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Research Article

Smart sustainability: Does a generative AI-driven environmental education influences social norms and environmental awareness?

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ABSTRACT

This study examined whether generative AI-driven environmental education changes university students' social norms and environmental awareness differently from conventional instruction when course content is held constant. Environmental awareness was operationalized as nature relatedness. A pre-test post-test control group quasi-experimental design was used with 257 undergraduate students enrolled in a green building environment course, 129 in the experimental group and 128 in the control group. The experimental group reached the course material through a custom ChatGPT module restricted to that material, while the control group received conventional instruction. The intervention lasted 14 weeks. Social norms were measured with a purpose-developed 10-item instrument distinguishing descriptive from injunctive norms, and nature relatedness with the 21-item nature relatedness scale. Data were analyzed with Bayesian paired samples t-tests and Bayesian ANCOVA. Both conditions produced large pre-test to post-test gains on all five dimensions, with Bayes factors above 10 to the power of 42 and effect sizes between d = 0.90 and d = 1.41. After pre-test scores were controlled, the evidence favored the absence of a group difference on every dimension: Bayes factors for adding group to the pre-test model ranged from 0.21 to 0.48, and the strongest evidence against a group effect was obtained for nature experience, BF10 = 0.24, the dimension on which an advantage for continuous access was most plausible. Men scored slightly higher than women on the nature-self dimension. The findings indicate that the quality of course content, rather than the medium through which it is delivered, accounts for the change observed here.

Keywords: generative AI, ChatGPT, environmental education, social norms, nature relatedness, Bayesian analysis

INTRODUCTION

Generative AI has entered higher education faster than the evidence supporting its instructional use. Large language models such as ChatGPT, Claude, and Gemini are now used to deliver immediate feedback and to adapt material to individual learners, and universities across a number of national systems have issued policies governing these tools before their effects on learning were established (Chan & Colloton, 2024; Jin et al., 2025). Hence, it is not surprising to see that the claims made for generative AI rest largely on studies of general learning outcomes rather than on evidence drawn from particular subject domains.

The evidence that does exist is encouraging but narrow. Systematic reviews report gains in academic skills development and learning efficiency (Daniel et al., 2025; Hon, 2026), and a meta-analysis of ChatGPT studies found a large positive effect on learning performance together with moderate effects on learning perception and higher-order thinking (Wang & Fan, 2025). Educators describe the technology as useful for feedback and material preparation while remaining uncertain about its contribution to deeper learning (Lee et al., 2024). What these studies share is an outcome space built around achievement, skills, and perceptions. Whether the same tools move the attitudinal and normative outcomes that certain subject areas are designed to change is a separate question, and it has attracted considerably less attention.

Environmental education is one such subject area. Its purpose is not the transmission of scientific facts alone but the formation of values and behavior, and it operates across cognitive, affective, and behavioral dimensions (McGuire, 2015; Virgolino et al., 2020). Digital tools have been absorbed into the field with some success; a systematic review of digital tools in environmental education reports gains in sustainability awareness across a range of implementations (Hajj-Hassan et al., 2024). It is believed that generative AI represents a further step along the same path, since it can produce locally relevant examples and adjust them to the learner. That expectation, however, has not been tested against the outcomes of environmental education actually targets.

Two such outcomes are well established, and together they constitute what the environmental education literature refers to as environmental awareness. Social norms, in the focus theory formulation, separate perceptions of what others do from perceptions of what others approve, and both types predict pro-environmental behavior (Cialdini et al., 1990; Helferich et al., 2023). Nature relatedness describes the cognitive, affective, and experiential connection an individual maintains with the natural world, and it has been linked to psychological well-being as well as to sustainable behavior (Nisbet et al., 2009; Zeng et al., 2025). These constructs suit the present purpose because they change slowly, they are measured with established instruments, and they are precisely what an environmental education course would be expected to influence if it influences anything at all.

Work on generative AI in environmental settings has so far concentrated on the quality of the output rather than on what learners take from it. Atkins et al. (2024) tested the alignment of model responses against IPCC hazard indices, Vaghefi et al. (2023) built and evaluated a climate-grounded conversational prototype, and Sachyani and Gal (2025) documented creative engagement among primary school students working with AI tools. None of these designs measured normative or affective change, and none compared the technology against conventional instruction while holding content constant. It is not possible to make a generalization about the effect of generative AI on social norms or nature relatedness from the evidence currently available.

The present study is an attempt to address that shortage. A pre-test post-test control group design was implemented in a university course on the green building environment. One group worked with a course-restricted ChatGPT module and the other with conventional instruction, while the material delivered to the two groups was constant. This arrangement separates two things that are usually confounded in research on educational technology, namely the content students encounter and the medium through which they encounter it. The comparison is framed without a directional expectation, and Bayesian estimation is used throughout so that evidence for the absence of a group difference can be reported as readily as evidence for its presence (Wagenmakers et al., 2018).

