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Generative AI and the future of higher education: a threat to academic integrity or reformation? Evidence from multicultural perspectives

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Abstract

In recent years, higher education (HE) globally has witnessed extensive adoption of technology, particularly in teaching and research. The emergence of generative Artificial Intelligence (GenAI) further accelerates this trend. However, the increasing sophistication of GenAI tools has raised concerns about their potential to automate teaching and research processes. Despite widespread research on GenAI in various fields, there is a lack of multicultural perspectives on its impact and concerns in HE. This study addresses this gap by examining the usage, benefits, and concerns of GenAI in higher education from a multicultural standpoint. We employed an online survey that collected responses from 1217 participants across 76 countries, encompassing a broad range of gender categories, academic disciplines, geographical locations, and cultural orientations. Our findings revealed a high level of awareness and familiarity with GenAI tools among respondents. A significant portion had prior experience and expressed the intention to continue using these tools, primarily for information retrieval and text paraphrasing. The study emphasizes the importance of GenAI integration in higher education, highlighting both its potential benefits and concerns. Notably, there is a strong correlation between cultural dimensions and respondents' views on the benefits and concerns related to GenAI, including its potential as academic dishonesty and the need for ethical guidelines. We, therefore, argued that responsible use of GenAI tools can enhance learning processes, but addressing concerns may require robust policies that are responsive to cultural expectations. We discussed the findings and offered recommendations for researchers, educators, and policymakers, aiming to promote the ethical and effective integration of GenAI tools in higher education.

Keywords: GenAI, Higher education, Potential, Concerns, Ethical regulations, Cultural dimensions

Introduction

Over the past few years, Higher Education (HE) worldwide has witnessed massive penetration of ubiquitous technology, particularly in areas of teaching and research (Yusuf & Tambuwal, 2018). The commonly accepted assumption is that HE systems would need to prepare citizens for lifelong learning in the age of information and communications technology (Rawas, 2023). More technology penetration is witnessed with the recent development of Artificial Intelligence (Zhang et al., 2023). Recent studies have reported the continual proliferation of Artificial Intelligence (AI) tools in HE (e.g., Chu et al., 2022; Crompton & Burke, 2023) owing to their potential benefits, including improved personalized learning (Bhutoria, 2022), automation of repetitive tasks (de la Torre-López et al., 2023), and provision of efficient administrative processes (Parycek et al., 2023), among others.

While AI has received a wider and more successful application in higher education institutions (HEIs), such application was previously restricted to large-scale educational activities such as automated grading and administration. Individual and small-scale applications penetrated HEIs recently when ChatGPT, a chatbot, was developed by OpenAI in November 2022. Since its inception, other open-access AI tools have been introduced into the AI market under a broad category: "Generative Artificial Intelligence" (henceforth referred to as GenAI). The primary function of most GenAI tools is to mimic human conversation and intelligence. With recent advancements, GenAI tools extend far beyond this function as they can now create new content such as poems, computer codes, written texts, and anything within their capability (Budhwar et al., 2023; Sun et al., 2024; Tlili et al., 2023).

However, such advancement comes with a cost as concerns have been about a possible decrease in students' cognitive and logical skills and a decline in academic competency (Ipek et al., 2023). Heightened concerns emerged at the onset of the 2023 academic year when educators reacted to reports of GenAI's ability to pass medical and MBA examinations (Kelly, 2023; Purtill, 2023). Additional reservations include the perceived tendency of GenAI to generate responses that are both inaccurate and overly authoritative (Ipek et al., 2023). Consequently, there has been an outright discouragement of their usage by some academic journals and HEIs (Chan, 2023; Strzelecki, 2023; Vincent, 2023).

Extensive research has been conducted to understand the potential impacts and concerns of GenAI in HE (see e.g., Bandi et al., 2023; Chan & Hu, 2023; Lim et al., 2023; Tlili et al., 2023). However, such impacts and concerns have not been reported from a multicultural perspective. Authors such as Jan et al. (2022) argued that the acceptance of any technological innovation is significantly contingent upon its alignment with cultural norms prevailing across diverse nationalities. In this context, Sun et al. (2019) assert that the failure of many technological tools stems from their inability to meet and adapt to people's ways of thinking and behavior as opposed to technical or professional incompetence.

The absence of a multicultural perspective in existing research raises questions about the universality of findings and highlights the need for a more comprehensive understanding of GenAI's impact across different cultural contexts. Acknowledging the significance of cultural influence, we propose that collecting opinions across diverse cultures will yield a more expansive insight and understanding of the dynamics associated with GenAI integration within the context of HE. In pursuit of this proposal, our study is designed to comprehensively explore the utilization, potential, and concerns related to GenAI from a multicultural perspective. Four research questions were addressed in this study:

1. What is the level of awareness and familiarity with GenAI tools in HE?
2. To what extent do different cultures in HE use GenAI tools?
3. What are the perceived potential and concerns of GenAI in HE across different cultures?
4. What are the proposed regulations and ethics concerning the use of GenAI in HE across different cultures?

Literature review

Conceptual understanding of GenAI

GenAI encompasses a diverse range of artificial intelligence techniques and models designed to create unique and human-like content across various media formats, including texts, images, audio, and video (Cooper, 2023; Strzelecki & ElArabawy, 2023; Tlili et al., 2023). Outputs from GenAI systems go beyond those of traditional pattern recognition or rule-based methods; they are programmed to emulate the creative and generative qualities of human thought (Dwivedi et al., 2023). To achieve this, they heavily rely on machine learning methodologies, particularly deep learning techniques and neural networks, to learn from vast datasets (Tlili et al., 2023). Through extensive training, they develop the ability to detect underlying patterns and structures within the data. In addition, they utilize probabilistic models to generate new content that adheres to the learned patterns, resulting in coherent and contextually relevant outputs (Tlili et al., 2023). In essence, GenAI represents a significant advancement in AI technology. Their transformative potential has a broad application, from creative content generation to natural language processing and beyond (Chan & Hu, 2023; Tlili et al., 2023).

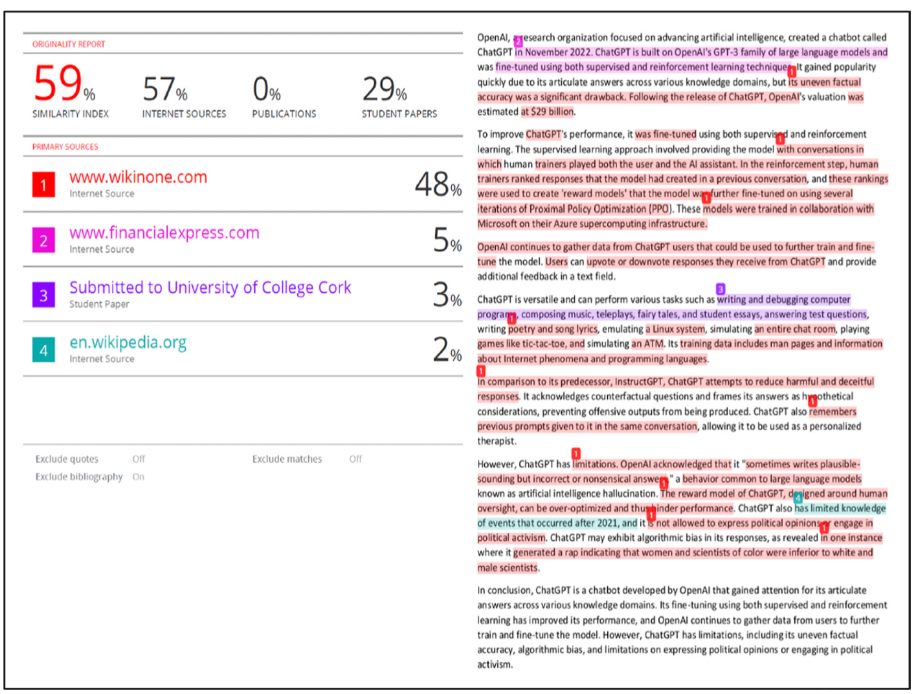
Potential and challenges of GenAI in higher education

Since its inception, the integration of GenAI into education has garnered significant attention. The potential benefits and concerns associated with GenAI in the classroom have been explored by various researchers, shedding light on its transformative potential and challenges. Stojanov (2023) emphasizes GenAI's role in revolutionizing teaching, specifically its capacity to customize education to individual needs. This sentiment is echoed by Kohnke et al. (2023), who investigated English language teachers' perspectives, highlighting GenAI's ability to foster individualized learning and training support. However, concerns such as biases, confidentiality issues, and the potential for inaccurate information are acknowledged. Tlili et al. (2023) shift the focus to the practical implementation of GenAI in educational settings. According to the study's findings, early adopters express excitement about ChatGPT's pedagogical potential, but skepticism exists, particularly regarding concerns like cheating. The authors emphasize the complex interplay between the promise of GenAI and the need for responsible implementation, cautioning against overlooking ethical and practical challenges.

In a similar vein, Chan and Hu (2023) examine university students' viewpoints on GenAI in higher education. Students express a positive disposition toward technologies like ChatGPT, appreciating their support in academic writing. This contribution was also highlighted by Malik et al. (2023) who reported the potential utility of GenAI to enhance writing creativity and facilitate the creation of original works of art and literature. However, both studies collectively report several concerns, with ethical issues and support for academic misconduct taking a more prominent role in the discourse. Lim et al. (2023) provide compelling evidence about GenAI's support for academic misconduct by revealing a significant self-plagiarism index of 59% (see Fig. 1). Such a high similarity index highlights the importance of critically evaluating textual responses produced by GenAI.

