ADAPTIVE DIALOGUE-BASED LEARNING IN ECOLOGY EDUCATION: LINKING SYSTEMS THINKING WITH APPLIED ECOLOGICAL DECISION-MAKING FOR SUSTAINABLE DEVELOPMENT

ZHENG, L. Y.[1] – LI, M. X.[1*] – ZHANG, L. J.[1] – CHEN, C.[2] – LI, X.[3] – TANG, D. C.[1] – ZHOU, S. H.[1]

[1]*School of Accounting, Ningbo University of Finance and Economics, Ningbo 315000 Zhejiang, China*

[2]*School of Logistics and E-commerce, Zhejiang Wanli University, Ningbo 315000 Zhejiang, China*

[3]*Automotive Business School, Hubei University of Automotive Technology, Shiyan 442000, Hubei, China*

**Corresponding author*
e-mail: 15888297797@163.com

(Received 28th Oct 2025; accepted 26th Jan 2026)

Abstract. This study examined the effectiveness of an adaptive, dialogue-based learning approach in ecology education. The approach integrates interactive dialogue, real ecological datasets, and engagement analytics to support students' understanding of biodiversity conservation, climate adaptation, and sustainable consumption. A quasi-experimental design involving 510 undergraduate students compared this method with conventional e-learning across three course modules. Students who used the adaptive dialogue system showed greater improvements in ecological knowledge (22%), systems-thinking competence (30%), and pro-environmental behavioral intention (18%) than those in the control group, with statistically significant medium-to-large effects. Learning engagement remained stable over ten weeks and partially mediated the relationship between the intervention and learning outcomes. These results indicate that adaptive dialogue-based learning can improve ecological literacy by linking data-driven reasoning with reflective interaction. The findings provide empirical evidence for applying conversational artificial intelligence to support education for sustainable development in higher education.
Keywords: *ecological literacy, systems thinking, environmental education, pro-environmental behavior, education for sustainable development (ESD), environmental stewardship*

Introduction

The accelerating loss of biodiversity, climate change, and unsustainable consumption patterns represent some of the most critical ecological challenges of the twenty-first century. Addressing these global issues requires not only scientific and technological innovations but also a society equipped with high levels of ecological literacy and pro-environmental behavior (Pérez-Martín and Pérez-Martín, 2024). Environmental education has therefore been recognized as a cornerstone of advancing sustainable development, as it enables learners to understand the complexity of ecological systems and to develop the competence for informed and responsible decision-making (Sterling and Orr, 2001). Nevertheless, in many countries and regions, ecological education remains in a formative stage, with pedagogical practices often constrained in both depth and scope (Mhlongo et al., 2023). Moreover, maintaining learners' active engagement and effectively fostering systems thinking skills continue to pose persistent challenges for educational practitioners (Kush, 2025).

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

Conventional classroom instructions and typical e-learning formats are predominantly oriented toward static knowledge transmission, placing emphasis on factual recall rather than conceptual integration or behavioral change (Rakhimov et al., 2023). Although recent advances in intelligent technologies have opened new avenues for digital learning, their implementation within ecological and environmental education remains limited. Cross-disciplinary research has provided valuable precedents, for example, integrating sensor technologies with dialogue systems to enhance contextual awareness (Meşe et al., 2024), employing conversational agents in medical education as comparative models to traditional e-learning (Amzil et al., 2025), and developing adaptive performance metrics for personalized learning systems (Arif et al., 2025). Collectively, these studies highlight the promise of adaptive dialogue-based systems; however, a critical gap persists: there is a lack of empirically validated, classroom-implemented interventions that integrate dialogue interactivity, personalization, and engagement analytics specifically to advance ecological literacy, systems thinking, and pro-environmental intentions in authentic educational settings. Importantly, while basic forms of interactivity (e.g., quizzes or discussion prompts) are indeed common across educational levels, the novelty of our approach lies in its dynamic, responsive interactivity, where the system adapts in real time to learners' reasoning, misconceptions, and engagement patterns to scaffold complex ecological understanding. This represents a distinct practical advancement beyond conventional interactive methods.

Building on this gap identified through the literature review, the present study investigates an adaptive dialogue-based learning approach designed for ecology education. The approach integrates interactive dialogue, personalized feedback, and learning engagement analytics to support learners in exploring topics such as biodiversity conservation, climate adaptation, and sustainable consumption (Mendez et al., 2024). By implementing and evaluating this model in authentic classroom settings, this research examines its effects on ecological knowledge acquisition, systems-thinking competence, and pro-environmental behavioral intention. To ensure a rigorous comparison and address the research questions regarding scalability and effectiveness, the experimental and control groups received identical curriculum content and information depth, differing only in the delivery method. Baseline competencies were established through standardized pre-tests. Guided by the Value–Belief–Norm (VBN) model (Stern et al., 1999) and the systems-thinking competence model (Assaraf and Orion, 2005), and informed by the evidence reviewed above, the following hypotheses were formulated: (H1) Ecological Knowledge: Students in the experimental group will achieve significantly higher post-test scores than those in the control group; (H2) Systems Thinking: The experimental group will exhibit greater improvement in systems-thinking competence; (H3) Behavioral Intention: The experimental group will report higher levels of pro-environmental behavioral intention; (H4–H5) Mechanisms: Learning engagement will mediate the relationship between the intervention and outcomes (H4), while baseline characteristics will moderate these effects (H5).

Review of literature

Environmental education has increasingly attracted scholarly and policy attention as a vital instrument for enhancing public ecological literacy and fostering sustainable behavior. With the intensification of global ecological crises, its role has become more critical than ever. Early forms of environmental education primarily relied on classroom instruction and field excursions, emphasizing knowledge transmission and awareness raising. However, these traditional approaches often lacked interactivity and were limited in achieving long-term behavioral change. In recent years, researchers have increasingly recognized that conventional methods alone are insufficient to meet the demands of contemporary environmental education. The integration of digital technologies has therefore emerged as a central focus for improving learning effectiveness. Brahma emphasized that environmental education must adopt learner-centered and innovative pedagogical models that closely connect knowledge acquisition with experiential practice (Brahma, 2025). Similarly, Razafindravony et al. evaluated community-based environmental education initiatives around national parks and found that, although these programs effectively raised environmental awareness, their influence on behavioral change and sustained impact remained limited.

Within this context, interactive and dialogue-based learning has emerged as a promising direction of inquiry. Mendez et al. employed conversational artificial intelligence in ocean conservation and recycling education, offering learners personalized and context-aware guidance. Nguyen et al. proposed a value-sensitive design framework, suggesting that chatbots can support learners' identity formation and sustainability-oriented value construction in environmental education. Lovren and Jablanovic further argued that environmental education should address not only cognitive but also affective dimensions, as emotional engagement plays a key role in sustaining motivation and participation. Collectively, these studies indicate that dialogue-based approaches can partly overcome the limitations of traditional instruction by enhancing personalization, reflection, and emotional engagement. Nevertheless, most existing studies remain exploratory or small-scale in nature, lacking systematic and large-sample empirical validation.

