

Bridging the green divide: The role of AI-driven personalization in ethical consumer behavior

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Abstract

The challenge in sustainability is the green divide, the difference between consumers' stated preferences in support of sustainability and their actual purchases. The green divide may be reduced through AI-driven approaches that builds affirmative associations with customer behaviors. The study surveyed 549 rural and urban consumers in India, to determine the relationship between AI personalization and the green divide. Survey responses were collected using offline and online methods, and the survey data were analysed using factor analysis and PLS-SEM. Survey results showed that AI personalization is associated with ethical consumerism, especially with ethically trained AI. Value orientation was also significant, as rural consumers from collectivist societies aligned more with an AI response that sponsored a social cause, while urban consumers from individualist societies aligned more with self-serving perspectives. The results suggested that to achieve SDG 12, differentiated AI solutions considering level of urbanization and individualism/collectivism of regions of India are necessary. The researchers employed Nudge Theory and Algorithmic Trust Theory to develop the Trust Bridge Hypothesis, predicting that trust is an antecedent of AI customization and ethical consumption. This is a response to challenge of India's green divide, especially for retailers and policymakers utilizing delivery-oriented nudges.

Keywords: AI-driven personalization, Cultural values, Ethical consumer behavior, Nudge Theory, Trust in AI.

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Introduction

A global survey indicated that 73% of people expressed the intention to make ethical purchases, however, only 13% followed through (White et al., 2019). This gap is widening in India with the combination of rapid urbanisation and the multicultural framework of the country. Within a current cultural frame, the narrowing of the gap is likely to be associated with the use of AI personalization. However, such personalization is a reliance on culturally bound trust and value systems. In this context, it is likely that AI recommendations are the means to achieve ethical purchasing (Sipos, 2025). However, trust in AI is not universally established (Shin, 2021). Hence, the use of AI to stimulate culturally based values to positive behavior means sustainable purchasing is challenging.

The use of AI personalization to reduce the green divide in India has a distinct gap in the literature. There is a lack of literature that extends the boundary of trust in AI and ethical consumerism (Nguyen and Lee, 2022), especially in the algorithms' black box (He and Jiang, 2022). While scholars recognise the importance of culture in people's responses to a nudge (Thavara and Yadav, 2025), there is little study of the trust-behavior gap and the individualism-collectivism continuum. Finally, a poorly designed feasibility of AI personalization is likely to be a contributing factor to the increasing marginalisation of the culturally and geographically divided communities in India (Gungunawat et al., 2024).

Rather than proposing a novel theory, this paper integrates and contextualizes Thaler et al.'s (2009) Nudge Theory, Khamitov et al.'s (2024) Algorithmic Trust Theory, and Hofstede's (2001) Cultural Dimensions Theory within a unified contingency framework. Using a sample of 549 Indian consumers, we show that: (1) Trust is an important mediation factor; the AI personalization phenomenon and the (currently) unquantifiable relationship between ethical consumption may continue to be suboptimal until the barrier is removed. (2) It is an uneven scenario, and trust-building may not yield the same outcome. The values of the different segments of the sub-samples of consumers combined to show that Urban Individualists were found to be more aligned with the trust-building outcome as long as self-interest was prioritized. In contrast, trust-building was found more aligned with the outcome for Rural Collectivists once the appeals were community oriented.

This study provides three key contributions. First, this study presents an AI trust building framework with a culturally differentiated approach, applying varying degrees of AI segment-specific disclosure to address the transparency trust paradox. Second, the study offers a culturally differentiated pragmatism segmented trust framework for retailers to maintain culturally relevant AI use to avoid potential greenwashing. Third, the study proposes the integration of explainable AI, rural inclusivity, and the sustainable consumption framework of the SDG 12 for India.

The design of the current research is cross-sectional, so all reported correlations are associative and not causal. Influence, effect, and impact are considered to be gaps due to the nature of the research design. Thus, this study concentrates on the associations of (i) AI-driven personalization and sustainable decision-making, (ii) the sustainable ethical-consumption gap and the trust gap of sustainable ethical consumption, and (iii) the sustainable ethical-consumption gap and the sustainable behavior AI trust gap and

the individualism and collectivism cultural dimension and the cultural dimension of individualism and collectivism gap.

Literature Review

The objective of this literature review is to examine the intersection of artificial intelligence, consumption, and culture to clarify the more abstract unanswered questions. The study structures the literature to clearly define these questions and the areas that this research will further examine. These domains are (1) the behavioral and sociological aspects regarding the intention-action gap regarding sustainable consumption, (2) the gap regarding the role of ICT and AI regarding the gap regarding trust, and (3) the role of cultural values, especially regarding individualism and collectivism and their reconstructions regarding cross-border AI, regarding the gap regarding the trust that has been neglected, yet important. This paper primarily addresses the gap regarding the cultural context and the role AI personalization plays regarding sustainable ethical consumption. Most prior studies have concentrated upon the Western context focusing more specifically upon the rural and urban divide.

