Exploring the Challenges of LLMs in Higher Education: Is ChatGPT a Boon or Bane for the Students?

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Abstract— **Artificial intelligence (AI) chatbots such as ChatGPT are rapidly becoming integral to higher education, creating new possibilities for learning while also raising concerns about their broader impacts. Recognizing the need to understand how students engage with these tools and how aware they are of their environmental implications, this study examines usage behaviors and data-storage practices among undergraduate engineering students. A four-level structured opinion survey was designed to capture both behavioral tendencies and emotional responses related to AI use. The findings show that students' inherent behavioral dispositions strongly influence how they adopt AI tools and manage their associated search data. Although most students initially lacked explicit knowledge about the environmental footprint of large language models (LLM), many intuitively associated AI use with increased water and energy consumption, suggesting emerging environmental consciousness. The sustainability attitude among the students was found to be closely related to their levels of awareness and emotional engagement. These insights highlight the need for a phased, pedagogically grounded approach to AI integration in higher education, emphasizing conceptual learning and problem-solving skills in early semesters while regulating the intensity of AI exposure. The study underscores key behavioral factors that can guide institutions in fostering responsible and sustainable AI practices and offers a foundation for future research on designing environmentally conscious AI-literacy frameworks for academic settings.**

Keywords—**AI in higher education; impacts of LLM; responsible AI; digital usage behavior; attitudinal patterns**

ICTIEE Track—*Assessment, Feedback, Learning outcomes*
ICTIEE Sub-Track—Measuring higher order thinking and critical thinking.

I. INTRODUCTION

The advent of Artificial Intelligence (AI) has marked a transformative era across diverse sectors, with higher education being no exception. The rapid publicization of generative AI tools, particularly large language models (LLMs) such as

ChatGPT, has brought advanced computational capabilities directly into the hands of young generation of students, educators, and researchers. As a Natural Language Processing (NLP) model developed by OpenAI, ChatGPT is capable of responding to questions, comments, and prompts by utilizing a sizable dataset and can mimic human-like discussions with the users (Hariri, 2023; Alqahtani et al., 2023). Unlike earlier AI applications limited to automation or data processing, the latest developments in the generative AI tools help us simulate human-like reasoning, produce contextually relevant content, and offer immediate solutions to complex queries (Alomari, 2023). This unprecedented accessibility has catalyzed both excitement and apprehension, raising fundamental questions about their long-term implications for academic practices.

Within the education sector, students have been among the earliest and most enthusiastic adopters of generative AI. They find these tools highly useful in writing assistance, problem-solving, coding support, exam preparation, and brainstorming project ideas (Cardon et al., 2023; Baltà-Salvador et al., 2025; Zhao, 2025). There is a clear trend of increased usage of AI tools based on rapid adoption, diverse applications, and over-reliance on their results (Hunter et al., 2024; Zhai et al., 2024; Karamuk, 2025). While such practices can enhance learning efficiency, they also pose many critical challenges, including over-dependence on AI outputs, reduced critical thinking, and fading boundaries between legitimate learning support and academic misconduct (Kumar et al. 2024; Zhu et al. 2025). Considering the alarming trend of data faking observed in various domains, LLMs face critical challenges in discerning truth from falsehood, as indicated by various measures such as the bullshit index (Rudolph et al. 2023; Hicks et al. 2024). When AI-generated content presents biased, incomplete or

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false information, it can certainly (mis)lead the younger generation to a dangerous indifference to truth and falsity and their associated consequences (Fisher, 2024; Costello, 2024). Unfortunately, students are the most susceptible community to this hallucinating flow of AI-contents especially when they are exposed to unrestricted data access with simultaneous inability to differentiate between the real and fake information. The attractiveness for AI tools among undergraduates therefore necessitates a closer examination of their impacts on study patterns, behaviors, and overall attitudes towards social and environmental concerns.

Various aspects of increased usage of AI tools on behavioral responses can be understood in terms of cognitive processing, self-management, and levels of social interaction, while emotional responses are least explored due to their mixed nature of interaction within personal and institutional settings. Sharma and Yadav (2022) reported that even while ChatGPT seems promising at first, it is still in its early phases of development when the benefits are balanced against disadvantages. Fuchs (2023) addressed a few challenges that NLP models may bring to the academic sector, including the potential loss of human interaction, bias, and ethical implications. Based on the observations, he made the following recommendations for regulating the usage of NLP models: (i) Universities should make sure that NLP models are utilized in addition to human contact rather than as a substitute for it. (ii) In order to preserve student privacy and reduce bias, institutions should also create policies and ethical frameworks for the usage of NLP models. (iii) Colleges should invest in training their teachers to use and adapt to the technology in order to help students use the models efficiently. As supervised and directed education remains the main element of learning for the student community at large, some educators feel that the responsibilities of humans and AI-based chatbots like ChatGPT must coexist.