Related to writing support, Yilmaz and Yilmaz (2023a) reported the potential of GenAI to improve students' coding ability through quick coding feedback. They also noted that such coding support improves students' problem-solving and critical thinking skills and enhances coding confidence. Challenges such as the risk of student complacency and concerns about professional growth are also identified. In contrast, Lim et al. (2023) take a holistic perspective to synthesize the transformative potential and challenges of GenAI in education. They identify paradoxes within GenAI and advocate for a strategy that embraces its role in the classroom. Similarly, Ipek et al. (2023) provide a literature synthesis, discussing both the benefits and drawbacks of ChatGPT's implementation in education. Collectively, while appreciating several benefits, the syntheses highlight the need for a comprehensive guideline that would guide the responsible use of GenAI technologies.

In conclusion, the studies collectively highlight the transformative opportunities presented by GenAI in education, including customized learning, research support, and enhanced problem-solving skills. However, they also underscore the importance of addressing challenges such as biases, ethical considerations, and the need for responsible implementation. Thus, the integration of GenAI in higher education requires a careful balance between harnessing its potential and mitigating associated risks.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OpenAI, a research organization focused on advancing artificial intelligence, created a chatbot called ChatGPT in November 2022. ChatGPT is built on OpenAI's GPT-3 family of large language models and was fine-tuned using both supervised and reinforcement learning techniques. It gained popularity quickly due to its articulate answers across various knowledge domains, but its uneven factual accuracy was a significant drawback. Following the release of ChatGPT, OpenAI's valuation was estimated at $29 billion.

To improve ChatGPT's performance, it was fine-tuned using both supervised and reinforcement learning. The supervised learning approach involved providing the model with conversations in which human trainers played both the user and the AI assistant. In the reinforcement step, human trainers ranked responses that the model had created in a previous conversation, and these rankings were used to create 'reward models' that the model was further fine-tuned on using several iterations of Proximal Policy Optimization (PPO). These models were trained in collaboration with Microsoft on their Azure supercomputing infrastructure.

OpenAI continues to gather data from ChatGPT users that could be used to further train and fine-tune the model. Users can upvote or downvote responses they receive from ChatGPT and provide additional feedback in a text field.

ChatGPT is versatile and can perform various tasks such as writing and debugging computer programs, composing music, teleplays, fairy tales, and student essays, answering test questions, writing poetry and song lyrics, emulating a Linux system, simulating an entire chat room, playing games like tic-tac-toe, and simulating an ATM. Its training data includes man pages and information about Internet phenomena and programming languages.

In comparison to its predecessor, InstructGPT, ChatGPT attempts to reduce harmful and deceitful responses. It acknowledges counterfactual questions and frames its answers as hypothetical considerations, preventing offensive outputs from being produced. ChatGPT also remembers previous prompts given to it in the same conversation, allowing it to be used as a personalized therapist.

However, ChatGPT has limitations. OpenAI acknowledged that it "sometimes writes plausible-sounding but incorrect or nonsensical answers," a behavior common to large language models known as artificial intelligence hallucination. The reward model of ChatGPT, designed around human oversight, can be over-optimized and thus hinder performance. ChatGPT also has limited knowledge of events that occurred after 2021, and it is not allowed to express political opinions or engage in political activism. ChatGPT may exhibit algorithmic bias in its responses, as revealed in one instance where it generated a rap indicating that women and scientists of color were inferior to white and male scientists.

In conclusion, ChatGPT is a chatbot developed by OpenAI that gained attention for its articulate answers across various knowledge domains. Its fine-tuning using both supervised and reinforcement learning has improved its performance, and OpenAI continues to gather data from users to further train and fine-tune the model. However, ChatGPT has limitations, including its uneven factual accuracy, algorithmic bias, and limitations on expressing political opinions or engaging in political activism.

Fig. 1 Similarity index of paraphrased text by ChatGPT. Source: Lim et al. (2023)

Theoretical explanations of multicultural dimensions

First, culture is "the collective programming of the mind which distinguishes the members of one human group from another" (Hofstede, 1980, p. 25). It is "a learned set of shared interpretations about beliefs, values, and norms, which affect the behaviors of a relatively large group of people" (Lustig & Koester, 2013, p. 25). According to Hofstede (1980), cultural values are measured along six dimensions: power distance, uncertainty avoidance, individualism versus collectivism, masculinity versus femininity, long- and short-term orientation, and indulgence versus restraint.

The dimension of power distance focuses on people's willingness to accept unequal distribution of power within an institution or organization. In various societies, people are seen to be superior due to their attainment of certain social status e.g., age, wealth, gender, and personal achievements, and are therefore respected by those of lower class. Index scores show that power distance is lower for English-speaking Western countries and higher for Asian, African, Latin, and East European countries (Hofstede, 1980). The uncertainty avoidance dimension focuses on the extent to which societies are tolerant of uncertainty and ambiguity. Zainuddin et al. (2018) explained that societies with strong uncertainty avoidance are more likely to display strict behavioral codes, rules, and laws compared to uncertainty-accepting cultures with fewer regulations that make members accept different opinions. Available evidence indicates that Nordic and English-speaking nations are uncertainty-accepting countries while countries such as Japan, Germany, and Latin America are uncertainty-avoiding nations.

In the individualism versus collectivism dimension, the focus is on the inter- and intra-personal relationship among individuals. Individualist cultures tend to have loose bonds and display self-interest and self-dependence compared to collectivist societies with strong social bonds that encourage group harmony. Individualism is more practiced in Western and developed countries, while collectivism prevails in Eastern and less developed nations (Zainuddin et al., 2018). The masculinity versus femininity dimension focuses on the extent to which certain values are gender-stereotyped. Hofstede argued that masculine societies have more preference for assertiveness and competitiveness, while feminine culture recognizes values such as politeness, modesty, and caring. Although politeness, modesty, and caring are shared equally by both men and women in feminine nations, this equality differs in masculine nations, and hence there exists a gender gap in values. Masculinity is prevalent in countries such as Germany, Italy, Japan, and Mexico, whereas femininity prevails in Denmark, Norway, and the Netherlands.

In long- and short-term orientations, achievable goals are the key. According to Hofstede, societies with long-term orientation display more persistence, thriftiness, modesty, planning, and lifelong investment. In contrast, societies with short-term orientation expect quick results. The last dimension (indulgence vs. restraint) indicates that indulgent culture encourages pleasures, enjoyment, fun, spending, and leisure, whereas restraint culture suppresses needs for enjoyment and pleasure, controls desires and impulses, and regulates behavior by strict social norms.

Although Hofstede's framework has been replicated and evaluated by several studies, it has attracted many criticisms. For example, Fang (2003) argued that the last two dimensions are surrounded by methodological limitations and inherent philosophical flaws. Other criticisms centered on its restriction to a particular company, and as such, information from a particular context cannot be assumed to reflect the complex realities of national cultures. Nevertheless, extensive validation of the theory is sufficient to prove that the model can be applied to different cultures. Thus, the original version of Hofstede's framework is still popular and widely in use.

Implications of cultural values to perceived potentials and concerns of AI technologies

Studies have examined the impact of cultural values on technology usage and acceptance. For example, Kovacic (2009) revealed that countries with strong individualistic cultures are more likely to hold positive perceptions toward technology usage and adoption. In contrast, Tarhini et al. (2017) argued that the relationship between culture and technology acceptance is stronger in a collective society, with the assumption that people are more likely to be influenced by the opinions of colleagues. On another note, Bagchi et al. (2004) revealed that countries with significantly low masculinity are more likely to acknowledge the potential of computer technologies with the belief that they will make significant impacts. This was supported by Tarhini et al. (2017) who revealed a significant relationship between technology acceptance and low masculine society.

In a more recent study, Sun et al. (2019) maintained that countries with high collectivism and long-term orientation are more likely to hold positive perceptions about technology innovations compared to their counterparts with individualism and short-term orientation. In a similar study that examined the impact of cultural dimensions of clinicians on the adoption of AI in healthcare (Krishnamoorthy et al., 2022), only uncertainty avoidance was found to have an impact on AI acceptance and adoption. In conclusion, these studies collectively emphasize the relationship between cultural dimensions and the perceived importance of technology in a society. However, it appears that the results are contradictory and hence the relationship between cultural dimensions and technology acceptance is far from clear.

Methodology

Research approach

The study was conducted within the lens of quantitative and qualitative paradigms, focusing on embedded mixed-method design. This design has a strong philosophical underpinning and is largely used when there is a need to provide additional information within a larger quantitative or qualitative dataset, with one dataset serving as a primary or dominant component while the other serves as a secondary or supportive component (Creswell, 2014). Thus, the research benefit of embedded mixed methods is that it permits one method to lead the analysis, with the secondary method providing crucial supplementary information (Creswell, 2014). In this study, we recognized the quantitative datasets as the primary data component while results from the qualitative dataset served as supporting information. Therefore, the qualitative component was embedded in the larger quantitative approach.

Participant recruitment

One thousand two hundred and forty (1240) students and lecturers of higher education institutions across 76 countries were recruited through various social media platforms (e.g., Facebook, Twitter, WhatsApp, LinkedIn, etc.), research repositories (e.g.,

Fig. 2 Distribution of participants by continent

researchgate), academic forums, and mailing lists. We requested potential participants to take part in an online survey by sending a link to the various online platforms. Inclusion criteria include participants lecturing or schooling within the confines of higher education institutions (HEIs). These include universities, colleges, polytechnics, and other postsecondary certificate-awarding bodies. Recruitment was based on a convenience sampling method that stressed the importance of participants' availability and willingness to participate in the study. Participation was completely voluntary with anonymized responses. The distribution of our participants represents a broad range of gender categories, academic disciplines, geographical locations, and cultural orientations. Figure 2 presents the distribution of the participants by continent. While the distribution of participants spans continents and countries, an apparent potential for disparity has been perceived in our study. Notably, the number of participants from Nigeria (n = 278) is twice that of participants from South and North America and Australia combined (total = 123). Additionally, there is an observed disparity in the number of participants from Spain, which is approximately 60% higher than those from Germany. We acknowledge this disparity but chose to maintain transparency in reporting the participants' demographics.

