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From Awareness to Action: Understanding Environmental Behavior in the age of Generative AI

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ABSTRACT

As generative artificial intelligence has grown, the environmental consequences of the technology have grown more severe. The development and execution of generative AI technologies has many environmental impacts, including increased carbon emissions, freshwater usage issues, waste of rare metals, environmental harm to local communities, and regional water scarcity issues. However, many people may not be aware of these environmental impacts due to generative AI's novelty as a technology and transparency issues, among others. High school students especially can be less aware of these environmental impacts, with previous research focusing on awareness levels of older groups. This study provides an original survey, gathering data on AI usage, awareness levels, and predicted changes in behavior, among other factors. The main finding of this study is that knowledge does not directly facilitate pro-environmental change in behavior. However, knowledge is a major factor, especially among certain impact groups, which could be targeted for effective behavioral changes to more pro-environmental behavior.

INTRODUCTION AND LITERATURE REVIEW

Introduction

Due to recent rapid developments in generative artificial intelligence technology, generative artificial intelligence has become increasingly popular among people across all spectrums. The youth with new, AI-generated social media memes or educators using generative AI to create lesson plans are just two examples of the beginning of the adoption of generative AI technology. Generative AI technologies (namely chatbots) have been lauded for being efficient, effective, and very easy-to-use (Roumeliotis & Tselikas, 2023), leading to much of the general public using generative AI platforms for both productivity and quality-of-life updates, such as AI-generated grocery lists, travel plans, and much more.

Due to their rapid adoption, there have been countless cultural effects, including the emergence of the AI technology bubble, the fear of jobs being taken by generative AI, or the creation of deepfake media, which significantly alters how humans interact with media. However, even with these changes to society, both good and bad, corporations are chasing generative AI growth with a vigor.

Many generative AI companies are growing at an exponential rate. Nvidia, for example, is a company that has recently switched to making AI chips. Nvidia's stock price has gone up 2200% in the past 6 years when it switched to being an AI centered company (Vendrell-Herrero et al., 2025). While Nvidia does not have a platform of its own, this is still evidence of the growth of generative AI as Nvidia is the main chip provider for most generative AI datacenters (Vendrell-Herero et al., 2025). Growth in the materials needed for generative AI datacenters to thrive is directly correlated to generative AI platform's growth. On the other end, generative AI platforms are certainly seeing exponential growth and an explosion of users.

Chat-GPT, Open-AI's generative AI chatbot, had about 1 million users after its first week in operation (Roumeliotis & Tselikas, 2023). This number grew to 100 million users after its first 2 months, making it the fastest growing internet platform ever (Hazari & Mohan, 2024). Today, Chat-GPT has 900 million weekly active users (OpenAI, 2026), indicating widespread adoption, and consequently, large influence on society. Chat-GPT is being adopted into multiple different sectors of work, such as being used in business functioning as a customer service representative and performing complex tasks or being used in entertainment to create smarter, more active NPCs (non-player characters) (Zhao, 2025) . These examples demonstrate Chat-GPT's impact on multiple sectors of the world and the extent to which it can be widely used as a tool.

The Environmental Impacts of Generative AI Usage

Although generative artificial intelligence can be an effective tool, there are many environmental externalities, such as high carbon consumption, freshwater usage, and e-waste pollution due to generative AI datacenter development. Due to generative AI's structure as a large language model, it utilizes deep reinforcement learning techniques to train the generative AI platform to think and talk like a human, which consumes an extreme amount of energy (Alfranah, 2025). One estimate for data centers from the year 2022 was 460 terawatt hours of energy combined (Dungo et al., 2025). Furthermore, it is predicted that as generative AI models become more complicated and prevalent in the near future, energy consumption will also increase significantly (Sachs, 2024). This electricity, for many datacenters, is being generated by the burning of fossil fuels and natural gases, which is one of the primary contributors to human-made climate change. The training of one large-scale language model uses about 37.6 million metric tons of CO_2 which is about equivalent to the carbon footprint of 7.5 million flights from Tokyo to New York (Kocak et al., 2025). Furthermore, the energy usage of the top 20 generative AI systems is estimated to be 103 million metric tons of CO_2 which is about the average carbon footprint of 22 million people. These numbers reflect a prioritization of human activities for human technological benefit, at the expense of the environment. Consequences of climbing greenhouse gas emissions (such as the ones being released as a byproduct of the training of generative AI datacenters) include mass extinction, the decline in the quality of most ecosystems, and agricultural failure. However, the greenhouse gas emissions as a byproduct of generative AI training is only one piece of the puzzle.

Generative AI datacenters require advanced, extremely specialized GPUs (graphical processing units) (GPUs) which are essential for development and training of generative AI models. However, these chips are made of non-renewable, rare earth metals, and produce an extensive amount of e-waste and pollution. It is estimated that from these chips, there is a buildup of 1.2M-5M tons of e-waste (Dungo et al., 2025). Additionally, chips are often thrown out before retirement, and replaced by a newer, more advanced chip prematurely, which creates a cycle of rapid retirement of GPUs. This raises questions about the superficiality of these practices and the corporations' actions, since this could be seen as a prioritization of innovation and profit or an unnecessary choice that creates more harm at the expense of the environment.

Generative AI also plays a large role in global water consumption. While its consumption is not as large as those of the agriculture or meat & dairy industry, it uses a significant amount of water to train and run datacenters that are used to operate generative AI platforms. The training phase of one model (specifically OpenAI's GPT-3) is estimated to utilize about 700,000 liters of water (George et al., 2024). However, the GPT-3 model is a year old, and OpenAI has come out with two more models (GPT-4 and GPT-5). With these models, it is estimated that training of these models can range from approximately 1.9 million liters of water to 4.9 million liters of water, about sevenfold the estimate for the training of GPT-3 (Herrera et al., 2025). In addition to this, OpenAI is not the only company that is creating platforms of generative AI. Google, Anthropic, SpaceX, and Microsoft are all companies with their own generative AI models, all with multiple models and new models being built and trained. This creates consumption on a much larger scale than a singular model, with consumption increasing as time goes on.