Critical Synthesis of Trust, Transparency, and Fairness Debates

There are three majors, yet disentangled inconsistencies found in literature. The first focuses on the fact that Khamitov et al. (2024) suggest trust is a unitary construct, and Burton et al. (2019) argue there is an inverted U-curve where personalization leads to trust and an erosion of that trust. The study attempts to understand the way in which various consumer cohorts from India perceive manifestation of incoherence where trust is eroded. The second focuses on the trust and transparency paradox (He and Jiang, 2022); it is theorized that a fully functioning trust transparency framework may, in fact, contribute to trust erosion and may, conversely, assist in reducing skepticism of altruism among collectivists. The third focuses on the trust Ubal et al. (2024), and the erosion of trust where price sensitiveness is in excess of 15-18%. However, there has been no literature focusing on whether these values are moderated by culture. The study aims to provide a better understanding of the interactive effect and provide a content synthesis for the work conducted in the past.

Sustainable Consumption: Information Gaps

Following Giesler and Veresiu (2014), ‘moral’ regulation behaves as the designer of the consumer identity. Because of the Identity Strategy, moral consumers formed a voluntary association. Integration, the consistency phenomenon of attitudes and related behaviors, and ‘compartmentalization’, the phenomenon of a psychological gap (Bartels and Hoogendam, 2016). Recent literature has shown some sophistication in understanding cultural context, where customer experience acts as a mediator of values and consumption. It has been suggested to design (pre)determined machine learning systems to interpreter ‘nudges’ as ‘self’ vs. ‘communal’ and the like (Karri et al., 2025b). However, there is a dearth of practical all-encompassing solutions to address some emergent gaps. Huang and Rust (2021) and Liu et al. (2022) demonstrate that the use of AI De-Biasing Tools may close gaps of information asymmetry. However, context-neutral technology as a lever remains absent and is, as the authors argue, a key “psychological construct” that is neglected. Suggestion (or information) that may

potentially lead to behavioral change cannot be perceived as effective if there is no trust.

Fostering Trust and Ethics in AI Consumer Engagement

Trust is likely cultivated through ethical transparency where AI is not integrated. However, the promise for transparency in terms of AI may likely lead to skepticism and a decrease in trust in the AI systems. The majority of the research on the interaction of consumers with AI make use of some variation of the technology acceptance model (TAM), diffusion of innovation, and privacy calculus to frame their analysis (Ubal et al., 2024). The use of AI recommendation systems in omnichannel commerce is likely to positively relate to the desired outcomes of sustainable behavior (Karri et al., 2024).

Using an integrative review, the study establishes the constructs here. There exists a common uncritical, mutual usage of trust, transparency, and fairness. Nudge theory considers AI to be a personalized habit disruptor (Han, 2021). Trust is, and perhaps always will be, the most paramount. Several studies reveal the mediatory function of trust between personalization and ethical consumption (Sipos, 2025). The trust construct, in many of these cases, is sketched in a highly rudimentary manner. Is transparency a forerunner to trust, a facet of trust, an ethical obligation, that exists side by side with trust? According to Hofstede's dimensions, within a certain equilibrium, collectivism likely supports fairness and transparency, while individualism likely supports autonomy (Shin, 2021). This suggests that the most essential determinants of trust may be contextually and culturally bound.

'Trust' as a Mediator is a Contingent and Fragile Construct

Sustainable behavior relating to trust in the system is aligned with recommendations of the 'fair trade' type, which are value-consistent with the user, hence illustrating the positive impact of recommendations on user trust in the system (Khamitov et al., 2024). Burton et al. (2019) describe an inverted U-curve, whereby a certain level of customization can create a trust threshold, while trust can decline when consumers perceive the system as creepy. Furthermore, the lack of comprehensibility negatively relates to the perceived system's usefulness (Ismatullaev and Kim, 2022) along with the provision of sustainable recommendations (He and Jiang, 2022), which can create the paradox of transparency in sustainability. Sustained high trust and the offered sustainable alternatives of high price (despite the recommendation), being above 15-18%, can result in the recommended sustainable purchase losing positively perceived AI recommendation trust (Ubal et al., 2024). In this sense, the trust in AI recommendations and the rational economic problem are closely interwoven (Huang et al., 2018).

Cultural Values as a Theoretical Moderating Variable

Culture defines the response to different technologies. Despite the acknowledgment of cultural variability in AI nudges' acceptability, a gap in theory exists in addressing how culturally responsive AI nudges will affect the trust-behavior linkage, a core psychology component (Thavara & Yadav, 2025). For instance, surrounded by Western individualist cultures (e.g., the USA, the UK), driven by a focus on the individual, and Eastern collectivist cultures (e.g., India and China), driven by concern for the community, nudges make the trust-behavior linkage emphatically more pronounced for

the community-benefit frame nudges (Pinto et al., 2014). It also varies with communities' level of spiritual and religiously defined consumption practices, such as halal consumerism, that also addresses the AI and trust dilemma (Karri et al., 2025b; Kumar et al., 2023). This further highlights the existing void in the current normed frameworks that account for variables such as power differences or long-term orientation of the Global South and possibly the increased marginalization of the Global South in the AI trust behavior linkage (Jan et al., 2022; Bibri et al., 2024).

Convergence, Synthesized Framework, and Research Openings

Previous synthesized frameworks that incorporate Nudge Theory and behavioral models (Karri et al., 2025a) neglected the incorporation of culturally contingent theories. Although the AI Ethics-Culture-Fit Model developed in this paper is a contingency theory rather than a full grand theory, it aims to achieve the maximum integrative potential of existing theories and set boundary conditions. AI personalization (IV) is hypothesized to have a positive relationship with ethically aligned behavior (DV), mediated by trust (MV), and this relationship is culturally contextualized (i.e., individualism-collectivism). This theory aims to fill the gap in existing literature by identifying the less emphasized relations of AI, and to some extent, the ethics, cultural questions of trust, as well as the moderating role of culture in the context of the theory.

