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# Environmental Perception Shaped By Recommendation Algorithms: A Study on Information Relevance and Human-AI Interaction

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**ABSTRACT:** This study explores the impact of digital recommendation algorithms on environmental awareness, focusing on the dynamic interplay among perceived information relevance (PIR), algorithmic content exposure (ACE), and human–machine interaction (HMI). Utilizing the Elaboration Likelihood Model and Uses and Gratifications Theory, the study reconceptualizes awareness as a dynamic product of cognitive, technological, and behavioral dimensions in AI-mediated contexts. A quantitative survey (N = 385) stratified by platform behavior across Southeast Asia revealed that PIR has the strongest predictive value ($\beta$ = 0.55), followed by ACE ($\beta$ = 0.49). HMI functions as a key moderator ($\beta$ = 0.57), suggesting that interactive engagement significantly strengthens cognitive assimilation of environmental content. These results suggest that AI platforms, when ethically designed, can serve as vehicles for ecological education. The findings call on platform engineers, sustainability advocates, and policymakers to implement value-sensitive design strategies, prioritize relevance-based content, and embed interactive features. Practical implications emphasize the role of value-sensitive design and interactive engagement in environmental communication. Limitations include reliance on self-report data and regional scope. Recognizing limitations in sampling and self-reported data, future research should employ longitudinal and behavioral methodologies to capture long-term attitudinal shifts. Overall, this study contributes to the integration of environmental psychology with algorithmic ethics by offering a robust, empirically grounded framework for digital ecological cognition.

## 1. INTRODUCTION

The development of environmental awareness is widely recognized as a critical catalyst for promoting sustainable behavioral patterns and advancing collective ecological stewardship. Although global discussions about environmental awareness have increased, public concerns continues to be fragmented. Hartig and Kahn (2016) attribute to selective media exposure and individual interest. Moreover, awareness of the systemic consequences of individual behavior is frequently limited by cognitive and informational constraints (Kollmuss & Agyeman, 2002). In this context, the interplay between cognitive limitations and algorithmically mediated digital environments may raise critical concerns regarding environmental perception. The operation of algorithmic systems within digital platforms may contribute to the reinforcement of existing ideological positions, thereby limiting access to critical environmental discourse (Bakshy *et al*., 2015). Consequently, the research problem lies in both the methodological challenge of assessing environmental awareness and the theoretical imperative to understand its mediated construction, highlighting the urgency of investigating the intersection between AI-driven content and human cognition in today's media-saturated environment.

The role of media in shaping environmental awareness has been widely investigated, with particular emphasis on how traditional media contribute to public awareness and understanding of environmental issues (Anderson, 2015). Digital personalization systems have the potential to unintentionally deepen existing disparities in environmental awareness by tailoring content to user preferences, thereby intensifying digital inequalities (Moravec *et al.,* 2025). While some studies explore the influence of algorithms on news exposure, their specific implications for environmental perception have received limited attention. In addition, a nuanced analysis of how perceived relevance and human-AI interaction dynamics mediate this exposure is frequently absent from the current literature. As Eslami *et al*. (2018) highlight the moderating effects of interactive models on perception and behavioral patterns have been largely neglected in prior research. This paper critically addresses to fill this gap by integrating algorithmic exposure, perceived information relevance, and human-AI interaction to foster a novel contribution to understanding variations in environmental awareness and advance a multidimensional approach rarely addressed in current scholarship.

To enhance the theoretical understanding of this subject, the study aims to investigate the following research questions:

1. How does perceived information relevance influence environmental awareness?
2. To what extent does algorithmic content exposure impact environmental awareness?
3. How does the human-machine interaction model moderate the relationship between perceived information relevance and environmental awareness?

The objectives of this study are to explore the potential intersection between computational personalization and environmental psychology by empirically investigating how digital recommendation algorithms influence individual environmental awareness. In this research, awareness is reconceptualized in this research in a dynamic process shaped by content relevance and human-AI interaction patterns rather than being assumed as a static psychological construct. This study advances of digital environmental cognition by isolating the effects of perceived relevance and algorithmic exposure, while also examining the moderating role of interaction models. In contrast to earlier approaches which narrowly concentrate on media content or audience reception, this study contribute to the field of synthesizing user interface dynamics and algorithmic logic into a comprehensive framework. The proposed framework bridges theoretical discourse and practical application by refining recommendation systems to promote ecological awareness, thereby facilitating a shift from passive exposure to active, informed environmental engagement.

## 2. LITERATURE REVIEW

### 2.1 Environmental Awareness

The concept of environmental awareness is described as the combination of knowledge regarding ecological concerns, the recognition of human influence on ecosystems and the willingness to take part in supporting environmentally responsible practices (Kollmuss & Agyeman, 2002). According to Frick *et al*. (2004), environmental awareness encompasses both cognitive and affective dimensions, including knowledge acquisition, emotional concern, and behavioral intention. Additionally, the perspective of environmental communication involves the ability to critically assess information concerning pressing environmental challenges such as climate change, pollution, and biodiversity loss (Cox, 2010). From a broader ideological view, environmental awareness serves as a core component of sustainability discourse, playing a crucial role in nurturing civic responsibility and ecological citizenship in modern societies (Latta, 2007). Throughout the advancement of environmental literacy, educational initiatives, digital platforms, and institutional policies can empower individuals to become informed and responsible stewards of the environment. In particular, the algorithmic curation and consumption of environmental information play a vital role in shaping collective sustainability consciousness.

