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Environmental Awareness and Perceived Responsibility regarding Generative AI

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Abstract

In recent years, Generative AI (GenAI) has become an integral part of student life. The growing use of GenAI demands substantial resources, such as electricity and rare earth metals. This study aims to identify the primary use case for GenAI among undergraduate students at Kyungdong University Global, as well as their awareness of its environmental impact and perceived responsibility. We examined the interconnections between usage frequency, awareness, responsibility attitude, and readiness to reduce AI use. The analysis showed that the students who use GenAI frequently are more aware of its environmental impact but find it hard to stop using it.

Keywords: Generative AI; Sustainable AI; LLMs; AI Environmental Impact

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1.0 Introduction

Recently, cutting-edge technologies such as Internet of Things (IoT), Artificial Intelligence (AI), and Blockchain have become very popular and are being used in diverse sectors (Zhang et al., 2023). As technology for Generative Artificial Intelligence (GenAI) improves quickly, students use it frequently. It is a functional tool for academic tasks, not merely a chat system (Black & Tomlinson, 2025; Yan et al., 2026). However, when people use GenAI more often, it causes environmental problems. Every request and response from AI involves large digital systems, including data centers, electricity, cooling systems, semiconductor hardware, networks, and user devices. Recent literature indicates that people should not view Generative AI solely as software. It is more accurate to categorize Generative AI as a digital service that alters the environment. Berthelot et al. (2025) state that the total environmental impact arises from multiple sources: training, inference, hosting, networking, and data storage. In addition, the equipment that people use to access the service contributes to this effect. Due to those factors, the impact is broader than the amount of electricity a model directly consumes. These impacts are important because AI relies on energy-intensive computing infrastructure, rare-earth metals, and cooling systems. Public and student awareness levels were observed to be unequal on these impacts. For instance, Dungo et al. (2025) found that students were more aware of GenAI's electricity demand than of its freshwater and rare-metal demands. Similarly, research on Japan and South Korea found that awareness of AI's environmental consequences is socially uneven and linked to factors such as gender, education, and income (Cho et al., 2025).

This study focuses on undergraduate students at Kyungdong University (KDU) Global Campus. The core purpose of this study is to examine students' primary use of GenAI, their awareness of environmental impact, their perceived responsibility, and their readiness to reduce AI use. We identified seven scored categories to better examine the data: Total AI Usage Score, Average AI Usage Score, Number of GenAI Use Categories, General Environmental Concern Score, GenAI Environmental Awareness Score, Responsible AI Attitude Score, and AI Reduction Feasibility Score.

1.1 Objectives

- To explain how often undergraduate students use GenAI and the main reasons why they use it.
- To measure students' general environmental concern, GenAI environmental awareness, responsible AI attitude, and AI reduction feasibility.
- To look for links between GenAI usage, environmental concern, awareness, responsible attitude, and the possibility of reducing AI use.
- To find how scores for GenAI environmental awareness and other metrics differ between academic groups.

1.2 *Research* Questions
R1 - What is the level of GenAI environmental awareness for undergraduate students at KDU Global Campus?
R2 - How are GenAI usage, general environmental concerns, GenAI environmental awareness, and responsible AI attitude linked to AI reduction feasibility?
R3 - What are the differences based on the department or the academic year in awareness and responsible attitude?

2.0 Literature Review

2.1 Environmental Implications of Generative AI
GenAI requires significant computational power, resulting in substantial energy use and environmental impact. GenAI consumes significant amounts of energy during both training and inference. To assess how GenAI affects the environment is difficult because the structure has many layers - those layers are model development, training, inference, data centers, hosting, networks and user devices. Measuring only electricity consumption and carbon emissions to evaluate GenAI can miss other important aspects, including metals and embodied impacts. Instead, we should assess GenAI as an end-to-end service using life-cycle assessment (Berthelot et al., 2025). GenAI has hidden environmental costs, such as the use of electricity, the release of carbon dioxide, the use of fresh water to cool data centers, the mining of rare earth metals, and the disposal of electronic waste. Since university students frequently use AI for academic work, these issues are particularly relevant for them. If AI becomes a standard learning tool, universities must broaden their focus from academic integrity to sustainable AI use.