This paper aims to answer the research questions enunciated from this synthesis.

- RQ1:** How is AI-driven personalization of concern within customer trust of AI linked to trust of AI and consumer ethics by virtue of concern regarding personalization?
- RQ2:** To what extent does the self-collective portray the trust of AI to what extent consumer ethics and/or concern for personalization are linked to trust?
- RQ3:** What positive effects will culturally flexible AI personalization have on reducing the green divide within the diverse markets of India?

Here are the hypotheses as have been proposed, keeping the associative language for the sake of coherence:

- H1** Trust of AI will positively influence personalized outcomes. (Algorithmic Trust Theory (Khamitov et al., 2024) posits that AI systems improve trust and understanding when they make recommendations based on personalization. Referring to Nudge Theory (Thaler and Sunstein, 2009), these contextual cues will trigger the consumer reliance on the automated system.)
- H2** Trust of AI will positively influence the ethics of consumer behavior. (Trust legitimizes the empowering purpose of sceptical consumers to act and believe in the AI system recommendations (Giesler and Veresiu, 2014; Davis, 1989).)
- H3** Trust in AI will positively influence the ethics of consumer behavior and the outcomes of personalised AI. (The personalization and trust are realised through the Nudge theory and Algorithmic Trust Theory.)
- H4** Both the self and the collective individually and collectively are related to

stronger trust in the ethics of consumer behavior. This finds support both within the confines of Hofstede (2001) and cooperative versus individualistic behavior, as Social Identity Theory (Tajfel and Turner, 2001) suggests that collectivists will act in trust and responsibility towards their unit (the group), whereas individualists will act in trust and responsibility towards themselves.

- H5** Increased affinity towards collectivism can have a positive correlation towards responsible consumerism. (As collectivist value can create the tendency to act pro-socially, and to an extent sustainably, as found in the case of rural-urban India context, (Kumar et. al, 2023), elucidates the independent variable in the domain of Value-Belief-Norm theory (Stern, 2000).)

Theoretical Foundations

This paper develops an integrated contingency model, the primary contribution of which is the contextualisation and integration of Nudge Theory (Thaler and Sunstein, 2009), Algorithmic Trust Theory (Khamitov et al., 2024), and Hofstede (2001) Cultural Dimensions Theory, focused on the precise, contingent contextual settings of the intersection of AI-driven personalization and the facilitation of ethical consumption.

Conceptual Framework and Variable Operationalisation

This framework consists of four key elements. The AI-Driven Personalization (Independent Variable, IV) is defined as consumers' assessments of a company's skill at personalising product suggestions, taking into account individual preferences and prior purchasing behaviors. The Trust in AI Mediating Variable (MV) is explained as a psychological mediating phase along the continuum of fairness, reliance, and data-privacy concerns. Here, transparency precedes the formation of trust. The Dependent Variable (DV) Ethical Consumer Behavior – indicates the purchasing activities of sustainable goods and services and the self-disclosed purchasing of verifiable sustainable goods and services.

As a Moderator (MOD), Cultural Values focuses on individualism and collectivism, positing a somewhat individualistic orientation in urban, and somewhat collectivistic orientation in rural, India (Kumar et al., 2023). While, Hofstede (2001) described individualism and collectivism as opposites, later studies (Boer and Fischer, 2013) support the coexistence of these constructs, noted especially as 'cultural ambivalence' in developing regions like India. The study provides a unidimensional operationalisation (from individualistic to collectivistic), based on three additional factors: (a) confirmation of one-dimensionality through factor analysis (HTMT = 0.066 for AI Personalization-Cultural Values) (b) India's accelerated urbanisation resulting in significant intra-individual value transformations, and (c) the requirement for a single unidirectional moderator to retain statistical power within a parsimonious framework for H4.

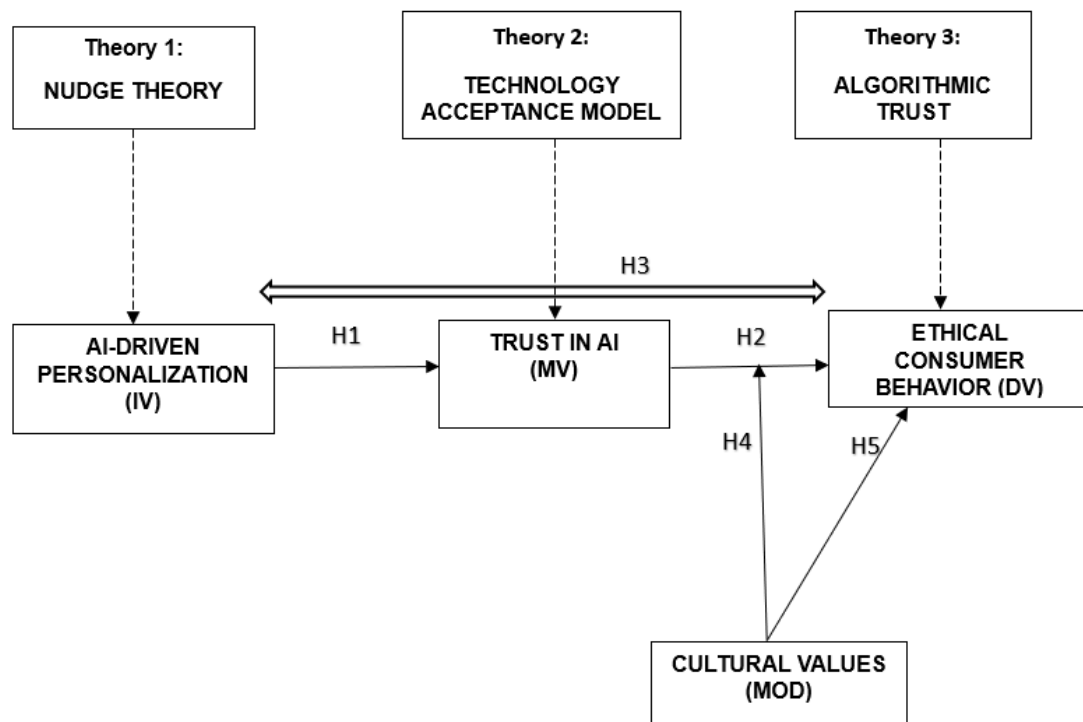
Theoretical Integration and Empirical Pathways