Recent literature has begun to explore the deeper educational implications of AI use by conducting several experiments with teaching-learning aids (Raje & Tamilselvi, 2024; Ramprakash et al., 2024). Many studies suggest that the learning outcomes can be improved with AI tools by offering personalized guidance and reducing barriers in comprehending concepts as well as developing problem-solving skills. At the same time, many are worried about their blind adoption, which can restrict the learning levels, suppress the academic engagement, and misguide students from traditional approaches to study and assessment (Amaro et al. 2023; Johnson et al. 2023; Zheng et al. 2023; Ngo et al., 2024; Berend et al. 2025).

Several studies have been conducted in the recent past to critically assess the potential boons and banes of LLM usage by the students. Chan and Hu (2023) examined the student surveys collected on ChatGPT's boons (e.g. customized and quick response, access to large database. etc.) and banes (e.g. over-reliance, blocking creativity and social interactions, etc.). Strzelecki (2024) identified the benefits of ChatGPT as a learning aid as well as the challenges it poses to academic integrity by conducting a technology-acceptance-based study on its adoption. Cotton et al. (2024) focused on the cheating risks as a major bane, with strategies for integration. Lund et al. (2023) discussed about the academia-wide boons in research aids and banes like misinformation for students. It is evident from these studies that ChatGPT does have a serious impact on the students' character and behavior, which are mostly related to the development of their cognitive skills and associated learning practices.

One critical dimension that remains underexplored and requires significant attention is the environmental impact of LLMs. As computational power and usage increase, the deployment and operation of generative AI tools require significant computational resources, leading to considerable energy consumption and water use for model training and maintenance (Ren et al., 2024; Graves et al., 2025). However, awareness of these hidden environmental footprints is quite low among student communities, despite their increasing dependence on AI. This ignorance makes them follow implausible patterns of technology use, with implications that extend beyond the academic context into broader societal and ecological domains.

While prior studies have addressed the pedagogical benefits and ethical concerns of modern educational tools (Sivapragasam & Natarajan, 2023; Sivapragasam et al. 2024), comparatively very few have examined the awareness of the environmental consequences of LLM use among the undergraduate student community. Apart from the independent investigations on behavioral patterns and emotional responses towards over-dependency on generative AI tools, studies on their intersections deriving hidden attributes are highly lacking in the literature. In addition to the challenges posed by ChatGPT to the educational sector, it also poses a severe threat to humanity through heavy consumption of water. Das (2023) highlighted the significant water footprint of large AI models like ChatGPT and BARD, which require substantial water for cooling data centers and generating electricity. They distinguished between water withdrawal and consumption, emphasizing that AI operations lead to large-scale water loss through evaporation. The findings reveal that ChatGPT's water use is extremely high, raising concerns amid the global water crisis. The study calls for urgent attention to AI's environmental impact and suggests strategies to reduce its water footprint.

As the practical aspects of sustainability begin with personal behaviors and attitudes, unrestricted dependency on generative AI tools can have deeper implications on general awareness and the formation of attitudes towards the environmental impacts of modern technological tools. We feel that addressing these gaps is essential for framing holistic strategies that promote responsible and sustainable engagement with AI in higher education. In this aspect, the present study aims to analyze the patterns of AI usage and data storage among students, assess the levels of awareness regarding the environmental impacts of LLMs, evaluate their emotional and attitudinal responses to these concerns, and identify critical behavioral elements that must be addressed to foster a culture of responsible and sustainable AI use. By evaluating the observations from an exclusive opinion survey framed with a four-tier questionnaire (usage, storage, awareness, and responsiveness) for prospective users of AI tools (undergraduate students), the study seeks to provide insights into whether ChatGPT and similar tools represent a boon or a bane for higher education students.

II. Materials and Methods

A. Background

A comprehensive questionnaire covering the major aspects of usage, storage, awareness, and emotions associated with the AI usage was framed for conducting an online survey. The design of the questionnaire comprised multiple-choice, multiple-answer, and short-answer type questions that included exclusive questions on the behavior of AI tool usage and associated emotional responses towards the environmental impacts of LLMs, in view of the increasing demand for searches with multiple queries (refer Table S1). The number of options for the multiple-choice and multiple-answer type questions was not uniform owing to the nature of the expected responses. Apart from the given options, an additional option, '*others*,' was also provided to capture the possibility of unique responses from individuals. The undergraduate engineering students with a typical age group of 17-21 (covering the first-year to fourth-year) was chosen for the study. The opinion polls were conducted with the help of a customized Google Form with an anonymous response option. The necessary instructions for answering the questions and objectives of the study were communicated through group emails to the students. Sufficient time (two working days and one holiday) was given for the participants to respond to the questions. The metadata of the online survey assessment is given in Table I.

