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Human-Curated AI-Assisted Scenario Design for Game-Based Sustainability Learning: A Design-Oriented Case Study

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ABSTRACT

This paper presents a design-oriented case study of a human-centered model integrating artificial intelligence (AI) into game-based sustainability education. Unlike dominant AI-in-education approaches focused on automation, adaptive tutoring, or learner modeling, this study positions AI exclusively as a preparatory tool for scenario generation, while preserving full pedagogical authority for human facilitators. The model was implemented in a non-formal scout-based learning environment with 24 adolescents working in cooperative teams. Participants engaged in a tabletop simulation addressing water stress and interdependencies among forest ecosystems, water bodies, and urban systems. Descriptive pre–post differences were observed in ecological reasoning, collaborative engagement, and related learner-response indicators. Cognitive scores increased across all measured indicators, while behavioral data showed higher participation, initiative, and decision justification over time. Findings suggest that structured scenario variability - generated with AI during design and curated by educators before implementation - can be integrated into socio-ecological learning while preserving human pedagogical control. The study introduces a conceptual framework for “AI-as-design-augmentation,” emphasizing human-centered control in educational design. Despite its exploratory nature, results support the feasibility of AI-assisted scenario design for sustainability education.

KEYWORDS artificial intelligence in education, game-based learning, sustainability education, water stress, serious games, systems thinking, non-formal learning

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Introduction

Water stress is an increasingly complex socio-ecological challenge shaped by climate change, urbanization, ecosystem degradation, and uneven resource distribution. It should be understood not as a simple resource shortage but as a systemic imbalance involving ecological, infrastructural, and governance interactions [1]. This complexity requires educational approaches that extend beyond factual knowledge toward systems thinking and causal reasoning. Non-formal education environments, such as scouting programs, provide suitable conditions for experiential and collaborative learning due to their emphasis on teamwork, responsibility, and action-based engagement [2]. Game-based learning further strengthens these conditions by embedding learning in structured decision-making systems that simulate real-world complexity [3]. At the same time, AI is increasingly used in education for adaptive instruction, analytics, and content generation [4], [5]. Much of this work treats AI as an instructional, adaptive, or automated component. The present study examines a narrower design-stage role: AI generates candidate scenario variability, while

human facilitators retain responsibility for selection, revision, pedagogical alignment, and final authorization of all learner-facing content.

The intervention is based on a cooperative simulation titled "Let Us Save the Forest", modeling interactions among forest, water, and urban systems under stress conditions. Rather than testing the causal effect of AI on learning, the study examines a documented human-curated design process in which AI expands the space of possible scenarios without receiving pedagogical authority and then describes implementation patterns observed in the resulting simulation.

The study makes three contributions. First, it proposes a human-curated AI-assisted scenario design framework that explicitly separates AI-based variability generation from pedagogical authorization. Second, it documents a transparent curation workflow, including generation, screening, adaptation, and retention of scenario materials. Third, it provides descriptive evidence from a non-formal sustainability simulation illustrating how such a workflow can be implemented without attributing learner outcomes causally to AI.

Research questions

RQ1. How can a human-curated AI-assisted workflow be structured to generate scenario variability while preserving full human pedagogical authority?

RQ2. How are AI-generated scenario elements filtered, adapted, and retained through human pedagogical curation?

RQ3. What descriptive patterns of systems-oriented reasoning, collaboration, and learner engagement are observed during implementation of the resulting simulation?

Background and related work

Water stress is widely conceptualized as a socio-ecological system outcome rather than a purely hydrological phenomenon. It emerges from interactions among natural processes, land use, governance structures, and consumption patterns. United Nations [1] emphasizes the importance of capturing feedback loops and multi-level dependencies in education. Non-formal education supports experiential learning and learner agency, defined as the ability to actively shape learning processes [6]. Scout-based environments are particularly suitable for sustainability education due to their emphasis on cooperation and real-world problem-solving [2].