Three questions guided the analyses. The first asks whether the green building environment course changes students' descriptive norms, injunctive norms, and the three dimensions of nature relatedness from pre-test to post-test under both instructional conditions; a positive change is expected here, given the consistency of the environmental education literature. The second asks whether, once pre-test scores are controlled, generative AI-supported instruction and conventional instruction differ in post-test performance; this question is treated as exploratory and no direction is predicted. The third asks whether any group effect varies by gender, and it is likewise exploratory.

LITERATURE REVIEW

Generative AI in Higher Education

Generative AI has moved from novelty to infrastructure in a very short period. Large language models are now used to produce explanations on demand, to generate practice material, and to give feedback outside class hours, and these functions have been documented across a wide range of institutions and disciplines (Chan & Colloton, 2024; Shahzad et al., 2025). Personalization is the capacity most often singled out. Jauhiainen and Garagorry Guerra (2024) worked with 110 pupils aged between eight and fourteen and showed that ChatGPT could adjust learning material to individual knowledge levels and progress, while Zhang and Tur (2024) report in their review of K-12 applications that the same adaptivity extends across subject areas.

Evidence on learning outcomes has begun to accumulate, although it is uneven. Wang and Fan (2025) synthesized the available experimental work and found a large positive effect of ChatGPT on learning performance, with more modest effects on learning perception and higher-order thinking. Reviews covering higher education specifically reach similar conclusions about skills development while noting the variability of implementations (Daniel et al., 2025; Hon, 2026). However, educators who use the technology in their own teaching describe a more qualified picture, valuing it for feedback and preparation but questioning whether it deepens engagement with the material (Lee et al., 2024).

The concerns raised in this literature are consistent. Academic integrity is the most frequently discussed, since text produced by a model can be submitted without the critical evaluation, paraphrasing, or attribution that scholarship requires (Cotton et al., 2024). Overreliance is a second concern, and students themselves report ambivalence about the effect of these tools on their own thinking (Chan & Hu, 2023). Institutions have responded by issuing policies and by reconsidering assessment, and a global review of such documents shows considerable variation in what they permit and how they are enforced (Jin et al., 2025). Hence, it can be said that the field has established what generative AI can produce more firmly than it has established what students take away from it.

Environmental Education

Environmental education aims to make the interdependence between human activity and the natural world intelligible, and to translate that understanding into responsible conduct (Virgolino et al., 2020). The field treats this as work across three dimensions. Knowledge about environmental systems is necessary but insufficient on its own; affective attachment and behavioral commitment must develop alongside it, and it is the interaction among the three that produces durable change (McGuire, 2015). Environmental education is therefore described as a lifelong process rather than a curricular episode, built through direct experience, emotional engagement, and social interaction (Husamah et al., 2023).

A substantial part of the literature argues that this process is value formation rather than information transfer. Zaikauskaite et al. (2020) show that moral orientation shapes how individuals judge environmental issues and how they report their own pro-environmental conduct, which suggests that content alone does not determine outcomes. Tseng and Wang (2020) argue on similar grounds that environmental education should integrate environmental and social systems and move beyond single-discipline treatments. Pan and Hsu (2022), following undergraduate students longitudinally, report that environmental literacy develops unevenly and that gains in awareness do not automatically extend to civic participation. Taken together, these studies indicate that the outcomes of environmental education are neither immediate nor uniform.

Program-level evidence supports the general effectiveness of environmental education while leaving the mechanism open. Imran et al. (2024) found that environmental education shapes sustainable values and attitudes among students, and Gopinath and Kumar (2025) report that a program built on empathy and reflective thinking altered preadolescents' environmental values and knowledge. Kowasch et al. (2022) describe forest education as a route to environmental citizenship and to non-anthropocentric perspectives. What these studies have in common is a focus on what is taught. The question of whether the medium of delivery contributes independently is rarely posed.

Digital tools have entered the field against this background. Hajj-Hassan et al. (2024) reviewed their use systematically and concluded that they improve environmental learning outcomes and sustainability awareness, and Liu and Zhang (2024) found among Chinese university students that digital platforms strengthen the link between environmental knowledge and behavioral change. These findings are generally read as evidence that technology helps. They may equally be read as evidence that well-designed content helps, since in most of these designs the technology and the content were introduced together.

Social Norms and Pro-Environmental Behavior

Social norms are the shared standards and expectations that operate within a group, and the focus theory of normative conduct distinguishes two kinds. Descriptive norms concern perceptions of what other people actually do in a given situation, whereas injunctive norms concern perceptions of what other people approve or disapprove of (Cialdini et al., 1990). The distinction matters because the two operate through different routes. A descriptive norm supplies information about what is probably effective, while an injunctive norm supplies information about what will be socially rewarded or sanctioned.