However, scholars disagree about the scale and nature of these environmental costs. One line of work emphasizes the sheer magnitude of AI's resource consumption. Strubell et al. (2019) were among the first to quantify the carbon footprint of training large Natural Language Processing (NLP) models, revealing that training a single transformer model with neural architecture search can emit over 626,000 pounds of CO_2, roughly five times the lifetime emissions of an average car. Patterson et al. (2021) later provided a more granular analysis from Google's infrastructure, concluding that while individual training runs are energy-intensive, optimizations such as selecting efficient data center locations and using carbon-aware scheduling can reduce emissions dramatically. Their findings suggest the problem is not the technology itself but rather how and where it is deployed. Luccioni et al. (2024) shifted the conversation toward inference, showing that multi-purpose generative models are substantially more energy-hungry during deployment than task-specific ones, and that over a model's lifetime, inference often outweighs training in total energy use. Desislavov et al. (2023) pushed this idea further by analyzing trends in inference energy consumption and finding that newer, larger models do not always consume proportionally more energy-efficiency gains in hardware and model architecture can partially offset the increased parameter count.

On the other side of the debate, several researchers argue that focusing exclusively on AI's carbon footprint overlooks its potential to reduce emissions elsewhere. Rolnick et al. (2022) provided a comprehensive survey of machine learning applications for climate action, including energy grid optimization, smart building management, deforestation monitoring, and climate modeling. They argued that AI-enabled efficiency gains in high-emission sectors could outweigh the technology's own energy costs by orders of magnitude. Along these lines, Vinuesa et al. (2020) assessed AI's contribution to all 169 targets of the Sustainable Development Goals and found that AI could enable 134 of them, though they cautioned that it might also inhibit 59 targets, particularly those related to inequality and resource consumption. The present study does not choose one side of this debate. Rather, it starts from the recognition that both perspectives carry weight — AI consumes real resources, and it also enables real efficiencies. The question we ask is narrower regardless of where the net calculation lands, do undergraduate students know about these impacts, and does that knowledge influence their behavior? Understanding this requires a view of AI that includes electricity, water, mining, and e-waste, as those are the dimensions most likely to feature in public discourse and environmental education.

2.2 Student Awareness of GenAI's Environmental Impact
Student awareness of GenAI's environmental impact has not yet fully developed. A survey done on Bulacan State University students showed that students had limited knowledge of GenAI's environmental implications. The students were more aware of electricity use but less aware of water and rare earth metals (Dungo et al., 2025). This is strongly relevant to our present study because the KDU survey measures the same key areas: electricity, water, mining, and e-waste.

However, the picture is not uniform across different student populations. Cho et al. (2025) surveyed university students and the general public in both Japan and South Korea and found that awareness of AI's environmental consequences differed substantially by country, gender, and educational background. Korean respondents showed higher awareness of specific AI-related environmental issues than Japanese respondents, which the authors attributed to differences in media coverage and educational emphasis. A parallel study conducted at the University of Glasgow using digital poster campaigns about AI's water footprint found that while the intervention moderately increased awareness, the effect on behavioral intention was small and inconsistent (Gibbons et al., 2025). Most participants acknowledged the issue intellectually but reported little intent to change their AI usage habits. Research from India further complicates the picture. Balakrishnan et al. (2025) found that GenAI users with lower usage frequency expressed stronger pro-environmental behavioral intentions than frequent users, suggesting that dependence on the technology may override environmental concern. This pattern — users know there is a problem but keep using the tool anyway — emerged in multiple studies and formed a central puzzle that our present research addresses.

What is notably absent from this literature is a clear understanding of how technical versus nontechnical students differ in their awareness. Most existing studies treat students as a single homogeneous group or focus on a single discipline. As Kyungdong University Global has four distinct departments with varying degrees of technical orientation, our study is positioned to fill this gap by comparing awareness levels across Smart Computing, Artificial Intelligence, and International Business Administration students.

2.3 Sustainable AI and Public Responsibility

The literature on sustainable AI tends to split along two lines. The first, often called "AI for sustainability," focuses on how AI can be deployed as a tool to tackle environmental problems — monitoring deforestation, optimizing energy grids, predicting climate patterns, and reducing waste in supply chains. The second, termed "sustainability of AI," focuses on reducing the environmental footprint of AI systems themselves — making models more efficient, data centers greener, and hardware supply chains more ethical. Van Wynsberghe (2021) argued that these two conversations are not merely different but can be in tension with each other. Promoting AI as a solution to climate change without also addressing the technology's own resource demands risks what she called a "legitimacy trap," where sustainability becomes a marketing narrative that justifies further resource extraction. Bender et al. (2021) made a related point from the perspective of model scale, arguing that the prevailing "bigger is better" paradigm in AI research carries environmental and social costs that are rarely accounted for in benchmark-driven evaluation.