TABLE I
META DATA OF THE ONLINE SURVEY CONDUCTED FOR OPINION ASSESSMENT

Particular	Count	Percent
Number of questions on general background	9	30
Number of questions on awareness	6	20
Number of questions on usage	8	26.7
Number of questions on concerns	7	23.3
Number of questions with multiple choices (single answer)	22	73.3
Number of questions with multiple answers	5	16.7
Number of questions with short answer	3	10

B. Opinion Survey Assessment Methodology

The responses received from the participants were downloaded and checked for data consistency and correctness by verifying duplicate entries and completeness of the information. The final response data from 297 participants was further categorized into four major groups by evaluating the count and percentage contribution for each category of options given in the questions. Based on the interconnected nature of responses, those related to the usage of AI tools and storage of search results were considered together for analyzing the behavioral trends among the students in their digital lifestyle. Similarly, the responses about awareness of the environmental impacts of AI tools and the corresponding emotional responses were evaluated together, reflecting the attitudinal patterns of the students. A detailed comparison of the responses was carried out by considering the distribution of answers among the given options, and several meaningful inferences were derived from the qualitative measures based on the opinions shared by the participants. In addition, the significance of their variations was evaluated using statistical measures for justifying the inferences. As there are opportunities for both smart use and misuse of the AI tools, certain recommendations were provided for transforming behavioral and attitudinal anomalies towards more sustainable and responsible usage by the students. A flow chart of the implemented methodology is presented in Fig. 1.

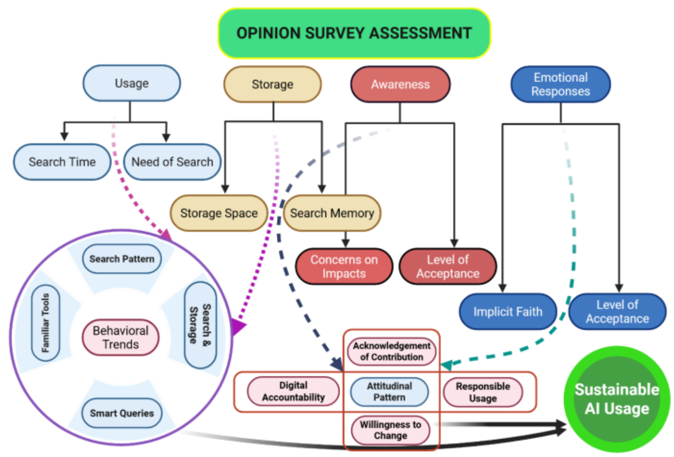

Fig. 1. Representation of the opinion survey assessment framework

III. Results and Discussion

A. Awareness towards Environmental Impacts of LLMs

With the broader objective of assessing the emotional and attitudinal responses of undergraduate students toward the environmental impacts of LLMs on physical environmental features, the opinion survey results were analyzed and interpreted according to the nature of the question groups, as indicated in Table 1. The responses to the first six questions, which focused on the general awareness of the environmental impacts of LLMs, are presented in Fig. 2. Despite highlighted less frequently in the literature, about half of the participants expressed lack of awareness regarding how a single search activity with LLMs can contribute to significant water and electricity consumption. Recent studies provide reasonable estimates of water use and electricity demand during the training and use of LLMs, primarily for cooling data centres as well as through virtual water requirements embedded in data transfer infrastructure (Bhaskar and Seth 2024; Jegham et al., 2025).

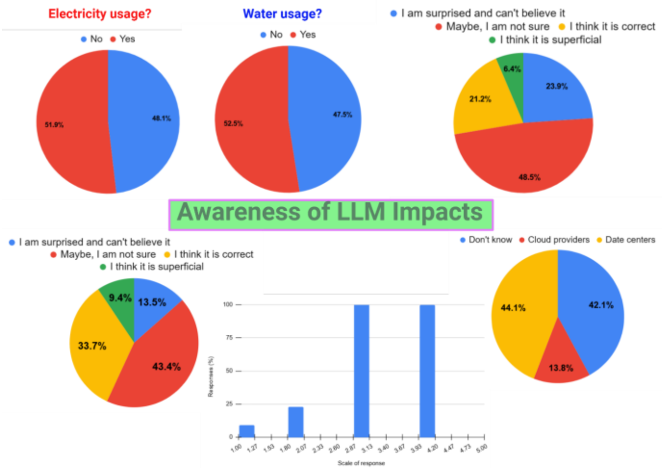

Fig. 2. Summary of students' responses to the questions on awareness of environmental impacts of LLMs