Game-based learning integrates educational content into structured systems of rules and feedback, enabling learners to engage with dynamic problem spaces [3]. Gamification and simulation-based learning should be distinguished analytically: gamification introduces game-design elements into non-game contexts [7], whereas the present intervention uses a rule-based simulation in which learner decisions modify an interconnected system state. AI in education is primarily associated with adaptive systems, automation, analytics, and increasingly content generation [4], [5]. These applications raise questions about transparency and the location of pedagogical decision-making. For the present study, the relevant distinction is therefore not simply between AI use and non-use, but between AI as an instructional agent and AI as a bounded design-support mechanism operating before learner interaction. Recent work has also examined the intersection of artificial intelligence and gamification, including adaptive, personalized, and feedback-oriented uses of AI in gamified educational environments [8]. This literature demonstrates the growing integration of AI into gamification, but its primary focus differs from the present study. Rather than using AI to adapt the learner experience or make learner-facing decisions, the present study restricts AI to the preparatory generation of candidate scenario materials, with final pedagogical selection and authorization remaining exclusively with human facilitators.

These studies establish an important broader foundation for human–AI collaboration, instructional-design support, and human oversight in educational contexts [9]–[11]. Recent work also demonstrates the growing integration of AI and gamification, particularly through adaptive and learner-facing applications [8]. The contribution of the present study is narrower and procedural rather than a claim of novelty for human-in-the-loop AI itself. It operationalizes human oversight as an explicit separation between AI-based candidate generation and human pedagogical authorization within a game-based sustainability-learning workflow. AI is used to expand the pool of possible scenarios and decisions, whereas facilitators independently screen, adapt, and authorize the materials before they become part of the learner-facing simulation. The study therefore contributes a documented curation procedure and a pilot illustration of how bounded, design-stage AI assistance can be integrated into scenario-based sustainability learning while preserving human pedagogical authority.

This distinction defines the research gap addressed here. The study focuses on a workflow in which AI-generated outputs remain candidate design material until they are reviewed and authorized by human facilitators. The contribution is therefore centered on the separation of scenario generation from pedagogical authority and on the documentation of human curation as an explicit stage of educational design.

Human-curated AI-assisted design framework

The proposed framework integrates three components: systems thinking, simulation-based learning, and AI-assisted scenario variability. Learning takes place within a coupled forest–water–urban system where each subsystem interacts through feedback loops and threshold effects. AI-assisted variability is treated as an expansion of the design space rather than as instructional agency (Table 1).

AI operates strictly at the design level, generating candidate scenarios and decision options. Human facilitators select, revise, reject, and structure these outputs according to pedagogical goals before any content enters the learner-facing simulation. Learners then engage only with human-authorized scenarios through iterative cycles of decision-making, feedback interpretation, and reflection. The proposed framework is illustrated in Fig. 1. This separation ensures that AI contributes scenario diversity without receiving instructional authority. In the proposed framework, AI output is treated as candidate design material rather than educational content until it has been reviewed and authorized by a human facilitator.