On the more optimistic side, Schwartz et al. (2020) proposed a "Green AI" framework that advocates for making efficiency a primary evaluation criterion alongside accuracy in AI research. They showed that many published models achieve state-of-the-art results through computationally expensive methods that could be matched by more efficient alternatives. Their argument was not that AI should be abandoned but that the research community should treat computational cost as a first-class metric. This perspective has gained traction, with major AI conferences now encouraging or requiring energy reporting.

For university-level education, the implications are clear but underexplored. Cho et al. (2025) emphasized that public engagement and responsible research and innovation both require that people understand AI's environmental effects, not just its capabilities. In the university context, this means students should learn not only how to use AI tools but also how to evaluate their broader consequences. In this study, a responsible AI attitude denotes students' personal beliefs that the environmental impact of AI is a serious issue, that individuals bear some accountability for their AI usage, that universities should educate students on this topic, and that other students may consider this issue important. What is less clear from existing work is whether students who already hold these beliefs are willing to act on them, and this is where our study aims to contribute.

2.4 Awareness–Action Gap in Sustainable Technology Use

A well-known finding in environmental behavior research is the gap between what people know and what they do. Kollmuss and Agyeman (2002) provided one of the most influential models of this phenomenon, arguing that environmental knowledge alone is rarely sufficient to produce proenvironmental behavior. They identified a range of barriers — demographic, external, and internal — that intervene between awareness and action. More recently, Colombo et al. (2023) reviewed the evidence on the climate awareness-action gap and concluded that while knowledge is necessary, it is not sufficient; factors such as habit, social norms, perceived behavioral control, and emotional engagement all play mediating roles. Hochachka (2024) extended this argument specifically to climate change, showing that even among populations with high levels of concern, behavioral change often fails to materialize due to structural constraints and psychological distance from the problem.

The awareness-action gap takes on a particular character when applied to technology use. Unlike behaviors such as recycling or reducing car travel, reducing AI usage directly conflicts with academic productivity for students. Students are not using AI recreationally in most cases — they are using it to complete assignments, understand difficult concepts, write code, and prepare for exams. Asking them to stop is asking them to sacrifice a tool they perceive as essential to their academic performance. This is fundamentally different from asking someone to carry a reusable water bottle or turn off unused lights. Difficulty in changing behavior may arise from genuine dependency rather than laziness or indifference.

At the same time, there are counterexamples in the literature where awareness did translate into behavioral change. Stern et al. (1999) demonstrated through their Value-Belief-Norm (VBN) theory that when personal values, ecological beliefs, and a sense of personal obligation align, proenvironmental action becomes more likely. The key is whether individuals perceive the problem as personally relevant and believe their actions can make a difference. Applied to our context, this raises an empirical question: do KDU students perceive GenAI's environmental impact as something they personally should act on, or do they view it as a problem for technology companies and governments to solve? This study does not assume that high awareness automatically leads to reduced usage. Instead, we treat the relationship between awareness, responsibility, and behavioral intention as an open empirical question and examine it directly through our survey data.

3.0 Methodology

3.1 Research Design

We used an exploratory quantitative survey design for this study. We surveyed Students using a Google Forms questionnaire, primarily using a 5-point Likert scale. The goal was to describe students' use of GenAI. Additionally, the study aimed to investigate the relationships among usage, environmental concern, GenAI environmental awareness, responsible AI attitude, and AI reduction feasibility. Our purpose was to identify patterns and relationships in students' responses, rather than to develop a full causal theory. Therefore, the design was appropriate for the study.

3.2 Participants and Data

The study was conducted based on the survey responses from undergraduate students at KDU Global Campus. The final valid sample size was 316 after cleaning the raw survey response data. Firstly, we identified and removed duplicate responses using the student ID. KDU Global Campus has four undergraduate departments – Smart Computing (SC), Artificial Intelligence (AI), International Business Administration (IBA), and International Hotel Management (IHM). Only one student from the IHM department participated in the survey. Thus, we excluded that specific data and the department from our dataset. For simplicity, we grouped students into two academic years: first and second-year students are grouped as Freshmen, while third and fourth-year students are grouped as Seniors.

Furthermore, we categorized all the subjective free-text responses received as "Other". The final demographic breakdown of the sample was as follows: SC students accounted for 53.2%, AI 24.1%, and IBA 22.8%. Freshmen accounted for 61.1%, while seniors comprised 38.9%. Male students accounted for 69.3%, female students 30.1%, and other genders 0.6%. Overall, the most common primary reason for using GenAI, reported by 63.3% of students, was academic work.