Both types predict pro-environmental behavior, and their effects are comparable in size. Helferich et al. (2023) synthesized 572 studies covering 312,127 participants and found that personal norms were the strongest single predictor, mediating most of the influence of descriptive and injunctive norms. Ren et al. (2024) reached a convergent conclusion by a different route, using eye-tracking to show that participants responding to injunctive norms engaged in pro-environmental behavior at levels similar to those responding to descriptive norms, with the strongest tendency among participants for whom both norms were high. Niu et al. (2023) add that personal cost moderates these effects, and that a social norm condition raised green product purchasing relative to control.

Interventions built on norms have produced mixed results in the field. Mundt et al. (2024) tested simple normative prompts across five field experiments and found the effects to be context dependent, which tempers the optimism of the correlational literature. Fu et al. (2024) report that injunctive norms operate most effectively when descriptive norms point in the same direction, and Liang et al. (2023) observe the same pattern in low-carbon purchasing. Divergence between the two creates difficulty. A strong injunctive norm may fail to produce behavior when the corresponding descriptive norm is weak, particularly where the behavior is effortful, since individuals then have grounds to ask why they should act when others evidently do not (Ai & Rosenthal, 2024).

For the purposes of the present study, two features of this literature are relevant. Social norms respond to what individuals learn about their reference groups, which places them within reach of instruction. At the same time they are anchored in observation of actual conduct, which suggests they may not respond readily to the medium through which instruction is delivered. Galeotti et al. (2024) note in their review of climate change education that normative outcomes are among the least consistently reported, and that most intervention studies rely on pre-test post-test designs without an active comparison condition.

Nature Relatedness

Environmental awareness, in the sense used here, is operationalized as nature relatedness: the connection an individual sustains with the natural world and the awareness of that connection. Nisbet et al. (2009) define it as a relatively stable trait spanning cognitive, affective, and experiential dimensions, and operationalize it through three subscales. The self-dimension captures the extent to which a person incorporates nature into their identity. The experience dimension covers physical contact with natural environments and the comfort found there. The perspective dimension concerns awareness of environmental problems and of how human conduct bears on them. Silva and Gonçalves (2024) confirmed this three-factor structure in a Portuguese adaptation, and Tseng and Wang (2020) caution that the conventional definitions may require adjustment across cultural contexts.

The construct has been linked consistently to well-being. Zeng et al. (2025) established in a meta-analysis that nature connectedness and nature contact both relate positively to psychological outcomes, and Barrera-Hernández et al. (2020) observed the same association together with sustainable behavior among children. Richardson et al. (2021) qualify the picture usefully, showing that the quality of engagement matters more than its duration. Duke and Holt (2023), working from student accounts, report that connection to nature accompanies better physical and mental health and a greater tendency toward sustainable conduct.

Nature relatedness also predicts pro-environmental behavior, although the pathway is indirect. Liu et al. (2022) demonstrate that nature contact mediates the relationship between connection and behavior, and Sierra-Barón et al. (2023) find that environmental identity and connectedness jointly predict pro-environmental conduct, with differences between rural and urban residents. Uchiyama et al. (2024) identify childhood nature experience as a consistent driver of later nature visits. However, these findings all concern contact with actual natural environments. Whether a classroom intervention that involves no such contact can move the experience dimension is an open question, and one the present design is positioned to address.

Intervention studies offer limited guidance. Pirchio et al. (2021) found that outdoor environmental education improved connectedness to nature, well-being, and prosocial behavior, but their program was built around direct contact with nature. Masson et al. (2025) report gains in nature relatedness from a citizen science intervention in secondary schools, again involving field engagement. It is not possible to make a generalization from these studies to instruction delivered entirely indoors, whether conventional or technologically mediated.

Generative AI in Environmental Education

Interest in generative AI as a vehicle for environmental and climate education has grown quickly, and the work to date is divided into two strands. The first evaluates the accuracy of model output. Atkins et al. (2024) compared ChatGPT's hazard assessments against IPCC risk indices and found close alignment for floods and hurricanes but inconsistency for drought, concluding that these tools can support climate literacy provided their biases are checked. Vaghefi et al. (2023) addressed the same problem by grounding a conversational prototype in the IPCC AR6 reports, and climate experts judged its answers more accurate than those of the underlying model. Wilby (2025) reports comparable potential for climate risk and adaptation assessment, with the caveat that expert oversight remains necessary.

The second strand examines classroom use. Sachyani and Gal (2025) observed fifth-grade students using AI tools to construct comic strips depicting ecological interactions and found that the exchanges encouraged creative learning. Xiaoyu et al. (2025) assessed ChatGPT's usability in environmental education and identified brainstorming support, collaborative learning, and continuous availability of personalized feedback as its principal contributions. Nikolopoulou (2025) maps the broader potential of generative AI for sustainability in higher education, while Raja et al. (2025) report that a substantial proportion of teachers already draw on ChatGPT for lesson planning. Hussein et al. (2025) place these applications within a wider review of the technology's sectoral effects.

