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Investigating the higher education institutions' guidelines and policies regarding the use of generative AI in teaching, learning, research, and administration

Yunjo An[1*], Ji Hyun Yu[1] and Shadarra James[1]

*Correspondence:
Yunjo.An@unt.edu

[1] Department of Learning Technologies, University of North Texas, Denton, TX 76207, USA

Abstract

This study examined the guidelines issued by the top 50 U.S. universities regarding the use of Generative AI (GenAI) in academic and administrative activities. Employing a mixed methods approach, the research combined topic modeling, sentiment analysis, and qualitative thematic analysis to provide a comprehensive understanding of institutional responses to GenAI. Topic modeling identified four core topics: Integration of GenAI in Learning and Assessment, GenAI in Visual and Multimodal Media, Security and Ethical Considerations in GenAI, and GenAI in Academic Integrity. These themes were further explored through sentiment analysis, which revealed highly positive attitudes towards GenAI across all institution types, with significant differences between faculty and student-targeted guidelines. Qualitative thematic analysis corroborated these findings and provided deeper insights, revealing that 94% of universities had faculty guidelines emphasizing the importance of establishing and communicating course-specific GenAI policies. This analysis also highlighted recurring themes such as academic integrity and privacy concerns, which aligned with the security and ethical considerations identified in the topic modeling. The study highlights the rapid evolution of GenAI guidelines in higher education and the need for flexible, stakeholder-specific policies that address both the opportunities and challenges presented by this technology.

Keywords: Academic integrity, Artificial intelligence, ChatGPT, Generative AI, Higher education, Institutional Guidelines, Policies

Introduction

Following the public release of ChatGPT, generative artificial intelligence (GenAI) tools have been increasingly adopted in various sectors, including higher education (Ghimire & Edwards, 2024). Initially, ChatGPT evoked mixed reactions. Early reports on the reactions of higher education institutions (HEIs) to GenAI showed a range of responses. Some universities banned the use of GenAI tools, while others fully embraced it, allowing their use for teaching and learning (McDonald et al., 2024).

The policy of banning the use of GenAI was later criticized as unsustainable and counterproductive in cultivating AI-literate citizens for the future (Chan, 2023; Lodge et al., 2023; Rudolph et al., 2023; Sullivan et al., 2023). Indeed, increasing numbers of students and faculty are using GenAI, and banning its use does not seem to be a feasible solution. *The Times Newspaper* reported that almost half of the students at Cambridge University in the United Kingdom admitted to using ChatGPT during their studies (Sleator, 2023). Similarly, *Forbes* magazine reported that 20% of college students in the United States admitted using AI to complete their schoolwork (Nietzel, 2023). The incredibly fast adoption of GenAI by students in higher education has intensified calls for guidelines and policies for its use in HEIs worldwide (Moorhouse et al., 2023).

While recent studies have begun to explore GenAI policies in higher education, our research offers several unique contributions to this rapidly evolving field. First, we focus specifically on the top 50 U.S. universities, providing a comprehensive analysis of how leading institutions are responding to GenAI. Second, our mixed-methods approach, combining topic modeling, sentiment analysis, and qualitative thematic analysis, offers a more contextualized and multifaceted understanding of institutional guidelines than previous studies. Third, we examine guidelines targeted at multiple stakeholders, including faculty, students, researchers, staff, and administrators, revealing a holistic picture of institutional approaches across various roles within higher education. Our application of natural language processing techniques to analyze GenAI guidelines contributes to the growing body of methodologically rigorous research in this area.

This study aims to examine the guidelines issued by the top 50 U.S. higher education institutions concerning the use of GenAI in their academic and administrative activities. By providing a detailed and comprehensive analysis of current guidelines and policies across multiple stakeholder groups, our research offers valuable insights for policymakers, administrators, and educators grappling with the challenges and opportunities presented by GenAI in higher education.

Literature review

Potential benefits and pitfalls of GenAI

GenAI holds the potential to significantly transform educational practices in higher education (Yan et al., 2024b). The literature shows that GenAI can facilitate personalized and adaptive learning, provide personalized guidance and support, offer immediate feedback, and facilitate communication and collaboration (Cotton et al., 2023; Hwang & Chen, 2023; Yan et al., 2024a). Indeed, GenAI can play a range of roles in teaching and learning processes. For example, the United Nations Educational, Scientific and Cultural Organization (UNESCO) identified 10 roles and examples of how ChatGPT could be incorporated and used to augment teaching and learning (UNESCO, 2023). The UNESCO (2023) suggests that ChatGPT can be used as "Socratic opponent," "collaborative coach," "guide on the side," "personal tutor," and "study buddy" among other roles. Similarly, Hwang and Chen (2023) categorized the roles of GenAI in education into six categories: teacher/tutor, student/tutee, learning peer/partner, domain expert, administrator, and learning tool. However, researchers caution that the benefits of GenAI can be achieved only when it is effectively used (McDonald et al., 2024).

