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Unintended Consequences of Algorithmic Platform Characteristics on Green Innovation Adoption: The Role of Perceived Erosion of Choice Autonomy and Digital Moral Disengagement

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ABSTRACT: This study investigates the unintended consequences of algorithmic platform characteristics on the adoption of green innovation, focusing on two psychological mechanisms: perceived erosion of choice autonomy (PECA) and digital moral disengagement (DMD). Conducted in 2025, the research surveyed 330 digital consumers in major urban areas of Vietnam—specifically Ho Chi Minh City, Hanoi, and Da Nang—from March to May, employing convenience sampling and paper-based questionnaires. Data analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 3.0 software. The most significant findings indicate that algorithmic personalization notably influences digital moral disengagement (DMD), while algorithmic framing and nudging significantly affect both PECA and DMD. Importantly, prominently displaying green information on digital platforms reduces the perception of manipulation (PECA), thereby narrowing the green attitude-behavior gap (GABG), which is identified as the primary obstacle to adopting green innovations. Consequently, the study suggests designing algorithmic platforms with transparency and user control, emphasizing the clear visibility of green information. The key strengths of the research include integrating diverse psychological theories, such as Self-Determination Theory and moral disengagement theory, within the context of sustainable consumption and employing advanced analytical models to clarify psychological mechanisms influencing sustainable consumer behavior. However, the study also acknowledges limitations, including its restricted scope within major urban centers, lack of behavioral experimentation for validation, and insufficient exploration of other algorithmic features. Information regarding the authors and the publication outlet is not explicitly provided in the document.

KEYWORDS: Algorithmic personalization, digital moral disengagement, green innovation adoption, perceived erosion of choice autonomy, platform nudging

1. INTRODUCTION

Despite decades of climate advocacy and policy ambition, the world remains entangled in a profound behavioral paradox: while public concern for sustainability intensifies, actual consumer behaviors remain stubbornly misaligned (IPCC, 2023; Pörtner et al., 2022; Carrington et al., 2010). This persistent green attitude–behavior gap (GABG) has emerged as a core impediment to achieving ecological transitions, not simply due to lack of motivation, but because of the evolving architecture in which decisions are made (Stern, 2000; Giddens, 2011).

Digital platforms-once heralded as democratizing tools of consumer empowerment-now increasingly operate as behavioral infrastructures governed by algorithmic logic. These systems personalize choices, curate attention, and structure visibility, becoming de facto agents in the sustainability equation (Lamberton & Stephen, 2016; Yoo et al., 2012; Dwivedi et al., 2020). While prior research has often celebrated the role of digital technologies in simplifying green decision-making, a parallel stream of critical scholarship suggests a more ambivalent truth: these platforms may also erode agency, obscure ethical responsibility, and reinforce unsustainable default behaviors (Zuboff, 2019; O'Neil, 2016).

This duality highlights an unresolved tension in contemporary research: can algorithmic systems simultaneously promote and undermine sustainable behavior? Current literature is largely bifurcated-one strand emphasizes cognitive efficiency and persuasive power (Adomavicius & Tuzhilin, 2005; Longoni et al., 2019), while another warns of digital moral displacement, where users outsource agency to opaque systems that attenuate moral salience (Bandura, 1999; Fan & Liu, 2022). However, few studies have empirically interrogated how specific algorithmic features-notably personalization, framing, and salience-may simultaneously activate and suppress pro-environmental action via latent psychological mechanisms.

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To address this theoretical lacuna, we propose a dual-pathway model of algorithmic influence on green innovation adoption. We argue that algorithmic personalization (AP), algorithmic framing and nudging (AFN), and prioritized salience of green information (PSGI) do not exert uniformly facilitative effects. Instead, they interact with individual cognition to shape behavior via two underexplored mechanisms: perceived erosion of choice autonomy (PECA) and digital moral disengagement (DMD). These constructs capture the subtle ways in which algorithmic governance may inhibit reflective agency or enable justification of unsustainable behaviors-regardless of users' explicit environmental values.

Further, we examine how contextual and dispositional moderators-online community and influencer norms (OCIN), trust and brand integrity (TBI), and value-conscious personalism (VCP)-may buffer or exacerbate these effects. These moderators reflect both relational and internalized anchors that mediate users' responses to algorithmic interventions in digital environments.

By reconceptualizing the role of algorithmic systems not merely as instruments of behavioral optimization but as agents of psychological disengagement, this study advances three key contributions. First, it introduces and validates PECA and DMD as pivotal mediators linking digital architecture to behavioral inconsistency. Second, it challenges the uncritical narrative of algorithmic benevolence in sustainable consumption, showing that design logics can be ethically ambivalent. Third, it positions green innovation adoption within the broader discourse of digital behavioral governance, illuminating new directions for research, policy, and platform design.

In doing so, we invite scholars across sustainability, behavioral science, and information systems to rethink how algorithmic ecologies shape not just what users choose-but how they reason, feel, and disengage in the face of urgent climate imperatives.

2.1. Theoretical background and hypotheses development

2.1. Algorithmic platforms and the psychology of sustainable consumption

Digital platforms increasingly rely on algorithmic systems to personalize content, frame options, and prioritize information-shaping consumer decision-making in powerful ways (Thaler & Sunstein, 2008; Weinmann et al., 2016; Schneider et al., 2018). These mechanisms, including algorithmic personalization (AP), algorithmic framing and nudging (AFN), and prioritized salience of green information (PSGI), form a complex digital choice architecture (Lambrecht & Tucker, 2019).

While these systems offer convenience and reduce cognitive overload, they may also produce unintended psychological consequences. In sustainability contexts, algorithmic cues have been shown to constrain user agency, diminish reflective reasoning, and weaken ethical engagement (van den Broek et al., 2021; Mathur et al., 2019; Fan & Liu, 2022). Self-determination theory (Deci & Ryan, 2000) posits that autonomy is key to value-aligned action. When perceived autonomy is undermined-what we term perceived erosion of choice autonomy (PECA)-users may disengage from green behavior, weakening their alignment with sustainable values (Puntoni et al., 2021; Kapoor et al., 2021).

Simultaneously, these platforms may foster digital moral disengagement (DMD)-a psychological process in which individuals rationalize unsustainable actions through mechanisms like displacement of responsibility or moral justification (Bandura, 1999; Kapoor et al., 2021). Sharma and Paço (2021) confirm that digital consumers frequently justify non-green behavior when the platform context diminishes accountability. DMD thus undermines consumers' moral consistency by cognitively distancing them from the impact of their decisions.

However, recent design interventions offer a potential corrective. The prioritized display of green information (PS)-highlighting eco-friendly options through visible cues and transparent labeling-has been shown to enhance perceived agency and moral salience (Gottselig et al., 2023; Carlsson Hauff et al., 2022). From the perspective of Self-Determination Theory, this may restore intrinsic motivation by making value-congruent choices more cognitively accessible.

Together, these concepts form a dual-pathway framework for understanding algorithmic influence on sustainable consumption. While AP and AFN may contribute to psychological disengagement, PS may counteract these effects, empowering users through clarity and alignment.