The relationship between environmental awareness and sustainable behavior has been conceptualized within the Theory of Planned Behavior, which posits that cognitive and attitudinal factors are foundational drivers of pro-environmental action (Ajzen, 1991). The Value-Belief-Norm theory similarly suggests that recognition of environmental consequences can activate personal norms that promote environmentally responsible actions (Stern, 2000). As a pivotal psychological variable, environmental awareness bridges the gap between ecological knowledge and behavior. In the context of policy and behavioral economics, this awareness facilitates green consumer behavior and strengthens public support for environmental policies, sustainable consumption, and grassroots conservation efforts (Shen & Wang, 2022). In the era of algorithmically driven information economy, the personalization of digital content introduces both opportunities and challenges for delivering environmental communication. Algorithmic filters may amplify meaningful message or reinforces echo chambers that obscure environmental risk (Pariser, 2011; Haim *et al.,* 2018). Investigating this impact is essential to understanding the role of digital media in informing policy and practice in sustainability education.

The "Our Planet" series produced by Netflix and the World Wildlife Fund (WWF), exemplifies a notable case of media-driven environmental awareness an prompt behavioral change. A study by Jones *et al.* (2019) have been shown the capacity of documentaries like "Our Planet" effectively raise public awareness of ecological threats, such as the loss of biodiversity. Beyond raising awareness, the report by WWF and TVE (Television for the Environment) also impact assessment found that "Our Planet" led to concrete behavioral change by the increased efforts to reduce meat consumption, avoid palm oil products, and minimize food waste by viewers (WWF, 2020). It is evident that these outcomes illustrate the influential role of strategically designed media in shaping environmental perceptions and individual actions.

### 2.2. Theoretical framework

#### *2.2.1 Elaboration Likelihood Model (ELM):*

The Elaboration Likelihood Model (ELM), proposed by Petty & Cacioppo (1986), persuasion communication is processed via two cognitive pathways as central and peripheral, which reflect how individuals evaluate messages based either on content scrutiny or via heuristic cues. The central route is characterized by deliberate and critical evaluation of message content, often leading to durable attitude change. In contrast, the peripheral route operates through reliance on surface-level cues and tends to result in more ephemeral attitudinal responses. In the context of algorithm-mediated content delivery, the ELM offers a dual-process framework for individuals engage with information related to environmental awareness.

The effectiveness of environmental messages has been shown to be significantly influenced by the processing route adopted by individuals. For instance, Zhang *et al.* (2024) investigated the extent to which variations in message structure influence tourists's predispositions towards environmentally responsible behavior. The study demonstrated that central-route processing, which involves high elaboration and critical engagement, resulted in more stable and persuasive pro-environmental attitudes than those processed through the peripheral route. This outcome suggests that underscores the importance of message relevance and cognitive quality in effectively enhancing environmental awareness.

Building on the ELM framework, the application of this model to online environmental engagement highlights the moderating role of cognitive processing. Wang *et al*. (2019) provided empirical evidence that perceived value and social influence are key determinants of participation, with these effects varying according to whether individuals adopt a central or peripheral route of message evaluation. According to ELM, this dual-process mechanism was evident in the differential effects of message components as individuals with a high propensity for elaboration are influenced predominantly by logical arguments via the central route, while those with lower elaboration engagement are more responsive to heuristic cues, including communicator credibility. This findings highlight the interplay between cognitive orientation and message framing in shaping the impact of persuasive environmental communication. Within the context of recommendation algorithms, the ELM provides a useful lens through which perceived content relevance functions as a critical determinant of information processing routes. High perceived relevance of environmental recommendations increases the likelihood of central-route engagement, resulting in the enhancement environmental awareness. Conversely, low perceived content relevance prompts users to adopt peripheral processing strategies, leading to less pronounced attitude shifts. This underscores the essential role of perceived relevance in optimizing the effectiveness of AI-facilitated environmental communication.

In addition, the human-machine interaction model can shape or moderate the influence of perceived information relevance on environmental awareness. Specifically, interactive AI can enhance users' motivation and cognitive resources for central information processing, by facilitating user engagement and offering personalized feedback, which subsequently amplifies the persuasive power of relevant environmental messaging. Therefore, applying the Elaboration Likelihood Model (ELM) in analyses of AI-mediated environmental communication helps illuminate the processes through which information relevance, algorithmic exposure, and human-AI interaction influence environmental awareness.

However, the Elaboration Likelihood Model (ELM) posits that variations in individuals' motivation and cognitive capacity dictate whether information is processed via central or peripheral routes. Notably, the former leads to more persistent attitude change, whereas the latter produces more ephemeral outcomes. The model contends that message characteristics and individual differences influence processing routes. In the realm of AI-mediated communication, it proposes that perceived information relevance and human-AI interaction act as key modulators of these routes.