The water is used mainly for cooling computers through a process called evaporative cooling. Cold water cools hot air, forming steam, which then gets expelled out of the hardware via fans. For this process, saltwater cannot be utilized because it can possibly leave salt and other minerals behind in the hardware, making the hardware jammed and unusable (FOE, 2026). Therefore, the water used to cool is pulled entirely from our freshwater sources (George et al, 2024). However, our drinking water is running out quickly. The 2026 United Nations has stated that the world is in a period of "global water bankruptcy", threatening agriculture, drinking water supply, and irreversible damage to water resources. Moreover, datacenters are constructed in water-scarce regions, further exacerbating present water issues (Xiao et al., 2025). The southwestern United States is a hot spot for data centers. Some of these states have favorable tax incentives, which lure industrial developers. Furthermore, across all of these states are arid climates which can evaporate water quickly and lack lots of extreme natural disasters other than heat (Chiari, 2025). However, the development of data centers in the southwestern United States threatens the already-stressed Colorado River, the main water source for 7 states, (Binkly, 2025), and henceforth creates extra stress for these regions.

On the other hand, there are multiple innovations to combat climate change utilizing AI tools or platforms. For example, China has used artificial intelligence to optimize its urban green footprint, utilizing AI technology to promote industrial structure rationalization and green technological innovation (Zeng & Wang, 2025). Generative AI is also capable of improving energy efficiency on a large scale, which utilizes less fossil fuel and therefore lowers greenhouse gas emissions, which is the main

contributing factor to climate change (EPA, n.d.). Artificial intelligence is one of the main playmakers in modern green innovation, and could do wonders for our current climate situation. Some researchers argue that artificial intelligence, while having many short-term disadvantages, could be a long-term solution to climate change. Not utilizing AI could possibly slow innovation to climate change (Zeng & Wang, 2025). This is further supported by scientists Slimani et al (2025), who argue that researchers often have a "superficial" stance about the detrimental effects of the adoption of artificial intelligence, and by doing that, they neglect "genuine green innovation." However, other scientists such as Dungo et al. (2025) explain "the rebound effect" in generative AI, arguing that the more adopted it is, the more emissions being put out anyways, essentially canceling out any help to the environment it could have had, allowing for no real impact. Therefore, it can be argued that short-term climate change goals must be prioritized because of the current vulnerable state of the climate.

It is important to note that many of the numbers presented in this paper are estimates of generative AI's impact in various environmental sectors. This is because of the lack of transparency presented by many large AI companies. Specifically, AI21 Labs, Alibaba, Amazon, Anthropic, DeepSeek, Google, Midjourney, Mistral, OpenAI, and xAI do not disclose any key environmental information (Luccioni et al., 2025) . However, transparency from AI companies regarding numbers about emissions, water usage, and chip usage is crucial. By providing key environmental metrics, scientists are able to make more accurate estimates of environmental impact, which is essential for applications of research. Additionally, restricted environmental metrics from AI companies makes it increasingly difficult to hold AI companies accountable for their environmental impacts, which could impact achievement of sustainability initiatives and lack of information to make informed decisions not just by the public but by policymakers as well.

Finally, transparency is vital for awareness. Withholding key environmental metrics allows for an awareness gap between the public and corporations (Luccioni et al., 2025). This in turn prevents the public from making informed decisions about issues pertaining to generative AI. Without the knowledge to make informed decisions, choices can often be heavily biased towards one side or the other, which can have (in the case of generative AI) large environmental, economic, and social consequences due to the nature of the datacenters. This can affect both local communities and global environmental health (Luccioni et al., 2025).

Generative AI's Usage for Learning

Generative AI can also be an extremely helpful tool, specifically for learning (for the cases of this paper). A few main causes of use are assisting in writing or translation or idea generation (Baig & Yadegaridehkordi, 2024). Generative AI can also be used in education to clarify or understand a textual or laborious subject, leading to enhanced learning and a better knowledge of said subject (Hugerth & Hugerth, 2026). Furthermore, generative AI utilizes natural language processing techniques and can provide adaptive content for learning, taking into account the user's tone, understanding, and prior knowledge, giving a truly personalized experience (Meakin, 2024). It is also observed that having a high

AI literacy can be correlated with higher participation in the classroom . Higher participation in the classroom can not only lead to better understanding of the material, but can also make the classroom a more engaging environment (Gao, 2025). AI literacy also plays a large role in trust of AI technologies, as it is observed that students who have less generative AI literacy tend to be more distrusting or apprehensive of the technology. In contrast, students who have a more cognitive outlook to generative AI have a better grasp of predicted AI conceptions and a better understanding of generative AI (Otermans et al., 2025) However, increased AI literacy does not mean that students are not susceptible to generative AI's filter bubbles, or where the information that generative AI gives them is limited or lacking in different nuances or viewpoints. This is due to generative AI algorithms catering to the user's preferences and perception. In theory, this leads to a more personalized and adaptive learning approach, however, this also leads to isolation in learning since generative AI systems are designed to appeal to the user and can leave the user with biased or narrow perceptions due to the filter bubble . Students are also at risk for an overreliance on AI technology, due to the widespread adoption of generative AI and the nature of the technology. Students can ultimately have issues with critical thinking, creativity, and decision making, which are all major critical-thinking aspects vital for school and later the workforce (Meakin, 2024).

Due to generative AI's large scale, efficiency, usefulness, and novelty as a new technology, many high school-aged students use generative AI frequently (Dungo et al., 2025). However, research on the environmental impacts of generative artificial intelligence is limited, and students tend to remain unaware of its impact (Dungo et al., 2025). Generative AI platforms or websites do not often disclose their environmental impacts, which also affects the overall awareness of generative AI's environmental impacts.