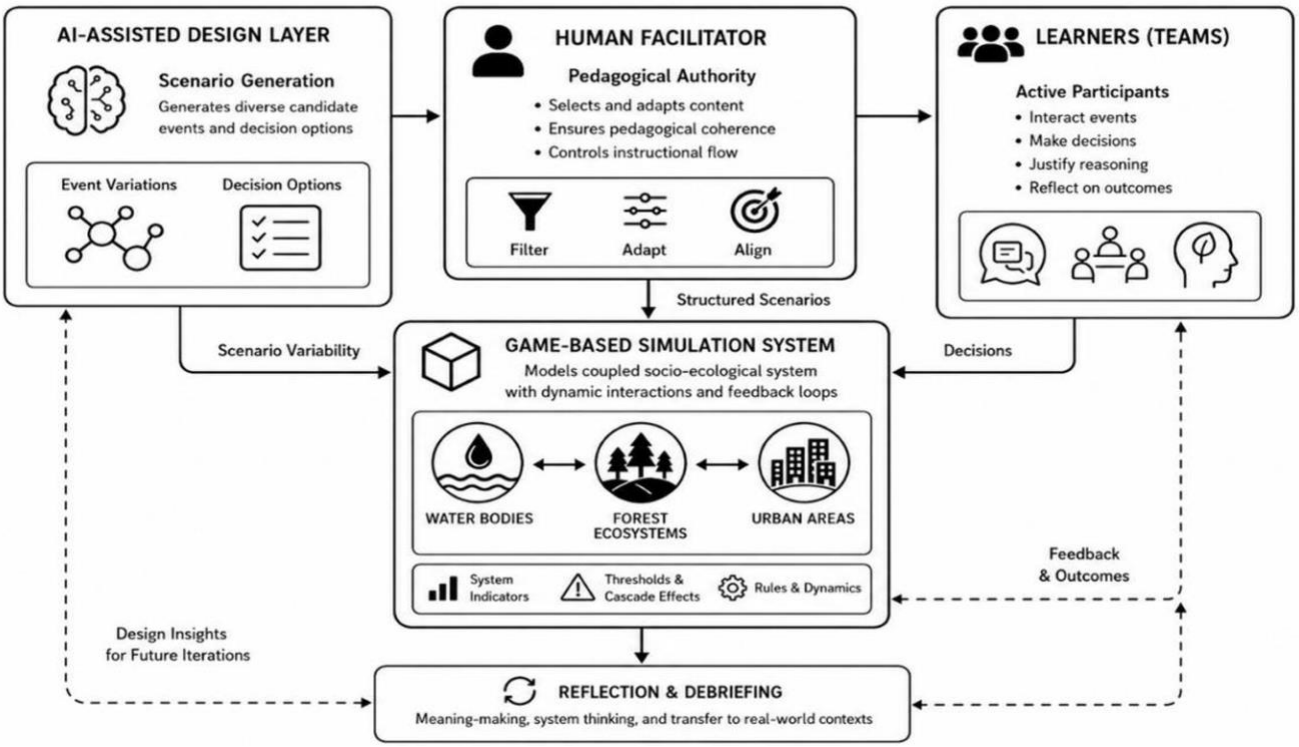


Fig. 1. Human-Curated AI-Assisted Scenario Design Framework for Game-Based Sustainability Learning.

Table 1. Role Distribution in the Human-Curated Design Framework.

Component	Function	Control
AI System	Generates candidate scenario variations	No pedagogical authority
Facilitator	Selects, revises, and authorizes content	Full pedagogical authority
Game system	Simulates ecosystem dynamics	Rule-based structure
Learners	Make decisions and reflect	Active participants

Methods or analytical approach

An exploratory design-oriented pilot case study with descriptive pre–post and structured observational components was used to examine feasibility and the design process rather than establish causality. The study involved 24 adolescents (ages 12–16) organized into eight teams of three. All participants were members of a scout organization with prior experience ranging from 5 months to 2 years. The study was not designed to estimate an independent causal effect of AI on learner outcomes.

Implementation was organized in two consecutive sessions involving the same eight teams of three participants. Session 1 used the basic scenario set (events E01–E12; decisions D01-D10) to familiarize participants with the rule system and the core forest–water–urban interdependencies. Session 2 used an extended scenario set (events E01–E24; decisions D01–D16), which incorporated the Session 1 materials together with additional scenarios and decisions to increase scenario variety and complexity. Thus, some scenario and decision content was repeated across sessions, while the second session introduced additional material. Because the same teams participated in both sessions, increasing familiarity with the game rules and task structure may have contributed to observed differences between earlier and later assessments. Decisions and assessments were organized collectively, so the primary analytical unit was the small team (n = 8), rather than the individual participant.

Simulation design

The simulation “Let Us Save the Forest” models interactions among three ecological subsystems using indicators on a 1–10 scale: Water Bodies, Forest Ecosystems, and Urban Areas. Each of eight gameplay rounds includes scenario interpretation, decision-making, and system updates.