These studies establish feasibility and describe engagement. What they do not establish is comparative effect. In almost every case the AI-supported condition also introduced new content, new tasks, or new modes of interaction, so any observed gain cannot be attributed to the technology as distinct from what accompanied it. The distinction is not academic. Steiner (2024) argues that the quality of instructional materials is the more consistent determinant of student outcomes, and Garay Abad and Hattie (2025) reach a similar conclusion regarding the influence of materials on instructional design. If content quality carries most of the effect, then studies that vary content and delivery together will systematically overstate what the delivery medium contributes.

The present study was designed with this confound in mind. The same course materials were supplied to both conditions, the experimental group accessing them through a ChatGPT module restricted to those materials and the control group through conventional instruction. Under this arrangement any between-group difference is attributable to the mode of delivery rather than to the material itself. Given the mixed record of norm-based interventions (Mundt et al., 2024) and the reliance of nature relatedness on direct contact (Pirchio et al., 2021), there is no strong basis for predicting an advantage in either direction, or the comparison is accordingly treated as exploratory.

MATERIALS AND METHODS

Research Design

A pre-test post-test control group quasi-experimental design was employed. The independent variable was the mode of instructional delivery, operationalized as generative AI-supported instruction in the experimental condition and conventional instruction in the control condition. Course content was held constant across conditions, so that any between-group difference at post-test could be attributed to delivery rather than to the material itself. The dependent variables were descriptive norms, injunctive norms, and the three dimensions of nature relatedness. Pre-test scores served as covariates in the between-group analyses.

Participants

The study was conducted with 257 undergraduate students enrolled in the green building environment course. The experimental group comprised 129 students and the control group 128. Men accounted for 61 students (47.3%) in the experimental group and 54 (42.2%) in the control group, and women for 68 (52.7%) and 74 (57.8%), respectively. Across the full sample there were 115 men (44.7%) and 142 women (55.3%). Gender was distributed evenly across conditions, Chi-square (1) = 0.49, $p = .486$. No demographic information beyond gender was collected. Assignment to the experimental and control groups was based on the sections the students were enrolled in. Participants were not assigned individually; instead, assignments were made at the class level.

Implementation and Course Content

The intervention was run for 14 weeks within the green building environment course. The syllabus covered ecological foundations, including matter and energy cycles and natural regulation in the built environment; global environmental threats such as the greenhouse effect, ozone depletion, water pollution, and acid rain; sustainable design and management, including regional and international environmental legislation and green building certification systems; and analytical work in which students interpreted environmental data and estimated the cost of human activity to ecosystems.

In the control condition this material was delivered through conventional instruction. The instructor presented the content, worked through the analytical tasks, and responded to questions during scheduled class hours. Instruction was supported by structured presentations and by discussion of the reading material.

In the experimental condition the same material was delivered through a custom GPT configured on the ChatGPT platform for this study. All course materials, readings, and presentations prepared by the researcher were preloaded into the module as its knowledge base, and the system was constrained to answer only from that base. This constraint served two purposes. It prevented the model from drifting outside the syllabus, and it ensured that the two conditions differed in how students reached the material rather than in what material they reached. Students could access the module at any time and work through the content at their own pace, and the module responded to their questions with explanations drawn from the loaded documents.

Instruments

Social norms scale

A 10-item instrument was developed for this study to measure perceptions of environmental social norms. Six items address descriptive norms, that is, perceptions of what people in the respondent's environment actually do, and four address injunctive norms, that is, perceptions of what those people consider appropriate. All items are positively worded and are answered on a five-point agreement scale. The instrument was developed on a separate sample of 614 undergraduate students, which was randomly divided into an exploratory subsample of 309 and a confirmatory subsample of 305.

Principal component analysis with varimax rotation produced a two-factor solution accounting for 63.4% of the total variance. Sampling adequacy was satisfactory, KMO = .865, and Bartlett's test of sphericity was significant, Chi-square (45) = 1,308, $p < .001$. Loadings ranged from .677 to .842 on the descriptive norms factor and from .769 to .866 on the injunctive norms factor, with no cross-loadings. Confirmatory factor analysis on the second subsample supported the two-factor structure, CFI = .989, TLI = .986, SRMR = .028,

Table 1. Internal consistency in the study sample (N = 257) And in the development samples

Dimension	k	Pre-test alpha	Pre-test omega	Post-test alpha	Post-test omega	Development alpha
Descriptive norms	6	.520	.541	.670	.680	.853
Injunctive norms	4	.559	.591	.693	.715	.833
NR-self	8	.679	.687	.826	.828	.862
NR-perspective	7	.660	.701	.801	.835	.875
NR-experience	6	.772	.781	.890	.900	.808

