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AI-Supported Environmental Education: Insights from a Qualitative Study of Sustainable Behavior Change

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Abstract: This qualitative study explores how AI-supported environmental education is experienced in corporate contexts and how it influences sustainable behavior among adult professionals. Drawing on semi-structured interviews with corporate practitioners engaged in AI-mediated sustainability learning, the research applies reflexive thematic analysis to identify key behavioral mechanisms. The findings reveal four interrelated themes: personalization as a driver of engagement, continuous feedback and habit formation, the role of social and organizational context, and psychological or practical barriers limiting sustained action. Rather than functioning as a deterministic driver of pro-environmental behavior, AI emerges as a conditional behavioral mediator whose effectiveness depends on motivation, organizational culture, and contextual reinforcement. The study contributes qualitative insight to the interdisciplinary intersection of environmental education, educational technology, and behavioral change research, highlighting the importance of human-centered AI design and institutional alignment for durable sustainability practices. These findings provide a foundation for future longitudinal and mixed-method investigations of AI-mediated environmental learning across organizational settings.

Keywords: AI-supported environmental education; sustainable behavior; corporate ESG learning; behavioral change; environmental sustainability; educational AI

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1. Introduction

The accelerating climate crisis has intensified global attention to environmental education as a key mechanism for fostering sustainable behavior (UNESCO, 2020)[1]. Although initiatives in Education for Sustainable Development (ESD) have expanded across institutions and organizations, increased environmental knowledge does not consistently translate into pro-environmental action. This persistent mismatch—commonly described as the awareness–action gap—remains a central challenge of contemporary environmental education (Kollmuss & Agyeman, 2002; Leal Filho et al., 2019)[2, 3].

At the same time, advances in artificial intelligence are transforming educational environments. In this study, AI-supported environmental education refers to digitally mediated learning systems that employ personalization, adaptive feedback, behavioral nudging, and real-time monitoring to support sustainability-related actions. Unlike traditional knowledge-centered pedagogies, AI-enabled systems provide continuous, individualized interaction that may help translate environmental intentions into everyday practice (Holmes et al., 2019; Fogg, 2009)[4,5].

Despite this potential, empirical research remains limited. Existing studies predominantly emphasize quantitative indicators such as academic performance, engagement, or knowledge acquisition (Chen, Chen, & Lin, 2020)[6], while comparatively little attention has been paid to lived experiences of AI-supported environmental learning and the mechanisms through which technological features shape behavioral decision-making. As a result, the capacity of AI-supported environmental education to produce sustained behavioral transformation—rather than short-term attitudinal change—remains insufficiently understood.

The corporate environment represents a particularly significant yet understudied context for examining this transformation. Because learning processes in organizations are embedded in routines, ESG strategies, and professional practices, they create conditions in which sustainable behavior can be structurally integrated rather than merely encouraged.

To address these gaps, this study adopts a qualitative research design to explore lived experiences of interaction with AI-supported environmental education and its perceived influence on sustainable behavior. Drawing on interviews with corporate professionals who actively use AI tools and participate in sustainability-related initiatives, the study investigates how AI-based environmental learning is interpreted in practice, which technological features are perceived as most influential for behavioral change, and which barriers constrain the transition from awareness to action.

Accordingly, the study addresses the following research questions:

1. RQ1: How do participants in corporate environments experience AI-supported environmental education and sustainability learning?
2. RQ2: Which AI functionalities are perceived as most influential in fostering sustainable behavior?
3. RQ3: What barriers limit the implementation of sustainable actions despite AI support?

By providing qualitative evidence on behavioral mechanisms within AI-supported environmental education, this research contributes to the interdisciplinary intersection of environmental education, educational technology, and behavioral change studies.

This study contributes by theorizing AI-supported environmental education as a form of situated behavioral mediation and by identifying experiential mechanisms through which personalization, feedback, and organizational context shape the durability of sustainable action.

2. Literature Review

A rapidly evolving technological landscape is increasing society's everyday reliance on digital tools while shifting the formation of environmental responsibility beyond formal education into corporate environments, where sustainability becomes embedded in ESG agendas and organizational culture (Li, 2025; Klonowska-Matynia, 2025; Cui, 2025)[7,8,9]. Within this context, artificial intelligence can support environmental learning among adult professionals through personalization, adaptive feedback, micro-goal setting, and habit-formation mechanisms such as reminders and progress monitoring (Fortuna et al., 2025; Chiam et al., 2024)[10,11]. These features indicate a transition from information-based education toward behavior-oriented interventions capable of narrowing the gap between environmental awareness and real-world sustainable action (Strielkowski et al., 2025; Mohammadian, 2024; El Dandachi, 2025)[12,13,14].