### *2.2.2 Uses and Gratifications Theory (UGT):*

The Uses and Gratifications Theory (UGT), developed by Katz et al. (1973), maintains that individuals purposefully select media to satisfy needs, including information acquisition, personal identity affirmation, social integration, and entertainment. This theory redirects attention from media effects on individuals to individuals' active engagement with media, highlighting the audience's agency in the consumption process. In the context of environmental awareness, UGT offers a valuable framework for understanding how people engage with algorithmically curated environmental content.

Recent studies applying the Uses and Gratifications Theory (UGT) have explored the motivations driving social media use and its implications for psychological well-being. For instance, Al-Menayes (2023) identified that individuals leverage social media platforms to fulfill needs related to information acquisition and social connection, which in turn influence their psychological well-being. These results reinforce the significance of UGT as a theoretical framework for understanding the mechanisms by which individuals navigate media content selection and engagement based on their underlying gratifications. Within the domain of AI-mediated environmental communication, UGT suggests the proposition that individuals' engagement with environmental content is significantly shaped by the satisfaction of their underlying psychological and informational needs. The ability of recommendation algorithms to customize content to users' preferences plays an important role in elevating perceived information relevance, ultimately fostering greater user engagement and enhancing environmental awareness. Conversely, a misalignment between recommended content and users' gratifications is likely to result in users disregarding the content, thereby limiting its potential to enhance environmental awareness.

Interactions between users and algorithmic systems, as conceptualized in the human-machine interaction model, can significantly affect users' perceptions of and engagement with algorithmically recommended content. The customization of content preferences and feedback mechanisms in interactive AI systems has the potential to optimize the congruence between algorithmically delivered content and individual gratifications, which can increase perceived content relevance and promote both engagement and environmental awareness. Intergrating ELM into the analytical framework of AI-mediated environmental communication enables a deeper understanding of how the cognitive engagement with algorithmically curated content—mediated , information relevance, and human-AI dynamics influence environmental awareness.

However, Uses and Gratifications Theory (UGT) conceptualizes media users as active agents who deliberately select information to satisfy particular needs and desires. Because media use is inherently goal-oriented, and the utility of content depends largely on its perceived capacity to meet those gratifications. Recommendation algorithms and human-AI interaction models, as the central mechanism in AI-mediated communication plays a critical role in aligning media content with user preferences, consequently shaping user engagement and environmental awareness.

**2.3 Perceived Information Relevance (PIR):**

In the context of information behavior theory, Perceived Information Relevance (PIR) is understood as a personal judgment that explains how individuals filter and prioritize content based on the perceived relevance, utility, and contextual fit of information in relation to their goals and cognitive frameworks (Saracevic, 2007; Greisdorf, 2000). The concept of perceived information relevance also reflects a multidimensional assessment shaped by the dynamic interplay between the subjective fit of information within a user’s mental model and the surrounding context—underscoring the importance of interpretive coherence over mere factual precision (Schamber *et al*., 1990). Moreover, PIR is moderated by contextual dimensions such as topic salience, source reliability, presentation format, and user motivation, making it a highly adaptive construct within in digital knowledge environments (Park, 1994).

From a theoretical perspective which rooted in Relevance Theory (Sperber & Wilson, 1995), PIR is guided by the principle that individual evaluates information based on its highest informational value relative to the cognitive resources required for its interpretation.The Value of Information Principle, as articulated by Arrow (1974), aligns with the theoretical basis of PIR by emphasizing that the value of information lies in its potential to reduce uncertainty and enhance decision-making outcomes. Through the analytical lens of Value-Sensitive Design (Friedman, 1996), PIR underscores the ethical obligation in system design to ensure that information delivery upholds user autonomy, promotes clarity, and supports empowered decision-making.

Wang *et al.* (2023) highlighted the importance of trust and relevance in governmental communication, demonstrating that high-quality, context-sensitive information can enhance environmental awareness. Moreover, empirical studies consistently confirm that relevant information has a greater capacity to influence individual attitudes and behaviors. Similarly, Kang et al. (2013) demonstrated that when individuals perceive environmental information as relevant to their values, which significantly predicts ecological behavioral intention, particularly among urban consumers. The alignment of sustainability messages with personal beliefts fosters greater cognitive engagement, encouraging deeper information processing, improved risk perception, and also heightened awareness of long-term environmental outcomes.

The effectiveness of perceived information relevance (PIR) appears to be context-dependent rather than universally robust. Wang et al. (2023) reported that while urban populations responded positively to PIR stimuli, rural populations exhibited weaker engagement, suggesting that structural and cultural factors—such as access to digital resources and interpretive context—may mediate these effects. Strother and Fazal (2011) further argued that user responsiveness may decline due to a phenomenon known as "relevance fatigue," wherein overexposure to environmentally themed messages reduces their perceived novelty and overall effectiveness.

