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International Journal of Curriculum and Instruction 17(3) (2025) 874–891

IJCI
International Journal of Curriculum and Instruction

Awareness of New Generation Environmental Problems: Scale Development for Pre-service Science Teachers

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Abstract

This study investigates pre-service science teachers' awareness of the environmental impacts of digital technologies—specifically artificial intelligence (AI), cryptocurrency mining, and E-sports games. While traditional ecological concerns are widely addressed in education, the environmental footprint of digital activities remains underexplored. To bridge this gap, the New-generation Environmental Problems Awareness Scale (NEPAS) was developed and validated with 291 pre-service teachers from two major Turkish universities. Data were collected via a mixed-method process that included exploratory qualitative inputs and a finalized 22-item Likert scale. Confirmatory factor analysis supported a three-factor model: Environmental Awareness, Attitude Toward AI, and Attitude Toward Cryptocurrency, with high reliability and validity (Cronbach's alpha = 0.92). Results revealed that although participants frequently used digital tools—especially smartphones and AI systems—awareness of their environmental consequences was moderate. Awareness levels varied significantly by gender, academic year, and exposure to environmental education. Notably, pre-service science teachers who took environmental courses scored higher in environmental awareness, but not in technology-specific dimensions. These findings highlight the necessity of incorporating emerging ecological risks tied to digital technologies into teacher education curricula. The NEPAS offers a domain-specific tool for assessing such awareness and can guide curriculum reform toward a more sustainable and digitally informed future.

Keywords: environmental awareness, AI, cryptocurrency, e-sports games, scale development.

1. Introduction

Individual consumption habits—such as water and energy waste, the intensive use of disposable products, and reliance on personal vehicles—are frequently emphasized in public awareness campaigns and educational content as contributors to environmental degradation. As a result, avoiding these conventional behaviors is often the first action associated with eco-friendly living. However, as technology becomes increasingly integrated into daily life, environmental problems are evolving into more complex and less

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tangible forms. Technological developments not only create direct effects but also indirect environmental consequences, which are often recognized too late or not considered at all (Syzdykova, 2023; Stoll, Klaaßen & Gallersdörfer, 2019).

Digital activities such as artificial intelligence (AI) applications, cryptocurrency mining, and E-sports games systems contribute significantly to fossil fuel dependency and carbon footprint expansion due to their high energy demands (De Vries, 2018). Because these activities occur online, there is a widespread misconception that their environmental impact is intangible or negligible. In reality, each digital transaction carries considerable environmental consequences through elevated electricity use, carbon emissions, and electronic waste (Malmo, 2017; Strubell et al., 2019).

Understanding these technology-based environmental issues requires basic comprehension of how digital systems function and how they interact with ecological systems. For example, cryptocurrency mining—particularly in proof-of-work algorithms such as Bitcoin—demands high computational power to solve complex algorithms. This operation is carried out via continuously running specialized hardware (e.g., ASICs), leading to excessive energy consumption (De Vries, 2018). Stoll, Klaaßen, and Gallersdörfer (2019) found that the annual electricity consumption of the Bitcoin network is comparable to that of an entire small country (Figure 1). This sharpens the carbon footprint, particularly in regions reliant on fossil fuels. Additionally, Bitcoin mining exacerbates environmental degradation by increasing particulate air pollution, with significant health consequences (Harvard T.H. Chan School of Public Health, 2023).

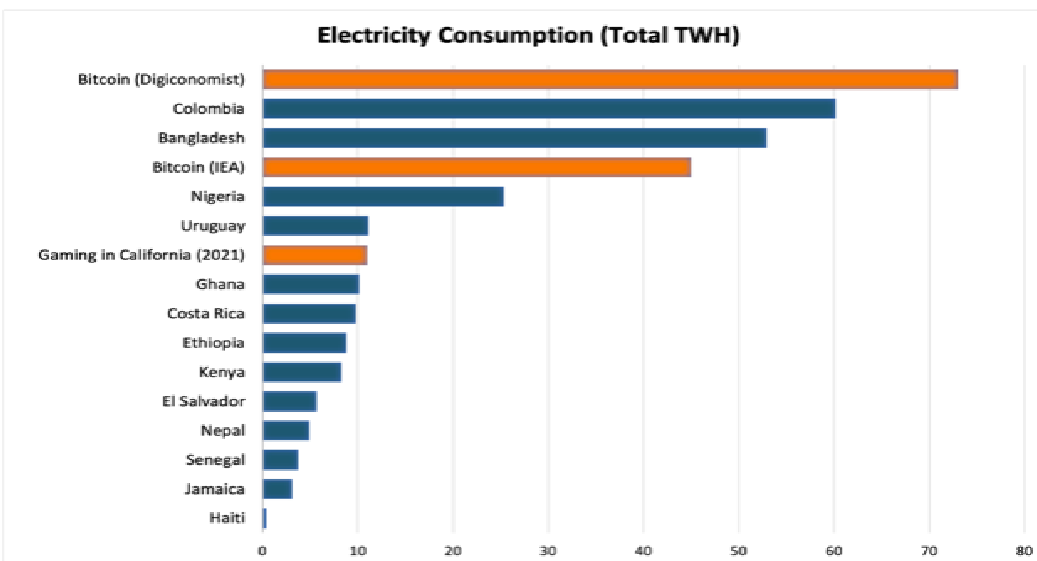

Figure 1. Electricity Consumption (Total TWh) (Moss & Kincer, 2021).