The primary concerns regarding the use of GenAI in higher education have been the issues of academic integrity and academic dishonesty (Chan, 2023; Cotton et al., 2023; Moorhouse et al., 2023; Rudolph et al., 2023; Sullivan et al., 2023). Many people are concerned that students may use GenAI to cheat or plagiarize their written assignments or exams by submitting AI-generated content. The release of ChatGPT was quickly followed by the development of AI content detection tools, such as ZeroGPT, GPTZero, and Winston AI. However, many researchers have questioned the accuracy of these tools, and a general consensus is that these detection tools still remain unreliable (e.g., Dalalah & Dalalah, 2023; Kohnke et al., 2023; Lodge et al., 2023; McDonald et al., 2024; Moorehouse et al., 2023). Kohnke et al. (2023) note that the use of these detection tools may lead to a cat-and-mouse game, with GenAI developers and detection tools constantly trying to outpace each other, leaving users with no assurance of reliable detection.

In addition to the academic integrity and academic dishonesty issues, researchers have argued that students could become overdependent on GenAI, potentially negatively impacting their writing and critical thinking skills (Chan & Lee, 2023; Darvishi et al., 2023). There are also concerns about unequal access to GenAI tools, student privacy and data security, biases in AI algorithms, and the spread of fraudulent information generated by AI (Ghimire & Edwards, 2024; Luo, 2024; Rudolph et al., 2023; Sullivan et al., 2023; UNESCO, 2023; Yan et al., 2024b).

The need for institutional guidelines and policies

The increased adoption of GenAI has had a disruptive effect on the assessment practices in HEIs worldwide, and the disruptive nature of GenAI places significant pressure on universities to develop policies and guidelines in response to GenAI (Luo, 2024; Rudolph et al., 2023; Sullivan et al., 2023). For example, Rudolph et al. (2023) suggests the HEIs "develop policies and clear, easy-to-understand guidelines for the use of language models in learning and teaching—the guidelines should include information on the proper use of these tools and the consequence of cheating" (p.356).

Although many AI-related guidelines were published before the release of ChatGPT, most are generic and do not specifically address issues and challenges caused by GenAI in higher education (Nguyen et al., 2023; Schiff, 2022;). Ghimire and Edwards (2024) found that the majority of institutions lacked specialized guidelines for the ethical use of GenAI and that existing policies often overlooked critical issues such as student privacy. Many international organizations, such as the United Nations Educational, Scientific and Cultural Organization (UNESCO, 2023) and the Organization for Economic Co-operation and Development (OECD, 2023), have published guidelines on the use of GenAI in education. However, these guidelines focus on wider issues related to GenAI's impact (e.g., national regulations, digital poverty) rather than on the specific problems faced by higher education (Luo, 2024).

Researchers have emphasized the need for institutional policies for the effective integration of GenAI within higher education (Jin et al., 2024; Moorhouse et al., 2023). The lack of clear guidelines and policies on GenAI adds to the difficulty for universities to effectively address GenAI-related challenges (Luo, 2024). In addition, the lack of clarity could be troubling for instructors and students who look to institutional guidelines to guide their practices (Kohnke et al., 2023; Moorhouse et al., 2023).

Prior research on GenAI guidelines and policies in higher education

Since the emergence of GenAI tools such as ChatGPT, universities worldwide have been working on guidelines and policies regarding the use of these tools in teaching, learning, and assessment (Chan, 2023), and several studies have examined those guidelines and policies. For example, Moorhouse et al. (2023) investigated the extent to which the world's top 50 higher education institutions have developed or modified their assessment guidelines in response to the emergence of GenAI tools. The results showed that the assessment guidelines covered three main areas, including academic integrity, assessment design, and communicating with students. However, it is worth noting that less than half of the institutions had developed publicly available assessment guidelines. Overall, the study indicates that HEIs have come to embrace GenAI as a part of the assessment process. Similarly, Luo (2024) focused on university policies regarding the use of GenAI in assessment. Focusing on the problems represented in assessment policies of the top 20 universities recognized by the 2024 QS World University Rankings, Luo (2024) found that students' use of GenAI was presented as a threat to the originality of their work. Further, the results showed that the originality of students' work was mainly framed as a concern of plagiarism or academic misconduct.

McDonald et al. (2024) analyzed guideline documents produced by 116 U. S. universities categorized as high research activity or R1 institutions to understand GenAI-related advice and guidance given to institutional stakeholders. They found that over 60% of the universities encouraged the use of GenAI and that about 40% provided detailed guidance for its use in the classroom. More than half of the institutions (56%) provided sample syllabi, and 50% provided sample GenAI activities that would help instructors integrate GenAI in their classroom. They cautioned that guidance for faculty can become burdensome since continuous revisions are recommended in the policies. Using the Diffusion and Innovations Theory, Jin et al. (2024) examined GenAI adoption strategies in higher education by exploring the characteristics of GenAI innovation as well as the communication channels and roles and responsibilities outlined in university guidelines. The findings revealed a cautious yet proactive approach by universities towards GenAI integration. The study highlighted the need for establishing effective communication strategies to foster broader stakeholder engagement. The study also suggested that clear roles and responsibilities among faculty, students, and administrators are critical for successful GenAI integration.