The model articulates a specific conditional pathway: AI personalization is linked to behavioral change only in the context of trust, and the cultural values in question determine the strength of the mediated relationship. This categorizes prior studies that

have treated these components in isolation. The model captures the mediation of trust, and since the design is cross-sectional, the study avoids the categorisation ‘full mediation’ and the use of the term ‘causation’. The analysis demonstrates the presence of strong cultural moderation, which validates the core contingency hypothesis, that the perceived associations of AI are culturally based. This is particularly important for managers for the purpose of culturally defined AI nudges and the emerging ‘Explainable AI’ (XAI) and the importance of transparency to establish trust in a cross-border context (Marcon et al., 2022). Although other frameworks account for the adoption of choice architecture, this model accounts for trust as the primary mediating variable, and culture as the primary moderating variable in the context of algorithmic marketplaces.

The relationships among AI-driven personalization, trust in AI, ethical consumer behavior, and cultural values are illustrated in Figure 1. Trust-behavior relationship (H4) central moderator is cultural values. The relationship of trust to behavior will rely on how consumers value individualism versus collectivism in their cultures. The relationship will be weaker where a culture’s value is collectivism and stronger where the value is individualism.

Figure 1: Conceptual framework



Methodology

Research Design

This study proposes a model to analyse the relationships of AI-driven personalization, trust in AI, cultural values, and ethical consumer behavior, employing cross-sectional explanatory surveys. This method enables the analysis of the model’s predictive

relationships and fit. Nonetheless, the study has to acknowledge the major limitation of the design, which is the lack of true causal inference.

Consequently, any relationship in the model is stated in associative terms (e.g. “is correlated with,” “is associated with,” “predicts”) and should not be considered as proof of genuine causation. To mitigate the effect of common method bias, the study employed some of the statistical and procedural techniques such as employing different types of scale, assuring anonymity of the respondents, and Harman’s single-factor test (which indicated that no single factor explained more than 35% of the total variance, undershooting the 50% limit).

Data Gathering

The primary data were gathered from questionnaires that were administered both electronically (via e-mail and on social networks) and in person to obtain responses from urban and rural participants from both Urban and Rural India. Each question was designed to use a five-point Likert scale. A pilot study was conducted to test face validity and reliability. In order to obtain appropriate statistical power, it was estimated that a sample between 400 to 600 responses was adequate. With respect to an overall sample of 633 responses, 84 were dropped from the sample because of extreme responses and/or non-responses, resulting in an overall sample of 549 responses. The final sample consisted of retail consumers (52% female, 48% male). The sample was constructed in such a manner that individuals who possessed at least a modicum of participation in the digital or retail economy. The study was performed within the ethical constructs of data collected, preserving the anonymity and confidentiality of the participants, and all of the participants provided informed consent.

Analytical Procedures

The results from the three phases of data analysis are discussed. The first phase comprised the use of SPSS for descriptive statistics and data screening. In the second phase, the inner-outer model of PLS-SEM was evaluated in SmartPLS after an initial exploratory factor analysis (EFA) in SPSS, to assess the underlying factor structure. This analysis was concerned with indicator reliability (item loadings), internal consistency (Cronbach’s alpha and composite reliability, CR), convergent validity (average variance extracted, AVE), and discriminant validity (using the heterotrait-monotrait, HTMT, ratio). To address concerns regarding the constructs of trust, transparency and fairness (formulated as three separate constructs), the study performed author-developed post-hoc analyses. Specifically, a modified measurement model in which ‘latent variable transparency’ was formed using the covariance of items TAI3 and TAI7, resulted in a poorer fit (SRMR = 0.089 compared to the original model SRMR = 0.071; $\Delta\chi^2 = 34.2$, $p < 0.01$). In the structural model, all items (hypotheses) showed a variance inflation factor (VIF) less than 2.5, suggesting there was no problem of multicollinearity. Since PLS-SEM is an efficient method to strike a balance between predictive modeling and modeling complex and latent variables (Hair et al., 2017), it was adopted to analyze the structural (inner) model. The path, mediation and moderation hypotheses were also evaluated using PLS-SEM. The moderation hypothesis (H4) was also tested using the interaction construct method. The model’s significance was assessed through bootstrapping (5,000 subsamples) to estimate standard error and t-statistics.