3.3 Measures and Scoring

- GenAI usage: Students reported how frequently they used GenAI for their primary purpose. The students had four options to choose from: once per week, several times per week, about once per day, and multiple times per day. We scored the responses from 1 to 4, with higher scores indicating more frequent use. The frequency of use for other categories, apart from the primary purpose of GenAI usage, remained blank. While cleaning the response data, we assigned 0 to those blank fields. We calculated the total AI usage score by summing the usage scores across categories. Similarly, we calculated the average AI usage score as the average across non-zero categories. The number of GenAI Use Categories represented the number of categories with a score greater than 0.
- General environmental concern: The survey form presented students with options from "Not at all concerned" to "Extremely concerned" to measure their general concern about environmental issues on a 1 - 5 scale.
- GenAI environmental awareness: This score measured awareness that GenAI consumes a significant amount of electricity, that it requires substantial amounts of fresh water for cooling, and that GenAI hardware involves mining for rare earth metals and e-waste. Responses were scored from 1 to 5, with higher values indicating greater awareness.
- Responsible AI attitude: This score measured whether students agreed with the statements about the seriousness of the environmental impact of GenAI, personal responsibility, the need to educate students at KDU Global, and whether other students considered the environmental impact of GenAI an important issue. We scored responses on a scale of 1 to 5.
- AI reduction feasibility: This score measured how easy or difficult students found it to reduce their GenAI use for environmental reasons. The higher score indicated that students found it easy to reduce GenAI usage, whereas the lower score indicated that students found it more difficult to reduce it.

We classified awareness level as low, moderate, or high. We decided to classify scores below 2.5 as low, from 2.5 to 3.5 as moderate, and 3.5 or above as high awareness.

3.4 Reliability

To assess the reliability of composite scales, we used Cronbach's alpha. GenAI environmental awareness had an alpha of 0.761, indicating acceptable reliability. Responsible AI attitude had an alpha of 0.800, indicating good reliability. These results supported our decision to use composite mean scores for the two constructs.

3.5 Data Analysis

We used descriptive statistics, reliability analysis, Spearman correlation, chi-square goodness-of-fit test, and regression analysis for analyzing the data. Since the main variables were based on Likert-type ordinal responses, we selected Spearman correlation. Mann-Whitney U tests were used for academic year group comparisons. Since there were three departments, to compare them we used the Kruskal-Wallis test. These non-parametric tests were appropriate because the data were ordinal and a normal distribution could not be assumed.

4.0 Findings

4.1 Descriptive Results

Table 1. Descriptive Scores

Variable	Mean	SD	Interpretation
Total AI Usage Score	3.136	1.003	Moderate-to-frequent use
General Environmental Concern Score	3.462	1.122	Moderate concern
GenAI Environmental Awareness Score	3.615	0.895	Moderate-to-high awareness
Responsible AI Attitude Score	3.779	0.689	Generally responsible attitude
AI Reduction Feasibility Score	2.522	0.934	Reducing AI use felt difficult

(Source: Prepared by the authors)

As shown in Table 1, the mean GenAI Environmental Awareness Score was 3.615, indicating students are generally moderate to highly aware. Responsible AI attitude Score was slightly higher at 3.779, indicating students generally feel personal responsibility, agree with the seriousness of the issue, and agree that the university should educate students regarding this topic. In contrast, the AI Reduction Feasibility Score is low, only 2.522, indicating that they did not find it easy to reduce their GenAI usage for environmental reasons.

Table 2. GenAI Environmental Awareness

Awareness Level	Count	proportion	GenAI Environmental Awareness Score (AAS)
High awareness	181	57.28 %	>3.5
Moderate awareness	104	32.91 %	>2.5
Low awareness	31	9.81 %	<2.5

(Source: Prepared by the authors)

In Table 2, the awareness classification showed that 181 students (57.28%) fell into the high awareness group. Furthermore, 104 students (32.91%) were in the moderate awareness group, and 31 students (9.81%) fell into the low awareness group.

4.2 Correlation Results

The Spearman correlation analysis indicated several significant associations, as illustrated in Table 3. The strongest association was observed between General environmental concern and Responsible AI attitude. This explains that students who are generally concerned about the environment are more likely to hold a responsible AI attitude. Moreover, GenAI environmental awareness and Responsible AI attitude show a positive association, indicating awareness is a major factor in a responsible attitude. Nevertheless, a negative association was observed between total AI usage and AI reduction feasibility, which led us to a major insight. The more frequently students used AI, the more difficulty they found in reducing AI usage. This reveals the coexistence of awareness and dependence.