Recent studies indicate that even if each ChatGPT interaction consumes only a small amount of water and electricity as seen in the big picture, the sheer scale of usage transforms it into a significant environmental concern. Whether the data centres are operating from onsite or offsite locations, the total water requirement for their cooling and power demands is a crucial matrix representing the direct and indirect components of their water footprint (Table 2). As water scarcity is one of the pressing global challenges, the concern is not only on the absolute amount of increasing water footprint, but also on the responsiveness to the shared responsibility of water shortage and drought. By 2027, the global demand for AI could require 4.2 – 6.6 billion cubic meters of water withdrawals: an amount exceeding the total annual water use of roughly half of the United Kingdom (Ren et al., 2024). Looking at these data, one can estimate how much lives can be saved by this water as so many people and animals are dying without water. It is important for the students to develop such empathy and concern for these global issues as they are entering to the larger social systems after the university graduation. When we presented the statement *"a single ChatGPT search's environmental impact is roughly equivalent to emitting 2 to 4.32 grams of CO_2"* as a question, about 48.5% of the participants reported doubtful acceptance, 21.2% indicated direct acceptance, and 23.9% expressed it as an unbelievable surprise. Most students attributed the increased water usage to data centres (44.1%) compared to cloud providers (13.8%), while a considerable proportion of participants (42.1%) admitted their lack of awareness about this fact.

TABLE II
APPROXIMATE WATER FOOTPRINT ESTIMATIONS FOR AI SEARCHES

Query Type / Task	Estimated Water Usage	Reference
20–50 short GPT-3/ChatGPT queries	~500 mL (≈ 0.5 L; one bottle)	Frost (2023); Syed (2023)
ChatGPT (~5–50 prompts)	~500 mL per session (0.5 L)	Vincent (2023)
10–50 ChatGPT queries	Earlier estimate: ~500 mL; later up to 2 L	Rucker (2024); Sellman (2024)
Per Gemini AI prompt	~0.26 mL (approx. 5 drops)	Chen (2025)
GPT-4o inference (annual scale)	1,334,991–1,579,680 kL (~1.3–1.6 billion liters)	Jegham et al. (2025)
GPT-3 training (full model)	~700,000 L	Li et al. (2025)

In response to another statement - *"greater use of AI in turn demands smarter algorithms, faster machines, high-speed internet, expanded data broadcasting services, higher susceptibility to radiation, and increased health risks"*- about 43.4% of the participants responded with doubtful acceptance, while 33.7% expressed direct acceptance. On a scale of 1-5, most responses about their level of surprise after reading these statements were reported as 3 (*more surprised*) and 4 (*very much surprised*). Overall, the results highlight the current level of student awareness of the environmental impacts of LLMs as these technologies become part of their everyday academic and personal lives.

Since the survey assessment follows an ex-post facto approach, it does not allow for direct causal inferences; however, certain observations about the sample space can provide insights that are extendable to the larger population (Jung et al., 2024; Zanotti et al., 2024). Out of the 297 students who participated in the opinion survey, about 75% belonged to the age group of 18–19 years, while 21% were between 19–21 years. Gender bias was negligible, with responses almost equally distributed (47.1% female and 52.2% male). The majority of respondents were second-year students (61.6%), while the representation from third-year (23.2%) and fourth-year (14.5%) students was comparatively lower. Among generative AI tools, ChatGPT emerged as the most preferred, followed by Gemini, Canva, QuillBot, and Grammarly. Students primarily reported using these tools for academics (study purposes), coding, entertainment, and career preparation. The relatively higher proportion of responses to awareness-related questions may be linked to the limited involvement of this younger generation in public or community-level activities beyond their academic commitments. From a sustainability perspective, a practical concern is that "*whatever we do will have an impact on the environment*." Hence, when the younger generation (with AI literacy) begin to reflect on these issues, it indicates not only how they perceive the present world but also how they may shape the future (Bhaskar and Seth, 2024; Bond et al., 2024). In reality, when direct environmental impacts are not yet perceived, it becomes even more challenging to recognize the hidden, multi-dimensional impacts associated with AI usage.