Similarly, training artificial intelligence systems also incurs serious environmental costs. Large-scale language models require repetitive training over vast datasets, demanding powerful GPUs and extended periods of operation. Strubell, Ganesh, and McCallum (2019) reported that training a single NLP model can emit up to 284 tons of CO_2—the equivalent of a car's lifetime emissions.

Recent estimates reveal that popular AI systems like ChatGPT consume approximately 500,000 kWh annually per data center, creating a substantial carbon footprint (Business Energy UK, 2025; USA Today, 2025).

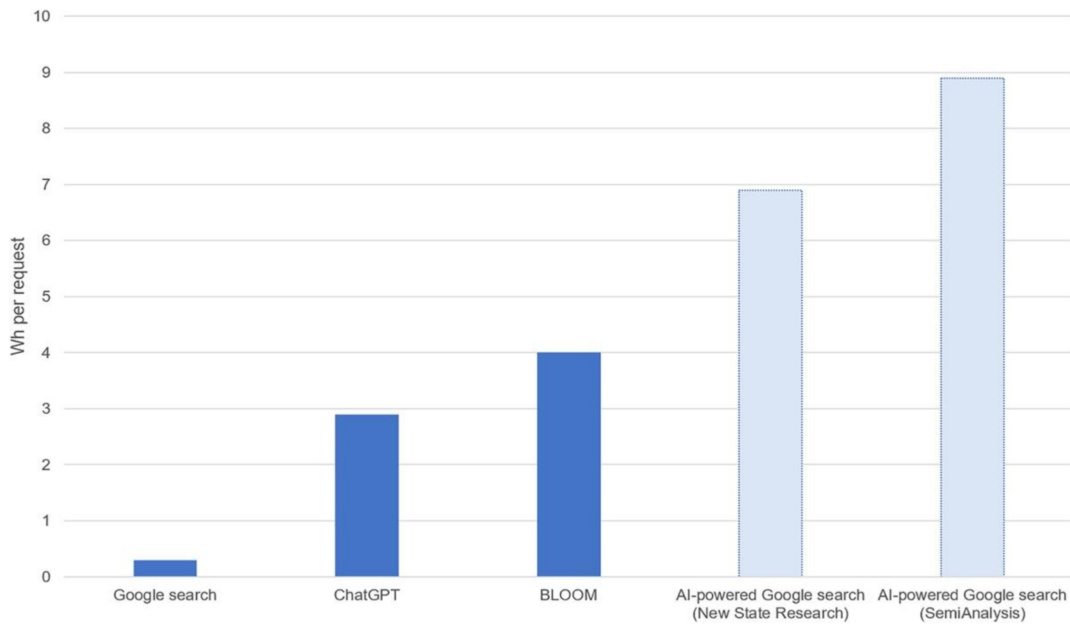

Figure 2. Estimated energy consumption per request across AI-powered systems, including ChatGPT and BLOOM, compared with standard Google searches (De Vries, 2023).

E-sports games, another widespread digital activity, is similarly far from environmentally benign. Its infrastructure—comprising high-resolution graphics, uninterrupted data streaming, and concurrent user participation—relies on massive data centers running around the clock. These centers consume vast amounts of electricity and require cooling systems that further strain water and energy resources (Malmo, 2017). The growth of the E-sports games industry has amplified these concerns, with even university tournaments contributing to measurable emissions (The Varsity, 2022; Daily Californian, 2023). Additionally, the frequent replacement of consoles, PCs, and peripherals contributes to an increasing volume of electronic waste (Baldé et al., 2021). The OECD (2024) has emphasized the urgent need for systemic assessments of AI and digital tools' environmental impact.

Anticipating and mitigating these impacts requires the development of critical awareness. Awareness extends beyond simply knowing about a phenomenon; it involves evaluating information, developing emotional engagement, and taking action. In environmental contexts, awareness includes recognizing ecological problems, understanding their causes and consequences, cultivating sensitivity, and becoming motivated to develop solutions (Hungerford & Volk, 1990).

According to Hungerford and Volk (1990), environmental awareness is directly shaped by a combination of knowledge, personal responsibility, and behavioral intention. Therefore, raising awareness of the environmental impact of digital technologies involves more than transmitting information—it requires the internalization of values and the development of action competence.

In this context, it becomes crucial to objectively measure awareness of technology-related environmental problems. However, very few instruments in the literature are designed to capture this specific awareness. Most existing scales focus on traditional environmental topics and fail to address the ecological consequences of emerging technologies.