Measures

The data collection instrument was a survey designed using Qualtrics. The survey largely comprised 20 closed-ended questions and 2 open-ended items that provided supplementary information. In the course of designing our survey, we adapted some items from the works of Denejkina (2023) and Chan and Hu (2023) and drafted other items from reviews of academic literature. We designed the survey to comply with the Web Content Accessibility Guidelines (WCAG) 2.0AA. This means that participants with cognitive disabilities and low vision are likely to find it easy to complete the survey. Because most online survey completion happens on mobile devices, we ensured that our questionnaire was mobile-friendly (by enabling the mobile-friendly setting) to increase the completion rate and data representativeness.

A preliminary analysis of the survey duration indicates an average of 7 min and 2 s, suggesting a possible association with low dropout and high completion rates. The length of surveys in academic research has attracted long-standing debate. While authors such as Rolstad et al. (2011) stress the importance of survey content as opposed to duration, other authors (e.g., Revilla & Ochoa, 2017) recommend a median of 10 min. We employed conditional display logic in the design of our survey. This means that questions are automatically displayed based on the response to a preceding question.

Our survey consists of 6 sections, including demography (gender, academic status, nationality, and residential location), usage level of generative AI (e.g., "have you ever (in any capacity) used GenAI tool", 1 = Yes, 2 = No, 3 = Unsure), plagiarism and cheating (e.g., "do you consider using Generative AI tools for students' assignments or teachers' research cheating", 1 = Yes, 2 = No, 3 = Unsure), skills and competency (e.g., "rate your skills/ability levels in using GenAI tools to generate information or content", 1 = not at all skilled, 4 = very skilled), perceived benefits and limitations (e.g., "generative AI provide personalized and immediate learning support", "generative AI tools can generate output that is factually inaccurate"; 1 = strongly disagree, 5 = strongly agree), and ethics and regulations (e.g., "do you think there should be educational policies regulating the use of GenAI in higher education", 1 = Yes, 2 = No, 3 = Unsure). The complete survey items can be found in the Supporting Information.

Cultural dimensions

To empirically associate the participants' perspective of GenAI with their national culture, we obtained the score index of each representative country based on Hofstede's cultural dimensions (see Additional file 1) from Hofstede Insight (https://www.hofstede-insights.com/country-comparison-tool?). We categorized representative countries according to their cultural dimensions using the index scores. Countries with index scores on the same scale are grouped together (see Table 1 for grouping). For example, Russia (93), Malaysia (100), India (77), and Saudi Arabia (72) are grouped as countries with high Power Distance. Greece (100), Japan (92), Chile (86), and Romania (90) are grouped as uncertainty-avoidant countries, while Austria (79), Kenya (60), Italy (70), and China (66) are grouped as masculine countries. We could not categorize 15 countries (e.g., Oman, Rwanda, etc.) because their index scores were not available at the time of conducting this research. Additionally, the index scores of three countries (Kenya, Kuwait, and Nepal) on Long-Term Orientations and Indulgence dimensions were not available, therefore, their classification on the mentioned dimensions was not possible.

Procedure

We invited participants to complete a survey on the prospects and concerns of GenAI in higher education via social media platforms from 25th August to 26th September 2023. During the invitation, we provided a brief introduction about the objectives of the study to the potential participants along with information on the average duration of the

Table 1 Country category of cultural dimensions

Cultural dimension	Rating	Country example
Power distance		
Power is unequal	56–100	Russia, India, Nigeria, Bangladesh etc
Power is equal	0–49	Denmark, Canada, UK, USA, Sweden etc.
No preference	50–55	Italy, Pakistan
Individualism		
Individual	51-above	Australia, Finland, USA, UK etc.
Collectiveness	0–49	Bangladesh, Malaysia, Nigeria etc.
No preference	50	NIL
Masculinity		
Masculine	51–above	Nigeria, Germany, China, Austria, etc
Feminine	0–49	Finland, Norway, Sweden, Saudi Arabia
No preference	50	Malaysia, Pakistan, Burkina Faso
Uncertainty avoidance		
Uncertainty avoidance	56–above	Greece, Bangladesh, Egypt, Japan, etc
Uncertainty accepting	0–49	UK, USA, China, India, Singapore, etc
No preference	50–55	Egypt, Nigeria, Kenya, Burkina Faso, etc
Long-Term orientation		
Long-term	56-above	China, Germany, Japan, Italy, etc.
Short-term	0–49	USA, Nigeria, Finland, Saudi Arabia, etc.
No preference	50–55	UK, India, Pakistan
Indulgence		
Indulgence	56-above	Canada, UK, USA, Nigeria, Sweden, etc.
Restraint	0–47	Saudi Arabia, Egypt, Bangladesh, etc.
No preference	48–55	Singapore

survey. On the first page of the online survey, we emphasized that participation is completely voluntary and that participants could quit the survey should they feel to do so. Information collected from the participants was anonymized, suggesting that personal identities such as names, phone numbers, email, and IP addresses were not collected. We designed the online survey so that multiple submissions were prevented. We also reiterated that only students and lecturers from HEIs were eligible for participation.

At the bottom of the introduction page, participants gave their consent before proceeding to the rest of the survey sections. Overall, a total of 1240 responses were recorded. Data collected from the online survey was exported to an Excel sheet and refined into readable form. We removed records of 12 participants who achieved only 3% of the overall survey progress. These participants read only the survey's introduction section and could not progress. We further removed records of 8 participants who did not give their consent. We removed an additional 3 records of participants who used insulting or sensitive words in their open-ended survey responses. The resulting data matrix yields 1,217 records.

Analysis

The collected and refined data were separated into quantitative and qualitative responses. The quantitative dataset was analyzed in SPSS (version 26) using descriptive statistics (to quantify and describe basic characteristics of the responses) and inferential statistics (to correlate responses with cultural dimensions and demographic data). The qualitative dataset was analyzed using content analysis. By utilizing this method, we were able to effectively identify and extract key themes and patterns from the collected data, allowing for a comprehensive exploration of the participants' opinions (Yilmaz & Yilmaz, 2023b). The identified themes were related to; (1) justifications of GenAI tools being considered or not considered cheating when used for assignments and research, and (2) specific education policies or regulations that need to be enforced on the use of GenAI.

As proposed by Yilmaz and Yilmaz (2023b), one of the researchers coded and categorized the qualitative responses, and a second encoder reviewed the code categories to ensure accuracy. The percentage of codes that shared the same category was calculated to evaluate the alignment of the two coders. Based on the percentage absolute agreement rating proposed by Miles and Huberman (1994), the coding reliability was determined to be 95%, indicating a high level of agreement between the coders. Discrepancies in the remaining 5% were resolved through discussion and consensus. We associated the agreed themes with the cultural dimensions using network models in Gephi software. As previously highlighted, 15 countries had no index scores of cultural dimension. Therefore, we only included the responses of participants from these countries in the descriptive analysis but excluded them from the correlation analyses to avoid the effect of missing data.

Results

Demography

Table 2 delineates the demographic characteristics of the survey participants. A total of 1217 respondents actively participated in our survey, comprising 58.18% students and 41.82% teachers. It's noteworthy that in this context, the term "teacher" encompasses individuals engaged in higher education instruction, including those presently under contract, sabbatical, visiting, and tenure.

In the teacher category, a significant majority (60.51%) possess a Ph.D. or its equivalent qualification. A substantial proportion (34.97%) hold a Master's degree or an equivalent credential, while only a small fraction (4.52%) possess a Bachelor's degree or its equivalent. Within the student category, 50.42% are undergraduate students or their equivalents, and 49.71% are postgraduate students or their equivalents. A minimal 0.42% chose not to disclose their student status. Overall, the gender distribution is as follows: 44.54% identify as female, 49.84% as male, 2.14% as non-binary or third gender, and 3.61% prefer not to disclose their gender category. The table further provides a clear breakdown of the distribution of respondents based on their geographic locations. A significant majority of the respondents, comprising 71.57% of the total, reside in major cities. Additionally, 17.83% of respondents are located in regional areas, while 10.27% reside in rural areas. A small fraction, equivalent to 0.33%, did not disclose their residential location.

Level of awareness and familiarity with GenAI tools in HE

We investigated the extent of awareness and familiarity with GenAI tools among the study participants (see Table 3). A significant majority (81.76%) acknowledged their awareness, while 14.95% reported being unaware of these tools, and 3.29% expressed

Table 2 Demographic features of the respondents

	Frequency	Percent
Respondent status		
Student	708	58.18
Teachers	509	41.82
Teacher qualification		
Degree or equivalent	23	4.52
Master or equivalent	178	34.97
PhD/equivalent	308	60.51
Student academic status		
Undergraduate or equivalent	357	50.42
Postgraduate or equivalent	348	49.15
Undefined	3	0.42
Gender		
Female	542	44.54
Male	605	49.71
Non-binary/third gender	26	2.14
Prefer not to say	44	3.61
Residential location		
Major city	871	71.57
Regional location	217	17.83
Rural area	125	10.27
Undefined	4	0.33

Table 3 Participants' level of awareness of GenAI

	Frequency	Percent
Aware	995	81.76
Not aware	182	14.95
Unsure	40	3.29

uncertainty regarding their familiarity with them. Among those who indicated awareness, a considerable segment (71.8%) reported being "highly familiar" with ChatGPT, followed by GrammarlyGo (48.5%), Bard (30.6%), and DALLE (23.3%, see Fig. 3). Conversely, JukeBox (70.2%) and Synthesia (69.5%) emerged as the least familiar GenAI tools, trailed closely by Stable Diffusion (69.4%), MidJourney (67.4%), ChatSonic (65.8%), and YouChat (63.3%).