My research aims to gauge how much knowledge high school students have on the environmental implications of generative artificial intelligence. Furthermore, adolescents are some of the most susceptible groups (compared to adults) to using generative AI frequently (Nagata et al., 2025). High school students could be one of the least aware about generative AI's environmental implications, which is why research on their awareness levels of generative AI's environmental implications are important, since high schoolers are a high usage and therefore high impact group. My research also determines the willingness to change behavior after learning about generative AI's environmental impacts, providing insight on how education can change environmental habits.

METHODS

To answer the research question of "How does knowledge of generative AI's environmental repercussions change behavior towards the usage of generative AI?", an original survey was conducted. This survey utilized a convenience sample due to easy accessibility. All participants were high school students ranging from freshmen to seniors. They took a three-part survey. The survey design assumed that some participants did not know about the environmental impacts of AI. This allowed for questions with the purpose of knowing how knowledge affects behavior and concern. The first part detailed background information about the participant, including grade, social media platforms used, amount of time on social

media, frequency of AI-generated content on social media, AI platforms used, frequency of AI usage, purpose of using AI, concern about the environmental effects of artificial intelligence, and concern about the current state of the climate. Students answered questions regarding concern about the environment on a scale from 1 to 5, where 1 was the most concerned and 5 was the least. Questions about social media were asked due to the influx of information that can be understood through social media and the sheer amount of AI-generated content on social media. Questions about personal usage of AI were used to gauge familiarity with the technology and to see usage patterns.

The second part listed 5 statements and asked the participants to state their knowledge level of each. The statements were:

1. Generative AI model training has an extremely large carbon impact- it can generate around 37.6 million metric tons of carbon, or around 7.5 million round trips from Tokyo to New York (Dungo et al., 2025).
2. Generative AI requires a large amount of freshwater because the water is needed to cool down the computers. One model (GPT-3) has an estimated consumption of around 700,000 liters during the training phase, or about the water usage of 6.38 years in an average American household (George et al., 2023).
3. Generative AI requires many rare metals to build chips for AI models, which causes a lot of pollution because the metals are non-renewable. Estimates for accumulation through 2030 are 1.2 million-5 million tons of e-waste (Dungo et al, 2025).
4. Many generative AI datacenters are being placed in water-scarce regions, which exacerbates the already-depleting water available (Xiao et al., 2025).
5. Local communities often suffer from poor air quality and water quality due to AI datacenters nearby. (Hosseini et al., 2025).

The purpose of these questions was to assess the respondents' knowledge level of generative AI's environmental impact. Participants were asked to assess their knowledge level based on a 1-5 Likert scale, with answer options ranging from "Not aware" to "Fully aware". These answers were respectively assigned to numbers 1-5 post-survey for analysis.

The final part of the survey focused on changes from thought and behavior post-survey. Firstly, participants were asked for their concern for the environmental impacts of generative AI and the environment in general before and after the knowledge statements were shown. The purpose of this was to gauge whether knowledge impacted concern, and if learning about detrimental impacts to the environment increases negative sentiment. Participants were then asked about their willingness to change behavior after learning about generative AI's environmental impact, with 5 answer choices ranging from "A drastic change" to "Not at all". However, a limitation to this question was the addition of the "I'm not sure" answer choice, since it could be interpreted by a participant as leaning either way, with interpretation ranging from participant to participant, therefore, it did not fit on the 1-5 Likert scale assigned, so during data analysis, the "I'm not sure" option on the scale was discarded and a 1-4 Likert scale was assumed. Finally, there was a short free-response question added at the end of the survey asking for any reasoning behind their decision and overall thoughts about the survey. This question,

"Why/why do you expect your behavior to change?" was to gain more insight and reasoning into the the decisions shown in the survey and to give participants a way to explain their answers.

Multiple hypotheses were tested, including:

1. Increased social media usage may be associated with greater awareness of generative AI's environmental implications.

Social media platforms play a major role in the circulation of information regarding both new technologies and environmental issues. Indeed, social media exposes users to a greater flow of information and therefore garners exposure to new and different ideas (National Academies of Sciences, Engineering and Math, 2024). Social media has increasingly shown more AI-generated content as AI generated content has become more widespread, leading to more discussion about AI-generated content and its environmental implications. Increased social media usage could be associated with greater awareness of generative AI's environmental impacts.

2. Stronger AI-generated content on social media may be associated with less willingness to change behavior.

It is possible that with strong levels of AI-generated content present on social media, subjects develop a sense of normalization in regards to seeing AI-generated content. This has previously been observed as normalization to crises, where global environmental epidemics, health pandemics, etc., start to feel normal or a part of everyday life, instead of needing change (Dubey, 2025). While a stronger level of AI-generated content on social media is not as severe as the examples listed above, it could be inferred that the human brain operates in a similar sense of normalizing behaviors that are seen often.

3. Low-awareness participants are more likely to change behavior.

Understanding is the basis for change. By gaining more knowledge, it can be inferred that some understanding is gained. Previous research shows that education gives individuals the tools for change (Udoudom et al., 2023), whether or not that be behavioral change as this hypothesis is testing. Therefore, it can be hypothesized that gaining knowledge and understanding could be a catalyst for change.

4. High AI usage participants are less likely to change behavior.

This hypothesis also involves the normalization of behavior as it becomes a habit (2025). However, this hypothesis focuses on not the content absorbed by the user but rather the choices intentionally made by the subject. The same normalization effect applies here: when a user has high AI usage, the AI usage can become a habit. This habit becomes normalized and therefore behavior surrounding AI can become harder to change, leading to high AI usage participants being less likely to change their behavior.

5. Participants who already have more knowledge about generative AI's environmental impacts are more likely to be a low-usage AI user.