Adopting a critical theoretical approach reveals that PIR is shaped not only by individual cognition but also by the systematic forces that govern information dissemination. As posited by the Social Construction of Technology (SCOT) theory, relevance is co-constructed through institutional power, mediated communications, and audience segmentation (Bijker et al., 1987). Consequently, PIR transcends individual cognition and is situated within complex networks of social and technological mediation.

The hypothesis supports the view that PIR, when aligned with user expectations and contextual factors, can function as a powerful driver of environmental awareness. Its ability to engage both cognition and emotion makes PIR particularly valuable in the implementation of sustainability communications, educational interventions, and digital communication frameworks.

H1: *Perceived information relevance positively influences environmental awareness.*

**2.4 Algorithmic Content Exposure (ACE):**

Algorithmic Content Exposure (ACE) constitutes a technologically mediated process whereby digital systems employ behavioral tracking, machine learning algorithms, and predictive analytics to curate and deliver information tailored to individual users. These algorithmic mechanisms filter vast amounts of digital content to prioritize what is perceived as most relevant or engaging, thereby shaping user's informational environments (Pariser, 2011). In the research by Brady, McLoughlin, and Crockett (2023), ACE exemplifies the convergence of machine learning, surveillance capitalism, and predictive analytics in shaping both perception and discourse.

ACE has been theoretically connected to Selective Exposure Theory, which asserts that individuals are more likely to consume content that aligns with their existing beliefs, thus reinforcing established attitudes and contributing to ideological entrenchment (Stroud, 2008). Cultivation Theory also points to cumulative impact of media in shaping perceptions of long-term environmental threats (Gerbner & Gross, 2017). Through the lens of economic, ACEcorresponds with rational-choice models of digital behavior, in which exposure patterns are guided by algorithmic calculations of utility and relevance (Brady *et al*., 2023).

Empirical research increasingly underscores the role of Algorithmic Content Exposure (ACE) in shaping environmental awareness. It has been demonstrated by Berkebile-Weinberg *et al.* (2025) that image search algorithms significantly shape public sentiment toward climate change, influencing subsequent behaviors such as environmental policy and participation in activism. In this context, ACE functions as a gatekeeping chachanism that governs perceived urgency and issue salience. Brady *et al.* (2023) further noted that algorithm-mediated interactions can trigger emotional synchronization and moral positioning, which can amplify public concern or provoke eco-anxiety, depending on how environmental topic are framed.

Despite its potential benefits, the influence of Algorithmic Content Exposure (ACE) is not uniformly advantageous. Also, Pariser (2011) introduced the notion of the “filter bubble,”, describing the ideological insularity created by algorithmic personalization. This can restrict exposure to diverse viewpoints and obscure scientifically balanced discourse. Additionally, Brady *et al.* (2023) highlighted that algorithmic models optimized for engagement over accuracy my amplify oversimplified or erroneous environmental content, thereby compromising public comprehension of multifaceted ecological issues.

The ethical implications of ACE systems challenge the notion of algorithmic neutrality. Through the lens of Value-Sensitive Design (Friedman, 1996), emphasizes embedding normative principles such as transparency and informational pluralism into algorithmic systems. As socio-technical assemblages, these systems co-construct social knowledge (Gerbner & Gross, 2017; Brady *et al*., 2023), reinforcing the imperative for ethically grounded and democratically accountable governance mechanisms.

The studies coverages on the premise that ACE, under conditions of responsible governance and value-sensitive design, can serve as a powerful catalyst for environmental consciousness by amplifying exposure to emotionally salient and contextually relevant sustainability narratives. Nonetheless, the informational accuracy and ideological impartiality of these systems remain conditional upon platform architecture, individual user behavior, and the presence of effective ethical oversight mechanisms.

Drawing upon the integrated theoretical perspectives outlined earlier, the second hypothesis is formulated as follows:
H2: *Algorithmic Content Exposure positively influences Environmental Awareness.*

### 2.5 Human–Machine Interaction:

Human–Machine Interaction (HMI) refers to the evolving set of communicative exchanges between individuals and digital systems, encompassing both passive behaviors such as scrolling and clicking, and active engagements like commenting and content curation. hese behaviors significantly influence the way information is cognitively processed and how attitudinal change occurs (Dix, 2007; Sundar & Bellur, 2014). In algorithmic ecosystems, HMI constitutes a reflexive layer of mediation, actively influencing how information is filtered, prioritized, and internalized by users.

The Stimulus–Organism–Response (S–O–R) framework, developed by Mehrabian & Russell (1974) conceptualizes Human–Machine Interaction (HMI) as an environmental stimulus that elicits cognitive and affective responses within the user. In conjunction with Cognitive Load Theory, it becomes evident that interaction intensity modulates the user's processing capacity for environmental content, with deeper engagement enabling greater message integration (Eppler & Mengis, 2004). Although Perceived Information Relevance (PIR) has been established as key determinants of environmental awareness (Wang *et al*., 2023), its influence is contingent upon the nature of user interaction with digital content, Active interaction fosters heightened cognitive elaboration and message internalization (Sundar & Bellur, 2014), whereas passive engagement may truncate attention spans and reduce memory retention, even when relevance is high (Strother & Fazal, 2011). Human–Machine Interaction (HMI) moderates the relationship between PIR and environmental awareness, with higher interactivity enhancing message processing through personalization and reflection. In contrast, low-interactivity contexts are more likely to foster cognitive disengagement, reducing the salience and perceived urgency of relevant environmental content.