Although research on AI in education has expanded rapidly (Park, 2025)[15], it remains largely focused on quantitative indicators such as academic performance, engagement, or knowledge acquisition. Far less attention has been given to participants' lived experiences, interpretive interactions with AI tools, and the behavioral mechanisms through which technological support shapes everyday sustainable practices. In addition, the influence of social and organizational contexts on the effectiveness of AI-supported environmental learning remains insufficiently understood (Chen, Chen, & Lin, 2020; Holmes et al., 2019; Leal Filho et al., 2019; Wu et al., 2025)[6,4,3,16].

Consequently, the literature still lacks qualitative insight into how AI mediates behavioral change in environmental education, particularly in adult learning and corporate settings (Wals, 2011)[17]. This study is additionally informed by established behavioral theories that clarify how intentions translate into sustained action.

First, the Theory of Planned Behavior (TPB) (Ajzen, 1991) conceptualizes behavior as a function of attitudes, subjective norms, and perceived behavioral control, providing a useful lens for interpreting how organizational culture and AI-mediated feedback shape environmentally relevant decision-making[18].

Second, Self-Determination Theory (SDT) (Ryan & Deci, 2000) emphasizes the roles of autonomy, competence, and relatedness in maintaining intrinsically motivated behavior, offering an explanatory framework for participants' ambivalent responses to personalization, reminders, and perceived intrusiveness of AI guidance[19].

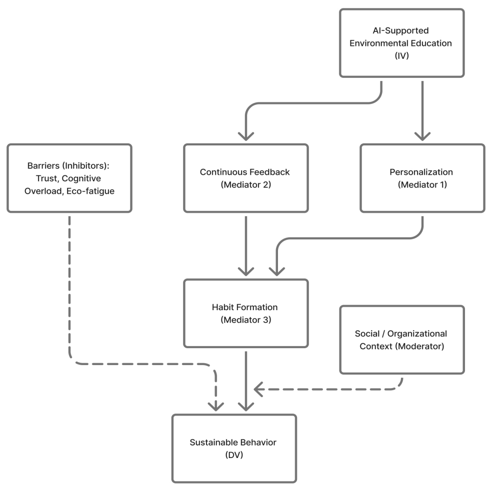

Figure 1. Behavioral mediation model of AI-supported environmental education.

Third, contemporary habit-formation models (Lally et al., 2010) highlight the gradual stabilization of behavior through context-dependent repetition and cue-response reinforcement, suggesting that AI-driven feedback and nudging mechanisms may function as external scaffolds that initiate—but do not guarantee—the internalization of sustainable routines[20].

By integrating TPB, SDT, and habit-formation perspectives, AI-supported environmental education can be understood not merely as an informational or technological intervention, but as a behaviorally mediated process situated at the intersection of cognition, motivation, and contextual reinforcement. This theoretical synthesis provides an interpretive foundation for the qualitative analysis that follows. To address this gap, the present study employs a qualitative design to explore experiences of AI-supported environmental learning and its perceived role in shaping sustainable behavior.

3. Methodology

3.1. Source: author's elaboration

The model illustrates how AI-supported environmental education influences sustainable behavior through the mediating roles of personalization, continuous feedback, and habit formation, while social and organizational context acts as a moderator and psychological or informational barriers constrain behavioral outcomes.

To strengthen analytic coherence, the behavioral mediation model presented in Figure 1 was not treated solely as a conceptual illustration but also as a sensitizing analytical framework guiding data interpretation.

While thematic analysis remained inductive in its initial coding stages, subsequent theme refinement involved a theory-informed mapping of emergent patterns onto the model's core dimensions:

(1) AI-enabled personalization and feedback as behavioral triggers,

(2) habit formation as a mediating stabilization process, and

(3) social-organizational context and psychological barriers as moderating conditions shaping behavioral outcomes.

This abductive integration of inductive thematic analysis with a theoretically grounded behavioral model ensured that empirical findings remained closely connected to broader behavioral theory while preserving openness to unexpected experiential meanings.

3.2. Research Design

This study adopts a qualitative research design to explore lived experiences of interaction with AI-supported environmental education and its perceived influence on sustainable behavior. Data were collected through semi-structured in-depth interviews that captured participants' interpretations, motivations, and reported behavioral changes associated with digital sustainability learning tools.

The research was conducted in Shanghai (China) and reflects the experiences of corporate professionals working in this urban context. Interviews were conducted remotely while participants were residing and professionally active in Shanghai. Data were analyzed using reflexive thematic analysis following Braun and Clarke (2006)[21].