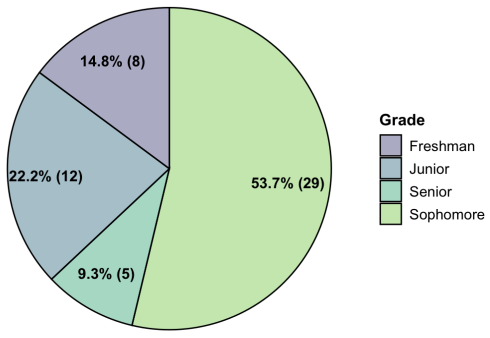
This hypothesis involves the inference that previous knowledge about negative impacts of generative AI can lead to the participant already being a low-usage generative AI user, due to their previous knowledge about generative AI and a possible initiative taken already to change their behavior, which has been observed regarding other studies, which show that knowledge of negative environmental impacts can possibly facilitate positive environmental behavior (Dopelt et al., 2020).

I ran multiple statistical tests on the data. Pearson correlation tests were largely used in R to find correlations and significance between two variables. For the purposes of analysis, the ordered response

categories are approximately interval-scaled. For the correlation output, r and p values were rounded to 3 decimal places in the results section. Graphs were also used effectively to see counts of how much people knew about generative AI's environmental impact. Qualitative analysis was also used in the free response portion of the survey to analyze motivation behind responses. Data itself was assigned numeric values for Pearson correlation tests, with 1-5 values largely being assigned. With data concerning exposure to generative AI on social media, 1 was assigned to answers that had less exposure and 5 was assigned to answers that showcased a larger amount of AI exposure on social media. Additionally, data concerning AI usage was assigned 0 for "I don't use AI", 1 assigned for "Yearly", 2 assigned to "Monthly", 3 assigned to "Weekly", 4 assigned to "Daily", and 5 assigned to "Multiple times a day." This is primarily to correspond with the 1-5 scale for concern levels, as 1 is considered to be the most concerned about generative AI's impacts/the overall climate and 5 being the least concerned. Additionally, knowledge levels were also converted to a 1-5 scale, with 1 being more knowledgeable and 5 being the least. This is due to a need for consistency across the assigned numeric values, i.e. 1 often being the more knowledgeable, concerned, and low-usage AI participants or fitting a more environmentally conscious respondent in regards to specifically the environmental impacts of generative AI, whereas 5 is a less knowledgeable, less concerned, and high-usage AI participant. Participants were also given a knowledge score, which was their responses to each knowledge question, then converted to the 1-5 scale (see above) and averaged. For analysis regarding low-knowledge and high-knowledge respondents, low-knowledge was treated as greater than or equal to knowledge score 3, and high-knowledge being less than knowledge score 3. This was used for correlation tests regarding overall knowledge levels and more specialized analysis regarding high and low knowledge levels. Finally, high-usage (multiple times a day, daily, weekly) and low-usage generative AI respondents (monthly, yearly, no use of AI) were separated into two separate groups regarding analysis of behavior. High and low-usage respondents were analyzed differently due to the behavioral implications of reducing AI use may differ according to respondents' baseline frequency of use. A change in frequency of AI use among a high-frequency user represents a different magnitude of behavior change (who would most likely decrease their usage) than a low-frequency user (who could increase their usage, since they are already a low-to-no frequency user).

RESULTS

Figure 1



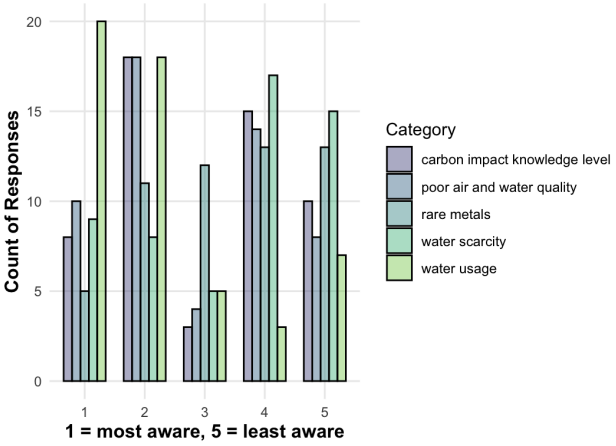
Fifty-eight high school students provided responses. Three responses were omitted from the data because they provided incomplete information. Figure 1 shows the data for participants sorted by grade. Almost everyone reported some kind of social media usage, with only one respondent reporting no social media usage. The most popular social media platforms were YouTube (51), Instagram (45), and Snapchat (43), followed by TikTok (30), with Facebook and Twitter only getting 8 and 9 respondents reporting activity on those platforms. Most people reported a moderate amount of time spent on social media, with 25 respondents who