A Sustainability Index was calculated as the mean of the three subsystem values, providing an internal summary of the simulated system state rather than a validated ecological measurement. Water stress was triggered when Water Bodies reached 3 or below. Once activated, at the end of each subsequent round Forest Ecosystems and Urban Areas each decreased by 1 point unless the selected decision included restoring or retaining water. The same decision could not be used in two consecutive rounds. These rules produced cascading system effects, delayed consequences, and constrained repetition of strategies. The basic configuration began with Water Bodies, Forest Ecosystems, and Urban Areas each set to 5, yielding an initial Sustainability Index of 5.00. The second session used a more difficult predefined starting configuration; because the preserved summary does not retain the complete

numerical starting configuration for that session, its starting Sustainability Index is not reconstructed here. The second session incorporated the materials from Session 1 together with additional events and decisions, thereby increasing scenario variety and complexity rather than constituting an entirely separate scenario system. Within each round, one event card was drawn without replacement from the active session set, so the same event could not recur within that session; its indicator effects were then applied; the team then discussed the resulting system state, selected one decision from the available decision set, applied its effects, and checked the water-stress threshold before advancing to the next round. The three system indicators are summarized in Table 2.

Table 2. System Indicators

Indicator	Description	Scale
Water Bodies	Water availability and quality	1–10
Forest Ecosystems	Ecological resilience and stability	1–10
Urban Areas	Urban system stability	1–10

AI-assisted scenario generation and human curation

AI was used only in the preparatory phase to generate candidate ecological events and decision options. Preliminary scenario materials were generated in ChatGPT using the GPT-5.4 Thinking model (OpenAI) via the standard web interface, accessed on 5 March 2026. The same model configuration was used across six prompting iterations. Across these iterations, 32 event drafts and 24 decision drafts were produced; 24 events and 16 decisions were retained after human review, corresponding to retention rates of 75.0% and 66.7%, respectively.

Prompting and curation procedure

The prompting procedure followed two recurring patterns: (a) event-generation prompts requesting short, age-appropriate situations representing natural, anthropogenic, or mixed pressures on the forest–water–urban system; and (b) decision generation prompts requesting ecologically meaningful response options compatible with the three-indicator rule structure. Outputs were screened for thematic relevance, internal logical consistency, age appropriateness, comprehensibility, sufficient variability, strategic balance, and compatibility with the rule system. Materials were excluded when they were overly generic, duplicated already retained scenario logic, were strategically unbalanced or pedagogically unclear, or produced effects too extreme to be meaningfully represented within the 1–10 indicator structure. Retained outputs were pedagogically edited by standardizing wording, calibrating difficulty, aligning effect structures across cards, and removing ambiguities in causal relations.

Representative prompt templates

To illustrate the structure of the prompting approach, two representative prompt templates are provided below. These templates reflect the two recurring prompt functions used in the scenario-generation process; they are presented as representative templates rather than as verbatim records of individual prompts. Event-generation template: “Generate a short, age-appropriate ecological scenario involving interactions among water bodies, forest ecosystems, and urban areas. The scenario should represent a natural, anthropogenic, or mixed environmental pressure and should be compatible with a 1–10 indicator system. Specify the affected indicator(s) and indicate the direction and magnitude of the expected effect.”

Decision-generation template: “Generate an ecologically meaningful decision option for a team-based simulation involving water bodies, forest ecosystems, and urban areas. The decision should provide a strategically relevant response to an environmental scenario, have identifiable consequences for the three indicators, and remain compatible with the existing water-stress and system-update rules.”

Accordingly, AI functioned as a creativity-support and variability-generation mechanism, while instructional design and final content authorization remained human-controlled. No AI-generated scenario or decision option was treated as learner-facing educational content solely on the basis of generation.