3.3. Participants and Sampling

Twelve corporate professionals were recruited through purposeful sampling. All participants had practical experience using AI-based tools and were involved in sustainability-related training, consulting, or ESG initiatives within organizational settings. Inclusion criteria required experience with AI-supported digital tools, participation in environmental or sustainability programs, and willingness to reflect on behavioral change in professional practice. Participants occupied senior or executive-level roles with substantial experience in ESG, digital technologies, or organizational learning.

3.4. Data Collection and Ethics

Online interviews lasting 30–45 minutes followed a semi-structured guide addressing experiences of AI-supported environmental learning, perceived behavioral changes, and contextual facilitators or barriers. Interviews were audio-recorded with informed consent and transcribed verbatim.

All procedures followed internationally accepted ethical standards for qualitative social research. Participation was voluntary, confidentiality was ensured, and all data were anonymized and securely stored.

3.5. Data Analysis

Analysis followed the six-phase reflexive thematic analysis procedure outlined by Braun and Clarke (2006)[21], including familiarization, coding, theme development, review, definition, and narrative interpretation. Coding and thematic construction were conducted by a single researcher, supported by reflexive memo-writing to enhance transparency and analytical rigor. Themes were developed inductively from meaning units in the transcripts and iteratively refined to ensure coherence and distinction across the dataset.

3.6. Trustworthiness

Credibility was strengthened through the use of verbatim quotations, transparent analytic procedures, and sustained researcher reflexivity, consistent with contemporary qualitative research standards in education and sustainability studies. An audit trail was maintained through iterative memo-writing and versioned theme development. To enhance interpretive credibility, discrepant cases were actively sought and incorporated into theme refinement.

4. Results

The analysis of interview data revealed several recurring thematic patterns reflecting the perceived mechanisms through which AI-supported environmental education contributes to the formation of sustainable behavior.

Through reflexive thematic analysis, four key themes were identified:

1. Personalization as a driver of engagement;
2. Continuous feedback and habit formation;
3. The role of social and organizational context;
4. Barriers to sustainable action.

When interpreted through the behavioral mediation framework introduced in **Figure 1**, the four themes can be understood as empirically grounded manifestations of distinct yet interrelated components of AI-supported behavioral change.

Personalization and feedback function primarily as behavioral activation mechanisms, habit-related dynamics reflect mediated stabilization processes, and social-organizational embedding together with psychological tensions represent contextual moderators and constraints influencing the durability of sustainable action.

This model-aligned interpretation does not replace inductive thematic meaning but situates participants' lived experiences within a coherent behavioral structure.

This approach ensured a transparent transition from empirical data to theoretical interpretation and demonstrated how specific elements of AI-supported environmental learning experiences contribute to the emergence of the identified thematic structures.

The table presented below provides examples of characteristic codes illustrating the content of each theme and confirming their grounding in the interview data.

Table 1. Themes and illustrative codes from thematic analysis

Theme	Illustrative codes
Personalization and perceived relevance	tailored advice; lifestyle fit; visibility of personal impact; perceived genericness; intrusiveness of recommendations
Feedback, reminders, and routine formation	reminders; progress tracking; impact visualization; notification fatigue; selective disengagement
Social and organizational embedding	institutional endorsement; shared norms; peer modeling; infrastructural constraints; informal resistance
Tensions and barriers in sustainable action	distrust in AI advice; cognitive overload; eco-fatigue; competing priorities; convenience–effort trade-offs

Theme 1. Personalization and Perceived Relevance

Participants frequently described personalization as a central feature shaping their engagement with AI-supported environmental learning. Recommendations tailored to individual routines or consumption patterns were often experienced as more concrete and actionable than generalized sustainability guidance. As one respondent explained, advice linked to everyday energy use "does not feel abstract anymore but resembles a practical plan that can actually be followed." Another participant noted that personalized prompts made it possible to "see personal environmental impact in measurable terms rather than as a distant global issue."

At the same time, experiences of personalization were not uniformly positive. Several participants questioned the depth or contextual sensitivity of algorithmic tailoring, suggesting that some recommendations appeared "too generic to truly reflect real-life constraints." In a few cases, highly targeted prompts were even perceived as intrusive or subtly pressuring, producing mild resistance rather than motivation.

A small number of accounts illustrated a more pronounced deviation from the dominant pattern. One senior professional reported largely ignoring personalized sustainability suggestions because they conflicted with time-critical work routines, indicating that perceived relevance alone did not guarantee behavioral uptake. These variations suggest that personalization functions less as a universally effective mechanism and more as a conditional facilitator of engagement shaped by situational and psychological factors.