Hypotheses:

H1a: Algorithmic personalization (AP) positively influences perceived erosion of choice autonomy (PECA)

H1b: Algorithmic personalization (AP) positively influences digital moral disengagement (DMD)

H2a: Algorithmic framing & nudging (AFN) positively influence perceived erosion of choice autonomy (PECA)

H2b: Algorithmic framing & nudging (AFN) positively influence digital moral disengagement (DMD)

H3a: Prioritized salience of green information (PSGI) negatively influences perceived erosion of choice autonomy (PECA).

H3b: Prioritized salience of green information (PSGI) negatively influences digital moral disengagement (DMD)

2.2. Psychological mechanisms and behavioral outcomes

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The green attitude–behavior gap (GABG) refers to the discrepancy between pro-environmental attitudes and actual consumer behavior (White et al., 2019; Moser, 2015). PECA diminishes value-congruent behavior by reducing volitional control (Michaelsen et al., 2021), while DMD allows users to justify inconsistencies between values and actions (Runions & Bak, 2015). These mechanisms are particularly salient in digital ecosystems, where platform design obscures consequences and shifts accountability (Faas et al., 2024).

Hypotheses:

H4: Perceived erosion of choice autonomy (PECA) positively influences green attitude–behavior gap (GABG)

H5: Digital moral disengagement (DMD) positively influences green attitude–behavior gap (GABG).

2.3. The green attitude–behavior gap and green innovation adoption

Adopting green innovations often requires risk tolerance, autonomy, and ethical commitment (Rogers, 2003; Claudy et al., 2013). When the green attitude–behavior gap **(**GABG) is high, these psychological capacities may be weakened. Behavioral inconsistency-especially when repeated-creates cognitive dissonance and reinforces inaction (Zhuo et al., 2022). In digital contexts, this effect is exacerbated by fragmented feedback and passive user roles, reducing openness to innovation (Hatzithomas et al., 2024).

Hypothesis:

2.4. Moderating influences

While digital architectures impact user psychology, these effects are not universal. Contextual and individual moderators shape how users respond to algorithmic systems. This study explores three key moderators.

Online community & influencer norms (OCIN): Social norms transmitted through online communities or influencers can shape perceived legitimacy and moral standards. In environments with strong green norms, users may reinterpret algorithmic cues as value-aligned rather than manipulative (Veckalne et al., 2025; Wu & Yu, 2025).

H7: OCIN moderates the relationship between AP and PECA, such that the effect is weaker when OCIN is high.

Trust & brand integrity (TBI): When digital platforms and associated brands are perceived as trustworthy, transparent, and ethically aligned with sustainability goals, users are more likely to engage in reflective processing rather than relying on cognitive shortcuts. High TBI can mitigate digital moral disengagement (DMD) by enhancing moral accountability and diminishing users' reliance on rationalization strategies such as displacement of responsibility or distortion of consequences. Prior research shows that perceived brand ethicality and transparency strengthen green purchase intentions, particularly by reducing skepticism and reinforcing consumer-brand value congruence (Chen et al., 2020; Moorman et al., 1993; Echchad & Ghaith, 2022). In this way, TBI acts as a buffer that weakens the influence of DMD on the green attitude–behavior gap (GABG).

H8. Trust & brand integrity (TBI) moderates the relationship between digital moral disengagement (DMD) and the green attitude–behavior gap (GABG), such that the effect is weaker when TBI is high.

Value-conscious personalism (VCP) refers to individuals who actively strive to align their consumption behavior with deeply held ethical and environmental values. This trait reflects an internalized moral compass that supports behavioral consistency even under psychological or structural tension (Young & Middlemiss, 2012). In the context of sustainable consumption, VCP can serve as a self-regulatory buffer-mitigating the negative effects of attitudinal-behavioral inconsistency by restoring volitional alignment. Research shows that consumers who identify strongly with ethical values are less likely to rationalize unethical choices and more likely to convert green attitudes into pro-innovation behavior (Young & Middlemiss, 2012). Furthermore, recent studies highlight the role of moral identity in driving sustainable consumption (Salciuviene et al., 2022; Li et al., 2022) and how pro-environmental behavior can moderate consumer resistance to green innovations, implying that strong internal values reduce barriers to new green solutions (Khan et al., 2022). Concepts like mindfulness and self-efficacy also reinforce how conscious internal drivers support consistent sustainable actions (Kumar & Panda, 2025; Jiang et al., 2025).

H9. Value-conscious personalism (VCP) moderates the relationship between the green attitude–behavior gap (GABG) and Intention to adopt green innovation (IAGI), such that the negative effect is weaker when VCP is high.

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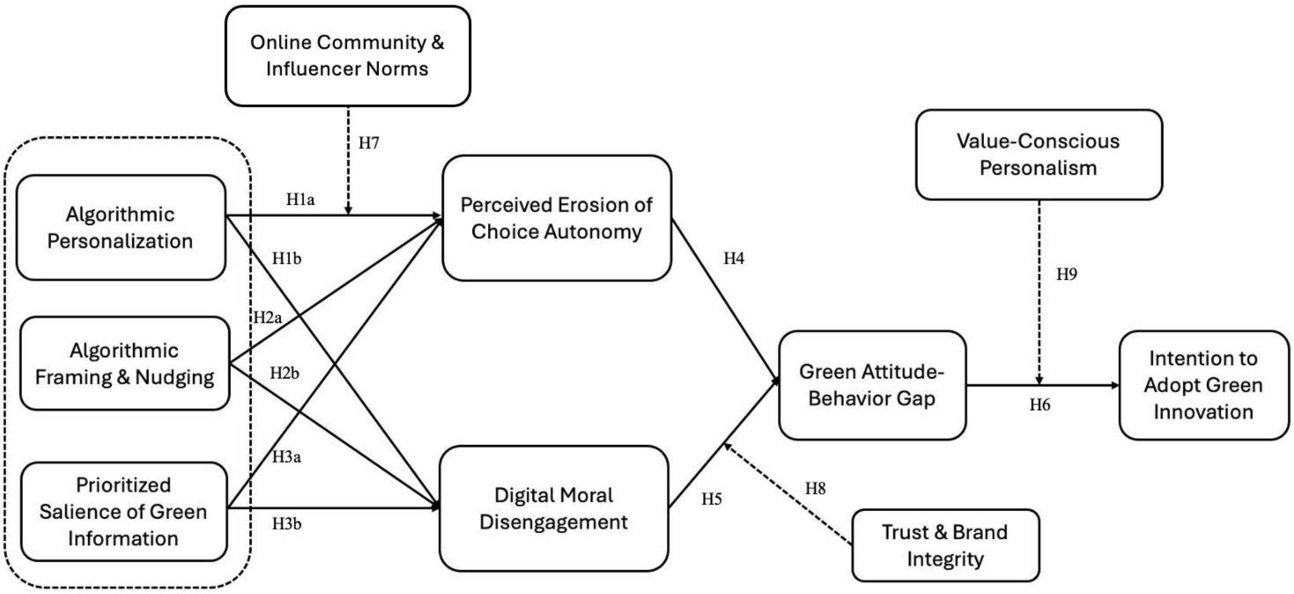

Figure 1. Research model

3. METHODOLOGY

3.1. Data collection and data analysis

This study employed a structured, paper-based survey to empirically examine the psychological mechanisms through which algorithmic digital platforms influence green innovation adoption. The questionnaire comprised eight conceptual blocks, each measuring a latent construct in the proposed model. All items were rated on a five-point Likert scale ranging from 1 (“Strongly disagree”) to 5 (“Strongly agree”), ensuring response standardization appropriate for variance-based structural equation modeling (Hair et al., 2019). The original instrument, developed in English, was translated into Vietnamese using the forward–backward translation method (Brislin, 1970) to ensure linguistic and semantic equivalence. A pilot test (n = 30) was conducted with Vietnamese digital consumers to evaluate clarity and reliability. Based on their feedback, minor wording adjustments were made.