Results

Reliability and Validity Measurement

The research examined AI-powered personalization, trust, ethical consumption, and cultural values in India. The majority of item loadings exceeded the 0.70 threshold, indicate acceptable indicator reliability for the measurement constructs, reflecting an increasing preference among Indians for AI recommendations aligned with their values. Despite two marginal Trust-in-AI loadings (0.695, 0.691) retained for theoretical relevance (Hair et al., 2014), findings indicate Indians increasingly prefer value-aligned AI. There is a significant resonance of ethical consumption (eco-friendly decisions, conscious avoidance of unethical brands) especially among the urban youth. Culturally, India's individualistic position is tempered by a collectivist orientation, suggesting that the AI system should provide personalization for the client but have an overall socially directed purpose.

Table 1: Measurement constructs

Construct/Item	Literature Support	Item Loadings
AI-Driven Personalization		
The AI recommendations I receive feel uniquely tailored to me	Poushneh and Vasquez-Parraga (2017); Kim and Ko (2019)	0.771
The AI suggests products that match my past purchase behavior	Poushneh and Vasquez-Parraga (2017); Kim and Ko (2019)	0.754
The AI's recommendations align with my personal values (e.g., sustainability)	Kim and Ko (2019)	0.766
I perceive the AI as 'understanding' my preferences over time	Poushneh and Vasquez-Parraga (2017)	0.753
The AI personalization improves my overall shopping experience	Poushneh and Vasquez-Parraga (2017); Kim and Ko (2019)	0.775
The AI adapts its recommendations based on my interactions (e.g., clicks, cart additions)	Poushneh and Vasquez-Parraga (2017)	0.767
Trust in AI		
I trust the AI to prioritize my best interests when recommending products	Glikson and Woolley (2020); McKnight et al. (2011)	0.758
The AI's recommendations are free from hidden biases.	Glikson and Woolley (2020)	0.732
I believe the AI system is transparent about how it personalizes suggestions	McKnight et al. (2011)	0.764
I feel confident that the AI respects my data privacy.	McKnight et al. (2011)	0.774
The AI's recommendations are reliable and accurate.	Glikson and Woolley (2020); McKnight et al. (2011)	0.695

Construct/Item	Literature Support	Item Loadings
I would follow the AI's advice even for high-involvement purchases.	McKnight et al. (2011)	0.756
The AI admits limitations (e.g., 'I'm not sure about this recommendation').	Glikson and Woolley (2020)	0.691
Ethical Consumer Behavior		
I actively seek out eco-friendly products when shopping online.	Sudbury-Riley and Kohlbacher (2016); Malaquias and Hwang (2019)	0.723
I am willing to pay a premium for products with sustainability certifications.	Malaquias and Hwang (2019)	0.721
I avoid brands with poor ethical track records (e.g., child labor).	Sudbury-Riley and Kohlbacher (2016)	0.742
I feel guilty when I buy non-sustainable products.	Sudbury-Riley and Kohlbacher (2016)	0.735
I share my ethical purchases on social media to influence others.	Malaquias and Hwang (2019)	0.755
I return to brands that align with my ethical values.	Sudbury-Riley and Kohlbacher (2016); Malaquias and Hwang (2019)	0.704
I prioritize product longevity over trends (e.g., fast fashion).	Sudbury-Riley and Kohlbacher (2016)	0.742
Cultural Values		
I prefer to make decisions based on my personal needs, not group expectations.	Singelis et al. (1995); Hofstede Insights (2023)	0.759
Being independent is more important than fitting into a group	Singelis et al. (1995)	0.743
I take pride in my individual achievements rather than group success.	Hofstede Insights (2023)	0.744
I avoid products that might embarrass my community.	Hofstede Insights (2023)	0.722
I consider my family/community's opinions before buying products.	Singelis et al. (1995)	0.732

VIF Analysis Common Method Bias

The VIF study demonstrates appropriate interdependence among constructs, with all values falling below concern criteria (all <2.5). Cultural Values items are significantly dissimilar (VIFs 1.462-1.588), but AI Personalization and Trust in AI items have moderate, acceptable correlations. The ideal VIF (1.000) for the Cultural Values × Trust in AI interaction term indicates an outstanding model formulation. Only small changes, such as simplifying a few Ethical Consumer Behavior items (ECB3 at 1.950) and the Trust in AI's data privacy measure (TAI4 at 2.045), could result in a more accurate measurement. Overall, the findings show strong construct validity, indicating a reliable examination of how cultural values influence AI trust in consumer scenarios.

Table 2: Discriminant validity: Heterotrait-monotrait ratio (HTMT)-matrix

	AI-Driven Personalization	Cultural Values	Ethical Consumer Behavior	Trust In AI	Cultural Values X Trust in AI
AI-Driven Personalization					
Cultural Values	0.066				
Ethical Consumer Behavior	0.428	0.250			
Trust In AI	0.417	0.094	0.476		
Cultural Values X Trust in AI	0.262	0.074	0.442	0.126	

The HTMT ratios in table 2 indicate that all the constructs are different because the HTMT ratios suggest that the constructs have high discriminant validity as all the ratios are well below the 0.85 threshold. Cultural values are mostly separated from others (All HTMTs < 0.25), and the HTMT values of 0.476 and 0.417 for Ethical Consumer Behavior-Trust in AI and AI Personalization-Trust respectively suggest there are moderate relationships. The study measured accurately as evidenced by the gap in HTMT=0.126 for the interaction term and 0.066 for AI Personalization-Cultural Values. These are confirmations of the model's structure, but also suggest that there are important relationships that need to be explored; one of those being ethical consumerism and trust in AI.