Table 3. Spearman correlation

Relationship	Spearman ρ	p-value	Interpretation
Total AI usage → GenAI environmental awareness	0.202	0.0003	Higher usage associated with higher awareness
Total AI usage → Responsible AI attitude	0.126	0.0249	Higher usage weakly associated with stronger responsible attitude
Total AI usage → AI reduction feasibility	-0.148	0.0084	Higher usage associated with greater difficulty reducing use
General environmental concern → GenAI environmental awareness	0.174	0.0019	General concern associated with AI-specific awareness
General environmental concern → Responsible AI attitude	0.338	<0.001	General concern associated with responsible attitude
GenAI environmental awareness → Responsible AI attitude	0.301	<0.001	Awareness associated with responsible attitude

(Source: Prepared by the authors)

4.3 Department and Academic Group Comparison Results

The result from the Kruskal-Wallis test showed a statistically significant difference in general environmental concern between departments ($p = 0.0194$). Similarly, a significant difference was also found for GenAI environmental awareness ($p = 0.0004$). Fig. 1 illustrates that the IBA students showed the greatest general environmental concern, while SC students showed the highest AI-specific awareness. This may be because computing-related students are more exposed to AI technology and infrastructure. The chi-square test further supports this result ($\chi^2 = 16.537$, $p = 0.0024$).

For the academic year, we used the Mann-Whitney U test. It showed a statistically significant difference in GenAI environmental awareness ($p = 0.0113$), as shown in Fig. 2. The senior students showed higher awareness than the freshmen. However, the academic year did not significantly affect total AI usage, general environmental concern, responsible AI attitude, or AI reduction feasibility. The chi-square test also showed that academic year was not significantly associated with categorical awareness ($\chi^2 = 2.762$, $p = 0.2513$).

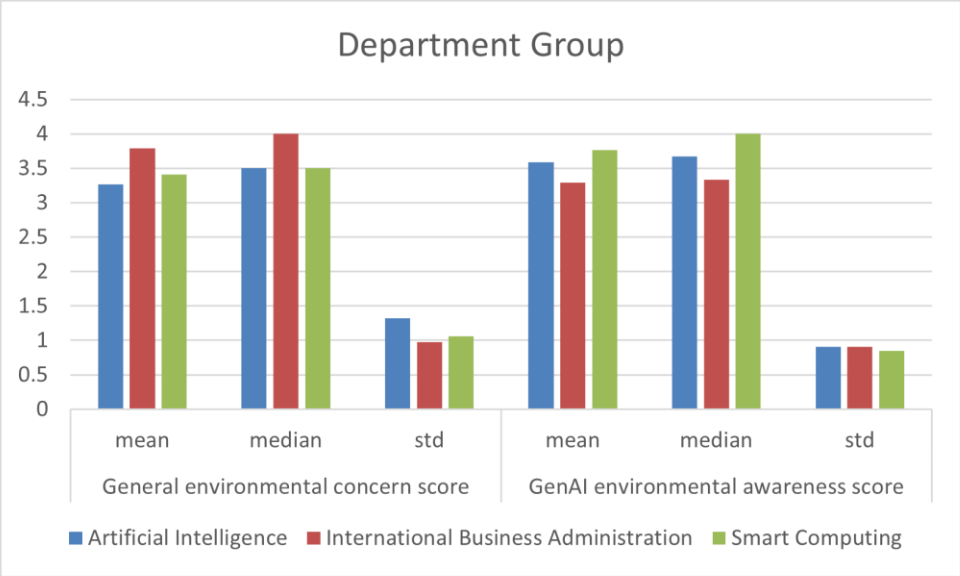

Fig. 1: Comparison of general environmental vs GenAI environmental concern among departments.
(Source: Prepared by the authors)