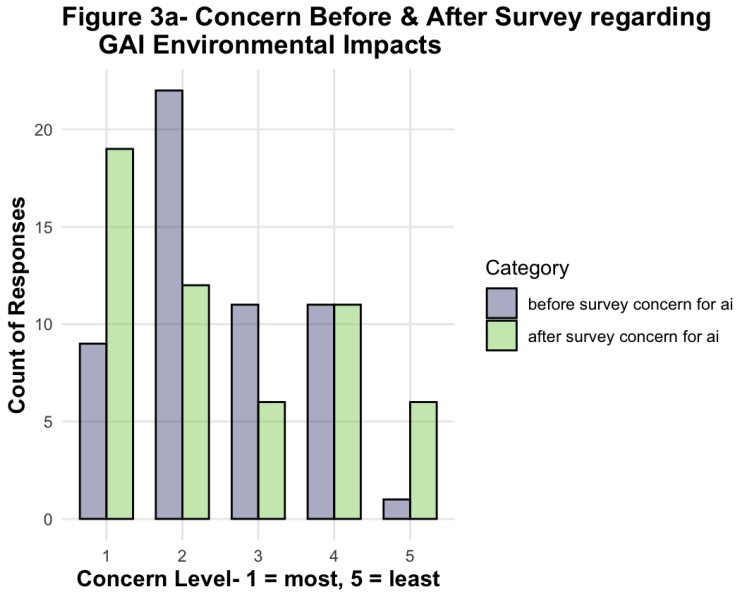
reported 1-3 hours on social media. However, 8 respondents reported less than 1 hour on social media, 15 respondents reported 3-5 hours on social media, 3 respondents reported 5-7 hours on social media, and 2 respondents reported over 7 hours on social media. Participants also reported a heavy presence of AI generated content on social media with 19 respondents saying 'Often', 23 saying 'Somewhat', 3 saying 'Occasionally', 6 saying 'Rarely', and 1 saying 'Never'. Participants also reported a high frequency of AI usage, with only 9 participants saying that they don't use AI. However, 7 participants reported using AI multiple times a day, 19 participants reporting using AI daily, 8 participants using it weekly, 9 participants using it monthly, and 2 participants using it yearly. The most popular AI platform was Chat-GPT with 44 respondents reporting using Chat-GPT. Google Gemini was the second most used platform, with 30 respondents reporting using Gemini. While 19 respondents reported *only* using Chat-GPT, only 2 respondents *only* used Google Gemini. The other 28 respondents used Gemini in a combination with other AI platforms, such as Chat-GPT, Claude, Grok, Microsoft Copilot, and Gauth AI.

Figure 2 illustrates the awareness levels of respondents, regarding carbon impact, poor air and water quality, rare metal usage, water scarcity issues, and water usage issues. As seen in Figure 2, respondents tended to be most aware of water usage issues, and least aware of issues surrounding water scarcity issues and heavy rare metal usage.

The final questions were regarding concern and behavior. Participants were asked for their concern about the environmental impacts of generative AI and the current state of the climate both before and after the awareness section of the survey. The responses were analyzed on a scale from 1 to 5 with 1 being the most concerned and 5 being the least. Figures 3-6 have concern levels for both before and after the main survey questions. They also show both concern levels for generative AI's environmental impacts and the overall climate. As seen through the plots, before

Figure 2- Knowledge Levels of GAI's Environmental Impacts





survey concern levels for generative AI were more uneven than the before survey concern for climate, and were largely concentrated as 2s. After survey concern levels for generative AI's environmental impacts and climate were higher than the before survey concern levels, with a much more concentrated number of 1s and 2s compared to the before survey concern levels.

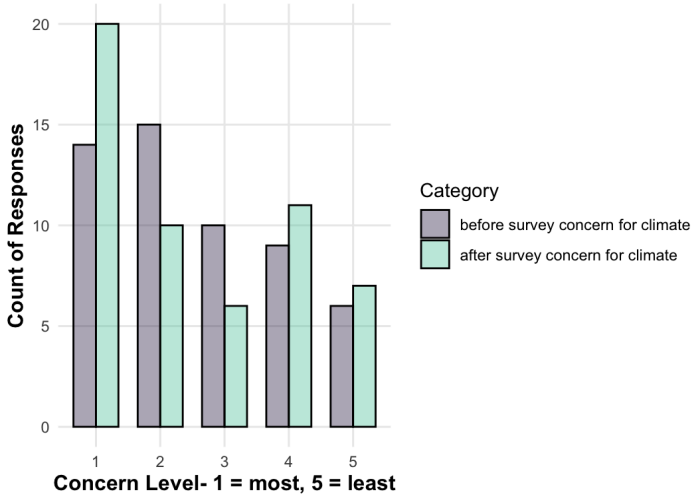
The correlation between the frequency of generative AI usage and original concern for AI's environmental impacts is inconclusive ($r = 0.133$, $p = 0.336$) due to being not statistically significant. While not a hypothesis, it was important to test due to the possibility of biased concern. However, frequency of AI usage and all knowledge levels had a strong positive correlation. Specifically, carbon impact knowledge levels had the highest positive correlation ($r = 0.443$, $p = 0.001$), which indicates that lower AI usage indicates more knowledge about the carbon footprint of generative AI. Likewise, frequency of AI usage and water usage knowledge level ($r = 0.332$, $p = 0.015$), rare metals knowledge level ($r = 0.286$, $p = 0.035$), water scarcity knowledge level ($r = 0.374$, $p = 0.005$), and poor air and water quality knowledge level ($r = 0.382$, $p = 0.004$), are all positively correlated with statistical significance. These results all confirm hypothesis 5.

Another significant result is the correlation between low-usage AI users (meaning monthly, yearly, or never) and their change in behavior, which had a significant negative correlation ($r = -0.708$, $p < 0.001$). This indicates lower likelihood of future use of generative AI among respondents who are already low

usage users of generative AI. However, high-usage AI users (multiple times a day, daily, or weekly) had a slight positive correlation ($r = 0.386$, $p = 0.024$) with prediction of change in behavior, which means that high-usage participants are more likely to not change behavior, supporting hypothesis 4.

Also observed was that grade has no significance with overall knowledge level ($r = 0.074$, $p = 0.591$), conflicting with the hypothesis that grade and knowledge level has a significant positive correlation. In addition to this, grade and all 5 subcategories of knowledge level had no statistical significance ($p > 0.05$ for all). Grade also has no statistically.

Figure 3b- Concern Before & After Survey regarding Overall Climate



significant relationship with usage of generative AI ($r = 0.214$, $p = 0.120$). Furthermore, time spent on social media and knowledge about generative AI's environmental impacts has no correlation and is statistically insignificant ($r = 0.074$, $p = 0.592$), which refutes hypothesis 1, which predicted that increased social media usage could lead to more knowledge about generative AI's environmental impacts.