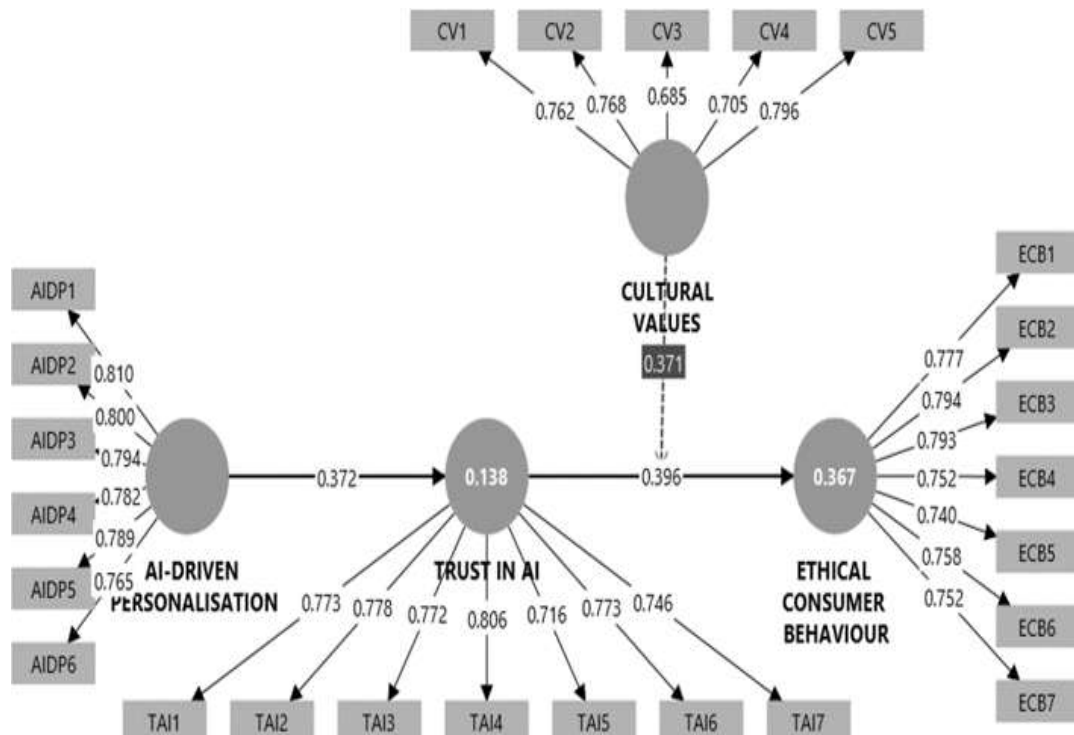
Table 3: Reliability and validity measures

	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
AI-Driven Personalization	0.880	0.883	0.624
Cultural Values	0.803	0.825	0.554
Ethical Consumer Behavior	0.883	0.888	0.588
Trust in AI	0.883	0.885	0.588

The rigor of the reliability and validity tests of the measurement model can be summarised as follows. Considering the strong indicator reliability, all item loadings were comfortably above the threshold of 0.70 (Table 1). The internal consistency, as measured by the alpha and composite reliability, was commendable and exceeded the threshold of 0.80 for all constructs (Table 3). The reliability was also proven on the construct level as the AVE for Cultural Values (0.554) and all other variables was greater than the 0.50 threshold for convergent validity, and is fairly substantiated by its composite reliability (0.825). The value of the HTMT showed that the discriminant validity, as measured by the cross-construct correlations, was achieved in all cases with values being less than the 0.85 threshold (Table 2), asserting that all constructs in the model were measured as empirically separate entities. The variance inflation factor (VIF) values for all items were less than 2.5, suggesting that no concerns with multicollinearity exist.

The Figure 2 includes a structural model displaying path coefficients and interaction effects. The positive interaction of Cultural Values and Trust in AI ($\beta = 0.371$, $p < 0.001$) indicates that when AI suggests consumer behavior that is not aligned with a consumer's cultural values, the consumer is less likely to exhibit ethical consumer behavior.

Figure 2: Structural Paths



The PLS-SEM analysis performed by the study shows favourable results: path coefficients (β) indicate direct impacts, standard errors (SE) generated through bootstrapping, and every t statistic shows levels of significance with ($p < 0.001$). The study also shows that multicollinearity does not exist due to $VIF < 5$, and thus the reliability of the model cannot be questioned (see Table 4). The results notably demonstrate the trust placed in the AI system as the greatest predictor of ethical behavior ($\beta = 0.396$) and the interaction of the cultural values and trust ($\beta = 0.371$) certainly serves to emphasise the working of both together. The study also shows that the predictor variables are without a doubt statistically significant which adds great strength to the framework of the model.