For procedural transparency, the scenario-generation record is specified as follows: AI system/model: ChatGPT, GPT-5.4 Thinking (OpenAI); interface: standard web interface; access date: 5 March 2026; number of generation iterations (n = 6); number of facilitators conducting curation (n = 3); review mode: independent. Each facilitator screened candidate items independently against the stated criteria. The archived record does not preserve item-level curator votes or a formal majority-vote or unanimity threshold; therefore, the manuscript reports the three independent reviews and the final retained set without claiming a voting rule. Because the archived curation record does not preserve the item-level ratings assigned independently by each facilitator, an inter rater agreement coefficient cannot be calculated retrospectively. Retained materials were implemented through two scenario sets rather than assigned as fixed card sequences to individual rounds: Session 1 used E01–E12 and D01–D10, while Session 2 used E01–E24 and D01–D16; in each round one event was drawn without replacement, preventing event repetition within the same session, and one decision was selected by the team.

Data collection and descriptive analysis

Data sources included system performance indicators, the Results Assessment Sheet, the Observation Assessment Form, and structured facilitator observations. Participant discourse was used as contextual observational evidence for reasoning patterns rather than as a separately reported qualitative dataset. The Results Assessment Sheet recorded the start, end, and change in the three system indicators and the overall Sustainability Index, together with three cognitive outcomes: understanding of water stress, understanding of the role of forests and ecosystem services, and sustainable strategy choice. Cognitive outcomes used a 1–3 rubric, where 1 indicated limited or

inaccurate understanding, 2 partial understanding, and 3 a clear, accurate, and convincing explanation supported by the post-game discussion.

The Observation Assessment Form was completed in real time at intervals of approximately 10 minutes and used a 1–5 scale for participation, initiative, collaboration, ecological reasoning, and decision justification. The supporting rubric distinguished between almost absent participation or collaboration at the lower end of the scale and active, consistent, and well-argued participation, initiative, collaboration, and systems-oriented reasoning at the upper end. Behavioral dimensions included participation, initiative, collaboration, ecological reasoning, and decision justification. Two facilitators independently rated observations using predefined criteria after prior rubric calibration. The reported >85% refers to the aggregate percentage agreement recorded for paired facilitator ratings. Because the archived summary does not preserve the raw paired ratings or the exact denominator, the calculation cannot be reconstructed more precisely; accordingly, agreement is reported descriptively and no chance-corrected inter-rater reliability coefficient is claimed. Given the ordinal 1–3 cognitive scale and the exploratory case-study design, pre–post results are reported descriptively as initial, final, and change scores. No normalized-gain or causal-effect estimate is used in the revised analysis.

All descriptive values were aggregated at the team level (n = 8), consistent with the collaborative organization of the intervention. Each cognitive construct was represented by one rubric-scored indicator. For each cognitive indicator, the reported Initial and Final values are the arithmetic means of the eight team-level rubric scores obtained from the pre-game and post-game discussions, respectively. The reported Initial and Final behavioral values are the arithmetic means of the eight team-level scores recorded at the first and final structured observation points, respectively. For each team, the Sustainability Index was calculated as (Water Bodies + Forest Ecosystems + Urban Areas) / 3. For Session 1, the predefined starting value was therefore 5.00, based on the three initial indicators set at 5. The reported overall final value of 6.13 is the arithmetic mean of the eight teams' final Sustainability Index values. Because Session 2 used a different predefined starting configuration, its numerical baseline is not reported here. The available summary data did not include dispersion statistics; accordingly, descriptive means are reported without SD or IQR estimates.

The final methodological sequence was: AI-assisted scenario design/generation; facilitator screening, adaptation, and authorization; initial team assessment before gameplay; Session 1 implementation with structured observations; post-game reflection and assessment; Session 2 implementation with the extended scenario set and structured observations; and final team assessment after the second session. Accordingly, the reported cognitive pre–post comparison refers to the initial assessment conducted before gameplay and the final assessment conducted after completion of the second session. The behavioral comparison refers to the first and final structured observation points across the two-session implementation. Because the same teams participated throughout both sessions, these comparisons represent descriptive changes over the overall learning sequence and cannot isolate the effects of the extended scenario set or AI assisted scenario design.