Empirical research by Bucklin and Sismeiro (2003) affirms the role of user interaction behavior in cognitive outcomes, revealing a strong association between clickstream depth, revisit frequency, and increased knowledge retention as well as issue salience. Furthermore, structural features of the interface, including choice architecture and the presence of design friction, have been found to significantly mediate user engagement with environmental information, reinforcing the moderating influence of HMI (Thaler *et al*., 2014; Friedman *et a*l., 2013).

Building on the theoretical frameworks previously examined, the study puts forward the following third hypothesis:

**H3:** *Human–machine interaction moderates the relationship between perceived information relevance and environmental awareness, such that the relationship is stronger when users engage in high-interactivity behaviors and weaker in low-interactivity contexts.*

By firmly grounding the hypotheses in well-established theoretical frameworks, this study strengthens its potential to make a meaningful contribution to the academic literature with the following proposed conceptual framework:

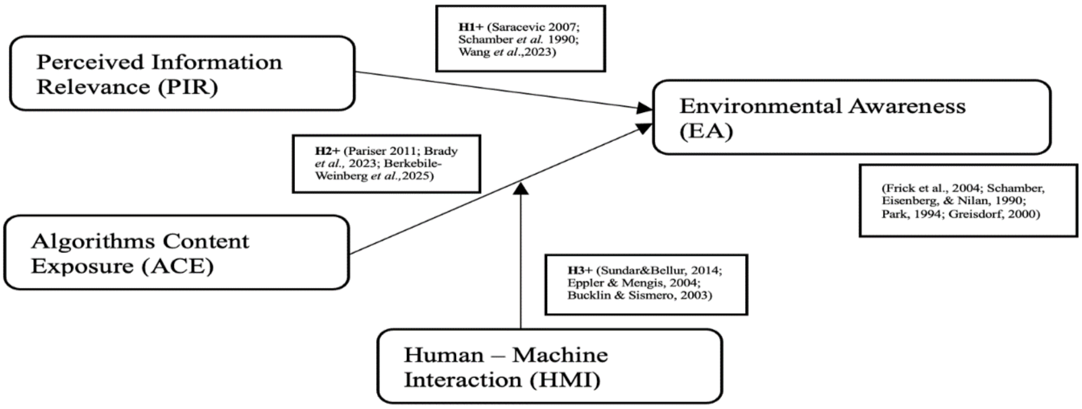


**Figure 1 The Paper's Conceptual Framework**

## 3. METHODS

This study aims to examine the interplay between algorithm-driven recommendations and environmental cognition. It also employs a quantitative methodological framework, utilizing purposive sampling to balance empirical rigor with representational accuracy (Creswell & Creswell, 2017). Participants were purposively chosen based on their varied levels of exposure to digital platforms that utilize AI-driven content delivery, encompassing a broad range of demographic, technological, and behavioral patterns relevant to the study.

The sample was stratified into four groups. The first included Vietnamese young adults aged 18–35 who are active users of social media platforms—particularly TikTok, YouTube, and Facebook—where algorithmic filtering is prominent. Individuals in the first group exhibited a pronounced sensitivity to emotionally and visually framed content, reflecting peripheral information processing in environmental messaging. In contrast, the second group included middle-income participants from Vietnam, Malaysia, and Indonesia, whose interactions with personalized content reflected a more reflective and rational approach to environmental information. Next, the third group consisted of international postgraduate students and early-career professionals based in Southeast Asia, characterized as cross-cultural digital consumers with diverse exposure to environmental narratives across multiple online platforms.The final group included digital influencers, environmental content creators, and globally connected users (e.g., Vietnamese residents in Australia and Canada), whose engagement with algorithmic recommendations significantly informs their environmental values and perceptions of ecological urgency.

To be eligible for inclusion in the study, participants must have encountered with a minimum of one environmentally oriented digital communications related to environmental issues such as videos, articles, or social media posts by an algorithmic system in the preceding six-month period.Stratification factors included participants age, nationality, cognitive style as central or peripheral processing, and the frequency of interaction with algorithm-based platforms. Data collection relied on online surveys shared through social media, university communication channels, Reddit discussions, and professional platforms like LinkedIn. Notably, regional sample diversity was further strengthened through institutional collaboration with Chulalongkorn University and MARA University of Technology.

Following thorough data validation procedures, 385 responses were deemed complete and consistent, forming the final dataset out of an initial 604 entries. The questionnaire utilized a 5-point Likert scale (from 1, "strongly disagree," to 5, "strongly agree") to capture participant perspectives on perceived information relevance, algorithmic content exposure, and engagement with AI systems. The resulting participant structure enables comprehensive analysis of the role of algorithmic communication in shaping environmental awareness within varied digital contexts.