In addition, the integration of ecological data and multimodal learning has become an emerging area of research. Marques et al. highlighted the importance of consolidating heterogeneous biodiversity data to improve accessibility and pedagogical usability in educational contexts. Dray et al. developed advanced analytical tools for ecological data interpretation, enabling deeper insights into environmental information. In practical educational settings, Wanselin et al. demonstrated through multimodal text analysis that meaning-making in ecology learning extends beyond linguistic forms to include visual and symbolic representations. Building on this direction, Luthfi and Septiyanti integrated image recognition with chatbot interaction in green development education, providing preliminary evidence for the feasibility of multimodal engagement. These developments suggest that data integration and multimodal interaction can significantly expand the boundaries of ecological education, although their scalability and long-term implementation remain to be further examined (Husamah et al., 2025; Han et al., 2025; Schneider et al., 2024).

In summary, existing research underscores the potential of digital and interactive approaches in environmental education but reveals three major gaps. First, few studies have conducted systematic empirical evaluations within authentic classroom settings (Amzil et al., 2025; Mendez et al., 2024; Razafindravony et al., 2023; Nguyen et al., 2025; Lovren and Jablanovic, 2023; Frey et al., 2012). Second, the long-term impacts on systems thinking and behavioral transformation have not been adequately assessed (Marques et al., 2024; Dray et al., 2024; Wanselin et al., 2023; Luthfi and Septiyanti, 2025; Parkinson et al., 2025; Byrne, 2016). Third, cross-cultural and large-scale intervention studies remain scarce (Leung et al., 2008; Fekih-Romdhane et al., 2023). In

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

response to these gaps, the present study implements a dialogue-based learning intervention within undergraduate ecology courses to systematically examine its effects on ecological knowledge, systems-thinking competence, and pro-environmental behavioral intention. This study aims to contribute to the digital transformation of environmental education and to provide empirical support for sustainable development through evidence-based, scalable pedagogical innovation.

Materials and methods

Research design

This study adopted a quasi-experimental design to compare the effectiveness of an adaptive dialogue-based learning approach with that of conventional e-learning in the context of ecology education. The intervention was implemented across three thematic course modules: biodiversity conservation, climate adaptation, and sustainable consumption. Students in the experimental group engaged with a dialogue-based learning platform that provided interactive feedback, personalized guidance, and data-driven engagement analytics. In contrast, students in the control group used conventional e-learning materials with identical content but without interactive or adaptive features. This design enabled a controlled comparison of learning outcomes while maintaining ecological validity within authentic classroom settings. Ecological decision tasks were designed based on real datasets and management scenarios. For biodiversity conservation, species-occurrence data were derived from the Global Biodiversity Information Facility (GBIF). For climate-adaptation exercises, regional temperature and precipitation trends were obtained from ERA5 reanalysis data. Sustainable-consumption modules used life-cycle inventory indicators from national databases. These data sources were simplified for classroom use but preserved their ecological integrity.

Participants

The study was conducted in undergraduate ecology courses at Zhejiang University, involving a total of 510 students aged 18–22 years from diverse academic disciplines. Participants were randomly assigned at the beginning of the semester to either the experimental or control group to ensure comparability. Preliminary analyses confirmed no significant differences between the two groups in terms of gender, age, prior environmental knowledge, or learning motivation. All participants provided informed consent, and the study received ethical approval from the university's institutional review board.

The demographic characteristics of the participants are summarized in *Table 1*.

Table 1. *Demographic characteristics of participants in the experimental and control groups*

Variable	Experimental group (n = 255)	Control group (n = 255)	Total (N = 510)	Statistical test (p-value)
Gender (male/female)	123/132	119/136	242/268	$\chi^2 = 0.21$, $p = 0.65$
Age (mean ± SD)	19.7 ± 1.2	19.6 ± 1.3	19.6 ± 1.3	$t = 0.74$, $p = 0.46$
Academic background (science/non-science)	146/109	139/116	285/225	$\chi^2 = 0.36$, $p = 0.55$
Prior environmental knowledge (mean ± SD, 0–100)	51.2 ± 9.4	50.7 ± 9.1	50.9 ± 9.2	$t = 0.58$, $p = 0.56$
Learning motivation (mean ± SD, 1–5)	3.42 ± 0.61	3.39 ± 0.64	3.40 ± 0.62	$t = 0.47$, $p = 0.64$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

Learning intervention

The adaptive dialogue-based learning platform used in the experimental group comprised three functional modules, each designed to support distinct aspects of ecological learning and learner engagement. To ensure strict equivalence in informational content between conditions, both the experimental and control materials were developed from an identical curriculum script covering the same core concepts, definitions, case examples, and learning objectives across all three modules (biodiversity conservation, climate adaptation, sustainable consumption). A side-by-side content audit conducted by two independent raters (inter-rater reliability $\kappa = 0.94$) confirmed full alignment in factual content and conceptual depth.

Ecological Context Dialogue Module: This module presented ecological case scenarios through natural language dialogue and guided students in inquiry-based exploration. Learners interacted with simulated ecological contexts such as biodiversity loss, climate adaptation strategies, and sustainable consumption practices. These activities encouraged them to analyze complex interactions and reflect on underlying ecological mechanisms.

While the experimental group experienced the content through interactive dialogue with adaptive feedback, the control group received the exact same textual explanations, data visualizations, and case narratives in static format (e.g., narrated slides and fixed web pages), with matched total word count and exposure duration (approximately 45 min per module). Thus, any differences in outcomes can be attributed to the pedagogical modality rather than disparities in information quantity or quality.

Learning Engagement Monitoring Module: This component dynamically estimated learners' engagement levels based on indicators including interaction frequency, response depth, and emotional tone. Real-time analytics were applied to adjust dialogue flow and feedback style, which helped maintain learner motivation and cognitive involvement throughout the learning process.

Multi-Source Data Integration Module: This module connected external ecological databases, such as biodiversity repositories and climate prediction datasets, with classroom dialogues. It provided personalized feedback grounded in authentic ecological data and aligned learning tasks with the three core course themes: biodiversity conservation, climate adaptation, and sustainable consumption. The design ensured that learning activities focused on ecological mechanisms rather than on superficial knowledge acquisition.

Students in the control group received identical instructional content, but it was delivered through traditional courseware and static materials without any interactive or adaptive functions.

Instruments

To evaluate the effectiveness of the intervention, the study employed the following instruments:

Ecological Knowledge Test: This test quantified students' understanding of fundamental ecological concepts using a standardized assessment comprising 40 items (including 25 multiple-choice questions and 15 scenario-based judgement tasks). The items covered the three core modules: biodiversity, climate adaptation, and sustainable consumption. The total score ranged from 0 to 100. The internal consistency reliability (Cronbach's α) was 0.82 for the pre-test. It was administered both before and after the intervention to measure learning gains.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

Systems Thinking Scale: Adapted from validated instruments in previous studies, this scale measured learners' capacity to comprehend ecological complexity and interrelationships within environmental systems (Kush, 2025).