Results and findings

Human-curated scenario design

The curation process resulted in the retention of 24 of the 32 candidate event drafts (75.0%) and 16 of the 24 candidate decision drafts (66.7%). Thus, 8 event drafts and 8 decision drafts were not retained for implementation. These retention patterns provide descriptive evidence of the role of human curation: AI expanded the pool of candidate content, whereas human facilitators determined which materials entered the educational simulation. The retained materials were subsequently standardized and pedagogically adapted by the facilitators, including adjustments to wording, difficulty, card effect structures, and causal clarity. Because item-level records do not preserve the frequency of individual rejection reasons or distinguish systematically between unchanged and adapted retained items, the results are reported as aggregate retention outcomes rather than as item-level modification statistics.

Simulation implementation

Across the two consecutive sessions, each structured around eight gameplay rounds, system performance was examined descriptively. The arithmetic mean of the eight teams' final Sustainability Index values was 6.13. For reference, the basic configuration used in Session 1 started at an Index of 5.00. Because Session 2 used a different predefined starting configuration, the overall final value of 6.13 is reported as a descriptive final system-state value and is not interpreted as a cross-session change from the initial configuration. Facilitator observations suggested more coordinated strategies and more stable system regulation in later gameplay than in earlier gameplay. Because round-level quantitative values are not available here, this pattern is treated as contextual observational evidence rather than as a quantified temporal trend or an independent effect of AI-assisted scenario generation.

Descriptive learner outcomes

Table 3 presents the descriptive cognitive outcomes. Facilitator observations suggested that participants increasingly connected forest conditions with water regulation and urban system stability. This is treated as contextual evidence compatible with systems-oriented reasoning, not as a direct measurement of a validated systems-thinking construct.

Table 3. Descriptive Cognitive Outcomes (1-3 Scale)

Indicator	Initial Score	Final Score	Change
Water stress understanding	1.0	2.5	+1.5
Forest ecosystem role	1.0	2.625	+1.625
Sustainable decision-making	1.0	2.0	+1.0

Because the measures are descriptive and the design lacks a comparison condition, the observed pre–post differences are not attributed independently to AI. At the pre-game assessment, all eight teams received the minimum score of 1 on each of the three cognitive indicators. This pattern reflects the scoring rule applied to the initial team discussion: responses that showed limited or inaccurate understanding were assigned 1, whereas scores of 2 and 3 required progressively more explicit and accurate explanations. The uniform baseline should therefore be interpreted descriptively rather than as evidence that the rubric was highly discriminative at the lower end of the scale. Because all teams started at the same minimum score, the observed pre–post differences should likewise be interpreted cautiously and descriptively rather than as evidence of a quantified treatment effect.

All recorded behavioral indicators were higher at the final observation than at the initial observation. These descriptive differences are presented in Table 4 and are interpreted as learner-response patterns observed during implementation of the human-curated simulation.

Table 4. Descriptive Behavioral Outcomes (1-5 Scale)

Indicator	Initial Score	Final Score	Change
Participation	2.0	4.0	+2.0
Initiative	3.0	4.5	+1.5
Collaboration	3.0	4.5	+1.5
Ecological reasoning	2.0	4.0	+2.0
Decision justification	2.0	4.0	+2.0

Facilitator observations suggested more explicit use of system relations and decision justification in later gameplay. This pattern is reported descriptively and is not interpreted as evidence of a measured developmental transition.

Discussion

The central contribution of this case study is the separation between AI-based generation and human pedagogical authorization. AI expanded the range of candidate scenarios and decision options, but it did not select instructional content, interact with learners, assess performance, or determine pedagogical goals. This design makes human curation a constitutive stage of the educational process rather than a post hoc correction.