Use of GenAI tools in HE

We extended our analysis to gain a comprehensive understanding of the global utilization of GenAI tools in the context of higher education (HE). Our examination revealed that a substantial cohort of participants (n = 691) has previously engaged with GenAI tools, while a considerable number (n = 522) reported no prior usage. A minor fraction expressed uncertainty. Notably, among these respondents, 35.7% expressed a strong inclination toward employing such tools in the future (see Fig. 4), with an additional 27.9% indicating a likelihood to do so. Conversely, 12.5% remained undecided regarding

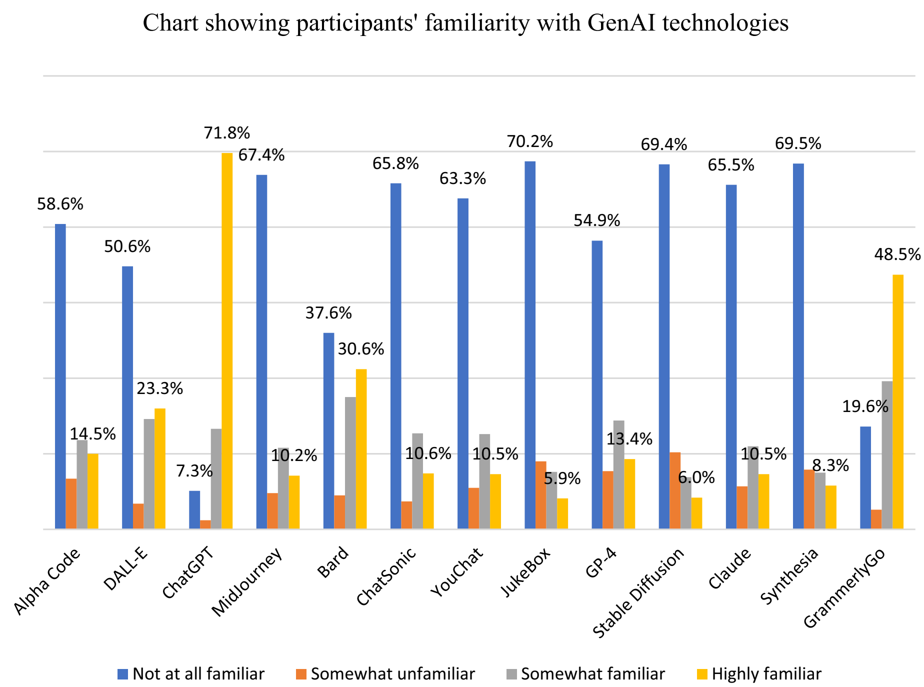

Fig. 3 Participants' familiarity with GenAI tools

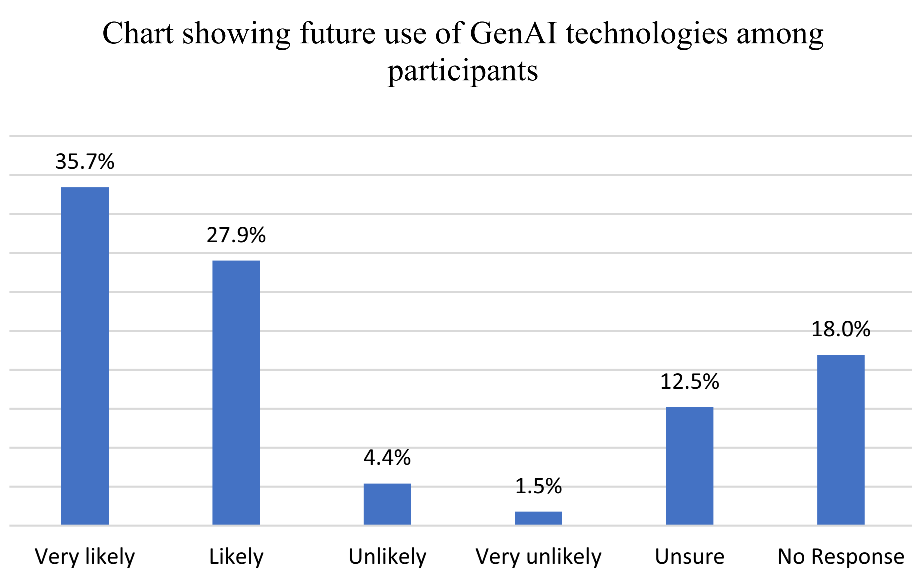

Fig. 4 Future use of GenAI

their future utilization, while 4.4% conveyed reluctance, and 1.5% exhibited a profound inclination against future use. It is worth highlighting that 18% did not submit their responses. These instances could potentially arise from question omission or automated survey engine skips, likely based on preceding questionnaire responses.

The use of GenAI tools in higher education serves a distinct and purposeful role (see Fig. 5). A notable majority of participants (44.3%) indicated their usage for information

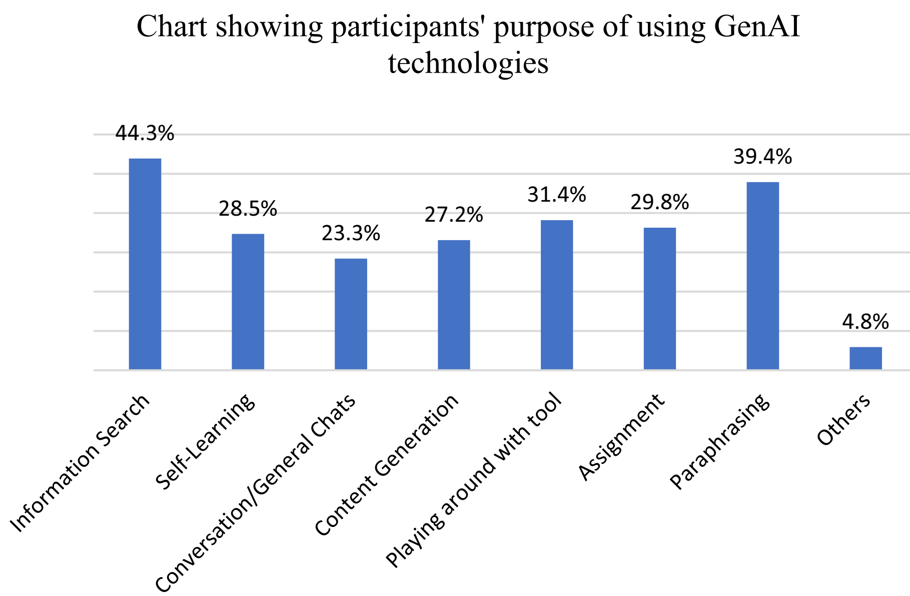

Fig. 5 Purpose of use of GenAI in HE

retrieval, while a closely comparable percent (39.4%) reported employing these tools for paraphrasing textual content. Furthermore, 28.5% acknowledged using GenAI tools for self-directed learning, while 31.4% found them engaging for recreational purposes. Additionally, 29.8% employed the technology for assignment and 27.2% harnessed these tools to generate written content. Lastly, 23.3% employed GenAI tools for facilitating conversational interactions within their educational pursuits.

Cheating and plagiarism

Our comprehensive analysis extended further to explore global perspectives regarding the classification of GenAI usage in HE as a form of academic misconduct (see Fig. 6).

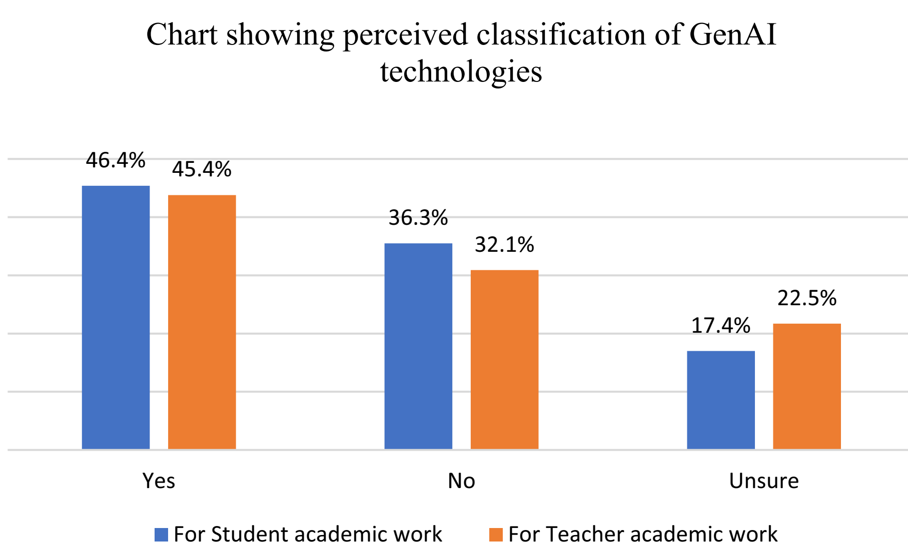

Fig. 6 Perceived classification of GenAI

A substantial majority of participants (n = 46.4% and 45.4%) expressed the firm belief that incorporating GenAI tools in academic endeavors, whether by students or educators, constitutes outright cheating. Conversely, 36.3% and 32.1% maintained a steadfast view that the use of GenAI tools within an academic context should not be deemed as cheating. Additionally, 17.4% and 22.5% remained undecided, expressing uncertainty regarding whether the utilization of GenAI tools should be categorized as cheating or otherwise. Notably, the close alignment of responses reflects a similarity in viewpoints regarding the classification of GenAI usage, both for students and educators, within the academic sphere.