B. Investigating the LLM Usage and Data Storage Patterns

Considering the potential impacts of attitudinal traits in developing habitual patterns, the opinion poll questionnaire was further extended to assess the nature of searches made using AI tools and their data storage patterns. The time used for a single search varied from 1 to 5 seconds for 42.8% of the participants, and 5–10 seconds for 35.4%, the main reasons being complexity of the query (41.8%), data types in search (33.7%), and weak internet connection (20.9%) (Fig. 3). A majority of the students (62%) replied that they frame their own query using selected words and frames. Another related question was on customized search by providing relevant scenarios or background initially so that a repeated number of modified queries can be avoided with an acceptable level of accuracy. There was a mixed response for this survey question with doubtful acceptance (38.4%), doubtful rejection (33.7%), and ready acceptance (24.2%). As quick adapters of the latest technologies, the students are explorative in nature and show no hesitation in making smart queries using all acceptable forms of multimedia such as text, image, code, audio, and video (Maule, 1998; Sarhaddi et al. 2025). As the majority of the students claimed to use framed searches to get what they wanted, there is an implicit sense of self-esteem and conviction to accept the results as true. In this context, the survey results indicate that a large majority of the students (84.8%) responded with remarkable faith in believing the AI search results as "*close to the right answer*" before confirmation. This analogy is extended in answering the survey questionnaire related to the search pattern, where one-third of the participants were tempted to accept the results even with doubt. As LLMs are continuously developing in offering personalized search experiences, it is important to understand this behavioral pattern as these tools are capable of producing predetermined and customized favors in predicting needs and answering queries.

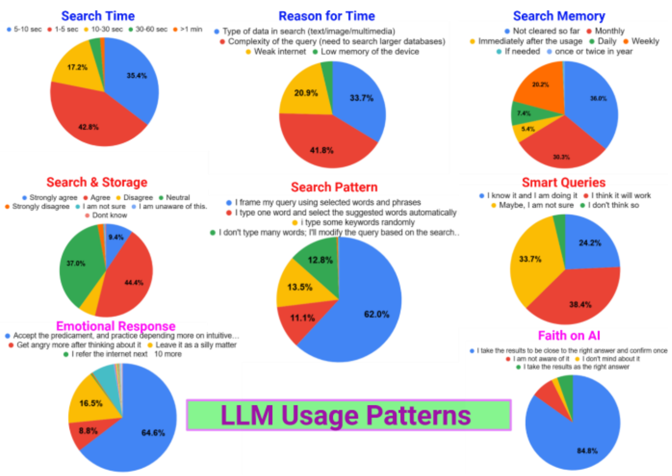

Fig. 3. Distribution of responses showing the usage patterns (search and storage) of LLM tools

Organized data management and search patterns definitely reflect the general characteristic traits of individuals in using the internet for browsing as well as with customized AI tools (Micarelli et al. 2007). In this aspect, two questions were specifically on the data storage habits of the youth participants. About 36% of the participants admitted that they have not cleared their search memory (including cache) so far, 30.3% of them used to clear it once a month, and 20.2% of them clear their memory weekly (Fig. 3). The mixed nature of responses indicates a diverse group of persons having differences in individual character and tastes, reflected in their digital habits as well. When asked their opinion about any correlation between storing the search results and the associated data storage costs (including cloud services) and environmental impacts, about 53.8% of students were either agreeing or strongly agreeing, while 37% remained neutral. This is another aspect of integrity where the availability of free memory space and lack of digital accountability together contribute towards excess data generation and increased memory space. Recent reports indicate that the global data volume is expected to expand from 149 zetabytes (ZB) in 2024 to 181 ZB by the end of 2025 (Mwinuka et al., 2025). With the advent of AI, IoT, and the availability of 5G technology, this increased data volume drives the digital market, especially for data centers and cloud servers. Even though minute in the selected sample space, this study demonstrates evidence of this global trend in individuals' behavior of data usage and storage.

C. Emotional Responses towards Environmental Impacts of LLMs

The observations from this study indicate a range of emotional responses regarding students' awareness of the environmental impacts of LLMs and their contributions. Although most students had limited prior knowledge about the energy and water consumption associated with training and maintaining LLMs, many expressed intuitive concern once these issues were revealed through the survey. The levels of concern expressed by the participants varied as *moderate* (46.1%), *significant* (26.9%), and *extreme* (14.1%). Similarly, a large majority of the students expressed surprising emotional responses such as "*shocked*," "*guilty*," and "*curious*" as their immediate reaction to the questions (Fig. 4).