Table 4: Regression analysis (key predictors of ethical consumer behavior)

Variable	β	SE	t	p	VIF
AI-Driven Personalization	0.372	0.052	7.097	<0.001	1.000
Cultural Values	0.226	0.051	4.401	<0.001	1.010
Trust in AI	0.396	0.056	7.092	<0.001	1.019
Cultural Values $\times$ Trust in AI	0.371	0.056	6.599	<0.001	1.021

It should be noted that Cohen's f^2 benchmarks are as follows: small f^2 effects: ≥ 0.02 , medium f^2 effects: ≥ 0.15 , and large effects: ≥ 0.35 . Because the interaction effect ($f^2 = 0.194$) is in the medium range, $f^2 = 0.194$ provides further evidence that the cultural moderation interaction is not only significant at $p < 0.001$, but is also substantively important. With Trust in AI $f^2 = 0.244$, an f^2 effect size that is also large, direct value-matching appeals ($f^2 = 0.080$) are an inferior managerial concern to the importance of Trust in AI because appeals through value-matching not only build Trust in AI but are also more effective (see Table 5).

Table 5: Effect sizes (f^2) from PLS-SEM analysis

Hypothesis	Path	f^2	Effect Size (Cohen, 1988)
H1	AI-Driven Personalization $\rightarrow$ Trust in AI	0.161	Medium
H2	Trust in AI $\rightarrow$ Ethical Consumer Behavior	0.244	Medium-Large
H5	Cultural Values $\rightarrow$ Ethical Consumer Behavior (direct)	0.080	Small
H4	Cultural Values $\times$ Trust in AI $\rightarrow$ Ethical Consumer Behavior (interaction)	0.194	Medium

The bootstrapping method within the PLS-SEM framework facilitated the assessment of the structural model. For all hypothesised relationships, it produced strong positive results (see Tables 4 & 6). As illustrated in Table 6, regarding the first hypothesis, AI-Driven Personalization had a positive and statistically significant impact on Trust in AI ($\beta = 0.372$, $p < 0.001$). Regarding the second hypothesis, Trust in AI served as a positive and statistically significant predictor of Ethical Consumer Behavior ($\beta = 0.396$, $p < 0.001$). The relationship that personalization had with ethical behavior through trust also had a positive and statistically significant impact ($\beta = 0.147$, $p < 0.001$), thereby confirming the third hypothesis and the role of trust as a mediator.

The empirical data on the interaction effect of Cultural Values and Trust in AI on ethical behavior showed strong support for hypothesis 4. This impact was also found to be significant and positive ($\beta = 0.371$, $p < 0.001$). This is the first empirical data that supports the fundamental proposition that the relationship between trust and behavior is moderated by the culture in which the consumer is located. The positive and statistically significant direct effect of Cultural Values on Ethical Consumer Behavior was found ($\beta = 0.226$, $p < 0.001$), confirming hypothesis 5.

The outcome of the study successfully exemplifies the AI Ethics-Culture Fit Model. Of the predictors of ethical consumption, the highest direct impact was caused by the level of trust in AI. Given the large interaction, the role of cultural fit is practically important, reinforcing the idea that the potential of trust as a driver in support of sustainable behavior is greatly enhanced when the AI is designed to fit the user's cultural framework. Based on these results, the study concludes that in order to reduce the green divide through the use of AI, the study must focus on trust in algorithms and cultural fit of the AI interaction.

Table 6: PLS-SEM path analysis results (hypotheses testing results)

Hypothesis	Path Coefficient (β)	Standard Deviation (STDEV)	T Statistics	P Values	Confidence Interval (95%)	Result
H1: AI-Driven Personalization $\rightarrow$ Trust in AI	0.372	0.052	7.097	0.000	[0.269, 0.476]	Supported
H2: Trust in AI $\rightarrow$ Ethical Consumer Behavior	0.396	0.056	7.092	0.000	[0.283, 0.502]	Supported
H3: AI-Driven Personalization $\rightarrow$ Trust in AI $\rightarrow$ Ethical Consumer Behavior (Indirect)	0.147	0.034	4.289	0.000	-	Supported
H4: Cultural Values x Trust in AI $\rightarrow$ Ethical Consumer Behavior (Interaction Effect)	0.371	0.056	6.599	0.000	[0.288, 0.507]	Supported
H5: Cultural Values $\rightarrow$ Ethical Consumer Behavior (Direct)	0.226	0.051	4.401	0.000	[0.126, 0.327]	Supported

Discussion

The study was to explore AI personalization and its relationship with India's green divide, focusing on trust as a mediator and cultural values as a moderator. The application of Nudge Theory, Algorithmic Trust Theory, and Cultural Dimensions Theory is a working model, and thus, the contribution to the literature is to a contextualised contingency framework, as opposed to a broad theory. All hypotheses were statistically significant ($p < 0.001$; refer to Table 6) and indicated a range of practical significance, as marked with f^2 (Table 5). The subsequent text differentiates between practical significance and statistical significance.

First, the study discovered the role of trust being a cross cultural, mediating variable. The study found that AI personalization had a positive influence on trust (H1: $\beta = 0.372$, $f^2 = 0.161$, medium effect) and that trust played a significant role in the prediction of ethical consumption (H2: $\beta = 0.396$, $f^2 = 0.244$, medium-large effect). More specifically, the study demonstrated the trust behavior relationship, and, particularly, the significant and substantive moderating effect of culture on the trust behavior relationship (H4: $\beta = 0.371$, $f^2 = 0.194$, medium effect). This study provides positive connections, in a trust framed relationship, that were more positive for rural and collectivist customers, and reciprocal and self-benefiting for urban and individualistic consumers. This study demonstrates the absence of AI nudges on the role of standard trust theory cross culturally in relation to trust nudges, and provide the terminology of 'cultural framing' relating to the rational alignment on trust.