The target population consisted of Vietnamese adult digital consumers (aged 18 and above) who engage with online platforms at least weekly for shopping, browsing, or decision-making. The sampling frame focused on urban areas including Ho Chi Minh City, Hanoi, and Da Nang - cities with high digital engagement and exposure to green innovation initiatives. Participation was voluntary and based on self-selection.

A non-probability convenience sampling method was adopted for its practical accessibility and relevance in exploratory consumer research (Hair et al., 2019). The sample size of this study was determined based on the guidelines of Hair et al. (2019) and Sarstedt et al. (2022), which classify models with 10 or more structural paths, especially those including moderating effects, as highly complex. Given that the proposed model includes 12 structural paths, it falls into this high-complexity category. Therefore, a minimum sample size of 200 observations is recommended to ensure stable parameter estimates and adequate statistical power in PLS-SEM analysis. A total of 330 valid responses were retained for analysis, exceeding the minimum threshold recommended for complex PLS-SEM models.

Data collection occurred from March to May 2025. Trained assistants distributed and monitored surveys at malls, universities, and coworking spaces across selected cities. Respondents were screened for eligibility, informed of the research purpose, and completed the surveys on site. No incentives were provided. Written informed consent was obtained prior to participation.

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 3.0 (Ringle et al., 2015). PLS-SEM was selected for its suitability with small-to-medium sample sizes, capability to handle non-normal data, and support for complex models involving both mediation and moderation (Hair et al., 2019). The analysis followed a two-step approach. First, the measurement model was evaluated by examining indicator reliability (outer loadings ≥ 0.70), internal consistency reliability (Cronbach’s alpha, composite reliability, and rho_A ≥ 0.70), and convergent validity (AVE ≥ 0.50) (Fornell & Larcker, 1981; Nunnally & Bernstein, 1994). Discriminant validity was verified using the Fornell–Larcker criterion, cross-loadings, and the Heterotrait–Monotrait (HTMT) ratio, with values below 0.85 deemed acceptable (Henseler, Ringle, & Sarstedt, 2015).

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Second, the structural model was assessed using 5,000 bootstrap resamples to estimate path coefficients, t-values, and p-values (Hair et al., 2019). The model's explanatory power was evaluated through R^2 values, and the strength of each predictor was determined using f^2 statistics (Cohen, 1988). Multicollinearity was assessed via Variance Inflation Factor (VIF) values, all of which remained below the recommended threshold of 5.0 (Diamantopoulos & Siguaw, 2006). Model fit was evaluated using the Standardized Root Mean Square Residual (SRMR), with values below 0.08 indicating a satisfactory level of global fit (Henseler et al., 2015).

Moderation analysis was performed using the two-stage approach (Chin, Marcolin, & Newsted, 2003), which involved estimating the latent variable scores from the measurement model in the first stage, and subsequently using these scores to construct interaction terms and test moderation effects in the second-stage structural model. This approach is particularly suitable when both the predictor and moderator are continuous latent constructs and provides greater statistical power and interpretability (Hair et al., 2019).

3.2. Measurement

3.2.1 Dependent Variable

Intention to adopt green innovation (IAGI): This variable reflects users' willingness to engage with and adopt new environmentally friendly products or services, particularly when presented through digital platforms. A three-item scale was adapted from the unified theory of acceptance and use of technology (Venkatesh et al., 2003) and recent literature on green innovation adoption in digital contexts (Liang, Hussain, & Iqbal, 2025). Higher scores indicate stronger intention to adopt green innovations.

Items:

IAGI1: I'm willing to try new green products or services.

IAGI2: I tend to choose environmentally friendly tech solutions.

IAGI3: I will support sustainable innovations when given the chance.

3.2.2 Independent variables

Algorithmic personalization (AP): This construct captures users' perceptions of how digital platforms tailor content and product recommendations to their personal preferences. A three-item scale was adapted from personalization studies in digital media (Sundar & Marathe, 2010; Tam & Ho, 2006). Higher scores reflect stronger perceived algorithmic personalization.

Items:

AP1: I feel that the content recommended on this platform matches my personal interests.

AP2: This platform seems to understand my behavior and preferences.

AP3: What I see on this platform appears to be tailored specifically for me.

Algorithmic framing & nudging (AFN): AFN measures how users perceive the platform's presentation of content as shaping their decisions, including default settings, visual salience, or structured choice prompts. This three-item scale was adapted from nudge theory (Thaler & Sunstein, 2008) and recent applications in digital environments (Mirbabaie et al., 2023). Higher scores indicate stronger perceived nudging.

Items:

AFN1: The way the platform presents information influences my decisions.

AFN2: I feel guided toward a specific choice when using this platform

AFN3: The platform uses prompts to encourage me to act in a certain way.

Prioritized salience of green information (PSGI): This construct reflects the extent to which users perceive eco-friendly content to be prominent and easily accessible on the platform. A three-item scale was newly developed for this study, drawing from prior research on ecological packaging and sustainability cues (Koenig-Lewis et al., 2014). Higher scores indicate greater perceived salience of green information.

Items:

PSGI1: This platform often highlights eco-friendly products or information.

PSGI2: "Green" aspects are emphasized more clearly than others on this platform.

PSGI3: I can easily access sustainability-related information on this platform.

3.2.3 Mediating Variables

Perceived erosion of choice autonomy (PECA): PECA assesses users' perceptions of diminished control or freedom when interacting with algorithmic systems. A three-item scale was developed based on self-determination theory (Deci & Ryan, 2000), autonomy support measures (Hagger et al., 2007), and literature on algorithmic opacity and authority (Lu, 2024; van den Broek, Sergeeva, & Huysman, 2021). Higher scores reflect stronger perceived erosion of choice autonomy.

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Items:

PECA1: I feel I do not fully control my choices on this platform.

PECA2: My decisions are strongly influenced by how the platform presents information.

PECA3: I feel limited in the choices I can make on this platform.

Digital moral disengagement (DMD): DMD represents the psychological disengagement mechanisms users employ that allow them to rationalize or detach from the environmental consequences of their online consumption. This construct was operationalized with a three-item scale adapted from moral disengagement scales (Bandura et al., 1996) and specifically contextualized for digital and environmental contexts. Higher scores indicate a greater level of digital moral disengagement.