This study seeks to bridge that gap by developing the New-generation Environmental Problems Awareness Scale (NEPAS) to assess pre-service science teachers' awareness of digital environmental impacts. NEPAS focuses specifically on areas such as cryptocurrency mining, AI systems, and E-sports games. The study aims to answer the following research questions:

• What are the awareness levels of pre-service science teachers regarding next-generation environmental problems? • Do these levels vary by gender, academic year, or prior environmental education? • Is the developed NEPAS scale a scientifically valid and reliable measurement tool?

Ultimately, this research aims to expand the scope of environmental education and inform the restructuring of teacher preparation programs to address the environmental challenges of the digital age.

2. Method

2.1. Research design: The study was conducted with the aim of developing a valid and reliable measurement instrument to assess preservice science teachers' awareness of new generation environmental problems, including the ecological impacts of digital technologies such as AI, cryptocurrency mining, and E-sports games. A quantitative research design was employed, specifically using the general survey model, which enables the description of individuals' knowledge, attitudes, and behaviors as they currently exist (Karasar, 2015; Büyüköztürk et al., 2016). Given the scale development focus of the study, both descriptive and relational survey model characteristics were integrated into the research framework (Karasar, 2015). The study also employed a non-experimental, cross-sectional, and descriptive-correlational design. Participants were not exposed to any interventions or manipulated conditions. All measurements were conducted at a single point in time and relied on voluntary self-report data. The study's design was chosen to reflect participants' existing awareness levels without researcher interference, making it suitable for scale validation and psychometric analysis. No experimental manipulations or interventions were conducted in this study. The study's aim was strictly observational and descriptive, focusing on the development and validation of the NEPAS instrument.

2.2. Participants

Participants consisted of 291 preservice science teachers enrolled in undergraduate science education programs at Gazi University and Hacettepe University during the 2023–2024 academic year. The sample included pre-service science teachers from all academic years (1st to 4th grade), enabling an examination of awareness levels in relation to exposure to environmental education courses.

Eligibility criteria required participants to be actively enrolled in the science education department. No exclusions were made based on gender, age, or other demographic characteristics. Participation was voluntary, and informed consent was obtained from all participants. No personal identifiers were collected, ensuring anonymity throughout the study. The research adhered to ethical principles, and approval was obtained from the Ethics Committee of Hacettepe University Graduate School of Educational Sciences (Approval No: [E-66777842-300-00003425143]).

2.3. Sampling

A convenience sampling method was employed to recruit participants due to time and resource constraints. This method enabled the collection of data from readily accessible individuals in classroom settings and online environments. While this limits generalizability, it was appropriate for the initial scale development phase. Future studies are planned to use stratified random sampling across different geographical regions in Türkiye to validate the scale further.

Data were collected in face-to-face settings and via Google Forms when in-person access was not feasible. No financial or material incentives were provided. The study fully complied with institutional ethical standards.

2.3.1. Sample size, power, and precision

In scale development studies, a commonly accepted rule is that the sample size should be at least 5 to 10 times the number of items in the scale (Tavşancıl, 2010). The initial item pool consisted of 51 items, and the final sample of 291 participants met this requirement. Field (2009) also recommends a minimum of 200 participants for factor analysis, which was exceeded in this study. The sample broadly reflected the target population of preservice science teachers in Türkiye, with no known systematic differences between the sample and the general population.

2.3.2. Measures and covariates

Data were collected through a two-stage process:

- Stage 1 (Exploratory phase): An open-ended questionnaire comprising 8 items was developed by the researchers to assess participants' familiarity and experience with AI tools, cryptocurrency usage, and E-sports games. Participants were also asked to express their views on technologies that they believed could pose future environmental threats. This qualitative exploration involved 118 preservice teachers and revealed low levels of structured awareness regarding the environmental impacts of these technologies.

- Stage 2 (Scale development): Based on the open-ended responses and an extensive literature review, an initial item pool of 77 items was created, focusing on the ecological implications of AI, cryptocurrency, and E-sports games. After expert review by eight specialists (two language experts, three measurement and evaluation experts, and three environmental education experts), the pool was refined to 51 items, ensuring content validity, linguistic clarity, and relevance to the target audience. A 5-point Likert scale was used (1 = Strongly Disagree to 5 = Strongly Agree). The scale was named the New Generation Environmental Problems Awareness Scale (NEPAS) and was structured around three thematic subdimensions: artificial intelligence, cryptocurrency, and E-sports games.

A pilot test was conducted with 5 preservice teachers. Feedback regarding item clarity, redundancy, and technical wording was used to finalize the scale before large-scale administration.