In general, knowledge level and behavior change are statistically insignificant ($r = -0.197$, $p = 0.153$). However, low knowledge and behavior change has a negative correlation ($r = -0.453$, $p = 0.006$) for specifically low-usage generative AI users, which indicates that low-knowledge users who do not use AI that often are not likely to change behavior. If a respondent is a high-frequency AI user, low knowledge and behavior change has a positive correlation ($r = 0.532$, $p = 0.018$), which could be associated with more of a willingness to change behavior among high-usage, low-knowledge respondents, supporting hypothesis 3. Along with this, AI generated content presence on social media does not play a significant role in willingness to change behavior for both low-usage and high-usage users ($p > 0.2$), leaving hypothesis 2 inconclusive. After-survey concern levels for generative AI also played a significant role in willingness to change behavior. Among high-usage users, higher concern indicated more willingness to change behavior with a positive correlation in environmental impacts of generative AI ($r = 0.462$, $p =$

0.047). However, among low usage users, the relationship between after survey concern levels regarding generative AI and willingness to change behavior was inconclusive ($r = 0.300$, $p = 0.07$). Original concern and overall knowledge levels also had no significant correlation, with $p > 0.05$ for concern levels regarding both concern for the climate and for generative AI's environmental impacts.

In addition to these numerical tests, a free-response section was utilized to provide further insight into answers. Many high-usage respondents who predicted no behavior change all said in the free-response that AI had become a part of their daily life, being described as a "crutch" to one student. "It just helps me so much" or "I need it" was a response not uncommon to see. Furthermore, some respondents said that everyone around them uses AI, which in turn makes it harder for them to stop using AI, leading to no behavior change reported. Other respondents described a gap between the negative environmental impacts of generative AI and their usage. These respondents generally fell into two categories. The first category of respondents mainly said that they feel that their usage does not have that much of an impact on global climate health, so they don't find a need to stop using generative AI. The second category of respondents said that it is hard for them to stop using generative AI since the negative impacts often don't hit them directly, which makes it harder to change their behavior.

In addition to the free responses above, some high-usage respondents expressed wanting to change their behavior. While many implied that they were not going to give up AI directly, respondents said that they were going to be more courteous of their use, for example, "using Google or Safari instead of AI to answer small, stupid things.", or using it "much less" than before but not completely eradicating AI from their lifestyle. In addition to these respondents, many low-usage respondents gave very similar responses, with many expressing even less willingness to use generative AI than before due to not wanting to impact the environment negatively. While not many reported that they use no generative AI, some specified different reasons were different reasons unrelated to the environmental impacts of generative AI. For example, one respondent said that they do not use generative AI because of other issues such as plagiarism of art. However, the majority of respondents who said that they were willing to change their behavior mainly cited environmental impacts as their reason for changing their behavior towards generative AI, saying specifically that "I don't want to be a contributor to negative environmental effects", or "because I want to save the polar bears." In addition to this, others acknowledged the unethicality of the environmental impacts of generative AI, but instead stated that they believe that it is scientists or the government's duty to address this issue and that policymakers need to pass serious legislation on generative AI due to its unethicality.

DISCUSSION

Overall, quantitative statistics showed high social media usage and high generative AI usage, which could possibly showcase a pattern of high technology usage in general by teenagers, especially because teens and young adults are the most exposed to technology. The vast majority of students reported using generative AI for productivity purposes, which lines up with many describing generative AI to be a crutch in their schoolwork. In addition to these, teens were relatively aware of generative AI's environmental

impacts, however, some more than others. Water usage in particular has a lot of awareness, compared to water scarcity and rare metals issues. This could be because water usage statistics are easier to share via the news or social media, and are often more attention grabbing than water scarcity or rare metals issues. This opens up future research opportunities to further understand patterns and motivations in awareness trends, and why some issues have more awareness than others, since this study just observes that water usage statistics have more awareness than other issues such as water scarcity or rare metals issues. Future research could look upon the concentration of different environmental impacts of generative AI in media, research, and social media, and determine the level of exposure for each issue, which could potentially explain the differences in awareness per issue as found in this study.

Frequency of AI usage was a variable frequently tested among other variables to determine correlation. One finding was that lower AI usage indicated the respondent was more likely to have more knowledge on the environmental impacts of generative AI. Again, this supports hypothesis 5, in addition to being supported by Dopelt et al. (2020), which observed that knowledge of negative environmental impacts led to pro-environmental practices. This was also somewhat observed in this study, where respondents who were already low-usage AI users knew more about the environmental impacts of generative artificial intelligence. To some extent, this could also suggest that knowing about negative environmental impacts and consequently participating in positive environmental behavior could be somewhat correlated. Low-usage and high-usage respondents also differed greatly in their willingness to change behavior, especially if the respondents had a low knowledge score. Among low-frequency users, knowledge of generative AI's environmental impacts and willingness to change behavior had a negative correlation. However, high-frequency users who displayed low knowledge had a slight positive correlation with willingness to change behavior. This partially shows knowledge could be a catalyst for change. This is especially since other high-usage users who did not necessarily have low knowledge had no correlation with willingness to change behavior, which stems from factors such as habit and perceived impact, as observed by the free response section. However, despite factors such as habit and perceived impact, high-usage, low-knowledge users are still slightly associated with behavior change, which could make this specific group an important target group for change. On the other hand, their predicted behavior change might stem from a quick reaction to the negative environmental impacts instead of a more thoughtful analysis, which respondents with more knowledge could've had due to them having more time.

The most significant finding was the finding of higher concern levels post-survey leading to less or more willingness to change behavior in high-usage participants. If the participant was high-usage, high concern post-survey means that they were usually more willing to change behavior. These results show that higher concern levels lead to more positive behavior changes regarding an environmental perspective but are moderated by current AI use. This makes sense, since if one is concerned, it is natural to try and change behavior somewhat so the impact of actions is less than before, as talked about by Dopelt et al. (2020) (i.e. negative environmental impacts can facilitate positive environmental behavior). While this was true for most, it was not true for this particular study , and it is still possible to have a high concern level and not be willing to change behavior. This could be because generative AI is so easy to use and helps so much with productivity, which was the overwhelming reason for the use of generative AI. Some can say

that the cons do not outweigh the pros of using generative AI, and while concerning, choose not to change their behavior. However, it is important to note that while concern level plays a part in willingness to change behavior, pure knowledge does not necessarily facilitate pro-environmental behavior.