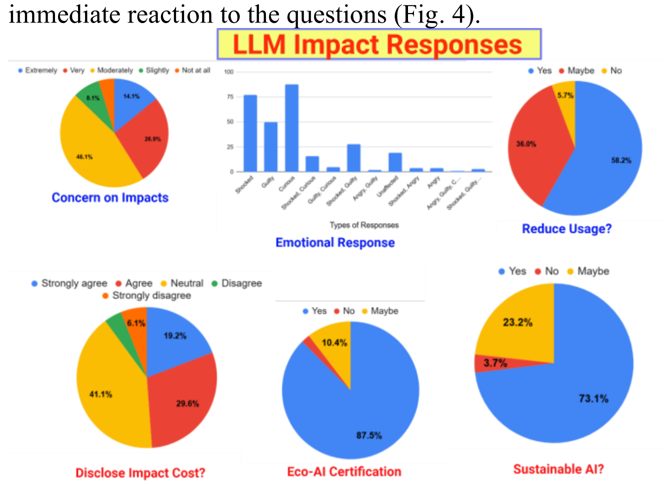

Fig. 4. Summary of responses towards LLM impacts and attitudinal trends

As evident from the recent literature, these are not superficial questions; instead, they postulate the reality of future world where AI-based technologies surpass (and replace) human involvement and create many unforeseen challenges to the ethic and environment. If the students fall prey to these temptations without knowing the reality of situations, it is a serious concern for the future of humanity at large. These emotions can be interpreted as adaptive responses that promote critical reflection and cautious behaviour. Similar to how awareness of climate change induces lifestyle reconsiderations, the disclosure of AI's ecological costs may act as a catalyst for responsible digital practices. As some students recognized their frequent reliance on AI tools as somewhat guilt-inducing while being unaware of the associated ecological burdens, it may be considered a constructive influence by encouraging more mindful usage and promoting discussions around responsible AI. The survey also revealed curiosity and an eagerness to learn more about the unseen costs of LLMs.

D. Statistical Inferences

The survey results were analysed using descriptive statistics to measure the significance of variations in the responses among different student groups. Considering the three major categories of survey responses (awareness, usage and responsiveness), the consistency and normalization of the responses are further evaluated by assigning certain scores to the multiple-choice and multiple-answer-type questions as shown in the annexure (Table S1). Thus, the categorical responses to the questions under each category (refer to Table I) are converted to numerical values. A comparison of the simple descriptive statistics revealed that the average usage score is the highest for the first-year students (19.02±2.54) compared to the fourth-year students (18.61±1.90). The awareness score and responsiveness score are highest for the final-year students (7.85±2.20 and 12.12±3.70 respectively) considering their experience and exposure gained during the study period (Table III). The median values for the total scores are more or less centred around the mean values though the standard deviation values are higher for first-year students compared to the final-year students. It is interesting to note that the average scores are slightly higher for the female students compared to the male students, indicating the increased exposure to the AI tools in the developing economic situation of the society.

Further, the internal consistency of the responses was evaluated using Cronbach's alpha value (Adamson and Prion 2013) as mentioned in eq. 1.

$$\alpha = \left[\frac{k}{k-1}\right]\left[1 - \frac{var(category\ score)}{var(total\ score)}\right] \tag{1}$$

Where k represents the number of responses and *var ()* represents statistical variance.

TABLE III
SUMMARY OF STATISTICAL ANALYSIS CONDUCTED FOR THE RESPONSE DATA

Parameter	Range	Usage score	Awareness score	Responsiveness score
Age groups	<=17	19.02	7.12	10.40
	18-19	18.73	6.86	10.87
	20-21	18.76	7.54	10.93
	>=22	18.61	7.85	12.12
Gender	Female	19.08	7.45	11.49
	Male	18.64	6.92	10.15
α-value for the age groups	<=17	0.87	0.92	0.78
	18-19	0.88	0.93	0.79
	20-21	0.73	0.86	0.46
	>=22	0.96	0.94	0.83

The results indicate that the nature of responses is highly consistent among the age-groups as well as gender-groups. The average responsiveness score among the third-year students only showed a lower α-value (0.46). By comparing the Spearman coefficient among the average scores between the three categories, the level of positive association is moderate (0.30 for awareness versus responsiveness). The paired t-test for the average total score variation with the age group indicates a strong statistical significance for the nature of responses with the year of study.