Psychometric Properties

- Construct validity was assessed using Exploratory Factor Analysis (EFA) followed by Confirmatory Factor Analysis (CFA). Prior to EFA, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were applied. KMO exceeded .70, and Bartlett's test was statistically significant, confirming the appropriateness of factor analysis (Bekiş & Arı, 2021).
- CFA was conducted using AMOS 20.0 to test the model fit. Model indices such as GFI, AGFI, CFI, RMSEA, SRMR, IFI, PNFI, and PGFI were evaluated. All indices met acceptable thresholds (Savalei & Fouladi, 2021; Ziedzor, 2022), and the total variance explained exceeded 65% (Kenek & Sökmen, 2022).
- Reliability was assessed using Cronbach's alpha and McDonald's omega coefficients, both of which exceeded .70 across the entire scale and subscales, indicating high internal consistency.
- Normality of the data was evaluated using the Kolmogorov–Smirnov test. Due to the large sample size and acceptable skewness/kurtosis values, parametric tests were employed.
- For group comparisons, independent samples t-tests and one-way ANOVA were applied, depending on the number of groups. In cases where ANOVA results were significant, Sidak post hoc tests were used. The significance level was set at $p < .05$.
- Tukey's test of additivity was conducted to assess the appropriateness of combining subscales into a total score, while Hotelling's T^2 test was used to examine response homogeneity (Jahng, 2022).

3. Results

This section presents a detailed account of the demographic and digital technology usage characteristics of the prospective teachers participating in the study, the validity and reliability analyses of the developed scale, the findings regarding factor structures, and the relationships between variables. Additionally, participants' levels of environmental awareness and their attitudes toward artificial intelligence and cryptocurrency technologies are evaluated comparatively based on various variables.

3.1. Participant Profile

Table 1 shows the distribution of participants' demographic characteristics and daily technology usage.

Table 1. Demographic and Behavioral Characteristics of Participants

		n	%
Gender	Male	51	17.5%
	Female	240	82.5%
Class Level	1st Year	44	15.1%
	2nd Year	89	30.6%
	3rd Year	73	25.1%
	4th Year	85	29.2%
Have you taken an Environmental Course during your undergraduate education?	Yes	144	49.5%
	No	147	50.5%
How many hours a day do you use technological devices such as computers/phones/tablets?	1-3 hours	42	14.4%
	3-5 hours	150	51.5%
	More than 5 hours	99	34.0%

As seen in Table 1, among the 291 pre-service science teachers who participated in the study, 17.5% are male and 82.5% are female. The distribution of participants by academic year is relatively balanced. Approximately half of the participants (49.5%) have taken at least one environmental course during their undergraduate education, while 50.5% have not. Regarding daily technology usage time, 14.4% reported 1–3 hours, 51.5% reported 3–5 hours, and 34.0% reported more than 5 hours. These figures indicate that most participants use digital devices for several hours daily.

Table 2. Technological Devices Used

		n	%
Laptop	No	55	18.9%
	Yes	236	81.1%
Smart Phone	No	8	2.7%
	Yes	283	97.3%
Tablet	No	220	75.6%
	Yes	71	24.4%
Desktop Computer	No	254	87.3%
	Yes	37	12.7%

These results show widespread use of mobile devices, especially smartphones, among pre-service science teachers, while desktop computers are less common.

3.2. Construct Validity and Reliability Analysis

Figure 1 illustrates the structural equation model diagram showing the three-dimensional structure obtained from the confirmatory factor analysis (CFA) of the scale.

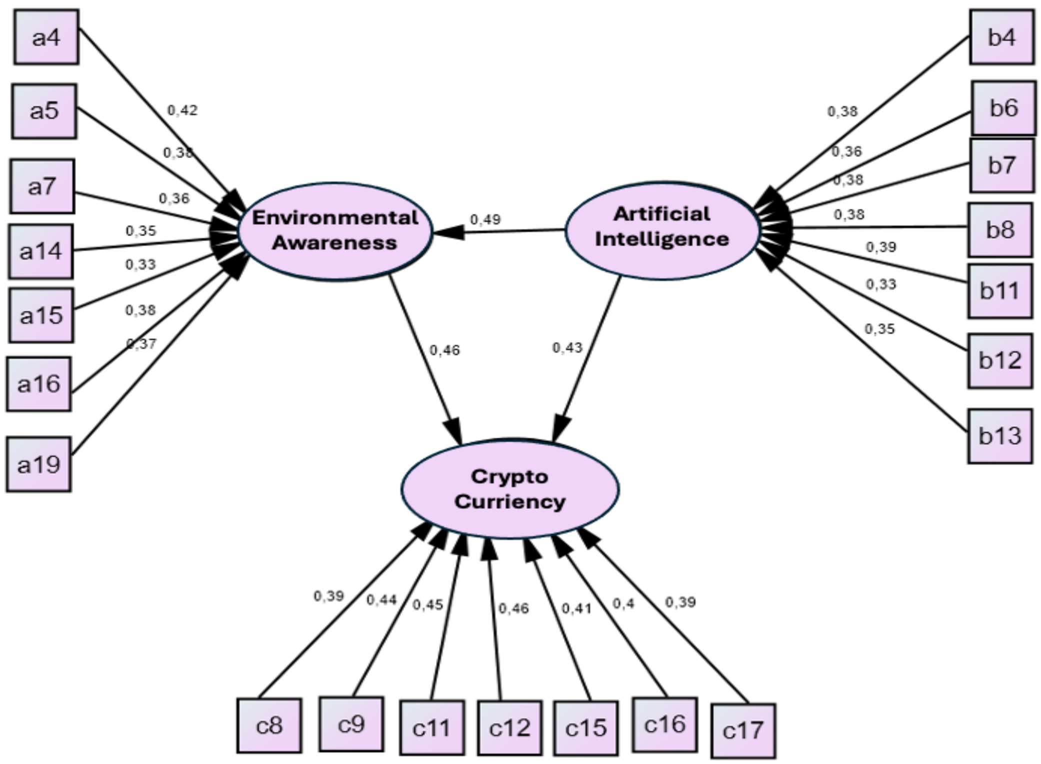

Figure 1. Structural Equation Model Diagram Showing the Three-Dimensional Structure Obtained from the Confirmatory Factor Analysis of the Scale