Knowledge levels did not play a significant role in willingness to change behavior in high-usage and low-usage participants, indicating that knowledge alone is not enough to sway people to change behavior and a certain emotional response has to be evoked to truly make an impact. While some learn about detrimental effects and immediately feel a higher concern level, others can learn and feel indifference to concern level, leading to no behavioral change. However, while some participants feel indifference, not all cite indifference as the reason for no behavioral change. In the free response section of the survey, many are not indifferent to the impacts of generative AI but instead for said participants the pros outweigh the cons. One participant said that while they know about the environmental impacts of generative AI, they fear they will fall behind without it, leading to no behavior change. Other participants described AI as something that they "need", "love," or is "a crutch", indicating that their reliance on AI makes it hard to give it up, regardless of if they are indifferent to generative AI's environmental impact.. However, while some simply stated that their behavior will not change, some stated that they intend on using generative AI less, but not never, due its central place in their routines. This is also reflected in the normalization gap observed by Dubey (2025), where habitual behavior becomes psychologically normalized. Since generative AI has become a habit to use when in need of help, it can feel more and more normal to use and also harder to give up. This is also supported statistically, as high-usage participants reported overall less change in behavior. This can indicate that willingness to change behavior relies less on knowledge but more on previously established habits, and if something is habitual, it is harder to change behavior.

Many also cited that generative AI is being used by everyone around them, even teachers, which makes it hard for their behavior to change since it is such an integrated part of daily life. "Everyone is still using it… it's in pretty much all parts of society", said one participant, claiming that they will not change their behavior. This could also possibly be expanded into a societal normalization of the use of generative AI, as many described less willingness to change behavior due to everyone around them using generative AI.

LIMITATIONS

Many of my hypotheses proved to be statistically insignificant when running through correlation data.. One possible reason for this could be due to the small sample size. My sample was a convenience sample taken at my local high school, and as a result, my survey only yielded 58 participants, which could be an explanation for statistically insignificant correlations since my results are vulnerable to more chance and error. I disclosed the topic of the survey beforehand and therefore non-response bias could have taken place, since it is possible that users who have high generative AI usage do not want to take a survey about the negative impacts of generative AI. In addition, participants could have social responsibility bias, since the topic of my survey was rooted in ethics of generative AI usage, and reported an answer due to a participant's possible desire to align themselves with "good" societal norms. In addition, the survey was

100% based on respondent answers, and it is possible that some respondents gave inaccurate data about themselves, which could also lead to flawed results and analysis. Furthermore, personal interpretation bias could also play a role in analysis, and it is possible that some interpretations of data were unintentionally skewed to align with personal beliefs about the environmental impacts of generative AI.

Another limitation regards the structure of the survey, i.e. the fact that the major "categories" of environmental impacts were presented as a statement, followed by a specific statistic. However, due to the formatting as such, the respondent could've answered not aware, which was interpreted as not aware of the overall statement, but in reality, the respondent could've indicated that they were not aware of the statistic, not the overall statement (i.e. being aware of generative AI using a lot of water, but not aware that it takes 500,000 liters of water to train GPT-3, thus indicating "not aware" on survey). This could potentially skew the results of the survey and lead to possibly more knowledge among the respondents than what is indicated in the data.

CONCLUSION

My work aimed to find overall awareness levels of high school students regarding the environmental impacts of generative artificial intelligence and consequential willingness to change behavior. I found relative awareness levels in high school students regarding the environmental impacts of generative artificial intelligence, with especially high awareness levels regarding water usage and lower awareness levels regarding water scarcity location issues and rare metals. This research can be applied by teaching about water scarcity location or rare metals issues via the news or social media, and in general having more information in circulation regarding water scarcity issues or rare metals issues. I also found that while knowledge does not directly impact willingness to change behavior, knowledge can lead to concern which does have a positive correlation with willingness to change behavior. This suggests that feelings, not statistics play a large role in willingness to change behavior regarding generative AI usage. This can be addressed through sharing stories of the direct consequences of generative AI's environmental impact. Overall, as generative AI becomes increasingly integrated into education and everyday life, understanding how young people perceive and respond to its environmental impact will become increasingly important. Encouraging informed and sustainable engagement with AI may play a key role in balancing technological innovation with environmental responsibility.

REFERENCES

Baig, M. I., & Yadegaridehkordi, E. (2024). ChatGPT in the higher education: A systematic literature review and research challenges. *International Journal of Educational Research*, *127*, 102411. https://doi.org/10.1016/j.ijer.2024.102411

Binkly, G. (Narr.). (2026, March). Rise of data centers in the Southwest raises concerns [Audio podcast episode]. In *KSJD*. KSJD. https://www.ksjd.org/podcast/ksjd-local-newscasts/2026-03-24/rise-of-data-centers-in-the-southwest-raises-concerns

Causes of climate change. (2017, January 19). EPA. Retrieved April 5, 2026, from https://19january2017snapshot.epa.gov/climate-change-science/causes-climate-change_.html

Chiari, M. (2025, February 27). *Are data centers depleting the Southwest's water and energy resources?* APM Research Lab. Retrieved September 27, 2026, from https://www.apmresearchlab.org/10x/data-centers-resource

De, D., El Jamal, M., Aydemir, E., & Khera, A. (2025). Social media algorithms and teen addiction: neurophysiological impact and ethical considerations. *Cureus*, *17*(1), e77145. https://doi.org/10.7759/cureus.77145