## 4. RESULTS

### 4.1. Reliability analysis

**Table 1: Reliability analysis of the dependent variable "environmental awareness". Source: (The authors, 2025)**

| Reliability Statistics | |
|---|---|
| Cronbach's Alpha | N of Items |
| .708 | 4 |

Item-Total Statistics

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Corrected Item-Total Correlation | Cronbach's Alpha if Item Deleted |
|---|---|---|---|---|
| EA1 | 9.116 | 7.638 | .597 | .616 |
| EA2 | 7.323 | 7.982 | .612 | .625 |
| EA3 | 7.447 | 7.483 | .664 | .672 |
| EA4 | 8.650 | 7.305 | .635 | .653 |

Where EA1 to EA4 are coded for survey questions 1 to 4 of environmental awareness respectively.

As shown in Table 1, all sub-variables of the dependent construct demonstrated adjusted item-total correlation coefficients of at least 0.3. The overall Cronbach's alpha was 0.708, exceeding the commonly accepted threshold of 0.6 and remaining higher than the alpha values that would have resulted from omitting any individual item. Additionally, each dependent sub-variable retained a Cronbach's alpha greater than its respective adjusted item-total correlation, even when specific items were hypothetically removed. Consequently, all items were preserved for subsequent analysis. A similar level of internal consistency was observed across the Cronbach's alpha results for the other variables as well.

### 4.2. Exploratory factor analysis (EFA)

**Table 2: Rotated Component Matrix. Source: (The authors, 2025)**

| **Rotated Component Matrix[a]** | | | |
|---|---|---|---|
| Component with loading factors | | | |
| 1 | 2 | 3 | 4 |
| AE1 .582 | PIR1 .626 | ACE1 .591 | HMI1 .715 |
| AE2 .579 | PIR2 .681 | ACE2 .661 | HMI2 .514 |
| AE3 .689 | PIR3 .711 | ACE3 .730 | HMI3 .670 |
| AE4 .584 | PIR4 .601 | ACE4 .650 | HMI4 .632 |
| Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. | | | |
| a. Rotation converged in 7 iterations. | | | |

Where survey items HMI1 to HMI4, PIR1 to PIR4, and ACE1 to ACE4 correspond to questions 1 through 4 designed to code the moderator variable and the two independent variables, respectively.

As illustrated in Table 2, the rotated component matrix effectively grouped the 16 sub-variables into four clear factors, corresponding to the dependent variable, the two independent variables, and the moderator variable. Each sub-variable exhibited a factor loading above 0.5, and the factor analysis process did not require the elimination of any items.

### 4.3. Multiple linear regression model

**Table 3: Coefficients[a]. Source: (The authors, 2025)**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 6.812 | .668 | | 4.818 | .000 |

| | | | | | |
|---|---|---|---|---|---|
| PIR | .541 | .709 | .550 | 3.591 | .027 |
| ACE | .473 | .655 | .490 | 3.005 | .000 |

a. Dependent Variable: AE

Where **AE**: mean of AE1 to AE4; **PIR**: mean of PIR1 to PIR4;
**ACE**: mean of ACE1 to ACE4

As presented in Table 3, the significance (Sig.) values obtained from the t-tests are .027 and .000, both falling below the standard alpha level of 0.05. This indicates that the independent variables— perceived information relevance and algorithmic content exposure—have a statistically significant influence on the dependent variable, environmental awareness. Consequently, both hypotheses are validated.

### 4.4. Moderator analysis

**Table 4: Results analysis of "human-machine interaction model". Source: (The authors, 2025)**

Model : 1
Y : AE
X : PIR
W : HMI
Sample Size: 385
**************************************************************************
OUTCOME VARIABLE:
AE
Model Summary

| R | R-sq | MSE | F | dl1 | dl2 | p |
|---|---|---|---|---|---|---|
| .691 | .477 | .623 | 5.723 | 3.000 | 381.000 | .000 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 6.565 | .421 | 48.337 | .000 | 6.384 | 6.269 |
| PIR | .710 | .758 | 4.516 | .000 | .667 | .656 |
| HMI | .663 | .769 | 4.328 | .000 | .583 | .564 |
| Int_1 | .570 | .902 | 5.892 | .000 | .525 | .519 |

Where **HMI**: mean of HMI1 to HMI4

As indicated in Table 4, the p-value for the interaction term (Int_1) is 0.000, which is well below the conventional significance threshold of 0.05. This provides strong evidence of a statistically significant interaction between the human-machine interaction model and perceived information relevance in shaping environmental awareness. The interaction coefficient of 0.570 suggests that stronger the human-machine interaction model amplify the positive impact of perceived information relevance on environmental awareness. Therefore, hypothesis H3 is supported.

## 5. DISCUSSION

### 5.1. Result summary

The results from linear regression analysis reveal that perceived information relevance (PIR) plays a dominant role in shaping environmental awareness, evidenced by a coefficient of 0.55 (β = 0.55). In comparison, algorithmic content exposure, while statistically significant, demonstrates a more modest effect (β = 0.49). The moderating role of human–machine interaction on the PIR–environmental awareness link was confirmed, with a moderation coefficient of 0.57. Collectively, these findings offer nuanced insights into the complex relationships driving environmental awareness in algorithmic communication contexts to address the three research questions.