As illustrated in Figure 1, each item in the final version of the scale is associated with one of three dimensions: Environmental Awareness, Attitude Toward Artificial Intelligence, or Attitude Toward Cryptocurrency. The placement of items within these factors was determined through confirmatory factor analysis and is detailed in Table 3.

The CFA confirmed a three-factor structure: (1) Environmental Issues Awareness, (2) Attitude Toward Artificial Intelligence, and (3) Attitude Toward Cryptocurrency. All items showed significant factor loadings (mostly > 0.50).

Table 3: Structural Validity and Item Properties of the NEPAS Scale

Code	Item	Factor Loading	Explained Variance	Internal Consistency
a4	I have knowledge about the recycling steps of different types of waste.	0.486	29%	0.83
a5	I feel happy when the type of energy I use is environmentally friendly.	0.642		
a7	I prefer energy-saving electronic devices because they contribute to the household economy.	0.584		
a12	I immediately turn off unnecessary lights at home or outside.	0.589		
a14	Even if I cannot personally impact environmental events in my surroundings, I cannot stay indifferent.	0.621		
a15	I believe technological developments will be effective in preventing environmental pollution.	0.554		
a16	I am concerned about the air pollution level in my area.	0.554		
a19	I am disturbed by unnecessary energy (water, light, etc.) consumption at home or outside.	0.636		
b4	I am aware of the environmental impact of questions asked to artificial intelligence.	0.513	26%	0.81
b6	I consider using cryptocurrencies like Bitcoin, Ethereum, Litecoin for investment now or in the future.	0.575		
b7	I am aware of the impact of cryptocurrency markets on the current economy.	0.636		
b8	I have knowledge about cryptocurrencies produced using renewable energy.	0.628		
b11	I enjoy playing E-sports games games like Counter-Strike, Dota 2, Fortnite, Call of Duty.	0.622		
b12	I regularly allocate time in my daily life to play E-sports games games.	0.687		
b13	I have knowledge to evaluate the environmental impact of E-sports games games.	0.633		
c8	I am aware of eco-friendly coins in the cryptocurrency market.	0.578	24%	0.79
c9	I have knowledge about the environmental aspects of cryptocurrency mining.	0.578		
c11	I enjoy discussing cryptocurrencies like Bitcoin with people around me.	0.580		
c12	I enjoy playing E-sports games games.	0.581		
c15	I want to play games with the latest technology devices.	0.520		
c16	Equipment needed for E-sports games must be up to date.	0.505		
c17	E-sports games is a means of socializing fr me.	0.596		

Bartlett's Test: χ^2 = 1256.35, p = 0.01, **KMO (Kaiser-Meyer-Olkin) Measure:** 0.91, **Reliability (Cronbach's Alpha):** 0.92

The CFA conducted as part of the scale adaptation study confirmed a three-factor structure. The identified subdimensions were named Environmental Issues Awareness, Attitude Toward Artificial Intelligence, and Attitude Toward Cryptocurrency. Each item loaded significantly and strongly onto its respective factor (most standardized factor loadings were above 0.50). As shown in Figure 1, the observed variables (scale items) are grouped under the relevant latent structures, and the inter-factor relationships were modeled consistently with theoretical expectations.

As a result of the exploratory and confirmatory factor analyses conducted to support construct validity, the scale was reduced from 51 to 22 items, achieving the optimal three-dimensional structure. The Kaiser-Meyer-Olkin (KMO) sampling adequacy coefficient was found to be 0.91, which is well above the acceptable threshold of 0.70, indicating that the data are suitable for factor analysis. The Bartlett's test of sphericity was also significant ($\chi^2 = 1256.35$; $p < 0.01$), confirming the suitability of item correlations for factor analysis.

The three-factor structure confirmed by CFA aligns with the original scale and explains 79% of the total variance. The Environmental Issues Awareness subdimension alone accounts for 29% of the variance, the Attitude Toward Artificial Intelligence accounts for 26%, and the Attitude Toward Cryptocurrency accounts for 24%. Each subdimension demonstrated high internal consistency (Cronbach's α = 0.83, 0.81, and 0.79, respectively). The overall reliability of the scale was also high (Cronbach's α = 0.92 for all items), indicating consistent and reliable measurement results. These findings demonstrate that the adapted form of the scale has sufficient measurement validity and reliability.

3.3. Distribution of Scale Scores

Descriptive statistics of the scale's subdimension scores are presented in Table 4.