E. *Awareness on Sustainability and AI usage*

For many students, exposure to the environmental dimension of AI was novel and sparked an interest in seeking further knowledge. This can be positively directed towards sustainability literacy and taken as an opportunity for green computing and responsible design. Most of the students expressed their interest in looking for an eco-AI certification for LLMs and their associated tools as a way to encourage sustainability in AI usage. We also observed that the students who expressed stronger emotional responses were more likely to show interest in proposing sustainable AI practices such as limiting unnecessary queries and advocating for greener technologies. Interestingly, there is a considerable group of students who are not yet sure about taking action based on this awareness. When asked about their readiness to reduce AI usage, about 36% expressed confusion or a lack of confidence in adopting such practices, although they accepted them theoretically. From an educational perspective, the emotional responses revealed in this study highlight the need to broaden the scope of analyzing the impacts of AI tools beyond cognitive performance and ethics. Incorporating the sustainability dimension of AI use within higher education could strengthen both environmental literacy and emotional resilience. In an educational organization, therefore, it is important to raise this awareness, address students' emotions, and guide them toward safe and sustainable practices. Certainly, there has to be a broader framework for addressing this topic, as students are not the only vulnerable stakeholders in the academic system. In this context, a progressive adaptational framework is proposed in this study for safe and sustainable AI integration in academics, especially for undergraduate engineering students (Fig. 5).

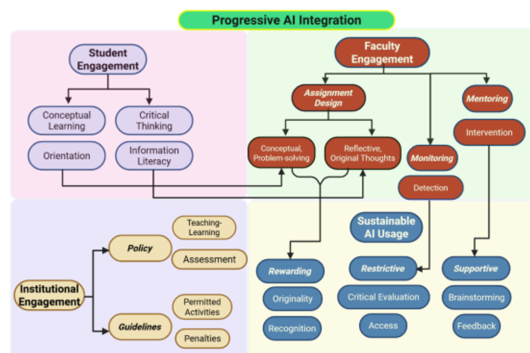

Fig. 5. Proposed framework for progressive AI adaptation in engineering education

F. *Progressive AI Integration Framework*

The proposed framework consists of selective engagements for three key stakeholders – students, faculty, and the institute – for crafting and executing academic exchanges that ensure the safe and ethical use of AI tools by students. In the growing world of technological development, the roles of humans and machines often complement each other. However, it is essential for students to have faculty supervision while being exposed to the virtual world of data abundance and free access. According to the authors, ChatGPT can be utilized as a teaching and learning aid; however, responsible use of digital technology is something that both educators and students must master. For student engagement, it is proposed that students up to the third year of study should be firmly restricted from the use of ChatGPT and similar AI tools. Instead, they should focus on learning the fundamentals properly and applying concepts independently through academic exercises. In particular, first- and second-year engineering students should be given strong emphasis on conceptual learning and critical thinking, with AI tool usage completely restricted during this period. This may seem harsh; however, when considering the personal, social, and environmental impacts of AI as discussed above, it must be seen as a necessary step to safeguard students from the dangers of virtual intelligence use at their critical stage of development. As part of institutional policy, organizations must prepare clear guidelines on permitted activities and penalties to ensure implementation in the true spirit. A well-planned orientation program and continued emphasis on information literacy should be promoted to enhance students' awareness of the multidimensional impacts of AI tools.

Faculty engagement is equally essential, particularly in three areas: assignment design, mentoring, and monitoring. Exercises for evaluation and assessment should be designed so that students perceive the system as rewarding and supportive, even while accepting restrictions on AI access with a positive spirit. It is also important to provide ample opportunities and recognition for original contributions without AI assistance, fostering a promising peer attitude toward easy adoption. Regular mentoring, reflective exercises, and formative assessments that address these concerns may help students channel anxiety, guilt, and curiosity into constructive learning outcomes. Such an approach can foster a culture where students not only benefit academically from AI but also engage critically with its broader ecological implications.

CONCLUSION

This study finds that undergraduate engineering students are active users of LLMs but remain unaware of the environmental consequences related to energy and water use associated with AI systems. After being informed, many showed concern and were willing to make changes in their digital behaviors, which points to the role of awareness in constructing responsible attitudes toward technology use. Emotional responses, such as worry and feelings of guilt, were important motivators toward changing behavior. To translate these insights into practice, each institution should focus on structured AI-literacy programs with emphasis on sustainability, critical evaluation of AI outputs, and ethical digital behavior. Clear guidelines on the integration, promotion of original student work, and supporting faculty-led mentoring will go a long way in reducing misuse and over-dependence on the emerging use of AI tools. A progressive AI adoption framework that strengthens conceptual understanding and problem-solving skills while discouraging unsupervised reliance only can foster a balanced and responsible AI culture on campuses. By embedding environmental awareness and ethical considerations into AI education, universities have an opportunity to make sure students benefit from generative AI while building the required mindset for socially and environmentally responsible citizenship.