The simulation component remains consistent with prior work emphasizing experiential feedback, structured decision-making, and learner agency in game-based and collaborative environments [3], [6]. In the present framework, however, these learning processes are analytically separated from the AI contribution: the AI contributes candidate variability at the design stage, while the educational mechanism is implemented through the human-authorized simulation. Unlike AI-in-education applications centered on automation or adaptive instructional functions [4], [5], the present framework constrains AI to design augmentation. AI-generated outputs are therefore provisional rather than pedagogically authoritative. The observed retention rates further illustrate this principle: a meaningful share of generated material was not carried forward, demonstrating that generation and educational authorization were separate decisions. Human curation should not be treated as evidence of validity. It functions as a governance safeguard, but facilitator review can still reproduce ecological oversimplifications, inconsistent assumptions, or normative biases. Future implementations should therefore document validation criteria and review decisions and, where feasible, include independent expert checking of ecological content. The descriptive learner patterns suggest that the resulting simulation was workable as a collaborative learning environment. Repeated decision cycles were accompanied by higher final descriptive scores for participation, collaboration, ecological reasoning, and decision justification, while cognitive scores were also higher at final than at initial measurement. These observations support the feasibility of the overall human-curated design, but they cannot isolate the contribution of AI-generated variability from the effects of simulation, facilitation, repeated practice, teamwork, or novelty.

The study is limited by its small sample, absence of a control or comparison condition, single non-formal educational setting, potential novelty effects, and reliance on facilitator-rated measures. The cognitive and behavioral rubrics used in the present pilot were study-specific descriptive instruments rather than validated standardized measures. The available summary data did not preserve the raw paired ratings or provide dispersion statistics; consequently, formal inter-rater reliability beyond descriptive percentage agreement could not be estimated, and variability around the reported team-level means could not be assessed using SD or IQR. The reported values should therefore be interpreted as aggregate descriptive evidence rather than as individual-level statistical estimates. The same facilitators were involved in implementation and observation, which may have introduced observer or expectancy effects, and no long-term retention measure was included. In addition, because the same eight teams participated in both consecutive sessions and the second session used the more complex extended scenario set, part of the observed improvement may reflect practice effects and increasing familiarity with the game rules and task structure. Future work should compare human-only scenario design with human-curated AI-assisted scenario design in order to preserve raw paired ratings and dispersion statistics, estimate inter-rater reliability from the underlying observations, and assess whether any observed differences persist over time.

Conclusion

This study introduced a human-curated AI-assisted scenario design framework for sustainability education. Its defining feature is a three-stage separation between AI generated variability, human pedagogical curation and authorization, and simulation-based learning execution. AI was used to expand the pool of possible scenarios, while all pedagogical decisions remained under human control. Descriptive cognitive and behavioral changes observed during implementation support the practical feasibility of the overall design, but they do not establish an independent causal effect of AI. The stronger contribution of the case study is therefore procedural and conceptual: it shows how AI can be bounded to a design-support role without acquiring pedagogical authority. Future research should

validate the framework across larger and more diverse educational contexts and directly compare human-only scenario design with human curated AI-assisted design. Such studies should also test long term learning retention and examine whether structured human curation can preserve transparency and pedagogical accountability while benefiting from AI-generated scenario diversity.

Declarations

Ethics approval and consent: Under the applicable local institutional context, the activity was treated as a low-risk non-formal educational practice and did not require separate institutional ethics committee approval. Participation was voluntary; participants and their guardians were informed of the educational and research character of the activity, and prior parental/guardian consent was obtained. Data were minimized and anonymized and were not used for formal assessment. The AI component operated only in preparatory scenario design: it did not process participant profiles, create individual profiles, classify learners, or make automated pedagogical, assessment-related, or organizational decisions concerning participants.

AI use disclosure: The authors used ChatGPT and NotebookLM during manuscript preparation for language editing, grammar correction, text polishing, and clarity. Perplexity was used as a search aid to identify candidate publications; every cited source and bibliographic entry was independently checked by the authors against the original publication. The design-stage use of ChatGPT (GPT-5.4 Thinking) to generate candidate scenario items formed part of the research procedure and is reported transparently in the Methods. The authors take full responsibility for the manuscript, data, interpretations, and conclusions.

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