Among the participants who disclosed prior utilization of GenAI tools, a noteworthy segment (54.5%) unequivocally affirmed their commitment to abstaining from any future engagement in academic misconduct, specifically refraining from using GenAI tools for plagiarism (see Fig. 7). Conversely, 6.4% conceded that while they had not employed these tools for such illicit purposes in the past, they might contemplate doing so in the future. Furthermore, 19.9% admitted to having employed GenAI tools for plagiarism, and they remained resolute in their stance that they would continue to engage in such academic misconduct in the future. In contrast, a significant percentage (19.2%) acknowledged past instances of using these tools for plagiarism but expressed their intention to discontinue such practices in the future. o

We conducted a correlation analysis between respondents' perspectives on the categorization of GenAI usage as academic dishonesty and their respective cultural dimensions through ordinal logistic regression (see Table 4). Notably, the results revealed significant associations between cultural dimensions and perceived classification. Specifically, cultures characterized by high uncertainty avoidance (UAI) exhibited a 3.67-fold greater likelihood of categorizing students' utilization of GenAI tools in their academic pursuits as instances of cheating (Odds Ratio [OR] = 3.671, 95% Confidence Interval [CI]

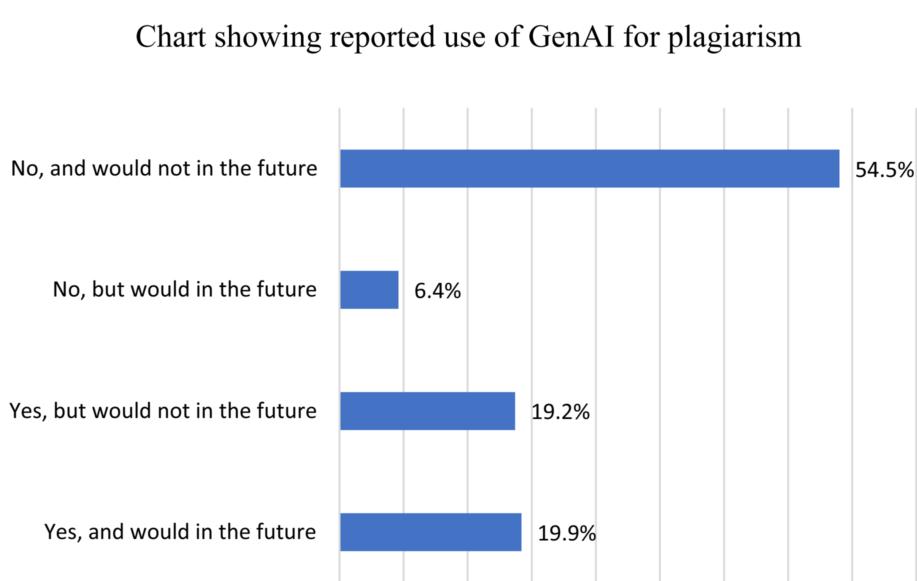

Fig. 7 Reported use of GenAI for plagiarism

Table 4 Association between cultural dimensions and classification of GenAI

	For students			For teachers		
	Est	**OR**	**CI [low–high]**	**Est**	**OR**	**CI [low–high]**
PDI						
High	0.37	0.415	0.56–1.87	0.349	0.572	0.27–1.28
Low	0.050	0.513	0.64–1.72	− 0.468	0.625	0.38–1.03
No preference	− 0.142	0.566	0.36–2.07	− 0.461	0.630	0.26–1.51
IDV						
High	0.302	0.412	0.14–1.44	0.433	0.599	0.21–1.34
Low	0.055	0.524	0.20–1.47	-0.012	0.987	0.68–1.41
No preference	0.233	0.354	0.13–1.52	0.176	0.682	0.13–1.16
MAS						
High	− 0.25	0.833	0.12–0.17	0.247	0.547	0.43–1.37
Low	− 0.027	0.972	0.71–1.32	− 0.325	0.722	0.53–0.98
No preference	0.282	1.326	0.78–2.24	0.295	1.344	0.79–2.29
UAI						
High	1.253***	3.671	1.56–3.68	0.157	0.492	0.31–1.41
Low	0.951**	1.775	1.20–1.95	− 0.247	0.780	0.60–1.19
No preference	0.179	0.835	0.59–1.18	− 0.162	0.849	0.54–1.13
LTO						
High	1.173**	2.870	1.76–3.98	0.302	0.522	0.76–1.75
Low	0.842*	1.410	0.78–2.04	0.279	1.322	0.92–1.89
No preference	0.460	0.631	0.37–1.05	− 0.264	0.767	0.45–1.29
IVR						
High	− 0.251	0.667	− 0.42–0.17	0.231	0.432	0.47–1.36
Low	− 0.123	0.883	0.65–1.19	0.010	1.010	0.74–1.37
No preference	− 0.373	0.688	0.37–1.26	− 0.360	0.697	0.37–1.29

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *OR* odd ratio, *Est.* estimate, *CI* confidence interval

[1.56–3.68], p-value < 0.001) compared to other cultural contexts. Furthermore, nations with a pronounced long-term orientation (LTO) were 2.87 times more inclined to classify students' use of GenAI as cheating (OR = 2.870, CI [1.76–3.98], p-value < 0.01). However, it is noteworthy that we did not observe any statistically significant association between other cultural dimensions and the classification of teachers' utilization of GenAI tools.

We conducted inquiries with the respondents regarding the rationale behind their classifications. Among 964 of the participants who classified GenAI usage as cheating or otherwise, 718 provided their reasons for such classification while others could not provide any justification. Our content analysis led to the emergence of two predominant thematic categories: (1) Self-Attribution of work, and (2) Assistive learning tools.

Self-attribution of work

Quite a large proportion of the respondents clarified that the act of attributing authorship entails a corresponding sense of responsibility and accountability for the work produced. Those holding this perspective emphasized the ethical dimension of solely relying on technological tools for academic content generation. They underscored the value of creativity in academic writing and advocated for the ethical use of GenAI tools. While acknowledging the significance of GenAI in facilitating self-learning, the conservatives among these groups firmly maintained that authorship criteria should always be accompanied by a sense of responsibility and ethical considerations and that the use of these tools should be discontinued in the academic environment.

One of the respondents submitted that: “writing should be done by the individual, not by an AI…..this defeats the purpose of creativity and renders one unsure if the researcher/student actually produced the work or just depended on a tool to submit it” [ID: 50]. Another one added that: “attribution of academic work should come with accountability for the work done, which is crucial for academic integrity” [ID 345]. Another participant commented that: "in all ramifications, it’s cheating when you cannot write your assignment or research by yourself…. people should be creative to do their academic work and not depend on AI tools…..it’s okay when you use them as writing assistants” [ID: 326]. One participant mentioned that: “as an academic tutor, I’m always on the part of groups that seek for justice to the academics. The introduction of AI tools has put us at the edge of sword….we can’t decide what to do, but I do feel using them for academic work while taking personal credit for the work you didn’t do is outright cheating” [ID: 784].

Assistive learning tools

Although the first theme tends to slightly dominate the discussion, a significant quarter of the respondents do not consider the use of GenAI for academic work cheating. Their justification was that GenAI tools are just assistive technologies that provide academic assistance similar to other technological tools such as Google. Within this quarter, some firmly believe in the “Technology for All” initiative, acknowledging the potential of technology for improving learning outcomes.

One of the respondents commented that: “they are assistive technologies….using them for academics does not matter, what matters is learning and experience gained” [ID: 416]. Another respondent added that: “the essence of all technologies is for students to learn as far as the goal will be achieved…. I see no harm in it because we are in a digital era where technology serves as assistive tools for self-learning and development”. [ID: 398]. One respondent affirmed that: “using them is just like using Google… they are tools purposely designed to help people do their work efficiently…. I don’t consider their use cheating because learning can occur in any form” [ID: 656].

Some groups believe in social justice, stressing the importance of equity and fairness. These groups submitted that classifying the use of AI technologies in learning as cheating could impede the attainment of sustainable development goals (SDGs) and present challenges to the pursuit of social justice. For example, one participant reported that: “classifying the use of AI technologies as a form of academic dishonesty raises concerns about its potential implications for social justice…Over the years, technology has seamlessly integrated into our lives and has proven to be a valuable asset to the academic community…. thus, it is imperative to critically assess whether labeling the use of AI tools as cheating would be equitable and fair to students” [ID: 518]. Another response reads: “…….as we strive to achieve sustainable development goals, promoting inclusive and accessible education for all is a paramount objective……embracing AI technologies in education aligns with this global aspiration….by discouraging their use through

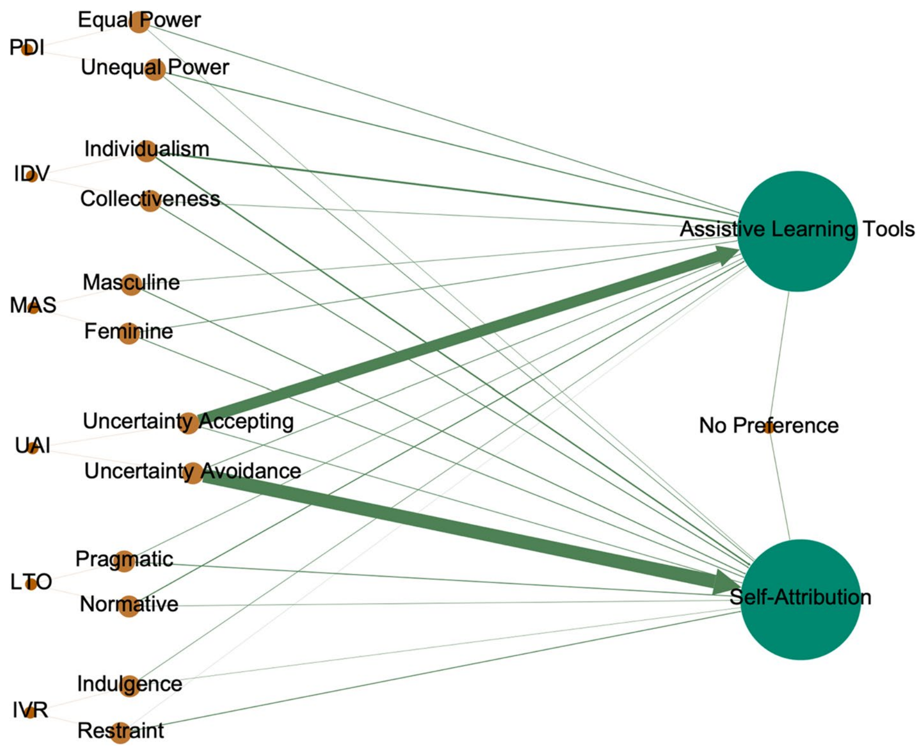

Fig. 8 Association between cultural dimensions and classification of GenAI

a broad-brush label of cheating, we risk inhibiting progress toward educational equity, which is a fundamental tenet of social justice" [ID: 614].