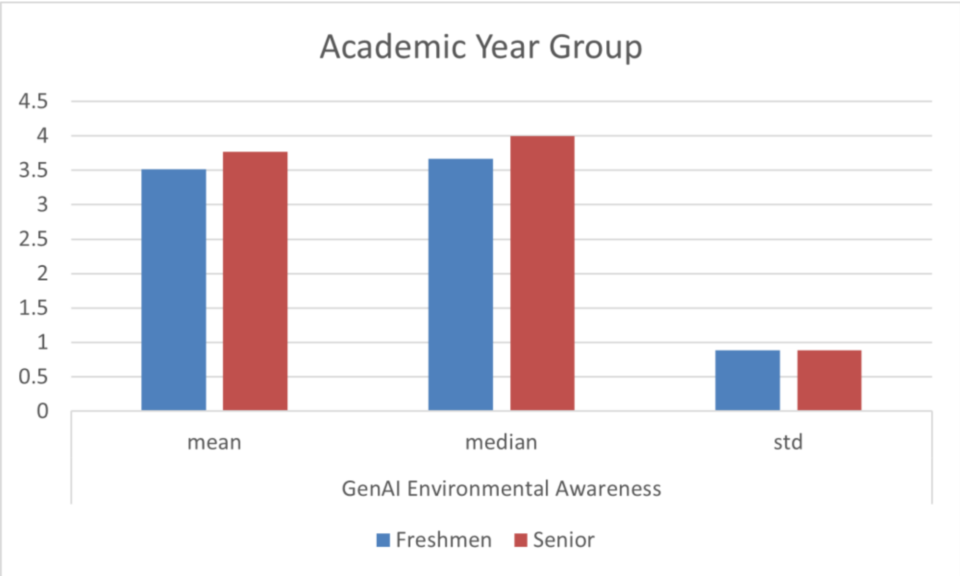

Fig. 2: GenAI Environmental awareness among students from different academic year groups.
(Source: Prepared by the authors)

4.4 Regression Results

We employed two Ordinary Least Squares (OLS) regression analysis models. The first model takes GenAI environmental awareness as the dependent variable. The model was statistically significant with $F = 8.162$, $p < 0.001$, and $R^2 = 0.156$, as depicted in Fig. 3. We identified total AI usage, General environmental concern, and gender as significant predictors. Higher AI usage and greater general environmental concerns were associated with higher GenAI environmental awareness. Additionally, male students showed higher awareness. However, with a low R^2 value, the model explained only 15.6% variation in awareness. This suggests other unknown factors, such as coursework, technical interest, media exposure, etc., may also matter.

The second model takes the Responsible AI attitude as the dependent variable. The model was statistically significant with $F = 12.51$, $p < 0.001$, and $R^2 = 0.246$, as depicted in Fig. 4. We identified GenAI environmental awareness, General environmental concern, and year group as significant predictors. At the same time, Total AI usage was statistically not significant. These findings indicate that a responsible AI attitude is more strongly connected with awareness and concern than frequency of use.

```
Regression sample size: 316
                                         OLS Regression Results
==============================================================================================
Dep. Variable:     Q('GenAI environmental awareness score')   R-squared:                  0.156
Model:                                       OLS   Adj. R-squared:             0.137
Method:                            Least Squares   F-statistic:                8.162
Date:                           Sat, 02 May 2026   Prob (F-statistic):      4.01e-09
Time:                                   17:03:30   Log-Likelihood:           -385.98
No. Observations:                            316   AIC:                        788.0
Df Residuals:                                308   BIC:                        818.0
Df Model:                                      7
Covariance Type:                       nonrobust
==================================================================================================================
                                                           coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------------------------
Intercept                                                2.3813      0.229     10.381      0.000       1.930       2.833
C(Q('Gender_clean'))[T.Male]                             0.3888      0.105      3.711      0.000       0.183       0.595
C(Q('Gender_clean'))[T.Other]                           -0.2140      0.598     -0.358      0.721      -1.391       0.963
C(Q('Department'))[T.International Business Administration]   -0.2548      0.144     -1.767      0.078      -0.539       0.029
C(Q('Department'))[T.Smart Computing]                    0.1194      0.136      0.880      0.379      -0.147       0.386
C(Q('Year_group'))[T.Senior]                             0.1208      0.115      1.054      0.293      -0.105       0.346
Q('Total AI usage score')                                0.1386      0.048      2.912      0.004       0.045       0.232
Q('General environmental concern score')                 0.1382      0.043      3.221      0.001       0.054       0.223
==============================================================================
Omnibus:                        9.931   Durbin-Watson:                   2.065
Prob(Omnibus):                  0.007   Jarque-Bera (JB):               10.015
Skew:                          -0.395   Prob(JB):                      0.00669
Kurtosis:                       3.369   Cond. No.                         64.0
==============================================================================
```

Fig. 3: OLS regression results when the dependent variable is set to the GenAI environmental awareness score