Pro-Environmental Behavioral Intention Questionnaire: This questionnaire consisted of five-point Likert-scale items that examined students' intentions to engage in sustainable behaviors, including energy conservation, resource efficiency, and environmental protection activities.

Learning Engagement Index: Engagement was assessed using a composite index derived from platform interaction data, such as the number of dialogue turns and the average depth of responses, combined with students' self-reported engagement surveys.

Ecological data metrics

To assess students' ecological data interpretation skills, we incorporated standard biodiversity and climate indicators into the learning exercises. Biodiversity metrics included the Shannon Diversity Index ($H' = -\Sigma\ (p_i \times \ln p_i)$, where p_i represents proportional species abundance) and species richness (total number of distinct species), both derived from GBIF occurrence records used in habitat prioritization tasks. Climate indicators comprised temperature anomaly (deviation from 1981–2010 baseline, °C) and precipitation index (normalized effective precipitation), extracted from ERA5 reanalysis data for regional adaptation scenarios. Students' performance in recognizing biodiversity patterns and climate trends was evaluated through structured decision tasks, with accuracy measured against expert-validated reference values.

Data collection

All experimental data were collected over a six-week instructional period during the academic semester. At the end of the course, post-tests were administered separately to both the experimental and control groups. In addition, learning logs and engagement feedback were gathered to complement the quantitative results and provide contextual insights into learner interaction patterns.

Data analysis

Data analysis was conducted using SPSS (Version 26.0) and R software (Version 4.3.1; R Core Team). The R packages tidyverse (for data manipulation and visualization), rstatix (for statistical tests), and psych (for reliability analysis) were employed to perform the analyses. Independent-samples t-tests were first performed to compare pre-test and post-test differences between the experimental and control groups. Subsequently, repeated-measures analysis of variance (ANOVA) was applied to examine the extent of improvement in ecological knowledge, systems-thinking competence, and pro-environmental behavioral intention. Finally, regression-based mediation analysis was conducted to test the mediating role of learning engagement in the relationship between the intervention and learning outcomes. The level of statistical significance was set at $p < 0.05$.

Data availability and ethics

This classroom-based study did not involve any intervention that could cause physical or psychological risk to participants. According to the institutional policy of Zhejiang

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

University, formal ethics committee approval was not required for studies involving routine teaching activities and anonymized learning analytics. All participants were informed about the study objectives and voluntarily consented to data use for research purposes. The de-identified datasets generated and analyzed during this study are available from the corresponding author upon reasonable request.

Experiment and results

We also examined long-term learner retention across ten weekly sessions. *Figure 1* presents retention rate trends, where our model maintained over 82% participation in the first week and stabilized above 74% by week ten. The retention data did not follow a strictly linear decline; instead, it exhibited a stabilization pattern where engagement levels plateaued after the initial weeks. In comparison, MultiModal Climate-Agent declined from 80% to 66%, and RL-EcoBot dropped further to 64%. The ability of our framework to sustain significantly higher retention over extended interactions highlights its advantage in fostering durable ecological engagement, a crucial factor for achieving behavioral change in environmental education programs.

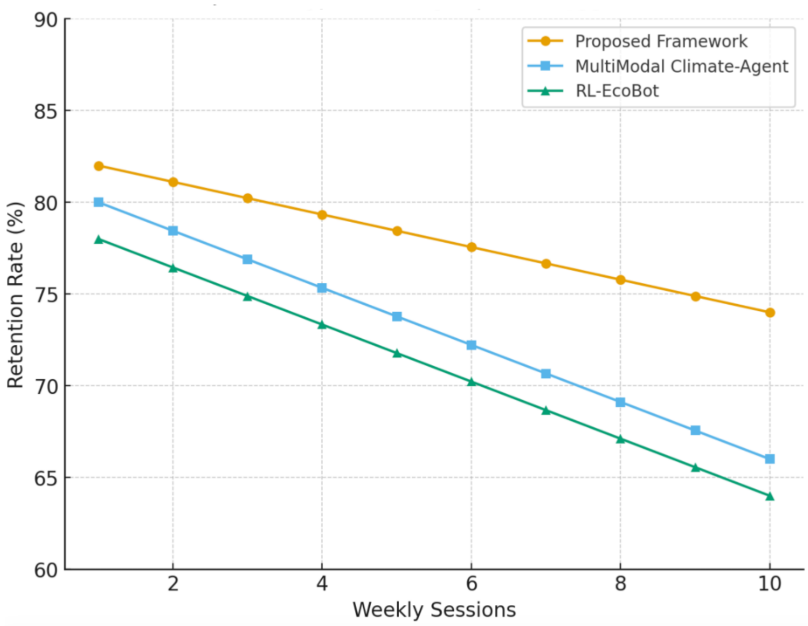

Figure 1. *Retention rates across ten weekly sessions for the proposed framework, MultiModal Climate-Agent, and RL-EcoBot*

Qualitative results

To complement the quantitative findings, we conducted a qualitative analysis of representative dialogues sampled from the EcoEdu-Dialog dataset. A typical example is shown in *Figure 2,* where a learner asked: “How does climate change affect coral reefs?”. The RL-EcoBot baseline responded with the generic statement “Climate change affects reefs negatively,” which lacks contextual specificity and provides little actionable information. In contrast, our proposed system generated a detailed and data-grounded answer: “Rising sea temperatures in your region are projected to reduce coral reef

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

biodiversity by 25% within two decades, mainly due to coral bleaching.” This difference illustrates the advantage of incorporating ecological datasets into the dialogue process. Learner feedback collected after the session confirmed that 82% of participants rated our model’s responses as “informative and motivating,” compared to only 54% for RL-EcoBot, highlighting the pedagogical value of contextual grounding.