From these opinions, it appears that the question of whether using GenAI by students constitutes cheating can be subjective and context-dependent. It depends on the educational institution's policies, the specific assignment or task at hand, and the intent behind using the tools. To further understand whether cultural dimensions influence the respondents' justifications, we correlated participants' responses with their country's cultural scores using a network graph. Our network graph (see Fig. 8) indicates that quite a number of participants from uncertainty-avoidance countries support the "self-attribution" theme while those from uncertainty-accepting countries support the "assistive learning tools" theme. Responses from other cultural dimensions displayed an approximate uniform distribution, implying the absence of influence from these dimensions on the classification of GenAI.

Perceived importance of GenAI to students and teachers in HE

In our survey, participants were requested to articulate their perceived importance of GenAI within the context of higher education, as it pertains to both students and educators (see Fig. 9). A considerable cohort of the respondents, comprising 38.5% and 36.2% of teachers and students respectively, expressed that GenAI holds a substantially high level of importance. Furthermore, 25.6% and 29.0% conveyed that GenAI possesses a moderate level of importance for both students and teachers, while a smaller subset of 8% and 9.4% indicated a perception of negligible importance. It is noteworthy that

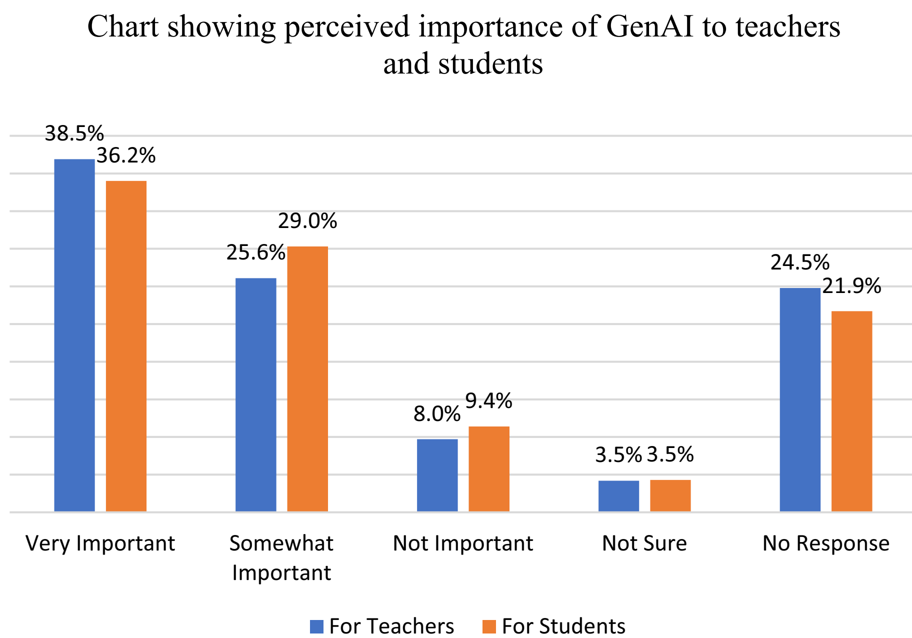

Fig. 9 Perceived importance of GenAI to teachers and students

certain responses could not be definitively categorized, primarily due to intentional omissions by respondents or automatic omissions triggered by prior survey responses.

Perceived potential and concerns of GenAI in HE

We conducted a comprehensive investigation to gain deeper insights into participants' perceptions regarding the potential and concerns associated with GenAI in higher education, utilizing a Likert scale response format. To facilitate the interpretation of participants' responses, we adopted the interpretative rating system proposed by Pimentel (2019). This rating system was employed to mitigate potential biases and rectify any inaccuracies present in prior assessments. Consequently, the rating scale is defined as follows: scores ranging from 1.00 to 1.79 denote a "strongly disagree" stance, while scores between 1.80 and 2.59 indicate a "disagree" perspective. A score within the range of 2.60 to 3.39 signifies a "neutral" position, while scores from 3.40 to 4.19 reflect an "agree" viewpoint. Finally, scores falling between 4.20 and 5.00 are indicative of a "strongly agree" standpoint.

The findings presented in Table 5 reveal noteworthy trends among the participants' responses. A substantial proportion of the participants (Mean $= 4.302 \pm 0.89$) strongly agreed with the notion that GenAI tools exhibit a high level of proficiency in responding to queries. Furthermore, a majority of the respondents indicated agreement with several other attributes of GenAI tools, including their capacity to deliver personalized and immediate learning support ($M = 4.082 \pm 0.96$), offer a valuable starting point and aid in the process of brainstorming ($M = 3.837 \pm 1.08$), assist in literature search and provide concise summaries of relevant materials ($M = 3.783 \pm 1.21$), facilitate knowledge acquisition and offer writing support ($M = 4.016 \pm 0.96$), as well as contribute to enhancing equity and accessibility in education ($M = 3.801 \pm 1.037$).

Table 5 Perceived potential of GenAI in HE

S/N	Items	Mean	Std. Dev.
1	Generative AI tools can respond to questions easily	4.302	0.891
2	They provide personalized and immediate learning support	4.082	0.961
3	They provide a starting point and brainstorming support	3.837	1.080
4	They facilitate literature search and summarized reading	3.783	1.201
5	They promote creativity and critical thinking skills	3.327	1.373
6	They help in problem-solving that is beyond the scope of the teacher	3.255	1.207
7	They facilitate knowledge acquisition and support writing tasks such as codes, essays, poems, and scripts	4.016	0.968
8	They have the potential to reform education	3.382	1.204
9	They promote equity and access to education	3.801	1.037

Table 6 Perceived concerns of GenAI in HE

S/N	Items	Mean	Std. Dev.
1	Generative AI tools can generate output that is factually inaccurate	4.181	1.021
2	They can generate output that is out of context or inappropriate	3.984	1.127
3	They can exhibit biases and unfairness in their output	3.592	1.234
4	They rely too heavily on online statistics, which can limit their usefulness in certain contexts	4.062	1.018
5	They have limited emotional intelligence and empathy, which can lead to output that is insensitive or inappropriate	3.807	1.154
6	They are too strong, so they may collect our personal information	3.149	1.150
7	They promote cheating and plagiarism without being easily detected	4.002	1.108
8	There is over-reliance on AI tools, and this may hinder students' and teachers' growth, skills, and intellectual development over time	4.037	1.119
9	Knowledge of Generative AI tools is limited as they cannot provide answers to every question	3.998	1.082
10	Generative AI poses threats to academic integrity	3.807	1.258

In contrast, a notable number of participants adopted a neutral stance regarding the assertion that GenAI tools promote creativity and the development of critical thinking skills ($M = 3.327 \pm 1.37$), aid in problem-solving beyond the purview of teachers ($M = 3.255 \pm 1.21$), and possess the potential to bring about transformative reforms in the realm of education ($M = 3.38 \pm 1.20$).

Despite the favorable perspectives on the potential utility of GenAI tools in HE, participants also expressed noteworthy concerns about these tools (see Table 6). A majority of respondents concurred that GenAI systems are susceptible to producing factually inaccurate outputs ($M = 4.181 \pm 1.021$), can generate content that is contextually inappropriate or irrelevant ($M = 3.984 \pm 1.13$), may manifest biases and unfairness in their generated outputs ($M = 3.592 \pm 1.23$), heavily rely on online sources, thereby potentially limiting their reliability and applicability ($M = 4.062 \pm 1.02$), and, due to their absence of emotional intelligence, may occasionally generate insensitive or inappropriate content ($M = 3.807 \pm 1.15$).

Moreover, a significant majority of participants shared the view that GenAI tools have the potential to facilitate academic misconduct, particularly in terms of cheating and plagiarism ($M = 4.002 \pm 1.12$). Concerns were also raised regarding the

Table 7 Relationship between culture and perceived concerns and potential of GenAI

	PDI	IDV	MAS	UAI	LTO	IVR	Potential	Concerns
PDI	1.00							
IDV	− 0.065	1.00						
MAS	− 0.120	− 0.264	1.00					
UAI	0.207	0.045	− 0.293	1.00				
LTO	− 0.087	0.092	− 0.082	− 0.201	1.00			
IVR	− 0.214	0.035	0.238	− 0.292	− 0.332	1.00		
Potential	− 0.113	0.017	0.271	− 0.375**	0.272*	0.281	1.00	
Concerns	− 0.242	− 0.009	− 0.068	0.539***	0.038	0.013	0.011	1.00

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

possibility that excessive reliance on these tools may impede the personal and professional growth of both students and educators ($M = 4.037 \pm 1.12$), as well as the recognition that these tools are not universally capable of providing answers to all types of queries ($M = 3.998 \pm 1.08$). Lastly, respondents expressed apprehension about the threats posed to academic integrity by the widespread use of GenAI tools ($M = 3.807 \pm 1.26$). Nevertheless, it remains unclear whether GenAI possesses the capability to gather personal information, given that a substantial proportion of the respondents ($M = 3.149 \pm 1.15$) adopted a neutral stance in response to this assertion. In conclusion, these findings underscore the complex landscape surrounding GenAI in higher education, necessitating further exploration and careful consideration of its implementation and regulation.