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SUPPLEMENTARY DATA
TABLE S1
LIST OF QUESTIONS AND THE OPTIONS USED IN THE OPINION SURVEY

Questions	Options	Scores
What are the AI tools that you are using regularly?	ChatGPT; Gemini; Grammarly; QuillBot; Otter; Canva; Other:	-
How often do you use it?	Hourly; Daily; 2-3 times a week; Rarely	4, 3, 2, 1
How much time do you spend per session on average?	10-15 minutes;15-30 minutes; 30-60 minutes; More than an hour	1, 2, 3, 4
For what purpose(s) are you using these LLM tools?	Coding; Entertainment; Academics; Chatting; Career preparation; Other:	
What type of content do you look for from LLMs?	Text; Image; Code; Audio; Video; Other:	-
Did you know that LLMs consume a lot of electricity and water during their training as well as usage?	Yes; No	1, 0
Are you aware that a single AI query may consume water indirectly for cooling their data centres?		1, 0
A single ChatGPT search's environmental impact is roughly equivalent to emitting 2 to 4.32 grams of CO_2 according to some estimates and analysis sites. Do you believe this?	I think it is superficial; Maybe; I am not sure; I think it is correct; I am surprised and can't believe it	0, 1, 2, 3
More use of AI in turn demands smarter algorithms, faster machines, high-speed internet, increased data broadcasting services, more susceptibility to radiation, and increased health risks. Do you believe in this sequence?	I think it is superficial; Maybe; I am not sure; I think it is correct; I am surprised and can't believe it	0, 1, 2, 3
On a scale of 1–5, how surprised are you by the environmental impact of LLMs? (1 = not surprised, 5 = very surprised)?	1; 2; 3; 4; 5	1, 2, 3, 4, 5
Where do you think LLMs get their water usage from?	Date centres; Cloud providers; Don't know; Other:	--
How concerned are you about the environmental impacts (especially water usage) of LLMs?	Not at all; Slightly; Moderately; Significantly; Extremely	0, 1, 2, 3, 4
What emotions do you feel after hearing about the water consumption by LLMs?	Shocked; Angry; Guilty; Curious; Unaffected	4, 3, 2, 1, 0
Would you consider limiting your LLM usage to reduce the environmental footprint?	Yes; No; Maybe	1, -1, 0
On average, how much time is taken for a single search result?	1-5 sec; 5-10 sec; 10-30 sec; 30-60 sec; >1 min	5, 4, 3, 2, 1
In your experience, what are the main reasons for the AI tool to take a longer time for your search?	Weak internet; Low memory of the device; Type of data in search (text/image/multimedia); Complexity of the query (need to search larger databases); Other:	
How often do you clear the search memory (including cache) of your browser/app after usage?	Immediately after the usage; Daily; Weekly; Monthly; Not cleared so far; Other:	5, 4, 3, 2, 1
Do you think that storing your search results will actually cause huge data storage costs and environmental impacts?	Strongly disagree; Disagree; Neutral; Agree; Strongly agree; Other:	1, 2, 3, 4, 5
How do you actually do the search for the query using an AI tool? Which one will work better for you?	I type some keywords randomly; I type one word and select the suggested words automatically showing up; I frame my query using selected words and phrases; I don't type many words; I'll modify the query based on the search result; Other:	-
How do you feel that feeding a scenario/background information before a search can fetch you more accurate results so that the repeated number of queries can be reduced significantly?	I don't think so; Maybe; I am not sure; I think it will work; I know it and I am doing it; Other:	0, 1, 2, 3
If you did not get a satisfying answer to your query for an important and urgent need, how do you respond normally?	Getting upset for a while; Get angry more after thinking about it; Leave it as a silly matter; Accept the predicament; and practice depending more on intuitive intelligence than AI; Other:	1, 2, 3, 4
The AI-generated results include a disclaimer that "the results may not be correct as it is experimental." How often do you believe in the credibility of your search results?	I take the results as the right answer; I take the results to be close to the right answer and confirm once before using it; I am not aware of it; I don't mind about it	4, 2, 3, 1
Should the tech companies disclose the environmental cost (energy & water) of using AI services?	Strongly disagree; Disagree; Neutral; Agree; Strongly agree; Other:	1, 2, 3, 4, 5
Would you support an "eco-friendly AI" certification for a feature?	Yes; No; Maybe	1, -1, 0
Are you interested in learning more about water sustainability and responsible AI usage?		1, -1, 0
In your opinion, what should be done to balance AI advancement and environmental sustainability?	-	-