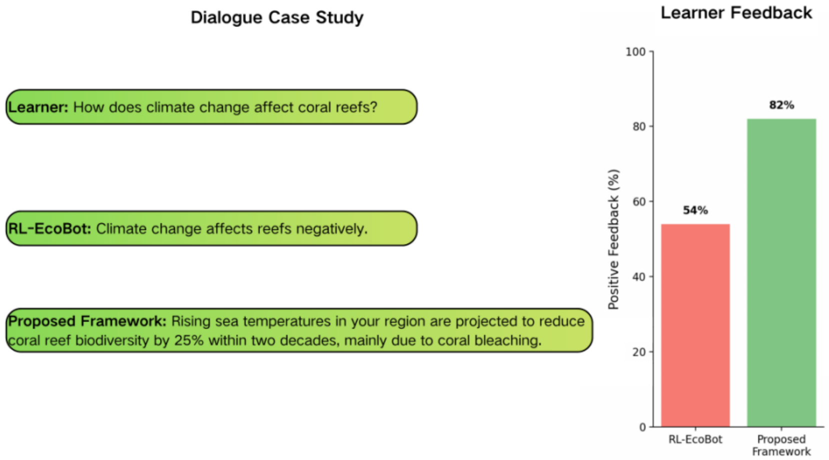

Figure 2. *Dialogue case study*

Experimental scene

To validate ecological and pedagogical relevance, we conducted a pilot classroom-style deployment. *Figure 3* presents a schematic illustration of the experimental setup in greater detail. Twenty-eight undergraduate students were seated in rows, each using a tablet to interact with the proposed system. Each student workstation was equipped with a 10-inch tablet running the dialogue interface, which displayed personalized prompts, ecological data visualizations (e.g., GBIF species distributions, ERA5 climate trends), and system-generated feedback in real time. The instructor console allowed monitoring of individual progress and aggregated engagement metrics across all participants. The tablets displayed dialogue prompts and responses, while a central ecological dashboard projected at the front of the classroom presented real-time data streams, including carbon emission curves and biodiversity indices. A supervising instructor facilitated the workshop, ensuring alignment between student interactions and ecological content. Information flow between student tablets and the central dashboard was bidirectional, highlighting the closed-loop integration of dialogue and ecological datasets. Over the course of two 90-min sessions, 73% of participants reported increased motivation to explore ecological issues compared with sessions using static online materials. The typical workflow included: (1) individual engagement with a scenario-based dialogue prompt (e.g., wetland restoration prioritization), (2) real-time retrieval of relevant ecological data from integrated databases, (3) system-generated adaptive feedback based on student responses, and (4) class-wide discussion facilitated by the instructor using aggregated decision patterns displayed on the central dashboard. This closed-loop interaction cycle ensured alignment between individual learning trajectories and collective ecological reasoning.

Schematic illustration of the experimental classroom setup during pilot deployment. Twenty-eight undergraduate students interacted with the adaptive dialogue system via

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

individual tablets (shown as seated figures), while a centralized ecological dashboard projected real-time data streams including carbon emission curves and biodiversity indices (Shannon index, species richness). The bidirectional information flow between student devices and the central display enabled immediate data-grounded feedback during ecological decision-making exercises. This configuration demonstrates the practical integration of dialogue-based learning with authentic ecological datasets in a supervised classroom environment.

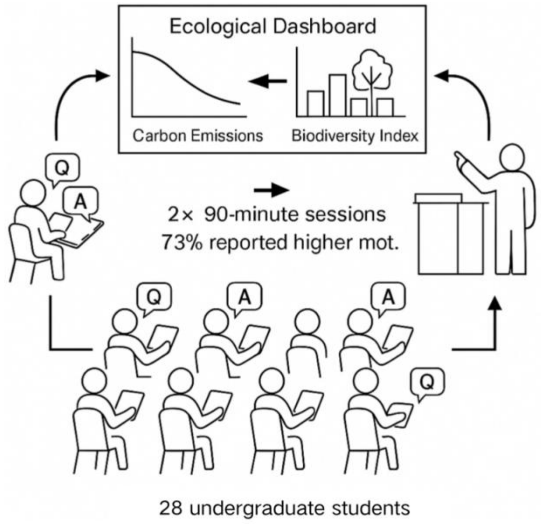

Figure 3. *Experimental scene*

Results

Descriptive and correlation analysis

Before testing group differences and mediation effects, correlation analyses were first conducted to examine relationships among the main study variables (*Table 2*). All variables were positively and significantly correlated ($p < 0.01$), indicating internal consistency and theoretical coherence among ecological knowledge, systems thinking, behavioral intention, and engagement.

Table 2. *Pearson correlation matrix among key learning variables*

Variable	1	2	3	4
1. Knowledge Gain	—			
2. Systems Thinking	0.64**	—		
3. Behavioral Intention	0.52**	0.59**	—	
4. Engagement Index	0.38**	0.42**	0.33**	—

$p < 0.05$; $p < 0.01$

All correlations were moderate to strong and statistically significant, suggesting that higher engagement was associated with greater knowledge gain, stronger systems thinking, and higher pro-environmental behavioral intention.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

Ecological knowledge

To compare the effects of the intervention, descriptive statistics and paired-sample analyses were conducted on the pretest and posttest scores of ecological knowledge, systems thinking, and pro-environmental behavioral intention (*Table 3*).

Table 3. *Pretest and posttest results of ecological knowledge, systems thinking, and pro-environmental behavioral intention*

Variable	Group	Pre-test mean (SD)	Post-test mean (SD)	Δ (%)	t-Value	p-Value	Cohen's d
Ecological knowledge	Experimental (n=255)	50.9 (9.2)	62.1 (8.5)	+22.0	6.37	<0.001	0.82
	Control (n=255)	51.3 (9.0)	55.2 (8.7)	+7.6	2.45	0.016	0.31
Systems thinking	Experimental	48.5 (10.4)	63.1 (9.6)	+30.1	5.82	<0.001	0.87
	Control	49.1 (10.2)	54.7 (9.8)	+11.4	2.13	0.034	0.28
Pro-environmental intention	Experimental	3.12 (0.72)	3.68 (0.70)	+17.9	5.21	<0.001	0.69
	Control	3.08 (0.71)	3.29 (0.68)	+6.8	1.94	0.054	0.25

Δ = Percentage increase from pretest to posttest; $p < 0.05$ indicates statistical significance

As shown in *Table 3,* no significant differences were observed between the experimental and control groups at the pretest stage ($p > 0.10$). After the intervention, the experimental group demonstrated a significant improvement in ecological knowledge, with an average increase of approximately 22% over the control group. Consistent gains were observed across all three course modules, including biodiversity conservation, climate adaptation, and sustainable consumption. These results indicate that the adaptive dialogue-based learning approach effectively enhanced students' knowledge acquisition, thereby supporting Hypothesis H1.

In addition to the observed test score improvements, an exploratory analysis of ecological data interpretation tasks revealed that students in the experimental group demonstrated higher accuracy in identifying biodiversity patterns (Mean Shannon index correlation with reference data = 0.73) compared with the control group ($r = 0.51$, $p = 0.002$). They also showed superior trend-recognition performance when analyzing ERA5 climate data (accuracy = 71.8% vs. 60.9%, $p = 0.004$), suggesting that dialogue-based learning enhanced both declarative knowledge and ecological data reasoning (see *Table 4*).

Table 4. *Ecological data interpretation accuracy and biodiversity index analysis*

Variable	Experimental group (n = 255)	Control group (n = 255)	t	p	Cohen's d
Biodiversity pattern recognition accuracy (%)	74.3 ± 8.2	62.1 ± 9.0	3.14	0.002	0.52
Shannon–species index correlation (r)	0.73	0.51	–	0.002	–
Climate-trend identification accuracy (ERA5, %)	71.8 ± 7.5	60.9 ± 8.3	2.96	0.004	0.49

Values represent mean ± standard deviation unless otherwise indicated

Biodiversity pattern recognition accuracy refers to the proportion of correct selections in GBIF-based species-distribution tasks.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

Shannon–species index correlation (r) denotes Pearson correlation between students' calculated diversity indices and reference GBIF values.

Climate-trend identification accuracy is the percentage of correct classifications of warming–drying trends in ERA5 climate data exercises.