Table 4 Evaluation of Dimension Scores and Normality Levels

Dimension	M±SD	K-S p	Skewness - Kurtosis
Environmental Awareness Dimension	3.35±0.56	0.20*	0.79-1.32
Attitude Toward Artificial Intelligence Dimension	3.19±0.68	0.14	0.96-0.45
Attitude Toward Cryptocurrency	2.91±0.73	0.18	1.09-0.65

*K-S p: Kolmogorov–Smirnov test p-value

- indicates normal distribution ($p > 0.05$)

The average score on the Environmental Issues Awareness dimension was 3.35 (±0.56) out of 5, indicating an above-average level of environmental awareness among pre-service science teachers. The average score for Attitude Toward Artificial Intelligence was 3.19 (±0.68), also reflecting a relatively high attitude level. The average score for Attitude Toward Cryptocurrency was 2.91 (±0.73), indicating a more moderate attitude. The distributions for all three dimensions were found to approximate a normal curve. Kolmogorov-Smirnov test statistics were $p = 0.20$, $p = 0.14$, and $p = 0.18$, respectively; these values being greater than 0.05 suggest no significant deviation from normality.

Additionally, skewness and kurtosis values were within the acceptable range (~–1.5 to +1.5), and the sufficient sample size confirmed normal distribution conformity.

3.4. Model fit indices

Model fit indices for the confirmatory factor analysis are summarized in Table 5.

Table 5. Examination of Sub-Dimension Fit Levels

Fit Indices	Value	Fit Status	Perfect Fit Criteria	Acceptable Fit Criteria
[1] ^{2}/sd χ	2.05	Acceptable Fit	$0 \leq \chi^2/sd \leq 2$	$2 \leq \chi^2/sd \leq 3$
[2]AGFI	0.87	Acceptable Fit	.90 ≤ AGFI ≤ 1.00	.85 ≤ AGFI ≤ .90
[3]GFI	0.94	Acceptable Fit	.95 ≤ GFI ≤ 1.00	.90 ≤ GFI ≤ 95
[3]CFI	0.96	Perfect Fit	.95 ≤ CFI ≤ 1.00	.90 ≤ CFI ≤ .95
[3]IFI	0.95	Perfect Fit	.95 ≤ IFI ≤ 1.00	.90 ≤ IFI ≤ .95
[1 4]RMSEA	0.05	Perfect Fit	.00 ≤ RMSEA ≤ .05	.05 ≤ RMSEA ≤ .08
[1 4]SRMR	0.06	Acceptable Fit	.00 ≤ SRMR ≤ .05	.05 ≤ SRMR ≤ .10
[5]PNFI	0.72	Acceptable Fit	.95 ≤ PNFI ≤ 1.00	.50 ≤ PNFI ≤ .95
[6]PGFI	0.61	Acceptable Fit	.95 ≤ PGFI ≤ 1.00	.50 ≤ PGFI ≤ .95

Sources: 1 Savalei ve Fouladi (2021), 2 Ziedzor (2022), 3 Nam ve Jin (2018), 4Jahng (2022), 5 Bringmann (2022), 6 Rahi ve Ghani (2018)

The results show that the model fits the data well. The Chi-square/degrees of freedom ratio (χ^2/df) was 2.05, which falls within the acceptable range. The fit indices AGFI = 0.89, GFI = 0.94, CFI = 0.93, PNFI = 0.88, and PGFI = 0.85 all meet the thresholds suggested in the literature for acceptable model fit. Some indices indicated excellent fit: IFI = 0.96, RMSEA = 0.05, and SRMR = 0.05. In summary, the combination of acceptable and excellent fit indices strongly supports that the three-factor model fits the data satisfactorily.

3.5. Analysis of Differences Based on Variables

According to Table 5, some subdimension scores show statistically significant differences depending on demographic and experiential variables.

Table 6. Examination of Dimension Scores According to General Characteristics

		Environmental Issues Awareness Dimension		Attitude Toward Artificial Intelligence Dimension		Attitude Toward Cryptocurrency	
		M±SD	p	M±SD	p	M±SD	p
Gender **	Male	3.38±0.66	0.59	3.62±0.59	0.01*	3.45±0.76	0.01*
	Female	3.36±0.54		3.10±0.66		2.8±0.67	
Class Level ***	1st Year	3.29±0.52	0.02*	3.35±0.65	0.01*	2.98±0.71	0.01*
	2nd Year	3.21±0.54		3.04±0.71		2.85±0.68	
	3rd Year	3.46±0.63		3.36±0.63		3.05±0.81	
	4th Year	3.46±0.51		3.12±0.66		2.83±0.70	
Environmental Course Taken During Undergraduate Education *	Yes	3.46±0.55	0.04*	3.22±0.63	0.37	2.9±0.68	0.51
	No	3.26±0.56		3.17±0.73		2.93±0.77	
Daily Use of Technological Devices***	1–3 hours	3.44±0.62	0.01*	3.39±0.81	0.01*	2.80±0.72	0.02*
	3–5 hours	3.13±0.53		3.07±0.65		2.80±0.68	
	More than 5 hours	3.15±0.57		3.08±0.67		3.04±0.79	
Investing in Cryptocurrency **	Yes	3.37±0.59	0.64	3.47±0.51	0.01*	3.53±0.74	0.01*
	No	3.36±0.56		3.17±0.69		2.87±0.71	
Close Circle Investing in Cryptocurrency **	Yes	3.38±0.63	0.66	3.31±0.79	0.01*	3.12±0.81	0.01*
	No	3.35±0.5		3.01±0.57		2.75±0.62	