Dopelt, K., Davidovitch, N., Loren, O., & Gapich, G. (2020). Does climate change matter to us? Knowledge, attitudes, and environmental behavior. *European Journal of Public Health*, *30*(Supplement_5). https://doi.org/10.1093/eurpub/ckaa166.079

Dubey, R. (2025). The normalization of (almost) everything: Our minds can get used to anything, and even crises start feeling normal. *Science*, *390*(6773), 585. https://doi.org/10.1126/science.aeb2654

Dungo, C. A. B., Beltran, Z. L. E., Declaro, B. C., Dela-Cruz, J. J. C., & Viray, R. U. (2025). Students' level of awareness on the environmental implications of generative AI. *Journal of Education in Science, Environment and Health*, *11*(2), 93-107. https://doi.org/10.55549/jeseh.777

Gao, F. (2025). Exploring the role of EFL students' AI literacy and readiness in their academic goal orientations: An achievement goal theory (AGT) perspective. *Learning and Motivation*, *92*, 102203. https://doi.org/10.1016/j.lmot.2025.102203

Geiger, S. M., Geiger, M., & Wilhelm, O. (2019). Environment-Specific vs. general knowledge and their role in pro-environmental behavior. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.00718

George, A. S., George, A. S. H., & Martin, A. S. G. (2023). The environmental impact of AI: A case study of water consumption by chat GPT. *Partners Universal International Innovation Journal*, *1*(2), 91-104. https://doi.org/10.5281/ZENODO.7855594

Hazari, B., & Mohan, V. (2024). Exclusion and the growth of AI technology: A trade-theoretic analysis. *Frontiers in Human Dynamics*, *6*. https://doi.org/10.3389/fhumd.2024.1203664

Herrera, M., Xie, X., Menapace, A., Zanfei, A., & Brentan, B. M. (2025). Sustainable AI infrastructure: A scenario-based forecast of water footprint under uncertainty. *Journal of Cleaner Production*, *526*, 146528. https://doi.org/10.1016/j.jclepro.2025.146528

Hugerth, M. W., & Hugerth, L. W. (2026). Seeking knowledge or efficiency: Profiling students' ai-use through survey-based latent class analysis. *Computers and Education: Artificial Intelligence*, *10*, 100531. https://doi.org/10.1016/j.caeai.2025.100531

Kocak, B., Ponsiglione, A., Romeo, V., Ugga, L., Huisman, M., & Cuocolo, R. (2025). Radiology AI and sustainability paradox: Environmental, economic, and social dimensions. *Insights Into Imaging*, *16*(1). https://doi.org/10.1186/s13244-025-01962-2

Lindo, M. R., & Cutad, C. A. (2024). Impact of generative AI on self-regulated learning and cognitive offloading. *IMCC Journal of Science*, *4*(2), 18-22. https://doi.org/10.65931/c7k2p5z9

Luccioni, Sasha & Gamazaychikov, Boris & Costa, Theo & Strubell, Emma. (2025). Misinformation by omission: The need for more environmental transparency in AI. https://doi.org/10.48550/arXiv.2506.15572

Meakin, L. (2024). Exploring the impact of generative artificial intelligence on higher education students' utilization of library resources. *Information Technology and Libraries*, *43*(3). https://doi.org/10.5860/ital.v43i3.17246

Nagata, J. M., Memon, Z., Huang, O., & Moreno, M. A. (2026). Adolescent health and generative AI-risks and benefits. *JAMA pediatrics*, *180*(1), 7–8. https://doi.org/10.1001/jamapediatrics.2025.4502

OpenAI. (2026). *Scaling AI for everyone*. OpenAI. Retrieved April 5, 2026, from https://openai.com/index/scaling-ai-for-everyone/

Otermans, P. C., Roberts, C., & Baines, S. (2025). Unveiling AI perceptions: How student attitudes towards AI shape AI awareness, usage, and conceptions. *International Journal of Technology in Education*, *8*(1), 88-103. https://doi.org/10.46328/ijte.995

Roumeliotis, K. I., & Tselikas, N. D. (2023). ChatGPT and Open-AI models: A preliminary review. *Future Internet*, *15*(6), 192. https://doi.org/10.3390/fi15060192

Sachs, G. (2024). AI is poised to drive 160% increase in data center power demand. *Goldman Sachs Insights. 14*. goldmansachs.com/insights/articles/AIpoised-to-drive-160-increase-in-power-demand.

Social media and adolescent health. (2024). *National Academies Press.* https://doi.org/10.17226/27396

Transparency in AI is on the decline. (2025, December 9). *StanfordReport.* Retrieved May 6, 2026, from https://news.stanford.edu/stories/2025/12/foundation-model-transparency-index-ai-companies-information

Udoudom, U., Aondowase, S. & Igiri, A. (2023). Impact of education and communication on behaviour change. *Journal of Language, Literature, Social and Cultural Studies. 1. 271-280*. 10.58881/jllscs.v1i3.120.

van der Ven, H., Corry, D., Elnur, R., Provost, V. J., & Syukron, M. (2024). Generative AI and social media may exacerbate the climate crisis. *Global Environmental Politics*, *24*(2), 9-18. https://doi.org/10.1162/glep_a_00747

Vendrell-Herrero, F., Vaillant, Y., & Bustinza, O. F. (2025). Scalability in incumbent firms: The case of Nvidia. *Long Range Planning*, *58*(4), 102540. https://doi.org/10.1016/j.lrp.2025.102540

Why do data centers need fresh water? (2026). Friends of the Earth. Retrieved September 27, 2026, from https://foe.org/blog/why-do-data-centers-need-fresh-water/

Zeng, J., & Wang, T. (2025). The impact of China's artificial intelligence development on urban energy efficiency. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-09319-x

Zhao, X., & Li, S. (2025). Artificial intelligence and public environmental concern: Impacts on green innovation transformation in energy-intensive enterprises. *Energy Policy*, *198*, https://doi.org/10.1016/j.enpol.2024.114469