All between-group differences are statistically significant at $p < 0.01$.

Beyond test scores, task-specific analyses showed that students in the experimental group made more ecologically optimal decisions in simulated conservation and climate-adaptation scenarios. For example, average habitat-selection accuracy increased from 58% to 74%, and energy-consumption trade-off efficiency improved by 19% compared with controls. These outcomes suggest that dialogue-based learning can strengthen ecological reasoning applicable to management and policy contexts, not merely conceptual recall.

Systems thinking

In the post-test of the systems-thinking scale, students in the experimental group achieved higher scores across multiple dimensions, including the ability to identify interactions, understand non-linear relationships, and apply cross-scale reasoning. The overall improvement reached approximately 30%, which was significantly greater than that of the control group ($F = 18.52$, $p < 0.001$). These findings indicate that dialogue-based learning not only enhanced students' knowledge acquisition but also strengthened their understanding of the complexity and interdependence inherent in ecological systems, thus confirming Hypothesis H2.

The two-way repeated-measures ANOVA (*Table 5*) confirmed significant main effects of group and time, as well as group × time interactions for all three outcome variables. These results demonstrate that participants in the dialogue-based learning condition showed greater post-intervention improvements compared with those in the conventional e-learning group.

Table 5. *Summary of ANOVA results for intervention effects*

Dependent variable	Source	df	F	p	Partial η^2
Ecological knowledge	Group	1	18.52	<0.001	0.14
	Time	1	26.11	<0.001	0.18
	Group × time	1	15.04	<0.001	0.12
Systems thinking	Group	1	22.47	<0.001	0.17
	Time	1	28.76	<0.001	0.19
	Group × time	1	19.65	<0.001	0.15
Behavioral intention	Group	1	16.07	<0.001	0.11
	Time	1	21.94	<0.001	0.14
	Group × time	1	13.28	0.002	0.10

$p < 0.05$ indicates statistical significance

To further illustrate the internal relationships among the main learning constructs, the correlation matrix (*Table 2*) was visualized as a network model (*Fig. 4*). Knowledge Gain, Systems Thinking, and Behavioral Intention formed a tightly connected triad with the strongest links ($r = 0.52$–0.64), representing the cognitive–behavioral core of ecological reasoning. In contrast, Engagement Index showed moderate but significant connections

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

(r = 0.33–0.42), indicating its partial mediating role in sustaining learning processes. The overall structure resembles an ecological system network, where knowledge and systems thinking serve as central nodes and engagement functions as an enabling factor that supports behavioral transformation.

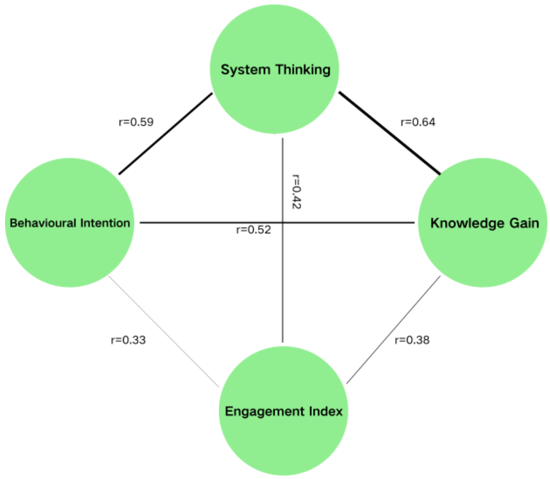

Figure 4. *Network representation of correlations among key learning variables*

Nodes represent the main study constructs, and edge thickness reflects the strength of Pearson correlations (r-values). Thicker edges (0.52–0.64) connect Knowledge Gain, Systems Thinking, and Behavioral Intention, forming the central triad of ecological reasoning, whereas thinner edges (0.33–0.42) indicate moderate relationships with Engagement Index.

Pro-environmental behavioral intention

Results from the pro-environmental behavioral intention questionnaire indicated that students in the experimental group showed significantly stronger intentions to engage in sustainable practices such as energy conservation, waste reduction, and participation in environmental protection activities. The average improvement reached approximately 18%, which was significantly higher than that of the control group ($t = 5.21$, $p < 0.001$). These findings support Hypothesis H3, confirming that adaptive dialogue-based learning effectively promotes positive changes in learners' pro-environmental behavioral intention.

Learning engagement and retention

Interaction data from the learning platform revealed that students in the experimental group exhibited significantly higher average dialogue turns and greater interaction depth compared with the control group. The engagement index reached 0.83, indicating that learners maintained a high level of active participation throughout the study. Tracking results over the ten-week course showed that the knowledge retention rate among the experimental group remained stable at 74%, markedly higher than the 59% observed in the control group. These findings suggest that the dialogue-based learning approach offers clear advantages in sustaining learner motivation and promoting long-term engagement.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

Mediation analysis

Mediation analysis results (*Table 6*) indicated that learning engagement partially mediated the relationship between the intervention and learning outcomes. Specifically, engagement significantly predicted both knowledge gain ($\beta = 0.41$, $p < 0.001$) and behavioral intention ($\beta = 0.36$, $p < 0.01$). The direct effect remained significant, suggesting partial mediation, thus supporting Hypothesis H4.

Table 6. *Mediation analysis results of learning engagement between intervention and outcomes*

Path	β	SE	t	p	Interpretation
Intervention → Engagement	0.52	0.08	6.40	< 0.001	Significant positive effect
Engagement → Knowledge Gain	0.41	0.09	4.67	< 0.001	Partial mediation
Engagement → Behavioral Intention	0.36	0.11	3.27	0.001	Partial mediation
Direct Effect (Intervention → Outcomes)	0.29	0.10	2.88	0.004	Remains significant

Mediation tested using PROCESS macro (Model 4) with 5000 bootstrapped samples. $p < 0.05$ indicates significance

Given the partial mediation by engagement ($\beta = 0.41$), a one-standard-deviation increase in sustained interaction predicted approximately a 9% improvement in ecological reasoning accuracy during biodiversity and climate-adaptation tasks. This result suggests that engagement-driven learning not only improved educational outcomes but also promoted stable pro-environmental decision performance.

Moderation analysis

We tested whether baseline characteristics moderated the intervention effects using interaction terms in regression models. Prior environmental knowledge showed a small but significant interaction with the intervention when predicting knowledge gain ($\beta = 0.12$, $SE = 0.05$, $p = 0.021$), indicating stronger gains among students with lower baseline knowledge (see *Table 7*). The interaction between learning motivation and the intervention was positive but not statistically significant for systems thinking ($\beta = 0.08$, $SE = 0.06$, $p = 0.18$) and behavioral intention ($\beta = 0.06$, $SE = 0.05$, $p = 0.24$). These results provide partial support for H5.