Notes: ***ANOVA, ** Independent samples t-test. * Significant relationship at the 0.05 level

No significant gender difference was found in environmental awareness scores ($p = 0.59$). However, gender differences were significant for both Attitude Toward Artificial Intelligence and Attitude Toward Cryptocurrency, with male participants scoring significantly higher than female participants in both dimensions ($p = 0.01$ for both).

All subdimensions showed significant differences based on academic year. Third- and fourth-year pre-service science teachers had higher Environmental Issues Awareness scores than first- and second-year pre-service science teachers ($p < 0.05$). Likewise, Attitude Toward Artificial Intelligence scores were higher for first- and third-year pre-service science teachers compared to second- and fourth-year pre-service science teachers ($p = 0.01$). Attitude Toward Cryptocurrency scores were especially high among third-year pre-service science teachers, whose mean scores were significantly higher than those of other year groups ($p = 0.01$).

Having taken an environmental course made a statistically significant difference only in the Environmental Issues Awareness dimension; pre-service science teachers who had taken at least one environmental course during their studies scored significantly higher than those who had not ($p = 0.04$). This variable had no significant impact on the other two subdimensions ($p > 0.05$).

Daily digital device usage also had an effect on group differences. Pre-service science teachers using digital devices for 1–3 hours per day had significantly higher scores in Environmental Issues Awareness and Attitude Toward Artificial Intelligence ($p = 0.01$ for both). On the other hand, pre-service science teachers who used devices for more than 5 hours daily had the highest Attitude Toward Cryptocurrency scores ($p = 0.02$).

Pre-service science teachers who had invested in cryptocurrencies scored significantly higher on Attitude Toward Artificial Intelligence and especially Attitude Toward Cryptocurrency than those who had not invested ($p = 0.01$ for both). However, no significant impact of crypto investment on environmental awareness was found ($p > 0.05$).

Similarly, having someone in their immediate circle who had invested in cryptocurrencies was associated with significantly higher scores in Attitude Toward Artificial Intelligence and Attitude Toward Cryptocurrency ($p = 0.01$), but had no significant effect on environmental awareness scores ($p > 0.05$).

3.6. Participants' Experience with Technology and Digital Systems

Table 7 shows the rates at which pre-service science teachers use AI-based digital tools. The results indicate that the most widely used AI application is ChatGPT, with 84.5% of participants stating they had used it at least once. In contrast, fewer participants reported using other AI assistants such as Microsoft Copilot (15.5%). Visual content-generating AI tools like DALL-E (3.4%) and Midjourney (1.7%) were used by very few. The usage rate for Google Gemini was 19.9%, indicating limited but existing awareness of upcoming AI technologies.

Table 7. Artificial Tools Used

		n	%
Chat GPT	No	45	15.5%
	Yes	246	84.5%
Microsoft Copilot	No	246	84.5%
	Yes	45	15.5%
DALL-E	No	281	96.6%
	Yes	10	3.4%
Google Gemini	No	233	80.1%
	Yes	58	19.9%
Midjourney	No	286	98.3%
	Yes	5	1.7%
Sora	No	287	98.6%
	Yes	4	1.4%

Overall, most pre-service science teachers have experienced at least one AI tool (especially ChatGPT), but advanced or specialized AI programs are not yet widely adopted. Findings related to pre-service science teachers' experience with cryptocurrency and digital games are summarized in Table 8.

Table 8. Characteristics Related to Cryptocurrency and E-sports games

		n	%
Do you have any cryptocurrency investments?	Yes	17	5.8%
	No	274	94.2%
Does anyone in your close circle have cryptocurrency investments?	Yes	126	43.3%
	No	165	56.7%
How many games are ready to play on your phone. tablet. or computer?	1–3	133	45.7%
	3–6	31	10.7%
	8 or more	12	4.1%
	None	115	39.5%
Experience with game consoles	None	154	52.9%
	Yes (Nintendo. PlayStation. Xbox)	137	48.1%

Only 5.8% of pre-service science teachers have invested in cryptocurrency, but 43.3% reported that at least one person in their immediate circle had done so. This suggests that while direct engagement is limited, indirect exposure to the crypto ecosystem is common among young adults.