### 5.2. Theoretical implication

The findings provide strong empirical support for the hypothesis that Perceived Information Relevance (PIR) significantly enhances environmental awareness, with a high coefficient (β = 0.55) indicating its central role. This finding is consistent with Relevance Theory (Sperber & Wilson, 1995) and Arrow's (1974) Value of Information Theory, both of which emphasize that individuals selectively engage with content that reflects their mental models and decision-making priorities. These frameworks suggest that relevance arises from the alignment between external messages and internal cognitive schemas. The strength of PIR in this context also reinforces findings by Kang et al. (2013) and Wang *et al*. (2023). However, this contradicts the concept of “relevance fatigue” (Strother & Fazal, 2011), which presumes declining user responsiveness to repetitive content. While SCOT theory (Bijker *et al*., 1987) emphasizes the socially constructed nature of relevance, the observed direct effect of PIR underscores the role of individual cognitive agency over socially mediated interpretations. As a result, The findings point to a more agentic model of interpretation, reaffirming PIR as an individually driven cognitive mechanism.

The data reveal that Algorithmic Content Exposure (ACE) has a statistically significant though relatively moderate effect on environmental awareness (β = 0.49), corroborating claims from Berkebile-Weinberg *et al*. (2025) and Brady *et al*. (2023) that algorithmic systems can amplify issue salience and emotional responsiveness. ACE's capacity to drive issue salience and emotional activation contrasts with theoretical concerns from Pariser (2011) and Haim *et al*. (2018) regarding viewpoint restriction and cognitive enclosure. Similarly, the results diverge from Cultivation Theory's deterministic model (Gerbner & Gross, 2017), which posits passive internalization of repeated narratives. These results support ethically designed algorithms, as recommended by Brady *et al*. (2023), while rejecting deterministic accounts of algorithmic influence.

The moderating role of Human–Machine Interaction (HMI) in the relationship between Perceived Information Relevance (PIR) and environmental awareness was confirmed (β = 0.57), illustrating that high interactivity intensifies cognitive engagement. The results support the S–O–R model and Cognitive Load Theory by showing that interactivity enhances elaboration and mitigates cognitive overload. In contrast to deterministic concerns raised by Strother and Fazal (2011), the findings suggest that well-designed interactivity fosters deeper processing, especially when content relevance is already high. In line with Sundar and Bellur (2014), the findings confirm that interactivity enhances both elaboration and memory. Conversely, the data reject Strother and Fazal’s (2011) argument that even relevant content is susceptible to processing fatigue in low-interactivity conditions. Furthermore, the study challenges core assumptions of Uses and Gratifications Theory (Katz *et al*., 1973), suggesting that AI-driven interactivity does not simply satisfy user needs but may activate previously unrecognized cognitive and affective gratifications. This bidirectional interplay between user behavior and system design contributes to a more nuanced understanding of digital ecological cognition.

### 5.3. Practical implication

From a theoretical and practical standpoint, these results have direct implications for digital platform architects, environmental advocates, and policymakers invested in advancing ecological awareness. The strong influence of Perceived Information Relevance (PIR) on environmental awareness underscores the need to tailor environmental content in ways that resonate with users’ cognitive frameworks and value orientations. In line with Value-Sensitive Design (Friedman *et al*., 2013), recommender systems should go beyond preference-matching to actively promote awareness-enhancing content. Feedback-driven personalization, as advocated by Kang *et al*. (2013) and Wang *et al*. (2023), could enable a reflexive loop wherein users influence the algorithm’s relevance criteria, thereby reinforcing pro-environmental values.

Second, although ACE positively influences environmental awareness, the findings emphasize that this effect is not universal but conditional. Echo chamber critiques (Pariser, 2011) remain theoretically relevant, yet the strategic amplification of affectively engaging environmental content (Brady *et al*., 2023) demonstrates ACE’s potential as a catalyst for pro-environmental cognition. Therefore, it is imperative that stakeholders, including platform regulators and sustainability-focused NGOs, push for ethical algorithm configurations that privilege scientifically robust messaging over algorithmically incentivized extremes or simplifications.

Third, Human–Machine Interaction (HMI) is shown to moderate the effect of content relevance on environmental awareness, implying that interactivity is critical to deeper cognitive processing. The presence of Human–Machine Interaction (HMI) as a moderating factor suggests that interactive features such as customizable dashboards, exploratory information trees, and participatory design elements are essential for promoting active user engagement (Sundar & Bellur, 2014). By allowing users to co-curate playlists or engage in impact simulations, platforms can enhance elaboration and align content more closely with users’ cognitive pathways.

Collectively, the implications advocate or a coordinated multi-stakeholder approach, involving platform designers, educators, and regulators, to ensure digital environments actively facilitate ecological learning. Failing to integrate elements such as relevance, user agency through interactivity, and exposure to diverse content may severely limit the capacity of AI-mediated systems to serve as effective instruments for long-term environmental change.