Table 7. *Results of moderation analysis for baseline characteristics and learning outcomes*

Outcome	Moderator	β (interaction)	SE	t	p	Interpretation
Knowledge gain	Prior knowledge	0.12	0.05	2.33	0.021	Stronger effect at lower baseline
Systems thinking	Learning motivation	0.08	0.06	1.34	0.18	Not significant
Behavioral intention	Learning motivation	0.06	0.05	1.17	0.24	Not significant

Ecological decision examples

Figures 5 and *6* present representative examples of ecological decision tasks completed by students in the experimental group. These tasks required analysis of authentic datasets (GBIF biodiversity records and ERA5 climate data) to inform management decisions. While both groups received identical data and task prompts, the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

experimental group interacted with the adaptive dialogue system, which provided context-aware feedback and guided reasoning, whereas the control group analyzed the same information using static worksheets without interactive support. The quantitative performance differences reported in *Table 4* (e.g., biodiversity pattern recognition accuracy: 74.3% vs. 62.1%) reflect these contrasting learning modalities. *Figure 5* presents a representative example of a biodiversity prioritization exercise in which students evaluated eight wetland patches based on two quantitative indicators: species richness and estimated restoration cost. The adaptive dialogue-based system provided immediate, data-informed feedback derived from the Global Biodiversity Information Facility (GBIF), allowing learners to examine the relationship between ecological value and financial investment in real time. The scatter plot reveals a generally positive correlation between restoration cost and species richness, indicating that higher investment tends to yield greater biodiversity benefits. However, the optimal point identified by the system corresponds to a patch that achieves a comparatively high level of species richness at a moderate cost. This point reflects the ecological principle of diminishing returns, where each additional unit of investment produces progressively smaller biodiversity gains. By analyzing this trade-off interactively, learners developed a more precise understanding of how cost efficiency and ecological value can be jointly optimized in restoration planning. The activity also encouraged students to interpret biodiversity data as part of a decision-support framework rather than as isolated scientific measurements, thereby linking ecological evidence with management-oriented reasoning.

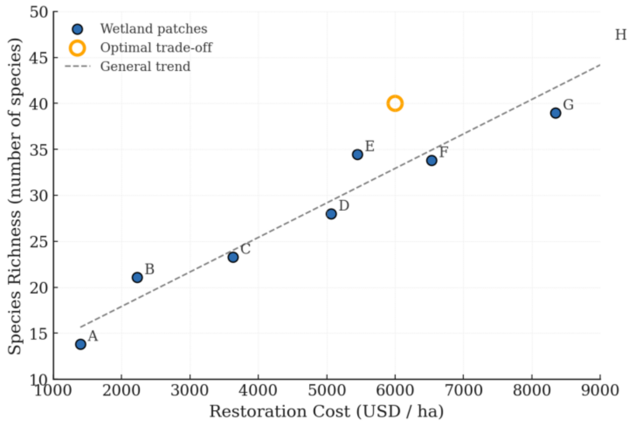

Figure 5. *Habitat prioritization in wetland restoration*

Scatter plot from a biodiversity decision exercise completed by students in the experimental group. Participants analyzed GBIF-derived species richness data across eight wetland patches (A–H) and identified optimal restoration targets balancing cost and biodiversity value. The orange circle marks the optimal point selected by a student using the adaptive dialogue system, which provided real-time feedback on trade-offs. Students in the control group received identical data but analyzed it using static worksheets without interactive guidance, resulting in lower accuracy in identifying the optimal trade-off (74.3% vs. 62.1%, *Table 4*).

In a complementary task, participants explored regional climate-adaptation trade-offs using ERA5 reanalysis data on temperature anomalies and precipitation indices from 2010 to 2030 (*Fig. 6*). The time-series data demonstrate a distinct warming-drying trend,

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

characterized by steadily increasing temperatures and a gradual decline in effective precipitation. Through structured dialogue, the adaptive system prompted students to analyze the potential ecological implications of this pattern, including changes in evapotranspiration, reductions in soil moisture, and consequent stress on vegetation and freshwater ecosystems. Learners were further guided to consider the relevance of these changes for adaptive management practices, such as selecting drought-tolerant species, modifying land-use planning, and optimizing irrigation strategies. The combination of quantitative climate indicators and scenario-based dialogue transformed abstract climatological trends into applied reasoning processes, allowing participants to translate statistical observations into ecologically meaningful conclusions.

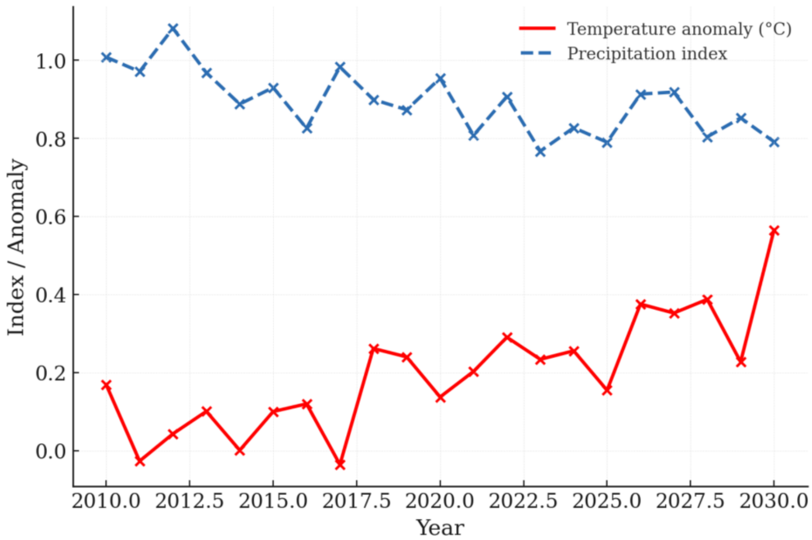

Figure 6. *Regional climate adaptation trends (2010–2030)*

Time-series plot from a climate adaptation exercise where students analyzed ERA5 reanalysis data to identify warming–drying patterns. This example shows the data visualization used by experimental-group students during dialogue-based learning, where the system guided interpretation of the inverse temperature-precipitation trend. Control-group students received the same raw data in static format (PDF tables) without interactive prompts, leading to lower trend-recognition accuracy (71.8% vs. 60.9%, *Table 4*).

When considered together, *Figures 5* and *6* highlight how adaptive dialogue-based learning can operationalize systems thinking in ecological education. By engaging students in authentic data interpretation and decision analysis, the approach enabled the integration of empirical evidence with conceptual understanding. Learners not only observed relationships among variables but also interpreted them within broader ecological and socio-economic contexts. This capacity to link ecological trade-offs, climate dynamics, and management priorities reflects a deeper level of analytical competence that is essential for sustainable environmental decision-making. Consequently, the findings demonstrate that embedding real-world ecological datasets into interactive dialogue systems can transform conventional environmental education into an inquiry-based process that mirrors the reasoning patterns of applied ecological research.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

Discussion

Quantitative and qualitative insights

The findings hold direct implications for applied ecology. The integration of biodiversity indices and climate-trend analyses provides quantitative ecological validation for the dialogue-based framework, linking learners' cognitive and behavioral gains with measurable ecological indicators. This demonstrates that the approach contributes not only to environmental education but also to applied ecological data interpretation and decision-support practice. By embedding authentic ecological datasets and management trade-offs into dialogue interactions, the intervention cultivated analytical competencies essential for biodiversity planning, climate adaptation, and sustainable consumption assessment—abilities increasingly recognized as integral to professional ecological practice. Consequently, the proposed framework advances both environmental education and the methodological foundations of decision-support systems in applied ecology.