Theme 2. Feedback, Reminders, and Routine Formation

Ongoing feedback and reminder systems were commonly associated with the gradual stabilization of environmentally oriented practices. Many participants described reminders as compensating for cognitive overload and competing professional demands. As one interviewee stated, without periodic prompts, "environmental intentions quickly disappear behind daily workload." Visualization of cumulative environmental impact was also reported to reinforce motivation, making small actions feel meaningful over time.

However, participants simultaneously emphasized limits to this mechanism. Repeated notifications sometimes became background noise, leading to selective ignoring or deliberate muting of alerts. In such situations, reminders shifted from supportive cues to sources of irritation or disengagement. One respondent reflected that "too many signals reduce attention instead of strengthening it," highlighting an ambivalent relationship between behavioral nudging and user autonomy.

A contrasting case further complicated the overall pattern: one participant reported maintaining several sustainable habits even after disabling reminder functions, suggesting that AI-mediated feedback may initiate—but not always sustain—behavioral routines. Together, these findings portray feedback not as a linear driver of habit formation but as part of a dynamic process of adoption, fatigue, and partial internalization.

Theme 3. Social and Organizational Embedding of AI-Supported Learning

Participants consistently situated their experiences of AI-supported environmental education within broader organizational and social environments. In contexts where sustainability values were visibly endorsed—through ESG strategies, institutional discourse, or peer practices—AI recommendations were more readily integrated into everyday professional behavior. One respondent observed that "when sustainability is already part of the organization's priorities, following AI suggestions feels natural rather than additional."

Yet this supportive alignment was not universal. Several participants described infrastructural limitations, ambiguous managerial signals, or subtle peer skepticism that weakened the practical influence of AI-generated guidance. In such environments, sustainable actions were sometimes postponed, selectively applied, or symbolically acknowledged without consistent behavioral change.

Notably, a minority of respondents reported pursuing individual sustainability practices despite limited organizational support, relying on personal motivation rather than institutional reinforcement. This deviation indicates that while social context strongly shapes behavioral outcomes, it does not fully determine them. AI-supported learning therefore appears embedded in negotiated organizational realities rather than uniformly enabling structures.

Theme 4. Tensions and Barriers in Translating Awareness into Action

Alongside enabling mechanisms, participants articulated multiple tensions constraining the translation of environmental awareness into sustained behavior. Distrust toward AI-generated advice emerged when recommendations seemed insufficiently adapted to local conditions or professional realities. Cognitive overload and competing priorities further limited consistent engagement, particularly in high-pressure work environments.

Emotional responses also played a significant role. Several respondents described forms of "eco-fatigue," characterized by exhaustion resulting from continuous exposure to climate-related information. Under such conditions, even well-designed personalized systems did not necessarily produce durable behavioral change.

Importantly, barriers were rarely absolute. Participants often described fluctuating engagement—periods of active sustainable behavior followed by phases of disengagement or selective adherence. These oscillations suggest that AI-supported environmental education operates within ongoing psychological and contextual negotiation, rather than producing stable linear change.

Table 2. Main Themes of the Influence of AI-Supported Environmental Education on Sustainable Behavior

Theme	Core content	Manifestations in participants' experiences	Interpretive insight
Personalization and perceived relevance	Algorithmic adaptation of sustainability guidance to individual routines, alongside perceptions of genericness or intrusiveness	Practical action orientation; visibility of personal environmental impact; occasional distrust in shallow tailoring; selective ignoring of misaligned recommendations	Personalization operates as a **conditional facilitator of engagement**, shaped by contextual fit, perceived autonomy, and competing priorities rather than producing uniform motivation
Feedback, reminders, and routine formation	Continuous prompts, progress visualization, and behavioral nudging coexisting with notification fatigue and disengagement	Gradual stabilization of some sustainable habits; reminders as cognitive support; muting or avoidance of excessive alerts; persistence of certain behaviors after reminders are removed	Feedback contributes to **dynamic and non-linear habit formation,** involving initiation, fatigue, and partial internalization rather than stable consolidation
Social and organizational embedding	Interaction between AI guidance and institutional norms, ESG culture, peer practices, and infrastructural constraints	Stronger uptake within supportive sustainability cultures; weakened or symbolic compliance under ambiguous organizational signals; individual action sometimes occurring despite limited support	Behavioral outcomes emerge through **negotiated organizational contexts,** where social environments shape—but do not fully determine—the influence of AI-supported learning
Tensions and barriers in translating awareness into action	Psychological, informational, and practical constraints including distrust, cognitive overload, eco-fatigue, and convenience–effort trade-offs	Fluctuating engagement; selective adherence; emotional exhaustion; episodic disengagement followed by renewed effort	AI-supported environmental education produces **uneven and reversible behavioral change**, embedded in ongoing psychological and contextual negotiation rather than linear transformation