(Source: Created by the authors)

```
Regression sample size: 316
                                         OLS Regression Results
==============================================================================================
Dep. Variable:     Q('Responsible AI attitude score')   R-squared:                  0.246
Model:                                    OLS   Adj. R-squared:             0.226
Method:                         Least Squares   F-statistic:                12.51
Date:                        Sat, 02 May 2026   Prob (F-statistic):      1.51e-15
Time:                                17:26:16   Log-Likelihood:           -285.58
No. Observations:                         316   AIC:                        589.2
Df Residuals:                             307   BIC:                        623.0
Df Model:                                   8
Covariance Type:                    nonrobust
==================================================================================================================
                                                           coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------------------------
Intercept                                                2.3213      0.194     11.948      0.000       1.939       2.704
C(Q('Gender_clean'))[T.Male]                             0.0067      0.078      0.086      0.931      -0.147       0.160
C(Q('Gender_clean'))[T.Other]                           -0.5537      0.436     -1.269      0.205      -1.412       0.305
C(Q('Department'))[T.International Business Administration]   -0.0612      0.106     -0.579      0.563      -0.269       0.147
C(Q('Department'))[T.Smart Computing]                   -0.0539      0.099     -0.544      0.587      -0.249       0.141
C(Q('Year_group'))[T.Senior]                            -0.1964      0.084     -2.347      0.020      -0.361      -0.032
Q('GenAI environmental awareness score')                 0.2113      0.042      5.086      0.000       0.130       0.293
Q('Total AI usage score')                                0.0302      0.035      0.860      0.391      -0.039       0.099
Q('General environmental concern score')                 0.2072      0.032      6.518      0.000       0.145       0.270
==============================================================================
Omnibus:                       10.515   Durbin-Watson:                   1.766
Prob(Omnibus):                  0.005   Jarque-Bera (JB):               14.012
Skew:                          -0.274   Prob(JB):                     0.000906
Kurtosis:                       3.874   Cond. No.                         79.1
==============================================================================
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Fig. 4: OLS regression results when the dependent variable is set to the Responsible AI attitude score

(Source: Created by the authors)

5.0 Discussion

5.1 Moderate-to-High Awareness among KDU students

The first major finding of this study is that KDU Global students showed moderate-to-high levels of awareness of GenAI's environmental impact. This finding differs from some previous student awareness research, where students showed limited awareness of GenAI's environmental implications, especially freshwater and rare metals (Dungo et al., 2025). One of the factors contributing to this difference can be the composition of the KDU Global students' sample. Most of the sample consisted of students from the SC and AI departments. Naturally, they have more knowledge about technologies and their impacts due to their field of study. Even so, we shouldn't overstate the finding. Though awareness levels were reasonably high, the regression model only accounted for about 15.6% of the variation, suggesting that factors our survey did not capture — things like prior coursework, personal interest in environmental topics, media exposure, or family attitudes — also play important roles.

5.2 The Awareness-Action Gap

The most important finding is the gap between awareness and action. Students were moderately to highly aware and held a responsible attitude, but the feasibility of AI reduction was low. They recognize the environmental impacts of GenAI; however, they find it difficult to reduce their use of it. Investigative research conducted at the University of Glasgow with AI water footprint digital posters demonstrated a similar result: only a small number of respondents expressed a strong intention to change their actual usage habits, even though awareness was moderately high (Gibbons et al., 2025). Frequent users were more aware of the environmental impact of GenAI but found it hard to stop using it, indicating that awareness alone is insufficient, and students require alternative solutions. This is understandable because students use AI not only for leisure but also for their academic work, coding, research, and learning. Hence, telling students to "use AI less" is ineffective. A better approach would be to show them how to use AI effectively, purposefully, and responsibly.

This gap can be understood through the lens of established behavioral theories. Davis's (1989) Technology Acceptance Model (TAM) proposes that two perceptions — perceived usefulness and perceived ease of use — drive technology adoption and continued use. For KDU students, GenAI is not just convenient; it is embedded in how they study, write, and complete assignments. When a tool scores highly on both usefulness and ease of use, cutting it back feels like a real sacrifice, not a minor adjustment. The Theory of Planned Behavior (Ajzen, 1991) adds another layer. It holds that behavior is shaped by attitude, subjective norms, and perceived behavioral control. Our students held a positive attitude toward responsible AI use and arguably felt some normative pressure to act environmentally, but their perceived behavioral control was low — they did not see a practical path to reducing usage without hurting their academic work. Stern et al. (1999) articulated a similar logic in their VBN theory, which traces pro-environmental behavior through a chain of personal values, ecological beliefs, awareness of consequences, and a sense of personal obligation. In our data, the first three steps of this chain appear fairly strong — students expressed general environmental concern, they were aware of GenAI's specific impacts, and many acknowledged the seriousness of the problem. But the final step, the activation of a personal norm that translates into actual behavior change, seems to break down. This is consistent with what Kollmuss and Agyeman (2002) described in their classic model: knowledge and concern flow into behavior only when internal and external barriers — habit, perceived control, structural constraints — are sufficiently low.