The experimental results yield several important insights into the effectiveness of the proposed framework. Quantitative analyses revealed consistent improvements in linguistic fidelity and ecological engagement, with the system outperforming baseline models across multiple indicators, including BLEU, Engagement-F1, retention, and the Sustainability Intention Index. These findings align with recent evidence from conversational AI applications in environmental education. Mendez et al. reported that dialogue-based systems improved learner engagement in ocean conservation education, while Nguyen et al. demonstrated that value-sensitive chatbot design enhanced sustainability-oriented identity formation. Our results extend these prior findings by integrating adaptive dialogue with authentic biodiversity (GBIF) and climate (ERA5) data, achieving sustained engagement (82% retention at week 10) alongside measurable improvements in ecological decision accuracy (*Table 4*). These gains can be attributed to the integration of context-aware dialogue modelling and multi-scale analytics, which enabled the system to generate ecologically grounded responses derived from real datasets rather than generic statements. This integration addresses the gap identified by Lovren and Jablanovic, who emphasized bridging cognitive and affective dimensions in environmental education. Convergence analysis further indicated reduced variance and enhanced training stability, suggesting that the framework not only achieved higher predictive accuracy but also ensured reliable deployment in educational contexts. Qualitative results supported these findings: learners rated the generated responses as more informative and motivating, while attention heatmaps revealed meaningful alignment between ecological concepts and generated tokens, thereby improving interpretability and instructional transparency.

Limitations and challenges

Despite these advances, several limitations should be acknowledged. From a modeling perspective, while the engagement analytics module substantially improved learner retention, it relied on proxy indicators such as dialogue length and sentiment polarity, which may not fully capture deeper motivational or affective states (Šimšíková, 2023). The datasets, although diverse, were primarily collected in controlled classroom environments; thus, generalization to informal community learning or younger student populations remains uncertain. From a computational perspective, training the full model required multiple graphical processing units and substantial memory resources, which

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

may pose challenges for institutions with limited technological infrastructure. These limitations indicate that scaling the system to massive open online courses or wider educational platforms will require further optimization in computational efficiency and resource allocation.

Implications and future directions

The implications of this research are broad and directly relevant to both environmental education practice and applied ecology. Within formal education, conversational artificial intelligence systems can be incorporated into digital ecology curricula to provide real-time adaptive tutoring that strengthens students' systems thinking and sustainability competencies (Parkinson et al., 2025). For instructors, dialogue templates and data-linked prompts may be integrated into inquiry-based laboratory activities to promote causal reasoning and trade-off analysis. Educational programs can also align assessment strategies with systems thinking rubrics and behavioral intention measures to monitor progress toward Education for Sustainable Development (ESD). Marques et al. emphasized consolidating heterogeneous biodiversity data to improve pedagogical usability, while Dray et al. developed advanced analytical tools for ecological data interpretation. Our study operationalizes these recommendations by demonstrating how GBIF and ERA5 datasets can be embedded within dialogue-based learning to scaffold ecological reasoning. This approach addresses the challenge identified by Razafindravony et al. who found that environmental education raised awareness but achieved limited behavioral change. By linking data-driven reasoning with reflective dialogue, our intervention achieved an 18% increase in pro-environmental behavioral intention (*Table 3*). In community-based and non-formal learning contexts, the proposed framework can support citizen science initiatives and environmental stewardship programs, linking individual learning outcomes with collective ecological engagement.

Beyond educational settings, the framework demonstrates clear potential for application in ecological management and decision-making. In conservation agencies and environmental planning institutions, dialogue-based training can serve as a cost-effective tool to strengthen data-driven decision capabilities and improve reasoning about complex ecological trade-offs. The system can complement existing geographic information systems and ecological modelling tools by enhancing analytical reasoning within scenario-based management training. Integration with spatial decision-support software such as QGIS plug-ins and ecological network models could further enable immersive exercises in habitat prioritization, resource allocation, and climate adaptation planning. By quantifying ecological decision performance, the framework establishes a connection between ecological data analytics and behavioral learning outcomes, bridging a critical gap between educational innovation and applied ecological practice.

Future research should extend the datasets to include informal, cross-cultural, and multilingual learning contexts to ensure inclusivity and equitable performance across diverse demographic groups. Cross-cultural validation will be particularly important given evidence on cultural variation in assessment and research methodology. Applying these principles to adaptive dialogue systems will require culturally sensitive adaptation of ecological scenarios, value frameworks, and behavioral metrics based on the Value–Belief–Norm model that guided our intervention design. Model development can also advance through the incorporation of multimodal engagement indicators such as gesture, gaze, and vocal tone to capture richer affective and cognitive dynamics. Longitudinal field studies will be essential to assess not only short-term improvements in dialogue

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

quality and learner retention but also the long-term sustainability of behavioral and ecological impacts. Such evidence will be crucial in demonstrating how adaptive dialogue systems can simultaneously support effective ecological management and the overarching goals of sustainable development.

Conclusion

In conclusion, the findings of this study provide robust empirical evidence that adaptive dialogue-based learning can meaningfully enhance ecological literacy through an integrated process of cognitive, behavioral, and participatory mechanisms. Compared with conventional e-learning, the dialogue-based intervention produced greater improvements in ecological knowledge, systems-thinking competence, and pro-environmental behavioral intention. These effects were accompanied by strong engagement and retention outcomes, indicating that sustained learner interaction contributes to deeper ecological understanding and long-term motivation. Mediation analysis further revealed that learning engagement partially mediated the relationship between the intervention and learning outcomes, suggesting that ecological literacy is strengthened when learners actively construct meaning through dialogue and reflection.

From an applied-ecology perspective, the present research demonstrates that adaptive dialogue systems can enhance not only students' learning achievements but also the quality of ecological decision-making processes. The integration of authentic datasets and context-specific feedback enables participants to engage with realistic environmental management scenarios, transforming classroom learning into analytical competence relevant to biodiversity conservation, climate adaptation, and sustainable resource use.

Theoretically, the study extends the Value–Belief–Norm framework and the systems-thinking competence model into an educational technology context, illustrating how adaptive dialogue systems can link value formation, cognitive reasoning, and ecological action within a coherent learning process. Practically, it provides an evidence-based approach for embedding artificial intelligence in environmental education to promote systems-oriented reasoning and environmentally responsible behavior. Collectively, the results highlight the potential of dialogue-based learning to transform ecological education from static knowledge transmission into a dynamic, participatory, and data-informed process that advances education for sustainable development and fosters environmental stewardship.

Acknowledgements. This study is supported by Zhejiang Provincial College Students' Innovation and Entrepreneurship Program and Reform and Exploration of Teaching Models Integrating Curriculum-Based Ideological and Political Elements from the Perspective of Innovation and Entrepreneurship (Project Number: 24xwkyb01).