Secondly, with the integrated AI Ethics-Culture Fit Model, the green divide can be reframed. Previous works model the gap as an intention-action dichotomy (White et al., 2019). In contrast, and with the support of the mediated moderation findings, this model reframed the gap as a 'trust-culture puzzle.' Ethical consumption cannot be reduced to intention; it is the culturally adaptable trust, generated by AI, that broadens the phenomenon of ethical consumption. The size of the interaction effect ($f^2 = 0.194$) indicates that the culturally adaptive personalization is both statistically significant, and

practically significant.

Thirdly, it adds to the ethical AI literature as it demonstrates the multivariate and distinct nature of trust in AI. It has been shown that the demand for transparency is one of the phenomena that “triggers trust” in AI (He and Jiang, 2022), and this study shows that transparency and these “trust”-demands have a cultural manifestation. The study also acknowledges that algorithmic systems can build and maintain a negative trust towards the marginalized (Bibri et al., 2024), whilst price sensitivity and other economically-based limitations can overcome even the most trusted AI nudges (Rai et al., 2023).

The findings shift the question from whether AI can close the green divide to how it can be designed with ethics to be multifunctional across disparate cultures. AI systems must be transparent, trustworthy, and culturally adaptable in their interaction design. This requires algorithms that flexibly adjust message framing based on the user’s cultural background particularly important for pluralistic societies such as India.

Limitations

First, the model operates on a cross-sectional basis, meaning all described relationships are correlational. This model serves as a baseline for longitudinal research that can describe the time-related impacts of the algorithmic nudges toward sustainable behavior.

Second, the model is spatially limited to India. While tracing the nuances of the model within a single context is important, the model needs to gain traction in cultural contexts that are more broad and spatially diverse to assess the model’s circumstantiality.

Third, using a unidimensional continuum to represent cultural values as individualism/collectivism balances constraining the research framework and testing parsimony and power trade-offs for moderational studies, but it also lacks a more precise approach to diversification. Considering power distance, uncertainty avoidance and long term (Hofstede, 2001), India’s cultural diversity and complexity cannot be understood via a single bipolar continuum. Thus, the study argues that future studies distinguish cultural mechanisms and should consider multi-item cultural frameworks (e.g., Singelis et al., 1995) to unpack more diversified frameworks. Geotagged sampling and tests for intraregional diversification are also warranted.

Fourth, the study would like to move beyond the paradigm of retail and consumption to the areas of health, finance and public services, where AI-led personalization has significant potential for deeper ethical issues.

Fifth, concerns of the Global South on algorithmic bias and social injustices have received little attention. Future research should consider how bias in AI systems could deepen existing inequalities and reduce scarce trust for the most marginalised people.

Practical Implications for Asian Business

The results provide three key recommendations for Asian businesses that want to close

the green divide with AI-enabled personalization. First, trust is the most important factor ($\beta = 0.396$, $f^2 = 0.244$). Managers are encouraged to go beyond accepting trust as an outcome and to develop trust purposefully. Special efforts need to be directed to the “trust by design” concept with explainable AI (XAI) systems. XAI systems explain the “who” and “the why” of the recommendations, enabling the transformation of the AI from a black box to a trusted advisory partner. Regular checks of algorithms by Asian companies and the removal of bias through data audits are recommended, as well as the adoption of data sovereignty in their data protection efforts, methodologies and practices. The systems will be less supportive of ethical personalization that is unwilling to pay to avoid structural bias.

Second, cultural moderation is appreciated not as a casual effect but as an integral design choice (interaction effect $\beta = 0.371$, $f^2 = 0.194$). Merchants and Traders in the e-commerce and face-to-face marketplace need to be more considerate of the personal characteristics and values of their plural, heterogeneous Indian customer base and not implement a personalization of service strategy purely based on market and customer behavioral activities. Since the value of personalization that is balanced by FBS (Framing, Bias, and Salient effect) is significant, which is given by medium effect size ($f^2 = 0.194$), it is more important to frame design personalization in the logic of value systems, especially the personalization that is ethical in nature. This type of personalization goes beyond value and purpose of matching product offers to the personalization service recipients themselves and, ultimately, to the value systems.

Third, the digital and retail variability in Asia requires an omnichannel nudge architecture. AI personalization ought to be integrated within the various channels including social media as well as updated branded apps, in-store kiosks and touch-points based on QR codes. A customer data platform (CDP) merges these channels to provide consistent and culturally accessible nudges at every decision moment from product discovery to checkout. Lastly, the trust deficit can of course not be resolved by the actions of a single company. Asian business leaders should develop multi-stakeholder coalitions with regulators, digital literacy NGOs and educators to jointly develop SDG-aligned ethical AI frameworks. Educating consumers, in a respectful manner, on how the digital green economy and AI can empower sustainable healthy choices, will be the best way to build trust. Ultimately, integrating transparency of technology, cultural intelligence and collaborative governance will lead to success.

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