Items:

DMD1: I don't think much about the environmental impact when shopping online.

DMD2: Since many others act the same way, I don't feel it's wrong.

DMD3: Technology makes me feel less responsible for unsustainable consumption.

Green attitude-behavior gap (GABG). This construct captures the perceived inconsistency between users' pro-environmental attitudes and actual behaviors. A three-item scale was synthesized from studies on the attitude–behavior gap in sustainability (Kollmuss & Agyeman, 2002; Rausch & Kopplin, 2021). Higher scores indicate a wider green attitude-behavior gap.

Items:

GABG1: I support sustainable values, but I often fail to act according to them.

GABG2: Despite having green consumption intentions, I still buy non-eco-friendly products.

GABG3: There is a gap between my environmental attitude and actual shopping behavior.

Moderating Variables

Online community and influencer norms (OCIN): OCIN assesses the influence of social and community expectations-especially from influencers or peers-on users' sustainable behavior. A three-item scale was adapted from social norm theory, emphasizing the role of subjective norms as perceived social pressure to perform or not perform a behavior (Ajzen, 1991), and the conceptualization of social norms as rules of behavior based on empirical and normative expectations within one's reference network (Bicchieri, 2006). Higher scores reflect stronger perceived normative influence.

Items:

OCIN1: Influencers I follow support green lifestyles.

OCIN2: My online community encourages sustainable consumption.

OCIN3: I'm influenced by the consumption behaviors of celebrities or trusted individuals.

Value-conscious personalism (VCP). VCP reflects the extent to which individuals align their consumption behavior with internalized ethical values and moral principles. A three-item scale was adapted from value consciousness measures (Lichtenstein, Netemeyer, & Burton, 1990), personal values theory (Schwartz, 1992), and ethical consumption literature (Shaw & Shiu, 2003). Higher scores represent stronger personal value alignment and ethical intentionality in consumption.

Items:

VCP1: I try to consume in a way that aligns with my personal values.

VCP2: My ethical values largely guide my consumption decisions.

VCP3: I am not easily influenced if it contradicts my life principle.

Trust & brand integrity (TBI). TBI reflects users' perceptions of a brand's sincerity and commitment to environmental responsibility. This three-item scale was adapted from brand trust and corporate responsibility literature (Delgado-Ballester & Munuera-Alemán, 2005; Sen & Bhattacharya, 2001). Higher scores reflect stronger trust and perceived brand integrity.

Items:

TBI1: I believe this brand is genuinely committed to the environment.

TBI2: I feel this brand is transparent and responsible.

TBI3: I will remain loyal to a brand if they maintain their green commitments.

4. RESULTS

4.1 Descriptive Statistics

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Table 1. Socio-demographic characteristics of the survey respondents (n = 330)

	Group	Frequency	Percentage (%)
Gender	Female	170	51.52%
	Male	160	48.48%
Age Group	18–25	80	24.24%
	26–35	100	30.30%
	36–45	70	21.21%
	46–60	50	15.15%
	Above 60	30	9.09%
Location	Ho Chi Minh City	130	39.39%
	Hanoi	110	33.33%
	Da Nang	90	27.27%
Occupation	Retired	76	23.03%
	Student	76	23.03%
	Self-employed	68	20.61%
	Office Worker	56	16.97%
	Other	54	16.36%
Income Range	< 5 million VND	62	18.79%
	5–10 million VND	78	23.64%
	10–20 million VND	86	26.06%
	20–30 million VND	64	19.39%
	> 30 million VND	40	12.12%

Source: Data derived from the authors' descriptive statistical analysis

The demographic composition of the survey sample (n = 330) demonstrates broad coverage across gender, age, geographic location, occupation, and income categories, as presented in Table 1. Gender distribution is nearly balanced, with 51.52% female and 48.48% male, allowing gender-based comparisons in subsequent behavioral analysis. In terms of age, the sample spans five age brackets. The largest group consists of respondents aged 26–35 (30.30%), followed by 18–25 (24.24%) and 36–45 (21.21%), indicating a concentration in younger and early middle-aged segments. Older participants are also represented, with 15.15% aged 46–60 and 9.09% above 60, enabling intergenerational analysis when appropriate. Geographically, the sample includes respondents from three major urban centers: Ho Chi Minh City (39.39%), Hanoi (33.33%), and Da Nang (27.27%). This urban distribution is appropriate given the focus on digital platform usage and green innovation adoption, which tend to be more prominent in metropolitan environments. Regarding occupation, the sample reflects representation across student, working, and retired populations. Students (23.03%) and retired individuals (23.03%) form the two largest subgroups, followed by self-employed respondents (20.61%), office workers (16.97%), and others (16.36%). This distribution enables cross-sectional insights into behavioral differences related to employment status and life stage. In terms of monthly income, the sample includes respondents earning across a range of self-reported brackets. The majority fall within the 10–20 million VND (26.06%) and 5–10 million VND (23.64%) ranges. Meanwhile, 18.79% reported earning below 5 million VND, and 12.12% reported incomes above 30 million VND. This suggests stratification across economic tiers, facilitating potential moderation analysis based on income level. In summary, the descriptive profile supports analytical robustness and reflects a demographically varied urban consumer population suitable for examining technology-driven behavioral constructs.

4.2 Measurement Model Evaluation

4.2.1 Reliability

The internal consistency of the reflective constructs was assessed using Cronbach's Alpha, rho_A, and Composite Reliability (CR). Cronbach's Alpha values ranged from 0.763 (AP) to 0.920 (PSGI). Most constructs exceeded the 0.80 threshold, including AFN (0.810), DMD (0.789), GABG (0.854), IAGI (0.784), OCIN (0.876), PECA (0.782), PSGI (0.920), TBI (0.868), and VCP (0.914), indicating good reliability. AP (0.763) was slightly lower but still above the acceptable threshold of 0.70.

Table 2: Internal Consistency and Composite Reliability of Constructs

	Cronbach's Alpha	rho_A	Composite Reliability

AFN	0.810	0.835	0.887
AP	0.763	0.767	0.863
DMD	0.789	0.854	0.871
GABG	0.854	0.855	0.911
IAGI	0.784	0.784	0.874
OCIN	0.804	0.858	0.875
OCIN*AP	1.000	1.000	1.000
PECA	0.782	0.783	0.873
PSGI	0.920	0.946	0.949
TBI	0.868	0.878	0.919
TBI*DMD	1.000	1.000	1.000
VCP	0.857	0.873	0.913
VCP*GABG	1.000	1.000	1.000

Source: Results from PLS-SEM data analysis

The rho_A values varied from 0.767 (AP) to 1.12 (OCIN), with most values closely aligned with Cronbach's Alpha. High rho_A values were observed for PSGI (0.946), DMD (0.854), and GABG (0.855). Notably, OCIN had a rho_A of 1.12, which exceeds the expected upper bound of 1.00, possibly due to estimation artifacts or multicollinearity, and should be interpreted with caution. Composite Reliability values for all constructs were above the 0.70 threshold, ranging from 0.863 (AP) to 0.949 (PSGI), suggesting strong construct reliability. Specific CR values include AFN (0.887), DMD (0.871), GABG (0.911), IAGI (0.874), OCI (0.913), PECA (0.873), PSGI (0.949), TBI (0.919), and VCP (0.944). All values remained below the critical limit of 0.95, indicating no redundancy or inflation due to overlapping indicators. The interaction constructs-AP*OCIN, DMD*TBI, and GABG*VCP-showed perfect values (1.000) across all reliability indices. These are expected results when using the two-stage approach in PLS-SEM, where interaction terms are modeled as single-indicator constructs derived from latent variable scores. As such, their reliability metrics are algorithmically fixed and not substantively meaningful. In summary, all reflective constructs demonstrated adequate to high reliability across Cronbach's Alpha, rho_A, and Composite Reliability, providing a strong empirical basis for subsequent validity assessments and structural model analysis.