Note. Development sample n = 614 for the norm subscales and n = 625 for the nature relatedness subscales

RMSEA = .035. Average variance extracted was .500 for descriptive norms and .566 for injunctive norms, and composite reliability was .856 and .838. Cronbach's alpha was .853 and .833, and McDonald's omega .856 and .838. The confirmatory analysis on the development sample returned an inter-factor correlation of -.261 between descriptive and injunctive norms, which the reviewer flagged as theoretically unexpected. Diagnostic work indicates a scoring-direction problem in the development data file rather than a substantive finding: none of the ten items is reverse worded; reversing the four injunctive columns leaves every fit index unchanged and turns the correlation to +.261; and the same two composites correlate +.53 at pre-test and +.65 at post-test in the study sample.

Nature relatedness scale

Nature relatedness was measured with the 21-item scale developed by Nisbet et al. (2009), which distinguishes three dimensions. NR-self covers the extent to which a person incorporates nature into their identity and comprises eight items. NR-perspective covers awareness of environmental problems and of the consequences of human conduct and comprises seven items. NR-experience covers physical contact with natural environments and comfort in them and comprises six items. Eight items are reverse worded and were recoded before scoring. Linguistic equivalence was established through translation and back-translation.

The adaptation was carried out on a separate sample of 625 undergraduate students, divided into an exploratory subsample of 302 and a confirmatory subsample of 323. Principal component analysis with varimax rotation produced the expected three-factor solution accounting for 53.6% of the variance, KMO = .909, Chi-square (210) = 2384, $p < .001$. Every item loaded on its intended factor, with loadings between .659 and .759 and no cross-loadings. Confirmatory factor analysis indicated good fit, CFI = .960, TLI = .955, SRMR = .046, RMSEA = .037, with standardized loadings from .504 to .777. Cronbach's alpha was .862 for NR-self, .875 for NR-perspective, and .808 for NR-experience, and McDonald's omega was .862, .875, and .809.

Scoring procedure

Both instruments were administered in paper form, with the nature relatedness items grouped by subscale rather than interleaved. Subscale scores were computed as the mean of the constituent items after reverse-worded items had been recoded, so that higher scores indicate stronger endorsement in every case. The item-to-subscale key used for scoring was verified against the administered form, since the order of items on that form differs from the order used during the adaptation study.

Reliability in the study sample

Because reliability is a property of a set of scores rather than of an instrument, internal consistency was recomputed on the 257 participants of the present study at both measurement occasions. These values are reported in **Table 1**. Coefficients at post-test ranged from .670 to .890 and were acceptable for the nature relatedness subscales. Pre-test coefficients were lower, ranging from .520 to .772, and this restriction should be borne in mind when interpreting the pre-test covariate. The two norm subscales in particular fell below the values obtained during development, and the between-group inferences that rest on them are correspondingly less precise.

Data Analysis

Shapiro-Wilk tests indicated departures from normality for every variable, $p < .01$. Bayesian methods were adopted in preference to a non-parametric alternative because they quantify the strength of evidence for competing hypotheses directly and, unlike null hypothesis significance testing, permit evidence in favor of the

Table 2. Pre-test equivalence of the experimental and control groups

Dimension	Experimental: M (SD)	Control: M (SD)	t	df	p	d	BF10
Descriptive norms	3.59 (0.55)	3.43 (0.62)	2.18	250.5	.030	0.27	1.29
Injunctive norms	3.70 (0.60)	3.60 (0.72)	1.21	245.3	.228	0.15	0.27
NR-self	3.83 (0.54)	3.71 (0.52)	1.86	254.8	.064	0.23	0.70
NR-perspective	3.46 (0.65)	3.31 (0.63)	1.89	254.9	.059	0.24	0.74
NR-experience	3.32 (0.74)	3.26 (0.81)	0.57	252.9	.573	0.07	0.16

Note. M: Mean; SD: Standard deviation; Welch t-tests; & BF10 from the Bayesian independent samples t-test with a JZS prior (r = 0.707)

Table 3. Pre- and post-test comparison by group (Bayesian paired samples t-test)