We conducted a correlation analysis to examine the associations between participants' perceptions of the potential and concerns related to GenAI and their respective cultural dimensions (see Table 7). The findings reveal a noteworthy negative and statistically significant relationship between the cultural dimension of uncertainty avoidance and the perceived potential of GenAI within the realm of higher education ($r = -0.375$, p-value < 0.01). Furthermore, a positive and statistically significant correlation is observed between uncertainty avoidance and concerns regarding the implementation of GenAI in higher education ($r = 0.539$, p-value < 0.001). Additionally, we find that the cultural dimension of long-term orientation exhibits a statistically significant correlation with the perceived potential of GenAI in higher education. However, it is important to note that this dimension does not exhibit a statistically significant relationship with concerns surrounding the utilization of GenAI in the higher education context. In conclusion, our analysis underscores the influence of cultural dimensions, particularly uncertainty avoidance and long-term orientation, on perceptions of GenAI within the higher education sector.

Perceived policies to regulate GenAI usage in HE

While participants expressed their perceptions regarding the potential and concerns associated with GenAI, they concurrently conveyed their viewpoints on the necessity of policy enforcement for regulating such technological tools (see Fig. 10). Notably, a substantial proportion of participants (42.7%) advocated for the implementation

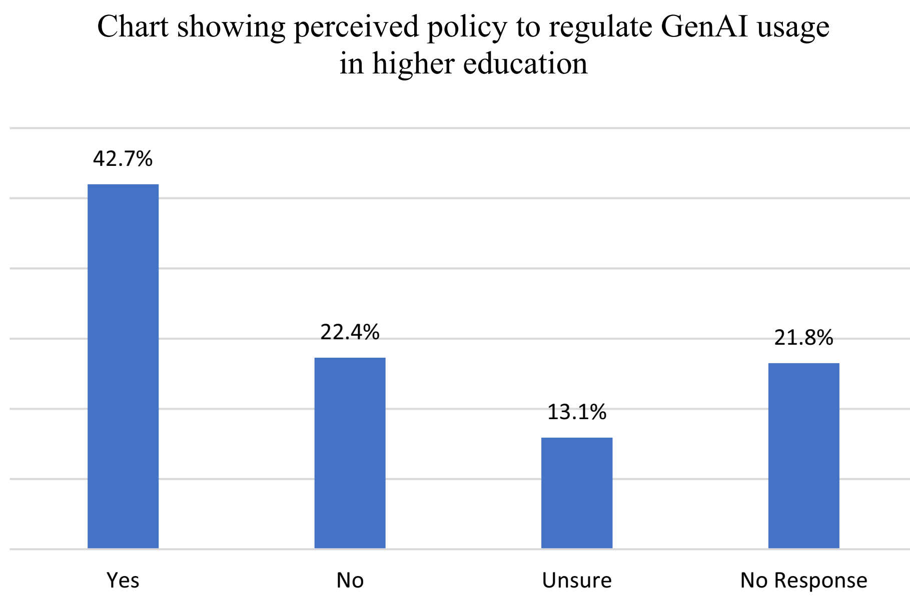

Fig. 10 Perceived policy to regulate GenAI usage in HE

of regulatory policies. In contrast, 22.4% articulated their stance that no regulatory policies should be imposed, while 13.1% remained uncertain on the matter. It is worth highlighting that 21.8% either chose to omit their response to this inquiry or encountered automatic question skipping facilitated by the survey engine, a mechanism triggered by preceding survey responses.

We conducted a follow-up question to understand the specific policies required to regulate GenAI. Among the cohorts that conveyed their viewpoints on the necessity for policy enforcement, a larger proportion indicated "restriction to self-learning", a considerable number indicated "prevention of use on assignment and research", while a more conservative group indicated a "total ban" of the tool in the academic environment. While these submissions were idiosyncratic to each respondent, more than two-thirds reiterated in their response that "strict penalty" should be enforced when used for cheating and plagiarism.

For example, one participant commented that: "……policies to prevent use in assignments and compositions related to research…. there should be strict regulations and accountability on the part of the people who are found to have used AI to generate assignments instead of creating them on their own" [ID: 49]. Another respondent added: "AI tools should be able to help students and teachers to save time…they can provide a strong basis for further brainstorming and development. The policies should allow that….anything beyond that should be detected, flagged as plagiarism, and penalized" [ID: 103]. In a more diverse view, one participant explained: "I think it can be used in the case of searching for information on any subject….due to which we will be able to gain a lot of knowledge about that. If we use it outside of it, we will fail to develop our talent properly….as a result, the entire nation will become unskilled, which is threatening to us" [ID: 83].

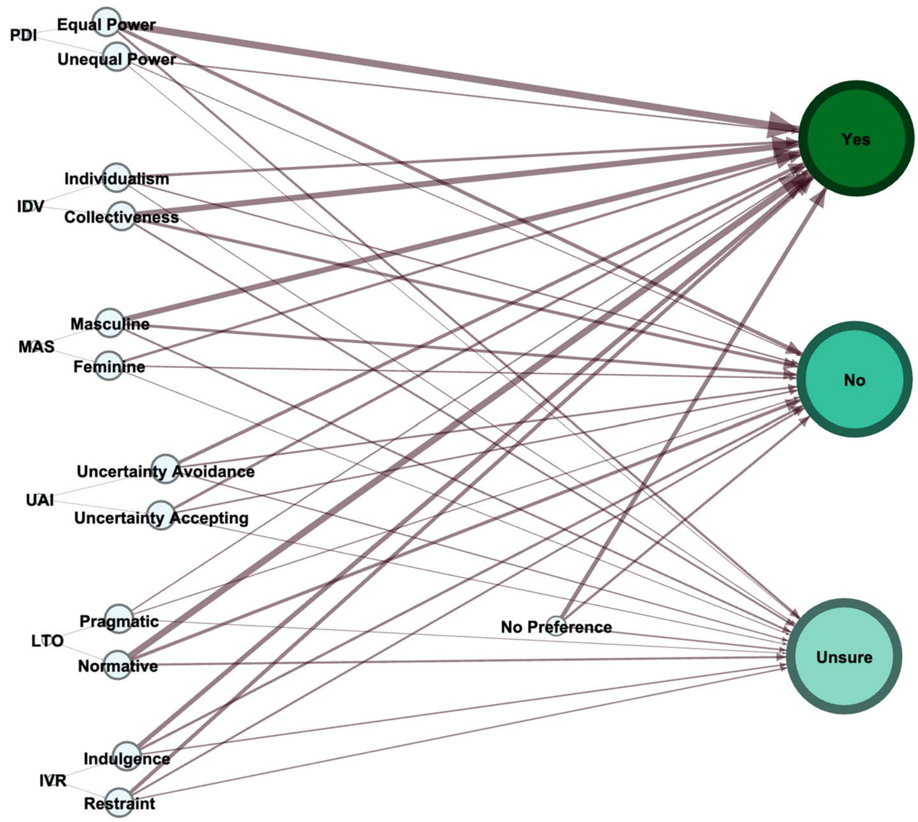

Fig. 11 Relationship between cultural dimension and perceived policy enforcement on GenAI usage in HE

These insights from the participants underscored the need for comprehensive and adaptable policies that balance the potential benefits of GenAI with the imperative to maintain academic integrity and foster genuine learning and creativity.

To conclude our analysis, we correlated the participants' viewpoints on the necessity for policy enforcement with their cultural dimensions (see Fig. 11). Except for the uncertainty-avoidance and indulgence-vs-restraint dimensions, our network graph shows a significant connection between cultural dimensions and the participant's perceived policy enforcement on GenAI usage in HE Specifically, participants from countries characterized to be dominated by low power distance, collectiveness, masculinity, and normative cultural practices expressed the view that policy regulation should be enforced on GenAI usage in higher education. This is contrary to their counterparts originating from countries with high power distance, individualism, femininity, and pragmatic cultural orientations.

Discussion

We conducted a comprehensive inquiry into the perceived potential and concerns surrounding GenAI within the context of higher education (HE), taking into account various multicultural dimensions. Furthermore, our investigation encompassed an exploration of the broader utilization of GenAI, the perceptions of its potential for academic dishonesty, and the perceived need for regulatory policies to ensure its responsible usage.

This empirical study was administered through an online survey and gathered responses from a diverse pool of 1217 participants hailing from 76 different countries. Our study yielded several findings.

First, our findings revealed a high level of awareness and recognition of GenAI in HE, aligning with the broader trend of AI integration across various domains (Chan & Hu, 2023; Jeon & Lee, 2023). Variances in familiarity with specific GenAI tools, with ChatGPT being the most recognized (Denejkina, 2023), may be attributed to differences in accessibility, marketing, and versatility. ChatGPT, known for its natural language generation, gained prominence due to its adaptability for tasks such as content generation and question answering (Yilmaz & Yilmaz, 2023b). Literature supports the influence of AI accessibility and user-friendliness on adoption (Ipek et al., 2023).