4.2.2 Convergent Validity

Table 3: Average Variance Extracted (AVE)

	Average Variance Extracted (AVE)
AFN	0.723
AP	0.677
DMD	0.693
GABG	0.774
IAGI	0.698
OCIN	0.700
OCIN*AP	1.000
PECA	0.696
PSGI	0.861
TBI	0.790
TBI*DMD	1.000
VCP	0.777
VCP*GABG	1.000

Source: Results from PLS-SEM data analysis

To evaluate convergent validity, the measurement model was examined through two standard criteria in PLS-SEM: outer loadings and average variance extracted (AVE). All outer loadings of reflective indicators exceeded the recommended threshold of 0.70, demonstrating a strong relationship between each indicator and its underlying construct. For instance, AFN ranged from

0.807 to 0.879, AP from 0.817 to 0.831, and PECA from 0.822 to 0.845. Constructs such as PSGI (0.903–0.941), TBI (0.885–0.895), and GABG (0.862–0.890) exhibited especially high loadings above 0.88. The lowest observed loading was 0.769 (DMD2), which nevertheless exceeded the acceptable threshold, confirming that all indicators meaningfully contribute to their respective constructs. Regarding AVE, all constructs exceeded the recommended threshold of 0.50, confirming that each construct explains more variance in its indicators than is attributed to measurement error. AVE values ranged from 0.677 (AP) to 0.861 (PSGI), with PECA (0.696), IAGI (0.698), DMD (0.693), and OCIN (0.700) also supporting acceptable levels of convergent validity. Higher AVE scores were reported for TBI (0.790), GABG (0.774), and VCP (0.850), reflecting strong construct quality. The interaction constructs-OCIN*AP, TBI*DMD, and VCP*GABG-reported AVE values of 1.000. This is expected in the two-stage PLS-SEM approach, where such constructs are modeled as single-indicator variables derived from latent scores. Accordingly, their outer loadings are fixed at 1.000, and their AVE values are fixed at 1.000 by model specification. These values are technically correct but not meaningful for evaluating measurement quality. Taken together, the results confirm that all reflective constructs demonstrate satisfactory convergent validity, as evidenced by strong outer loadings and AVE values above the 0.50 threshold. These outcomes support the adequacy of the measurement model and justify progression to discriminant validity assessment.

Table 4: Outer loadings

	AFN	**AP**	**DMD**	**GABG**	**IAGI**	**OCIN**	**OCIN*AP**	**PECA**	**PSGI**	**TBI**	**TBI*DMD**	**VCP**	**VCP*GABG**
AFN 1	0.807												
AFN2	0.862												
AFN3	0.879												
AP * OCIN							1.020						
AP1		0.817											
AP2		0.821											
AP3		0.831											
DMD * TBI											1.028		
DMD1			0.838										
DMD2			0.769										
DMD3			0.886										
GABG * VCP													0.928
GABG 1				0.862									
GABG 2				0.886									
GABG 3				0.890									
IAGI1					0.833								

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IAGI2					0.831								
IAGI3					0.842								
OCIN1						0.769							
OCIN2						0.856							
OCIN3						0.881							
PECA1								0.836					
PECA2								0.822					
PECA3								0.845					
PSGI1									0.939				
PSGI2									0.941				
PSGI3									0.903				
TBI1										0.885			
TBI2										0.886			
TBI3										0.895			
VCP1												0.890	
VCP2												0.849	
VCP3												0.904	

Source: Results from PLS-SEM data analysis

4.2.3 Discriminant alidity

The discriminant validity of the measurement model was evaluated using three complementary approaches: the Fornell–Larcker criterion, the Heterotrait–Monotrait ratio (HTMT), and cross-loadings. According to the Fornell–Larcker criterion, the square root of the AVE for each reflective construct was greater than its correlations with all other constructs. For instance, PSGI (0.928), TBI (0.889), and GABG (0.880) showed diagonal values that exceeded any inter-construct correlation, indicating that each construct shared more variance with its own indicators than with other constructs.

Table 5: Fornell-Larcker criterion

	AFN	AP	DMD	GABG	IAGI	OCIN	OCIN*AP	PECA	PSGI	TBI	TBI*DMD	VCP	VCP*GABG
AFN	0.850												

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AP	0.042	0.823											
DMD	0.103	0.144	0.832										
GABG	0.259	-0.074	0.056	0.880									
IAGI	0.193	-0.051	0.015	0.467	0.836								
OCIN	0.020	-0.008	0.000	0.056	-0.008	0.837							
OCIN*AP	-0.044	-0.054	0.035	0.050	0.040	-0.024	1.000						
PECA	0.299	0.066	0.015	0.383	0.274	0.073	0.051	0.834					
PSGI	0.035	0.122	-0.075	-0.273	-0.249	-0.006	-0.022	-0.238	0.928				
TBI	-0.007	0.022	0.040	-0.060	0.014	-0.042	-0.030	-0.006	-0.038	0.889			
TBI*DMD	-0.024	-0.011	-0.043	0.013	-0.018	0.036	-0.090	-0.015	0.045	-0.048	1.000		
VCP	-0.074	-0.017	0.032	-0.139	0.061	-0.009	0.078	-0.100	0.055	0.00	-0.032	0.881	
VCP*GABG	0.119	0.084	0.041	0.122	-0.042	0.033	0.062	0.095	-0.074	0.003	-0.067	0.074	1.000

Source: Results from PLS-SEM data analysis

All HTMT values fell well below the conservative threshold of 0.90, as recommended by Henseler et al. (2015). The highest HTMT ratios-between IAGI and GABG (0.569), and PECA and GABG (0.466)-were substantially lower than the critical limit, confirming empirical distinctiveness between all construct pairs.

