should compare branded versus unbranded executions and vary interface cues (e.g., privacy icons, recommendation badges) to test ecological robustness.

Fifth, the temporal design in Study 2 used two-week lags across ~ one month to reduce common-method bias and to align with short-lived advertising carryover (Sheeran, 2002; Griep et al., 2021). Crucially, each wave anchored measures to the immediately preceding 7–14 days to capture fresh, naturally occurring platform exposures; the design did not assume that a single ad exposure endures for a month. To avoid confusion, we note that Study 2 did not administer a researcher-controlled stimulus; a single, neutral, brand-free illustration at T1 served only to standardize construct interpretation, was non-persuasive, was not re-shown at T2/T3, and was not analyzed as an exposure. Future work could compare purely survey-based measurement to minimal standardization aids, employ weekly "burst" diaries to capture micro-dynamics, and run multi-month panels to test longer-run durability.

Sixth, although demographic covariates were collected and considered, richer sources of heterogeneity remain. Variables such as economic status, AI-use intensity, prior exposure to green advertising, and purchase histories could add explanatory power. Pre-registered blocking, stratified randomization, or panel-based propensity approaches may further strengthen causal inference. Seventh, the present studies focused on individual-level perceptions but did not incorporate broader institutional moderators (e.g., platform reputation, breach history, industry norms) or deeper psychographic traits. Recent work shows that privacy cynicism, algorithm awareness, and privacy fatigue shape responses to AI disclosures and data practices (Strycharz and Segijn, 2024). Future research should adopt multi-level designs that integrate system-level governance cues with individual-level privacy calculus to better explain consumer heterogeneity in AI-enabled sustainability advertising. Finally, although our theoretical framing is eco-specific, we did not directly measure altruism or general environmental concern. Future work should test whether these eco-dispositions amplify (or condition) the personalization → relevance → intention pathway and whether their inclusion alters the strength of privacy- and transparency-based boundary conditions.

CRediT authorship contribution statement

Usman Ahmad Qadri: Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Alsadig Mohamed Ahmed Moustafa:** Writing – review & editing, Supervision, Resources, Investigation, Funding acquisition. **Muhammad Waqas:** Writing – review & editing, Visualization, Supervision, Software, Methodology, Investigation, Data curation.

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Declaration of competing interest

The authors have no conflict of interest.

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APPENDIX. Study 1 Stimuli and Materials: Stimulus Mock-Ups (Brand-Neutral Product Cards)

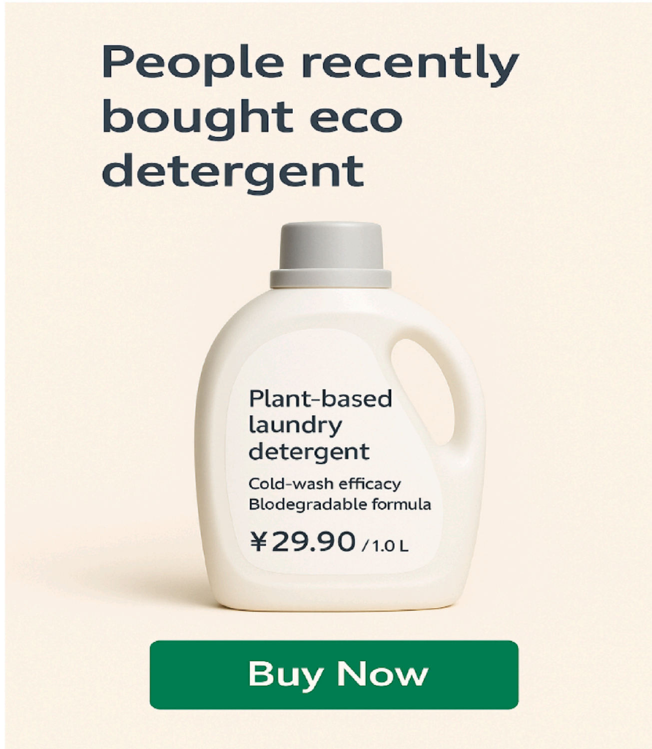

Fig. A1. *Low-personalization (Study 1).* Brand-neutral product card showing an eco-friendly laundry detergent with a single product image, brief claim, price (¥29.90 / 1.0 L), and a “Buy Now” call-to-action; no personal data cues.

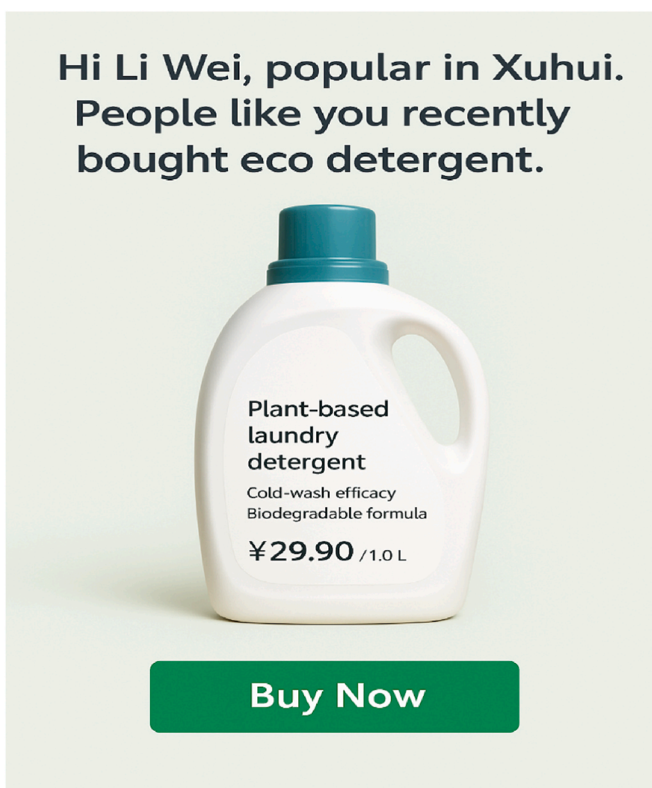

Fig. A2. *High-personalization (Study 1).* Identical product card plus a top personalization strip with given name, district-level location, and a generic prior-purchase cue (“Hi Li Wei, popular in Xuhui. People like you recently bought eco detergent.“).

Data availability

Data will be made available on request.

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