Additionally, a substantial number of participants reported prior GenAI use, with a majority inclined to continue using them in the future. This reflects the growing trend of integrating AI technologies into education (Glaser, 2023), aligning with the literature on adoption (Ali et al., 2023). AI's benefits, including personalized learning support and efficient information retrieval, contribute to this view (Rawas, 2023). We found that GenAI is primarily used for information retrieval and text paraphrasing in HE, supporting research and content creation. GenAI's human-like text generation streamlines these tasks, saving time and enhancing efficiency (Denejkina, 2023; Lim et al., 2023).

A substantial majority of respondents believe that the incorporation of GenAI tools in academic pursuits amounts to outright cheating. In contrast, a significant number of participants argue that using them within an academic context should not be classified as cheating. The former belief aligns with concerns in the literature about GenAI's potential to facilitate academic dishonesty, particularly in the form of plagiarism (Chan & Hu, 2023). Plagiarism detection and prevention have long been challenges in education, and the introduction of GenAI technologies has added complexity to this issue (Ali et al., 2023). Conversely, the belief that GenAI should not be deemed academic dishonesty may arise from the perspective that these tools can enhance learning experiences and productivity. Nevertheless, the diverse range of viewpoints among participants reflects the ongoing debate in the literature.

The ethical considerations and behavioral intentions of participants regarding the use of GenAI tools for plagiarism are particularly noteworthy. While a significant portion of those who have previously used GenAI for plagiarism express a commitment to abstain from future misconduct, a substantial number remain determined to continue engaging in such academic dishonesty. This divergence in behavioral intentions underscores the complexity of addressing academic integrity concerns in the digital era. The literature acknowledges the role of ethics education and the cultivation of a culture of academic integrity in mitigating plagiarism (Draper & Newton, 2017). In this regard, educational institutions must nurture a sense of responsibility and ethical awareness among students and educators concerning the use of these technologies.

A significant proportion of participants expressed confidence in GenAI's proficiency in responding to queries, reflecting their belief in these tools' abilities to provide accurate and relevant information. This aligns with the broader trend of AI advancements in natural language processing (Chan & Hu, 2023). Additionally, participants recognized GenAI's potential for delivering personalized learning support, facilitating literature searches, and promoting equity and accessibility in education. These perceptions mirror the growing interest in leveraging AI to enhance educational quality and inclusivity (Tlili et al., 2023).

However, alongside this optimism, participants also voiced notable concerns about GenAI. A majority were apprehensive about the potential for these tools to generate factually inaccurate outputs, produce contextually inappropriate or irrelevant content, and exhibit biases and unfairness. These concerns align with broader discussions on AI ethics, emphasizing the importance of transparency and fairness in AI systems (Chan & Hu, 2023; Naik et al., 2022). Participants also raised concerns about over-reliance on online sources, which could compromise the reliability and applicability of GenAI-generated content. Existing research agreed with our findings, highlighting both benefits and concerns in the integration of GenAI in education (De Cremer & Narayanan, 2023; Dwivedi et al., 2023).

Our study revealed diverse viewpoints on the necessity of policy enforcement for regulating the use of GenAI. Notably, a large proportion of the participants advocate for such policy implementation, including a total ban or restriction on personalized learning. Their stance reflects a proactive approach to addressing the challenges and ethical considerations associated with GenAI usage. These advocates likely recognize the potential benefits of GenAI but also acknowledge the importance of establishing clear guidelines to ensure responsible and ethical usage. In contrast, a considerable number of participants express opposition to the imposition of regulatory policies. Their viewpoint suggests a preference for a more permissive approach, possibly driven by a belief in individual autonomy and limited interference in academic practices. Consistent with prior studies (e.g., Chan, 2023), the regulation of GenAI in higher education requires a subtle approach that acknowledges both its potential benefits and the imperative to uphold academic integrity.

While our participants' viewpoints may exhibit idiosyncrasy, our study identified significant correlations across cultural dimensions. These correlations were notably present in responses related to the classification of GenAI as a form of academic dishonesty, perceived impacts and concerns, and the enforcement of regulatory policies. Specifically, we found that cultures characterized by high uncertainty avoidance displayed a significantly greater tendency to classify students' utilization of GenAI as instances of cheating. Additionally, nations with a pronounced long-term orientation were also more inclined to categorize students' use of GenAI as cheating.

In the context of the potential and concerns associated with GenAI, we observed a strong negative correlation between the cultural dimension of uncertainty avoidance and the perceived potential of GenAI in HE. Additionally, there was a positive correlation between uncertainty avoidance and concerns about GenAI. The study also identified a statistically significant correlation between long-term orientation (LTO) and the perceived potential of GenAI. Furthermore, there is a significant correlation between the dimensions of power distance, masculinity, collectiveness, and long-term orientations and the perceived enforcement of regulatory policies on GenAI.

Several explanations can be provided for the correlation between cultural dimensions and perspectives on the use of GenAI in HE. Firstly, the concept of uncertainty avoidance pertains to a society's capacity to tolerate ambiguity and its readiness to embrace risks (Hofstede, 1989). Consequently, nations characterized by a strong inclination to avoid uncertainty are more prone to perceive AI usage as a menace to academic integrity (Krishnamoorthy et al., 2022). We argued that such societies exhibit a diminished inclination to view the potential of GenAI positively and a heightened tendency to acknowledge concerns regarding GenAI. These concerns stem from apprehensions related to technological errors, ethical implications, or potential disruptions to conventional educational practices (Krishnamoorthy et al., 2022).

Secondly, nations characterized by a pronounced long-term orientation exhibit a greater tendency to categorize the utilization of GenAI as academic misconduct. This inclination arises from their prioritization of upholding traditional academic values, perceiving GenAI tools as a departure from these established norms. Conversely, they may also recognize GenAI as a means to enhance learning outcomes and adapt to future challenges, thus acknowledging its enduring advantages and transformative potential (Sun et al., 2019). In cultures characterized by low power distance, there is a prevailing emphasis on equality and collective decision-making. This aligns with the concept of establishing regulatory frameworks to ensure equitable and just access to GenAI tools in the educational context.

In contrast, cultures marked by high power distance may prioritize individual autonomy and discretion, which can lead to a preference for fewer regulatory measures. Collectivist cultures tend to uphold principles of fairness and equity within the academic community, which is in contrast to individualistic cultures that emphasize personal autonomy and advocate for reduced regulation, thus favoring individual choice in the utilization of GenAI (Kovacic, 2009). Cultures with high masculinity may be more receptive to technological innovations as a means of advancing in various domains. This could result in a greater willingness to explore and integrate GenAI-driven solutions in teaching, learning, and administrative functions within HE institutions (Tarhini et al., 2017). Due to the high propensity of these countries to embrace technological tools, we argued that they are more likely to call for strong policies that will shape the ethical usage of GenAI in HE.

In conclusion, the correlation between cultural dimensions and GenAI perceptions (ethical classification, impacts, concerns, and policy viewpoints) emphasizes the need for a subtle approach to regulation. Cultural factors significantly shape individuals' perceptions (Jan et al., 2022), and any policy framework must consider these variations to create a balanced and effective regulatory environment for GenAI in HE.

Conclusion and recommendations

This scholarly discourse undertook a thorough examination of GenAI technologies within the context of multicultural perspectives. Our research revealed a significant degree of awareness and familiarity with GenAI tools among our survey respondents. Furthermore, a substantial portion of the respondents had prior experience using these tools and expressed a likelihood of continued usage in the future. Their primary use of GenAI tools was for information retrieval and text paraphrasing. The findings revealed significant benefits of GenAI utilization in HE, along with associated concerns. On the one hand, fostering appropriate and responsible use of GenAI tools can enhance various aspects of the learning process. On the other hand, addressing these concerns may require the implementation of robust policies and guidelines.

Nevertheless, our findings indicate a strong correlation between responses regarding GenAI utilization and cultural practices. The recognition of such an association underscores the importance of tailoring educational strategies and policies to specific cultural contexts within higher education. It emphasizes the need for ongoing research and dialogue to better understand these dynamics and develop more effective guidelines for the responsible and equitable incorporation of GenAI technologies into the educational landscape. Such policies should be flexible enough to accommodate cultural variations in attitudes and expectations, fostering a fair and inclusive learning environment. To this end, we suggest that a one-size-fits-all approach to GenAI integration in HE may not be appropriate. Instead, institutions must take cultural diversity into account when formulating policies and strategies for GenAI adoption.

Limitation

Our study has confirmed the validity of the cultural dimension proposed by Hofstede. However, we have some concerns because in reality, culture is complex and multifaceted, and reducing it to a few dimensions may oversimplify the true diversity of cultural values and behaviors within a society. Within any culture, there can be significant variations in values, beliefs, and behaviors based on factors such as age, gender, education, urban–rural divide, and socioeconomic status. Hofstede's framework tends to treat cultures as monolithic entities, ignoring these internal variations. Nevertheless, this dimension has shown reliable results in several studies, informing wider replication. We, therefore, believe that our results may have substantial validity.

We also noticed a significant disparity in the participants' demographic distribution. While this is beyond our control, we recommend that further multinational studies employ a more balanced participant recruitment strategy toward preventing the noted disparity. Nevertheless, we believe that the disparity did not invalidate our findings as each cultural dimension has a representative country. Lastly, participants were not assigned unique links for accessing our online survey. While efforts were made to prevent multiple submissions and ensure an anonymous data collection process, the absence of personalized links for each participant may increase the risk of unauthorized access to the survey. We, therefore, propose the necessity of personalized links in future research but recommend anonymous data collection to prevent bias.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s41239-024-00453-6.

Additional file 1. Supporting Information.

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Author contributions

AY: Conceptualization; Data curation; Analysis; Investigation; Methodology; Project administration; Writing—original draft, review and editing. NP: Conceptualization; Data curation; Writing—original draft, review and editing. MR: Data curation; Writing—review and editing. All authors read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests

The authors declare no conflict of interest.

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