Table 6: HTMT

	AFN	AP	DMD	GABG	IAGI	OCIN	OCIN*AP	PECA	PSGI	TBI	TBI*DMD	VCP	VCP*GABG
AFN													
AP	0.069												
DMD	0.116	0.164											
GABG	0.302	0.09	0.072										
IAGI	0.23	0.068	0.052	0.569									
OCIN	0.061	0.102	0.038	0.059	0.061								
OCIN*AP	0.045	0.06	0.05	0.055	0.069	0.031							
PECA	0.369	0.086	0.068	0.466	0.349	0.084	0.077						
PSGI	0.057	0.155	0.09	0.304	0.292	0.043	0.021	0.274					
TBI	0.054	0.051	0.061	0.07	0.065	0.06	0.038	0.068	0.059				

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TBI*DMD	0.026	0.019	0.046	0.033	0.038	0.059	0.09	0.031	0.049	0.052		
VCP	0.119	0.042	0.045	0.163	0.074	0.070	0.082	0.126	0.063	0.062	0.036	
VCP*GABG	0.133	0.097	0.057	0.131	0.047	0.061	0.062	0.111	0.079	0.029	0.067	0.081

Source: Results from PLS-SEM data analysis

Cross-loading analysis further supported discriminant validity. Each indicator exhibited its highest loading on its assigned latent construct and lower loadings on all other constructs. For example, PSGI1–PSGI3 had primary loadings above 0.90 on PSGI, while their cross-loadings on unrelated constructs remained much lower. No indicator loaded higher on an unintended construct.

Table 7: Cross Loadings

	AFN	AP	DMD	GABG	IAGI	OCIN	OCIN*AP	PECA	PSGI	TBI	TBI*DMD	VCP	VCP*GABG
AFN1	0.807	0.004	0.045	0.140	0.108	-0.016	-0.002	0.234	0.081	0.004	-0.025	0.032	0.057
AFN2	0.862	0.088	0.084	0.220	0.127	-0.014	-0.038	0.223	0.007	0.016	-0.009	-0.129	0.160
AFN3	0.879	0.019	0.123	0.281	0.235	0.064	-0.064	0.294	0.010	-0.029	-0.027	-0.084	0.089
AP * OCIN	-0.044	-0.054	0.035	0.050	0.040	-0.024	1.000	0.051	-0.022	-0.030	-0.090	0.078	0.062
AP1	0.061	0.817	0.097	-0.036	-0.059	0.092	-0.036	0.066	0.153	0.033	-0.004	0.022	0.076
AP2	0.033	0.821	0.141	-0.082	-0.044	-0.082	-0.069	0.031	0.079	-0.011	-0.029	-0.028	0.055
AP3	0.012	0.831	0.115	-0.061	-0.026	-0.013	-0.025	0.069	0.079	0.036	0.008	-0.031	0.079
DMD * TBI	-0.024	-0.011	-0.043	0.013	-0.018	0.036	-0.090	-0.015	0.045	-0.048	1.000	-0.032	-0.067
DMD1	0.036	0.129	0.838	0.045	-0.010	-0.003	0.021	0.004	-0.101	0.046	-0.038	0.019	0.037
DMD2	0.058	0.041	0.769	0.060	0.043	-0.005	0.074	-0.011	-0.047	0.040	-0.024	0.027	0.075
DMD3	0.143	0.153	0.886	0.043	0.017	0.005	0.017	0.031	-0.041	0.021	-0.040	0.034	0.015
GABG * VCP	0.119	0.084	0.041	0.122	-0.042	0.033	0.062	0.095	-0.074	0.003	-0.067	0.074	1.000
GABG1	0.186	-0.049	0.031	0.862	0.432	0.057	0.058	0.334	-0.291	-0.085	-0.012	-0.166	0.104

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GABG2	0.261	-0.070	0.055	0.886	0.411	0.053	0.001	0.359	-0.240	-0.020	-0.009	-0.084	0.132
GABG3	0.237	-0.078	0.062	0.890	0.386	0.037	0.075	0.316	-0.183	-0.053	0.060	-0.117	0.084
IAGI1	0.165	-0.105	0.035	0.384	0.833	-0.017	-0.026	0.228	-0.208	0.047	-0.039	0.068	-0.032
IAGI2	0.214	-0.010	-0.009	0.409	0.831	-0.049	0.065	0.236	-0.163	-0.017	-0.025	0.005	-0.057
IAGI3	0.104	-0.013	0.011	0.376	0.842	0.048	0.062	0.223	-0.254	0.005	0.020	0.080	-0.016
OCIN1	0.053	-0.046	-0.045	-0.010	-0.015	0.769	-0.036	0.023	-0.005	-0.048	0.092	-0.023	0.081
OCIN2	0.005	0.002	0.027	0.060	0.003	0.856	-0.003	0.067	0.015	-0.047	0.041	-0.067	0.049
OCIN3	0.016	-0.003	-0.010	0.055	-0.013	0.881	-0.031	0.071	-0.024	-0.022	0.001	0.053	-0.009
PECA1	0.235	0.062	0.030	0.345	0.278	0.060	0.107	0.836	-0.180	0.053	-0.038	-0.076	-0.004
PECA2	0.260	0.070	0.051	0.323	0.215	0.097	0.039	0.822	-0.219	-0.060	0.016	-0.065	0.120
PECA3	0.253	0.032	-0.048	0.288	0.191	0.021	-0.024	0.845	-0.194	-0.006	-0.016	-0.113	0.121
PSGI1	0.061	0.124	-0.063	-0.234	-0.209	-0.055	-0.005	-0.220	0.939	-0.058	0.046	0.016	-0.071
PSGI2	0.033	0.083	-0.068	-0.275	-0.255	0.031	-0.037	-0.257	0.941	-0.036	0.023	0.068	-0.053
PSGI3	-0.001	0.144	-0.081	-0.246	-0.226	0.003	-0.015	-0.171	0.903	-0.008	0.062	0.070	-0.088
TBI1	0.041	0.059	0.011	-0.059	-0.034	-0.067	-0.039	0.011	0.010	0.885	-0.025	-0.043	-0.029
TBI2	-0.065	-0.009	0.049	-0.053	0.072	-0.043	0.006	-0.024	-0.045	0.886	-0.067	0.009	0.024
TBI3	0.002	0.002	0.051	-0.046	0.003	0.006	-0.049	-0.006	-0.079	0.895	-0.038	0.046	0.019
VCP1	-0.048	-0.008	0.065	-0.100	0.058	-0.034	0.063	-0.056	0.047	-0.007	-0.021	0.890	0.076
VCP2	-0.095	-0.044	0.003	-0.121	0.044	-0.030	0.039	-0.103	0.021	0.062	-0.042	0.849	0.077

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VCP3	-0.062	0.000	0.011	-0.148	0.056	0.037	0.097	-0.111	0.071	-0.040	-0.025	0.904	0.046

Source: Results from PLS-SEM data analysis

Collectively, the results from the Fornell–Larcker criterion, HTMT ratios, and cross-loading analysis provide robust and converging evidence of discriminant validity. These findings affirm that the reflective constructs in the model are empirically distinct and conceptually separate, allowing for valid interpretation of the structural model.