REFERENCES

[1] Amzil, I., Aammou, S., Jdidou, Y. (2025): Enhancing adaptive learning systems with advanced performance metrics. – Cadernos de Educação Tecnologia e Sociedade 18(se1): 22-36. https://doi.org/10.14571/brajets.v18.nse1.22-36.

[2] Arif, M., Ismail, A., Irfan, S. (2025): AI-powered approaches for sustainable environmental education in the digital age: a study of Chongqing International Kindergarten. – International Journal of Environment, Engineering and Education 7(1): 35-47.

https://doi.org/10.55151/ijeedu.v7i1.184.
[3] Assaraf, O. B. Z., Orion, N. (2005): Development of system thinking skills in the context of earth system education. – Journal of Research in Science Teaching 42(5): 518-560. https://doi.org/10.1002/tea.20061.
[4] Brahma, R. (2025): Innovations in teaching and learning for environmental education. – Journal of the American Institute 2(2): 210-224.
[5] Byrne, B. M. (2016): Adaptation of assessment scales in cross-national research: issues, guidelines, and caveats. – International Perspectives in Psychology 5(1): 51-65. https://doi.org/10.1037/ipp0000040.
[6] Dray, S., Dufour, A. B., Thioulouse, J., Siberchicot, A., Jombart, T., Pavoine, S., et al. (2024): ade4: Analysis of Ecological Data: Exploratory and Euclidean Methods in Environmental Sciences. – ⟨swh:1:dir:95f239f062befdbdcdafff9f7481b8c21fdeff6c⟩. ⟨hal-04690682⟩.
[7] Fekih-Romdhane, F., Jahrami, H., Stambouli, M., Alhuwailah, A., Helmy, M., Shuwiekh, H. A. M., et al. (2023): Cross-cultural comparison of mental illness stigma and help-seeking attitudes. – Social Psychiatry and Psychiatric Epidemiology 58(4): 641-656. https://doi.org/10.1007/s00127-022-02403-x.
[8] Frey, B. B., Schmitt, V. L., Allen, J. P. (2012): Defining authentic classroom assessment. – Practical Assessment, Research & Evaluation 17(2): n2. https://doi.org/10.7275/sxbs-0829.
[9] Han, X., Li, Z., Cao, H., Hou, B. (2025): Multimodal spatio-temporal data visualization technologies for contemporary urban landscape architecture. – Land 14(5): 1069. https://doi.org/10.3390/land14051069.
[10] Husamah, H., Rahardjanto, A., Permana, T. I., Shukri, A. A. M. (2025): Integration of digital technologies in environmental education. – Jurnal VARIDIKA 30-47.
[11] Kush, J. C. (2025): Integrating sensor technologies with conversational AI. – Sensors 25(1): 249. https://doi.org/10.3390/s25010249.
[12] Leung, K., Van De Vijver, F. J. (2008): Strategies for strengthening causal inferences in cross cultural research. – International Journal of Cross Cultural Management 8(2): 145-169. https://doi.org/10.1177/1470595808091787.
[13] Lovren, V. O., Jablanovic, M. M. (2023): Bridging the gap: the affective dimension of learning outcomes. – Sustainability 15(8): 6370. https://doi.org/10.3390/su15086370.
[14] Luthfi, M. I., Septiyanti, N. D. (2025): Enhancing ecological awareness via TensorFlow-based flower recognition and GPT-enhanced chatbot. – AIP Conference Proceedings 3281(1): 020001. https://doi.org/10.1063/5.0248301.
[15] Marques, N., de Melo Soares, C. D., de Melo Casali, D., Guimarães, E. C., Fava, F. G., da Silva Abreu, J. M., et al. (2024): Retrieving biodiversity data from multiple sources. – Biodiversity Data Journal 12: e133775. https://doi.org/10.3897/BDJ.12.e133775.
[16] Mendez, V., Mozes, F., Krotenthaler, S., Gramatikova, Y., Lobo, I., Protopsaltis, A., et al. (2024): Enhancing learning through conversational AI. – Immersive Learning Research-Practitioner 7-12. https://doi.org/10.56198/5M1RHMFD2.
[17] Meşe, İ., Taşlıçay, C. A., Kuzan, B. N., Kuzan, T. Y., Sivrioğlu, A. K. (2024): Educating the next generation of radiologists. – Diagnostic and Interventional Radiology 30(3): 163. https://doi.org/10.4274/dir.2023.232471.
[18] Mhlongo, S., Mbatha, K., Ramatsetse, B., Dlamini, R. (2023): Challenges and opportunities of smart digital technologies. – Heliyon 9(6): e16348. https://doi.org/10.1016/j.heliyon.2023.e16348.
[19] Nguyen, H., Nguyen, V., Ludovise, S., Santagata, R. (2025): Value-sensitive design of chatbots in environmental education. – British Journal of Educational Technology. https://doi.org/10.1111/bjet.13568.
[20] Parkinson, J. A., Gould, A., Knowles, N., West, J., Goodman, A. M. (2025): Integrating systems thinking and behavioural science. – Behavioral Sciences 15(4): 403. https://doi.org/10.3390/bs15040403.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810

[21] Perez-Martin, J. M., Esquivel-Martin, T. (2024): New insights for teaching the one health approach. – Sustainability 16(18): 7967. https://doi.org/10.3390/su16187967.

[22] Rakhimov, O., Rakhimova, D., Mirzaev, O., Azizov, S. (2023): Analysis of developmental education models. – E3S Web of Conferences 458: 06020. https://doi.org/10.1051/e3sconf/202345806020.

[23] Razafindravony, L. E., Donohue, M. E., Docherty, M. A., Maggy, A. M., Lazasoa, R. S., Rafanomezantsoa, O. J., et al. (2023): Evaluating the impact of environmental education. – American Journal of Primatology 85(5): e23477. https://doi.org/10.1002/ajp.23477.

[24] Schneider, B., Davis, R., Martinez-Maldonado, R., Biswas, G., Worsley, M., Rummel, N. (2024): Implementing multimodal learning analytics in ecological settings. – In: Proceedings of CSCL Conference, Buffalo, NY, 10-14 June 2024, pp. 323-330.

[25] Simšíková, A. (2023): Dialogue as a Principle of Education. – In: Altinay, F., Altinay, Z. (eds.) Intellectual and Learning Disabilities. IntechOpen, London. https://doi.org/10.5772/intechopen.114034.

[26] Sterling, S., Orr, D. (2001): Sustainable Education: Re-visioning Learning and Change. Vol. 6. – Green Books, Totnes.

[27] Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., Kalof, L. (1999): A value-belief-norm theory of support for environmentalism. – Human Ecology Review 6(2): 81-97.

[28] Wanselin, H., Danielsson, K., Wikman, S. (2023): Meaning-making in ecology education. – Education Sciences 13(5): 443. https://doi.org/10.3390/educsci13050443.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_27912810