Variable	Group	Pre: M (SD)	Post: M (SD)	BF10	d
Descriptive norms	Experimental	3.59 (0.55)	4.28 (0.47)	6.73×10^{54}	1.37
	Control	3.43 (0.62)	4.11 (0.58)	3.66×10^{58}	1.13
Injunctive norms	Experimental	3.70 (0.60)	4.34 (0.57)	4.27×10^{50}	1.10
	Control	3.60 (0.72)	4.21 (0.63)	7.21×10^{42}	0.90
NR-self	Experimental	3.83 (0.54)	4.54 (0.46)	2.70×10^{59}	1.41
	Control	3.71 (0.52)	4.41 (0.49)	3.88×10^{66}	1.40
NR-perspective	Experimental	3.46 (0.65)	4.30 (0.60)	3.74×10^{62}	1.35
	Control	3.31 (0.63)	4.13 (0.55)	6.63×10^{63}	1.39
NR-experience	Experimental	3.32 (0.74)	4.22 (0.73)	3.10×10^{58}	1.22
	Control	3.26 (0.81)	4.12 (0.70)	9.49×10^{56}	1.13

Note. M: Mean; SD: Standard deviation; n = 129 experimental; n = 128 control; & d computed as the mean difference divided by the pooled standard deviation

absence of an effect to be reported (Wagenmakers et al., 2018). This property is material here, since one of the research questions concerns whether two instructional conditions differ at all.

Within-group change from pre-test to post-test was examined with Bayesian paired samples t-tests using the default Jeffreys-Zellner-Siow prior with a scale of 0.707. Effect sizes were computed as the mean difference divided by the pooled standard deviation of the two occasions, and interpreted following Cohen (2013), for whom .20, .50, and .80 denote small, medium, and large effects. Between-group differences were examined with Bayesian ANCOVA, with the corresponding pre-test score entered as a covariate. Ten models were compared for each dependent variable, formed from the covariate, group, gender, and the group by gender interaction, with a uniform prior across models. Prior scales were 0.5 for fixed factors and 0.354 for the continuous covariate.

Bayes factors are reported as BF10, the ratio of the marginal likelihood of a model to that of the null model, and BFM, the change from prior to posterior model odds. Values are interpreted using the conventional classification in which 1 to 3 is anecdotal, 3 to 10 moderate, 10 to 30 strong, 30 to 100 very strong, and above 100 extreme evidence (Wagenmakers et al., 2018). This classification is applied consistently throughout; where the ratio falls below 1 the same bands apply in favor of the competing model. Analyses were carried out in R using the BayesFactor package.

RESULTS

Preliminary Analyses

Group equivalence at pre-test was examined before the main analyses, since the design is quasi-experimental and allocation was not randomized at the individual level. Results are reported in **Table 2**. Evidence favored the absence of a difference for injunctive norms and NR-experience and was inconclusive for NR-self and NR-perspective. Descriptive norms showed a small difference in favor of the experimental group, d = 0.27, with anecdotal evidence, BF10 = 1.29. Hence, it can be said that the two groups entered the course at broadly comparable levels, with the qualification that descriptive norms were marginally higher in the experimental group. Pre-test scores were controlled as covariates in all between-group analyses.

Within-Group Change

Table 3 reports the pre-test to post-test comparisons. Both conditions produced substantial gains in every dimension. Bayes factors exceeded 10 to the power of 42 throughout, which is extreme evidence against the

Table 4. Post-test descriptive statistics by group and gender

Variable	Group	Male: M (SD)	Female: M (SD)
Descriptive norms	Experimental	4.28 (0.43)	4.28 (0.50)
	Control	4.03 (0.70)	4.16 (0.47)
Injunctive norms	Experimental	4.32 (0.55)	4.36 (0.59)
	Control	4.17 (0.75)	4.24 (0.53)
NR-self	Experimental	4.57 (0.43)	4.50 (0.49)
	Control	4.46 (0.48)	4.38 (0.49)
NR-perspective	Experimental	4.38 (0.50)	4.23 (0.67)
	Control	4.18 (0.59)	4.10 (0.52)
NR-experience	Experimental	4.25 (0.72)	4.19 (0.75)
	Control	3.99 (0.83)	4.22 (0.58)

Note. M: Mean; SD: Standard deviation; n = 61 and 68 for experimental men and women; & n = 54 and 74 for control men and women

Table 5. Bayesian ANCOVA: Evidence for a group effect after controlling for pre-test

Dependent variable	P (M|data) pre-test only	P (M|data) pre-test + group	BF for adding group	BF10 group vs. null
Descriptive norms	.578	.280	0.48	4.01
Injunctive norms	.572	.255	0.45	0.61
NR-self	.189	.040	0.21	1.09
NR-perspective	.560	.210	0.38	1.80
NR-experience	.621	.207	0.33	0.24

Note. Ten models compared per variable with uniform prior model probabilities; the Bayes factor for adding group is the ratio of the marginal likelihood of the pre-test plus group model to that of the pre-test-only model; & values below 1 favor the simpler model

null by any classification, and effect sizes were large in all ten comparisons, ranging from d = 0.90 to d = 1.41. The largest gains in the experimental group were obtained for NR-self, d = 1.41, and descriptive norms, d = 1.37; in the control group the largest were for NR-self, d = 1.40, and NR-perspective, d = 1.39. Hence, it can be said that the course changed students' environmental norms and their relatedness to nature substantially, and that it did so under both modes of delivery.