### 5.4. Limitations

Despite offering novel contributions to the understanding of AI-mediated environmental cognition, this study is constrained by key methodological limitations. The cross-sectional nature of the research and its dependence on self-reported data hinder the ability to draw causal conclusions. Although the sample demonstrated demographic diversity, it was predominantly composed of digitally engaged users from Southeast Asia, which may limit the generalizability of the findings to populations with less exposure to AI-driven environments. Additionally, algorithmic exposure and interactivity were assessed through subjective perception rather than behavioral tracking, potentially affecting measurement accuracy. These constraints warrant cautious interpretation of the results, particularly when applying them to broader sociotechnical systems.

### 5.5. Future Research Directions

Future research should employ longitudinal and experimental designs to investigate the long-term effects of algorithmically curated environmental content on attitudinal consistency and behavioral change. The inclusion of behavioral analytics such as clickstream records or dwell time which can provide a complementary, data-driven perspective to self-reporting tools, enhancing interpretive validity. Cross-contextual studies comparing regulatory frameworks and digital ecosystems may further clarify how institutional and cultural factors influence algorithmic impact. Moreover, researchers should address intersections with misinformation and greenwashing narratives to evaluate algorithmic responsibility in filtering ecologically misleading content.

### 5.6. Conclusion

Through the integration of communication theory and algorithmic ethics, this study offers a conceptual framework in which perceived information relevance, algorithmic exposure, and human-machine interaction emerge as interdependent factors shaping digital environmental cognition. The evidence suggests that effective personalization requires more than relevance—interactive affordances and ethical content governance are equally vital. The study contributes to theoretical dialogues in environmental psychology and AI accountability while encouraging multi-sector collaboration to optimize the ecological function of algorithmic media infrastructures.

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**Table 5. Survey**
**Background information**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| What is your age group? | Under 18 | 18-24 | 25-35 | 35-44 | 45 and above | | |
| Which country or region are you currently living in? | Vietnam | Malaysia | Indonesia | Thailand | Australia | Canada | Other (please specify): ____________ |
| Which of the following best describes your current occupation? | University student | Early-career professional | Content creator / Influencer | Mid-career professional | Other (please specify): _____________ | | |
| How often do you access digital platforms that use personalized recommendation algorithms (e.g., TikTok, Facebook, YouTube, Shopee)? | Multiple times a day | Once a day | Rarely | Never | | | |

**APPENDIX: Survey**

| No. | Variables | Coded Sub-variables | Content |
|---|---|---|---|
| 1. | **Environmental Awareness** | AE1 | I am aware that my personal consumption habits can directly impact environmental sustainability (Frick, Kaiser & Wilson, 2004) |
| | | AE2 | I feel personally responsible for taking actions that support environmental protection (Kollmuss & Agyeman, 2002) |
| | | AE3 | I actively seek out information related to environmental issues such as climate change or biodiversity loss (Cox, 2010; Shen & Wang, 2022) |
| | | AE4 | I am willing to support environmental policies and initiatives in my community (Latta, 2007; Shen & Wang, 2022). |

| | | | |
|---|---|---|---|
| 2. | Perceived Information Relevance | PIR1 | I find that environmental content recommended to me is highly relevant to my personal interests (Saracevic, 2007) |
| | | PIR2 | The environmental messages I receive online help me better understand my responsibilities (Wang et al., 2023) |
| | | PIR3 | I usually engage more with environmental content when it matches my goals and values (Schamber, Eisenberg, & Nilan, 1990) |
| | | PIR4 | Information about environmental issues on digital platforms aligns well with my daily life (Park, 1994; Greisdorf, 2000) |
| 3. | Algorithmic Content Exposure | ACE1 | I often receive environmental content through recommendation systems on digital platforms (Pariser, 2011; Brady et al., 2023). |
| | | ACE2 | The content I am exposed to about environmental issues seems to be selected based on my online behavior (Brady et al., 2023) |
| | | ACE3 | AI-generated recommendations have increased my exposure to environmental topics. (Berkebile-Weinberg et al., 2025) |
| | | ACE4 | I believe algorithms prioritize environmental content that emotionally resonates with me (Brady et al., 2023) |
| 4. | Human-Machine Interaction | HMI1 | I frequently comment on, like, or share algorithmically recommended environmental content (Sundar & Bellur, 2014) |
| | | HMI2 | I actively personalize or adjust environmental content settings on digital platforms (Eppler & Mengis, 2004) |
| | | HMI3 | I spend time exploring different sources of environmental information recommended to me (Bucklin & Sismeiro, 2003) |
| | | HMI4 | My interaction with digital platforms enhances my understanding of environmental issues (Dix, 2007; Sundar & Bellur, 2010) |

Survey link:
https://docs.google.com/forms/d/e/1FAIpQLSfUGlFpsLcJIbKvZdzWW8rJvM7WENCwnxAc9vvHPsqviHAWXw/viewform?usp=header