Regarding digital gaming experience, 45.7% of participants stated they had 1–3 games installed on their phone, tablet, or computer. About 39.5% reported having no games at all, indicating a significant portion are not interested in digital games. A smaller group constitutes more avid gamers; 10.7% had 3–6 games installed, and 4.1% had eight or more games. Furthermore, 48.1% had used at least one gaming console (Nintendo, PlayStation, or Xbox), while 52.9% had no console experience. These findings suggest heterogeneous levels of digital game involvement among pre-service science teachers, with roughly half having limited or no gaming experience, while the other half have varying degrees of engagement. The variation in cryptocurrency and gaming engagement highlights how pre-service science teachers' interactions with digital technology differ based on personal interests and preferences.

4. Discussion

The findings of this study confirm the initial concern that next-generation environmental problems remain largely invisible within educational contexts. Despite living in a technology-saturated age, the participating pre-service science teachers demonstrated only moderate levels of overall environmental awareness. Awareness was significantly lower in digital-specific domains such as AI, cryptocurrency, and E-sports games. This supports the argument presented in the introduction: while conventional environmental threats are widely recognized, the ecological costs of digital technologies are often overlooked. In this regard, there appears to be a clear awareness gap—familiarity with digital tools does not necessarily translate into understanding their environmental consequences. (Syzdykova, 2023; De Vries, 2018).

One possible reason for this gap is the abstract nature of digital activities. Actions such as using AI or engaging in cryptocurrency mining are often perceived as "virtual" and disconnected from physical reality. However, every digital activity carries hidden environmental costs through energy consumption, carbon emissions, and electronic waste (Malmo, 2017; Strubell et al., 2019). Our results show that these impacts largely remain invisible to teacher candidates. For example, although 85.9% of participants reported using AI technologies, only a small portion demonstrated awareness of their environmental implications. The training and deployment of AI models demand substantial energy and emissions, yet such concerns are rarely part of mainstream educational narratives. This disconnect aligns with prior findings that the training and deployment of AI models demand substantial computational resources and generate significant carbon emissions—up to 284 tons of CO_2 in some cases (Strubell et al., 2019).

A similar pattern emerged with regard to cryptocurrency. While 71.8% of participants were aware of these technologies, only 12.7% were active users. The substantial environmental consequences of crypto mining—such as excessive electricity usage, CO_2 emissions, and e-waste—are largely disregarded (Stoll, Klaaßen & Gallersdörfer, 2019; De Vries, 2018). As noted in the literature, framing cryptocurrencies mainly as financial innovations has obscured their ecological implications (Syzdykova, 2023). Likewise, awareness of the environmental impacts of E-sports games was found to be quite limited. Although 62.5% of participants reported playing games regularly, few were aware of the resource-intensive data centers and server infrastructures that support these activities. (Malmo, 2017).

These findings highlight the urgent need to revise and update educational content. While environmental education courses were found to enhance general awareness, their effect did not extend to digital-specific environmental issues. This suggests that current curricula fail to adequately address the environmental dimensions of emerging technologies. Integrating digital topics into environmental education—such as the carbon footprint of training AI models or the energy demands of gaming platforms—could foster a more holistic awareness among teacher candidates. (OECD, 2024).

Another noteworthy finding is the positive correlation between the amount of time spent using digital technologies and levels of environmental awareness. This suggests that experiential interaction with technology can foster intuitive knowledge. For instance, everyday observations such as devices heating up during use or batteries draining quickly may make users more sensitive to energy consumption. These insights support the idea that environmental education should not rely solely on theoretical instruction but be enriched through practical, real-world experiences. Hungerford & Volk, 1990).

Lastly, participants who actively used AI tools exhibited more environmentally conscious attitudes. This finding implies that digital literacy, when applied critically, may enhance environmental awareness. Although this awareness may not immediately lead to behavioral change, it offers a promising direction for future research. Using digital tools to visualize environmental data and integrate sustainability into teaching practices could support the development of a more action-oriented sustainability mindset among teacher candidates.

5. Conclusions

This study revealed that pre-service science teachers' awareness of environmental problems related to digital technologies is generally at a moderate level, with notable deficiencies particularly in areas such as artificial intelligence, cryptocurrency, and E-sports games. The findings confirm that next-generation environmental problems are not adequately represented in educational discourse or curricula.

To address this gap, the NEPAS was developed as an innovative and domain-specific tool designed to measure awareness of the environmental impacts of digital activities. As one of the first instruments in its field, NEPAS holds significant potential for both academic research and teacher education practices.

Moreover, the study demonstrated that environmental awareness does not stem solely from technological familiarity; rather, structured and contextual education plays a critical role. Although experiential learning and hands-on interaction with digital systems can support awareness, such processes become meaningful only when guided by purposeful educational content.

These findings offer important implications for teacher education and environmental policy. Adapting environmental education to the realities of the digital age is essential for equipping future educators with the knowledge and perspective necessary to promote sustainable behaviors. NEPAS, as a foundational tool to support this transformation, enables educators, researchers, and policymakers to more effectively assess awareness gaps. In doing so, this study makes a concrete contribution not only to the academic understanding of digital environmental problems, but also to the broader effort to build a more sustainable and critically informed digital future.

Acknowledgements

This article is based on the first author’s doctoral dissertation conducted under the supervision of the second author.

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