Between-Group Comparison

Descriptive statistics for post-test scores by group and gender are reported in **Table 4**. The Bayesian ANCOVA model comparisons are summarized in **Table 5**, which reports for each dependent variable the posterior probability of the pre-test-only model, the posterior probability of the model that adds group, and the Bayes factor for that addition.

The pattern is consistent across all five dependent variables. In every case the model containing the pre-test score alone received the highest or near-highest posterior probability and adding the group term reduced that probability. The Bayes factors for the addition of group ranged from 0.21 to 0.48, which corresponds to anecdotal or moderate evidence against a group effect. The group main effect evaluated against the null model, that is, without adjustment for the pre-test, was likewise unsupported for four of the five variables, BF10 = 0.24 for NR-experience, 0.61 for injunctive norms, 1.09 for NR-self, and 1.80 for NR-perspective. The apparent exception, descriptive norms, BF10 = 4.01, reflects the small pre-test difference reported in **Table 2**; once that difference is controlled the group term is no longer supported, BF = 0.48.

Adjusted mean differences were correspondingly small. Expressed on the original five-point metric, the experimental group exceeded the control group by 0.047 on descriptive norms, 0.052 on injunctive norms, 0.025 on NR-self, 0.045 on NR-perspective, and 0.051 on NR-experience. Partial eta squared values ranged from .004 to .010, and none of the corresponding frequentist tests reached significance, with p values between .105 and .337. The nature experience dimension, in which an advantage for AI-supported instruction might have been expected on the grounds of continuous access, showed the strongest evidence against a group effect of any variable in the study.

Gender

One effect involving gender emerged. For NR-self the best-fitting model was the one containing the pre-test score and gender, P (M|data) = .621, BFM = 14.75, and this model outperformed the pre-test-only model by a factor of 3.29, which constitutes moderate evidence. After adjustment for pre-test scores, men scored slightly higher than women, with adjusted means of 4.51 and 4.44, respectively, $p = .010$. The difference is small in absolute terms and was not present on any other dimension. No group by gender interaction was supported for any variable, with Bayes factors between 0.02 and 0.06 relative to the null.

DISCUSSION

This study set out to determine whether generative AI-supported environmental education changes students' social norms and nature relatedness differently from conventional instruction when the content delivered to the two conditions is held constant. Two findings emerged. The course produced large gains in every measured dimension under both modes of delivery, and the mode of delivery itself made no detectable difference. The second finding is the more informative of the two, and the Bayesian framework permits it to be stated as a finding rather than as a failure to detect something.

Course Content and Instructional Outcomes

The within-group gains were substantial and remarkably uniform. Effect sizes between 0.90 and 1.41 across five conceptually distinct outcomes, obtained in both conditions, indicate that the green building environment course changed how students perceive environmental norms and how they relate to the natural world. These magnitudes are consistent with the environmental education literature. Imran et al. (2024) report comparable shifts in sustainable values and attitudes, and Gopinath and Kumar (2025) obtained similar movement in environmental values through a program built on empathy and reflective thinking. Kowasch et al. (2022) describe the same kind of change in the context of forest education. What the present design adds is that the gains occurred twice, under two quite different delivery arrangements, with the content the only element common to both.

That observation aligns with a strand of research that has received less attention in the educational technology literature than it deserves. Steiner (2024) argues that the quality of instructional materials is the more consistent determinant of student outcomes, and Garay Abad and Hattie (2025) reach a similar conclusion about the influence of materials on instructional design and teacher development. The present results are consistent with that position. When the material is held constant and the delivery medium is varied, the outcomes do not move. Hence, it can be said that the curriculum, rather than the technology through which it was mediated, carried the effect observed here.

The Absence of a Delivery Effect

The null result requires careful interpretation, since it stands in apparent tension with the meta-analytic literature. Wang and Fan (2025) report a large positive effect of ChatGPT on learning performance, and reviews of generative AI in higher education describe gains in skills development (Daniel et al., 2025; Hon, 2026). The discrepancy is largely a matter of what is being compared. In most of the studies contributing to those syntheses, the AI-supported condition received support, feedback, or material that the comparison condition did not; the contrast was therefore between augmented and unaugmented instruction. In the present design both conditions received the same material, and the AI module was restricted to that material. Under those conditions the technology has no informational advantage to confer, and none was observed.

A second consideration concerns the outcomes themselves. The meta-analytic evidence for generative AI rests largely on achievement, skills, and perception measures. Social norms and nature relatedness are neither of these. Norms are formed through observation of what others do and approve, which is a social rather than an informational process, and Mundt et al. (2024) found across five field experiments that even direct normative interventions produce context-dependent effects. Galeotti et al. (2024) note in their review of climate change education that normative outcomes are among the least consistently reported in the literature. Against that background, the absence of a delivery effect on norms is unsurprising. Lee et al. (2024) capture the same intuition from the practitioner side, valuing generative AI for feedback and preparation while doubting its contribution to deeper engagement.