4.3 Structural Model Evaluation

4.3.1 Collinearity Assessment

Collinearity was assessed by examining the variance inflation factor (VIF) values for all indicators in the measurement model. The results show that all VIF values range from 1.000 to 3.814, which are well below the commonly accepted threshold of 5.0, indicating no critical issues of multicollinearity among the indicators. Although the VIF values for the indicators of the PSGI construct are relatively higher-particularly PSGI1 (3.814), PSGI2 (3.408), and PSGI3 (3.037)-they remain within acceptable limits, suggesting moderate but not problematic collinearity. Therefore, multicollinearity is not a concern in this model, and the indicators can be retained for further structural analysis.

4.3.2 Path coefficients & hypothesis testing

Table 8: Hypothesis testing

Path	β	p-value	Result (α = 0.05)	Result (α = 0.10)
AFN → DMD	0.101	0.093	Not significant	Significant
AFN → PECA	0.306	0.000	Significant	Significant
AP → DMD	0.152	0.010	Significant	Significant
AP → PECA	0.089	0.117	Not significant	Not significant
DMD → GABG	0.053	0.328	Not significant	Not significant
GABG → IAGI	0.500	0.000	Significant	Significant
OCIN → PECA	0.068	0.319	Not significant	Not significant
OCIN*AP → PECA	0.064	0.216	Not significant	Not significant
PECA → GABG	0.382	0.000	Significant	Significant
PSGI → DMD	–0.098	0.074	Not significant	Significant
PSGI → PECA	–0.258	0.000	Significant	Significant
TBI → GABG	–0.059	0.345	Not significant	Not significant
TBI*DMD → GABG	0.018	0.757	Not significant	Not significant
VCP → IAGI	0.139	0.021	Significant	Significant
VCP*GABG → IAGI	–0.122	0.097	Not significant	Significant

Source: Results from PLS-SEM data analysis

Path coefficients were evaluated using bootstrapping with 5,000 subsamples. At the 5% significance level ($\alpha = 0.05$), several relationships were found to be statistically significant. These include the positive effects of AFN on PECA ($\beta = 0.306$, $p < 0.001$), AP on DMD ($\beta = 0.152$, $p = 0.01$), PSGI on PECA ($\beta = –0.258$, $p < 0.001$), GABG on IAGI ($\beta = 0.500$, $p < 0.001$), PECA on GABG ($\beta = 0.382$, $p < 0.001$), and VCP on IAGI($\beta = 0.139$, $p = 0.021$). These findings provide empirical support for several of the proposed hypotheses at the conventional confidence level. At the 10% significance level ($\alpha = 0.10$), three additional paths showed marginal significance: AFN → DMD ($\beta = 0.101$, $p = 0.093$), PSGI → DMD ($\beta = –0.098$, $p = 0.074$), and the moderating effect of VCP*GABG on IAGI ($\beta = –0.122$, $p = 0.097$). Although weaker in magnitude, these effects may hold theoretical relevance and deserve further investigation in future studies. In contrast, several paths did not achieve significance even at the 10% level, including AP → PECA, DMD → GABG, OCIN → PECA, OCIN*AP → PECA, TBI → GABG, and TBI*DMD → GABG. These results suggest that the corresponding hypotheses lack empirical support in the current model and context. Overall, the structural model reveals a combination of well-supported and weaker effects, partially validating the proposed relationships while highlighting areas for further research and model refinement.

4.3.3 Explained Variance and Effect Sizes

The coefficient of determination (R^2) indicates how much variance in each endogenous construct is explained by its predictors. The R^2 values suggest that the explanatory capacity of the model is generally limited. IAGI exhibits the highest R^2 value at 0.247, which is classified as weak according to the thresholds suggested by Hair et al. (2019). PECA and GABG follow with R^2 values of 0.167 and 0.153, respectively, while DMD shows a very low R^2 of 0.040, indicating that its predictors explain only a small portion of its variance. These results highlight that IAGI is the most effectively explained construct in the model.

This analysis evaluated the relative contribution of each exogenous construct using Cohen's (1988) f^2 guidelines. GABG's effect on IAGI ($f^2 = 0.319$) represents a strong medium effect, approaching the threshold for a large effect. PECA's impact on GABG ($f^2 = 0.172$) is considered moderate, while the effects of AFN on PECA ($f^2 = 0.112$) and PSGI on PECA ($f^2 = 0.078$) fall within the small range but remain meaningful. The effects of AP on DMD ($f^2 = 0.024$) and VCP on IAGI ($f^2 = 0.025$) are similarly classified as small. In contrast, DMD → GABG ($f^2 = 0.003$), TBI → GABG ($f^2 = 0.004$), and the interaction TBI*DMD → GABG ($f^2 = 0.000$) exhibited trivial effects ($f^2 < 0.01$), suggesting negligible contributions to the variance explained. These findings emphasize the central role of a few key relationships in the model, Gwhile other paths may warrant further theoretical consideration or contextual investigation.

4.3.4 Model Fit

Table 9: Model fit

	Saturated Model	Estimated Model
SRMR	0.049	0.067
d_ULS	1.132	2.072
d_G	0.530	0.576
Chi-Square	1095.418	1170.717
NFI	0.758	0.742

Source: Results from PLS-SEM data analysis

The model fit was primarily assessed using the standardized root mean square residual (SRMR), following the guidelines of Henseler et al. (2015) and Hair et al. (2019). The SRMR value of the estimated model is 0.067, which is below the recommended threshold of 0.08, indicating a satisfactory model fit. The SRMR for the saturated model is even lower at 0.049, reinforcing the model's absolute fit assessment. To provide additional support for model adequacy, supplementary discrepancy measures including d_ULS and d_G were examined. The estimated model yielded d_ULS = 2.072 and d_G = 0.576, which are relatively low and comparable to the saturated model (d_ULS = 1.132; d_G = 0.530). Although no formal cutoffs exist for these indices, lower values are preferable and the results here suggest an acceptable level of agreement between the model and observed data. The chi-square values for the saturated and estimated models were 1095.418 and 1170.717, respectively. As the chi-square statistic is highly sensitive to sample size and not considered a primary fit measure in PLS-SEM, it is reported here for completeness rather than evaluation. The Normed Fit Index (NFI) of the estimated model is 0.742, which falls below the conventional threshold of 0.90. While this suggests room for improvement in relative model fit, the overall results indicate that the model exhibits acceptable absolute fit.

4.4 Discussion

4.4.1 Divergent impacts of algorithmic personalization vs. framing

This study began with a comprehensive theoretical framework positing that various algorithmic platform characteristics (APCs) differentially affect sustainable consumer behavior through key mediating mechanisms. Specifically, hypotheses H1a and H1b proposed that algorithmic personalization (AP) would increase perceived erosion of choice autonomy (PECA) and digital moral disengagement (DMD), respectively, which would then widen the green attitude-behavior gap (GABG). While statistical analysis supported H1b (AP → DMD, $\beta = 0.152$, $p = 0.01$), H1a was not statistically significant (AP → PECA, $p = 0.117$). This suggests that consumers are more likely to perceive ethical manipulation via personalized suggestions rather than a loss of volitional control, diverging from predictions made by Self-Determination Theory (Deci & Ryan, 2000).