5. Discussion

The findings deepen understanding of artificial intelligence in environmental education by shifting attention from knowledge transmission toward the situated and conditional facilitation of behavioral change. Rather than acting as a uniformly effective driver of pro-environmental action, AI-supported learning emerges as a dynamic influence that may stabilize, reshape, or fail to sustain sustainable practices depending on psychological, organizational, and contextual conditions.

Participants described AI not merely as an informational resource but as an element embedded in everyday decision-making routines, reflecting broader debates on the cognitive implications of AI-assisted decision support (Gerlich, 2025)[22]. Personalized guidance and cumulative feedback sometimes supported gradual integration of environmentally responsible actions into daily life, yet selective disengagement, notification fatigue, perceived genericness of recommendations, and competing professional priorities frequently disrupted behavioral continuity. These variations suggest that AI functions less as a deterministic mechanism of transformation and more as a contingent and reversible behavioral mediator.

This interpretation extends prior research on personalization and digital nudging in adaptive learning environments. While quantitative studies report improvements in engagement and knowledge acquisition, the present qualitative findings reveal a more complex experiential landscape characterized by oscillation between adoption, resistance, and partial internalization. Sustainable habits may be initiated through AI-mediated reminders yet later maintained independently—or abandoned—highlighting the non-linear temporality of behavioral change.

5.1. Theoretical contributions

This study advances interdisciplinary scholarship in three ways.

First, it reconceptualizes AI-supported environmental education as situated behavioral mediation rather than a purely cognitive intervention, emphasizing the role of routines, emotions, and organizational constraints.

Second, it refines habit-formation models by demonstrating that AI-mediated sustainability practices develop through dynamic and potentially reversible trajectories shaped by fluctuating motivation and contextual reinforcement.

Third, it shows that AI effectiveness within corporate ESG environments is organizationally contingent: institutional endorsement and peer norms amplify behavioral uptake, yet individual agency may sustain selective action even in weakly supportive contexts. Aligning qualitative findings with TPB, SDT, and habit-formation perspectives further indicates that AI-supported environmental education operates across multiple behavioral layers—cognitive intention formation, motivational regulation, and context-dependent routine stabilization—explaining why its influence appears conditional rather than uniformly transformative.

5.2. Practical implications

Implications extend across educational, organizational, and technological domains.

For universities and Education for Sustainable Development (ESD) initiatives, the results highlight the importance of continuous, personalized learning ecologies embedded in everyday practice. For corporate ESG training, they emphasize alignment between technological tools and organizational culture to avoid merely symbolic adoption. For designers of educational AI, the findings underscore the need for human-centered systems sensitive to trust, cognitive load, emotional fatigue, and user autonomy.

5.3. Limitations and future research

The small qualitative sample limits generalizability, and reliance on self-reported experience may introduce interpretive bias. The exploratory design also precludes causal inference. Future studies should employ longitudinal and mixed-method approaches to examine the durability and contextual variability of AI-mediated sustainability practices across cultural and organizational settings.

5.4. Concluding interpretation

AI-supported environmental education does not simply close the awareness–action gap but reconfigures the conditions under which sustainable behavior may emerge, fluctuate, or recede. Its effectiveness depends on the interaction between psychological readiness, organizational context, and everyday practice. AI becomes most transformative not when it only delivers information, but when it participates—sometimes inconsistently—in the ongoing negotiation of environmentally responsible routines within lived experience.

6. Conclusion

This qualitative study explored how AI-supported environmental education is experienced in corporate contexts and how it is perceived to influence sustainable behavior. The findings suggest that AI contributes to behavior change not by increasing awareness alone, but by supporting how people act in everyday routines—through personalization, continuous feedback, and habit reinforcement. At the same time, the impact of AI remains contingent on organizational support and is constrained by psychological barriers such as distrust in recommendations, information overload, and eco-fatigue.

Overall, the study highlights that AI-supported environmental education is most effective when embedded in supportive institutional cultures and designed with human-centered safeguards. These insights provide a foundation for future research using longitudinal and mixed-method approaches to examine how durable such behavior changes are across organizational and cultural settings.

Disclosure statement

The author declares no conflict of interest.

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