More recently, Festinger's (1957) cognitive dissonance theory offers a complementary explanation. Students who use GenAI heavily are simultaneously aware that it harms the environment. These two cognitions are in conflict. Rather than resolving the conflict by reducing usage, students may reduce the dissonance through rationalization — telling themselves that their individual contribution is too small to matter, or that tech companies should solve the problem, not users. Our finding that frequent users hold both higher awareness and greater difficulty reducing use is consistent with this interpretation: awareness and dependence coexist not because students are indifferent, but because they have found a way to hold both thoughts at once.

5.3 General Environment Concern and AI-Specific Awareness

The result showed that general environmental concern is associated with both GenAI environmental awareness and responsible AI attitude. However, department-wise differences suggest that having general concern does not necessarily translate to AI-specific awareness. IBA students showed great general concern, but low AI-specific awareness compared to computing departments. This suggests that students may care about environmental issues but not understand the specific environmental cost of AI. This distinction can help us in curriculum design as AI literacy plays a significant role in influencing university students' attitudes toward GenAI (Wang et al., 2024). Universitas should introduce digital literacy courses that teach students about sustainability and the environmental consequences of AI. Universities should not assume that environmentally concerned students automatically understand AI environment footprints.

5.4 Responsible AI Attitude is More Than Usage Frequency

Total AI usage showed a positive correlation with responsible AI attitude. This finding aligns with a previous research study that concluded that less frequent users of GenAI demonstrate a greater tendency to adopt environmentally responsible practices (Balakrishnan et al., 2025). However, regression showed usage was not a significant predictor of responsible attitude. On the other hand, a responsible AI attitude was strongly associated with awareness and general environmental concern. This suggests that responsibility arises from awareness and general concern rather than frequent use of AI.

5.5 Department and Year Differences

The findings suggest that technical students are more aware of AI-specific environmental effects, whereas non-technical students are more concerned about general environmental issues. This creates an opportunity for interdisciplinary education. Technical students can benefit from strong environmental ethics, and business students can benefit from a technical explanation of AI resource consumption. Students in their senior year had higher awareness than freshmen. This can stem from greater academic exposure, more frequent use, and a deeper understanding of the underlying technology. Although the academic year affected awareness, it had no significant effect on responsible attitude and the feasibility of reduction. This further solidifies the need for the incorporation of sustainable AI education in the curriculum. Since the existing curriculum rarely explains the environmental consequences of AI in depth (Dungo et al., 2025).

5.6 Limitations and Future Research

The limitations of this study are: First, it was based on only one university, so generalizing the findings may be difficult. Second, the self-reported and cross-sectional data were not effective for causal relationships. Third, students were allowed to choose only one primary use, which limited the usefulness of the Number of GenAI Use Categories variable. In the future, we will use larger and more diverse samples across multiple universities, rely on longitudinal studies for establishing causal relationships, and allow students to choose multiple use categories.

6.0 Conclusion& Recommendations

The study investigated environmental awareness and perceived responsibility regarding GenAI among undergraduate students at KDU Global Campus. Students showed generally moderate to high awareness and a responsible AI attitude. However, we found that students had difficulty reducing AI usage for environmental reasons. Total AI usage had a positive association with GenAI environmental awareness and responsible attitude, and a negative association with AI usage reduction feasibility. Regression suggested that general environmental concern and GenAI environmental awareness were important predictors for responsible AI attitude.

In conclusion, awareness is necessary but not sufficient. Students mostly understand the impacts of GenAI in environments, but they are dependent on it for academic productivity. By observing this gap, universities should not only inform students about those problems but also create programs that teach students practical AI sustainability education.

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Paper Contribution to Related Field of Study

This paper provides real survey data from undergraduate students at KDU Global South Korea. It establishes a connection between GenAI use, environmental awareness, a responsible attitude, and the difficulty of reducing AI use. Universities can use the findings from this paper to design AI sustainable education and responsible AI guidelines.

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