In contrast, algorithmic framing and nudging (AFN) significantly predicted both PECA ($\beta = 0.306$, $p < 0.001$) and DMD ($\beta = 0.101$, $p = 0.093$). These findings indicate that overt and structured forms of digital influence-such as defaults or visual prompts-are more likely to provoke perceptions of manipulation. This aligns with choice architecture theory (Thaler & Sunstein, 2008), where users detect influence more readily in visible interface elements than in covert personalization. The differential effects highlight the importance of transparency and modality in determining whether algorithmic influence is perceived as undermining autonomy or morality.

4.4.2 Prioritized green salience and psychological outcomes

The construct of prioritized salience of green information (PSGI) showed significant influence on PECA but weaker effects on DMD. Hypothesis H3a (PSGI → PECA) was strongly supported ($\beta = -0.258$, $p < 0.001$), indicating that visually salient sustainability cues enhance users' sense of control in decision-making. However, H3b (PSGI → DMD) was only marginally supported ($\beta = -0.098$, $p = 0.074$), suggesting that while green salience can reduce perceived manipulation, it may not be sufficient to override users' tendency to rationalize unsustainable behavior. This supports prior findings (Gottselig et al., 2023) emphasizing that moral nudges need to be combined with value reinforcement to effectively reduce disengagement.

The central role of the attitude-behavior gap among all modeled pathways, the green attitude-behavior gap (GABG) emerged as the most significant negative predictor of intention to adopt green innovation (IAGI), confirming H6 ($\beta = -0.500$, $p < 0.001$). This indicates that perceived inconsistency between environmental attitudes and actual behavior acts as a substantial barrier to translating intention into action. Interestingly, H5 (DMD → GABG) was not supported ($\beta = 0.053$, $p = 0.328$), suggesting that in this sample, users may still feel guilt or moral conflict despite disengagement tendencies. This challenges assumptions that DMD always serves as an effective psychological buffer and indicates that the GABG may function as an independent and more dominant psychological barrier in sustainable decision-making.

4.4.3 Moderating effects and the primacy of internal values

This study also examined contextual moderators-social norms, brand trust, and personal values-on key relationships. H7 and H8, testing the moderating roles of online community and influencer norms (OCIN) and trust & brand integrity (TBI), were not statistically supported. This suggests that neither social cues nor perceived brand sincerity significantly altered users' reactions to algorithmic personalization or moral disengagement in this context. However, H9 (VCP × GABG → IAGI) was marginally significant ($\beta = -0.122$, $p = 0.097$), indicating that individuals with strong ethical value alignment are better able to maintain green innovation intentions even when experiencing internal value-action discrepancies. This supports prior work on moral self-regulation and personal values as buffers in ethical consumption (Young & Middlemiss, 2012).

4.4.4 Theoretical contributions

This study contributes to the literature on algorithmic decision-making, sustainable consumption, and psychological mechanisms of behavioral inconsistency by integrating self-determination theory, moral disengagement, and digital nudging perspectives. It introduces perceived erosion of choice autonomy (PECA) as a novel mediating construct linking algorithmic presentation to attitude-behavior gaps, expanding prior models focused on utility or persuasion. The articulation of prioritized salience of green information (PSGI) as a counteracting force within the same algorithmic environment also advances design-oriented theories of moral salience.

Moreover, by empirically demonstrating the stronger influence of internal ethical values (value-conscious personalism) over external moderators such as brand trust or social norms, this research extends values-based consumption theory into algorithmic contexts. Finally, the dual-pathway model of disengagement (via PECA and digital moral disengagement) clarifies the psychological structure of the green attitude-behavior gap in digital systems, offering a framework applicable to future cross-domain studies of ethical decision-making.

This integrative perspective not only expands current understanding of psychological mechanisms in sustainable consumption but also offers a platform for future empirical investigations. Scholars may examine how these mediating constructs operate across varied algorithmic ecosystems and cultural contexts, or how longitudinal exposure to algorithmic environments gradually reshapes moral identity and behavioral consistency. Such inquiries would deepen the explanatory power of existing frameworks and inform responsible digital design for sustainability transitions.

4.4.5 Implications for design, policy, and behavior change

The findings underscore that algorithmic environments affect sustainable behavior not merely through the type of content presented, but through how that content is delivered. Notably, PECA consistently influenced GABG, while DMD did not-highlighting that preserving perceived autonomy is more critical than simply mitigating moral disengagement. Design-wise, this calls for interface strategies that reinforce user agency, such as transparency in recommendations and customizable decision paths.

Moreover, emphasizing green salience through interface cues enhances perceived control and may serve as an indirect mechanism for restoring ethical alignment. At the behavioral level, addressing the GABG-through positive reinforcement, consistent value cues, and easy-to-adopt green options-is essential for activating innovation intention.

Finally, internal value alignment (VCP) appears more influential than external moderators like social norms or CSR signals. This suggests that long-term behavioral change will be more effectively supported by strategies that nurture ethical identity and moral consistency rather than relying on influencer campaigns or brand claims.

5. **CONCLUSION**

This study advances a novel dual-pathway framework that theorizes how algorithmic platform features shape the adoption of green innovations through two central psychological mechanisms: **perceived erosion of choice autonomy (PECA)** and **digital moral disengagement (DMD)**. By empirically validating the roles of personalization, framing, and green salience as drivers of both sustainable and unsustainable behavioral tendencies, the research illuminates the ambivalent nature of algorithmic design in the sustainability domain. Our findings challenge deterministic views of algorithmic efficacy and call for a more reflexive understanding of the cognitive and ethical dimensions embedded in digital consumption environments.

In doing so, this study contributes to several streams of literature. It bridges gaps between sustainability behavior research, moral psychology, and digital systems by introducing PECA and DMD as overlooked but essential mediators in the green consumption process. Furthermore, it enriches the discourse on algorithmic governance by showing how technological affordances may both empower and undermine ethical engagement. Finally, the inclusion of moderating variables-community norms, platform trust, and personal values-offers a more nuanced view of consumer variability in digitally mediated contexts.

However, several limitations warrant consideration. First, the study relies primarily on cross-sectional data, which limits causal inference. Future research should adopt longitudinal or experimental designs to test temporal dynamics and causality. Second, while the study focuses on green innovation adoption, its scope could be broadened to other behavioral domains such as ethical finance, fair trade, or carbon-neutral mobility. Third, cultural and demographic variation remains underexplored; studies across diverse regions may reveal critical contextual differences in how algorithmic features are perceived and enacted.

Future research should also interrogate the design ethics of platform algorithms-exploring not only what users experience, but how value-laden design decisions are encoded into technological systems. This opens up rich interdisciplinary possibilities linking behavioral science, AI ethics, and platform studies. Moreover, a deeper exploration into countermeasures-such as transparent recommender systems, value-congruent nudges, or participatory design-could help mitigate the risks of psychological disengagement.

In sum, by centering the psychological consequences of algorithmic mediation, this study invites scholars, designers, and policymakers to rethink the architecture of digital sustainability. Algorithmic systems, if designed with awareness of their double-edged influence, hold the potential not only to shape greener choices-but to sustain a deeper ethical connection between users and the planet.

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