The nature experience dimension merits separate comment, because it was the dimension on which an advantage for AI-supported instruction was most plausible. Continuous availability, self-paced access, and the removal of timetable constraints might reasonably be expected to increase engagement with material about contact with nature. The evidence went the other way, and it did so more clearly than for any other variable, BF10 = 0.24 for the group effect. The literature offers a straightforward explanation. Nature relatedness in its experiential aspect is built through contact with actual natural environments rather than through material about them. Pirchio et al. (2021) obtained gains in connectedness to nature through outdoor environmental education involving direct contact, and Masson et al. (2025) did so through a citizen science intervention with a field component. Liu et al. (2022) show that nature contact mediates the relationship between connection and behavior, and Uchiyama et al. (2024) identify childhood nature experience as a consistent driver of later engagement. It is not possible to make a generalization from a classroom intervention to this dimension, and neither delivery mode in the present study has involved contact with nature at all.

Norm Structure and the Gender Finding

Both norm dimensions moved together and to a similar degree, which is consistent with the meta-analytic evidence that descriptive and injunctive norms exert unique effects of comparable size (Helferich et al., 2023). Ren et al. (2024) reached the same conclusion using eye-tracking, and Fu et al. (2024) add that the two operate most effectively when they point in the same direction. The present results neither support nor challenge that literature directly, since the design did not manipulate norms as such, but the parallel movement of the two subscales is at least compatible with it.

The one effect involving gender was small and confined to a single dimension. After adjustment for pre-test scores, men scored slightly higher than women on NR-self, and the evidence for including gender in the model was moderate. This dimension concerns the extent to which a person incorporates nature into their identity, and identity-related measures are known to vary with social context. Sierra-Barón et al. (2023) report differences in environmental identity between rural and urban residents, and Tseng and Wang (2020) caution that conventional definitions of nature connection may not transfer across cultural settings. The present finding was not predicted, it was not replicated on the other four dimensions, and it should be treated as a candidate for future investigation rather than as an established difference.

Implications

The practical implication is not that generative AI has no place in environmental education. It is that the case for adopting it should be made on grounds other than learning outcomes. The AI-supported condition delivered the same gains as conventional instruction while removing timetable constraints and allowing students to work at their own pace, and these are real advantages in a higher education context where access and scheduling are genuine obstacles. Nikolopoulou (2025) and Xiaoyu et al. (2025) describe the same set of affordances. What the present study indicates is that these affordances should be understood as improvements in accessibility rather than as improvements in effectiveness.

A second implication concerns research design. Studies that introduce a new technology together with new content cannot separate the contributions of the two and will tend to be attributed to the technology what belongs to the material. The design used here, in which the knowledge base of the AI module was restricted to the materials used in the comparison condition, offers one way of holding that confound in check and could be applied in other subject areas.

Limitations

Several limitations qualify for these conclusions. The study was conducted within a single course at a single institution, and the findings may not extend to other disciplines, other course structures, or other cultural settings. No measure was taken of how frequently or for how long students actually used the AI module, so the intervention is defined by availability rather than by use, and a group that used the module little would be difficult to distinguish from one that used it extensively. Long-term retention was not assessed, and whether the observed changes persist beyond the end of the course is unknown. Demographic data other than gender were not collected, which prevented examination of age, prior environmental education, or academic achievement as moderators.

Two measurement limitations deserve particular emphasis. Internal consistency in the study sample was lower than in the development samples, especially at pre-test and especially for the two norm subscales, where alpha fell to .520 and .559. Estimates based on those scores are correspondingly less precise. In addition, the item-to-subscale key for the nature relatedness scale had to be verified against the administered form, because the item order on that form differs from the order used in the adaptation study. The analyses reported here use the verified key. Readers should note that the three nature relatedness subscales did not display the pattern of positive intercorrelation reported in the original validation, and this anomaly, which is present in the adaptation sample as well, has not been fully resolved.

CONCLUSION

Generative AI-supported environmental education and conventional environmental education produced equivalent outcomes in this study when the content delivered to students was the same. Both conditions produced large gains in descriptive norms, injunctive norms, and all three dimensions of nature relatedness, and the evidence favored the absence of a difference between them on every dimension, including the one where an advantage was most plausible. This study is an attempt to separate the contribution of instructional content from that of the delivery medium, and its result points toward the former. It is recommended that future studies measure actual usage of AI-supported systems rather than their availability, follow participants beyond the end of the course, and test whether the same equivalence holds in subject areas where the outcomes are cognitive rather than normative.

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