Purpose of the study

This study aimed to examine the guidelines issued by the top 50 U.S. higher education institutions regarding the use of GenAI in their academic and administrative activities. While previous studies often focused on assessment guidelines or guidelines for faculty, this study included all GenAI-related guidelines given to all institutional stakeholders, including faculty, students, researchers, staff, and administrators. The research was guided by the following research questions:

- What topics are most prevalent in the GenAI guidelines issued by the top 50 U.S. universities?

- How do sentiments in the GenAI guidelines from these universities vary based on institution characteristics and target audience?
- What specific themes do these leading U.S. universities address for different stakeholders (faculty, students, researchers, staff, and administrators) in their GenAI guidelines?

Methods

As Fig. 1 shows, this study used a four-step procedure: (1) data collection, (2) topic modeling, (3) sentiment analysis, and (4) qualitative thematic analysis.

Step 1: data collection

In step 1, we established a search protocol to systematically collect GenAI guidelines from the selected universities. We decided to include the top 50 universities in the United States and used the Times Higher Education (THE)'s best universities in the United States 2024.

(https://www.timeshighereducation.com/student/best-universities/best-universities-united-states) to identify the 50 universities for inclusion. Table 1 lists the names of the 50 top universities and their locations, types (public/private), and sizes.

To locate the GenAI guidelines and policies, the researchers visited all the top 50 universities' official websites and conducted manual searches. For the manual search, various key words were used, including "Generative AI guidelines", "Generative AI guidance", "Generative AI policy", "ChatGPT guidelines", "ChatGPT guidance", and "ChatGPT policy". The following inclusion criteria were used for selecting the guidelines:

- University-wide guidelines and policies
- Publicly available
- Published in English

We obtained a corpus of 214 documents from this process, which formed the basis for our extensive textual analysis. The data contains 214 entries from 50 universities in the US. The total number of sentences is 9,475, and the total number of words is 235,118.

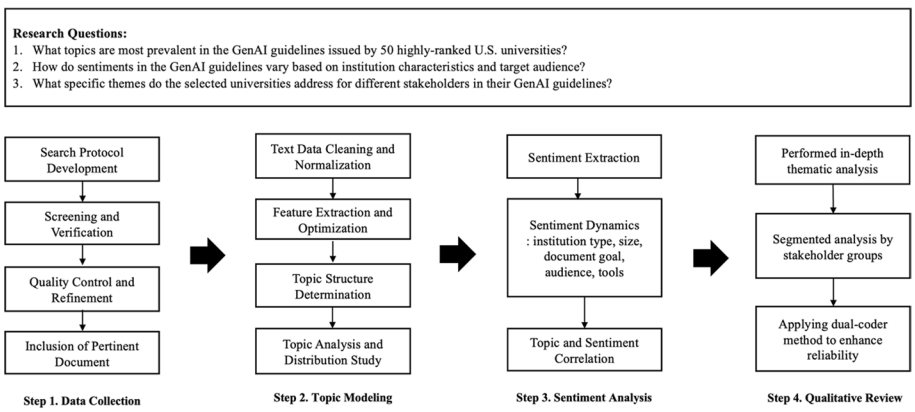

Fig. 1 Study procedure

Table 1 50 Top universities selected for the study

Rank	Name	City	State	Type	Size
1	Stanford University	Stanford	California	Private	Large
2	Massachusetts Institute of Technology	Cambridge	Massachusetts	Private	Medium
3	Harvard University	Cambridge	Massachusetts	Private	Large
4	Princeton University	Princeton	New Jersey	Private	Medium
5	California Institute of Technology	Pasadena	California	Private	Small
6	University of California, Berkeley	Berkeley	California	Public	Large
7	Yale University	New Haven	Connecticut	Private	Medium
8	The University of Chicago	Chicago	Illinois	Private	Medium
9	Johns Hopkins University	Baltimore	Maryland	Private	Large
10	University of Pennsylvania	Philadelphia	Pennsylvania	Private	Large
11	Columbia University	New York City	New York	Private	Large
12	University of California, Los Angeles	Los Angeles	California	Public	Large
13	Cornell University	Ithaca	New York	Private	Large
14	University of Michigan-Ann Arbor	Ann Arbor	Michigan	Public	Large
15	Carnegie Mellon University	Pittsburgh	Pennsylvania	Private	Medium
16	University of Washington	Seattle	Washington	Public	Large
17	Duke University	Durham	North Carolina	Private	Large
18	New York University	New York City	New York	Private	Large
19	Northwestern University	Evanston	Illinois	Private	Large
20	University of California, San Diego	San Diego	California	Public	Large
21	Georgia Institute of Technology	Atlanta	Georgia	Public	Large
22	University of Illinois at Urbana-Champaign	Champaign	Illinois	Public	Large
23	University of Texas at Austin	Austin	Texas	Public	Large
24	University of California, Davis	Davis	California	Public	Large
25	University of Wisconsin-Madison	Madison	Wisconsin	Public	Large
26	Brown University	Providence	Rhode Island	Private	Medium
27	Washington University in St Louis	St Louis	Missouri	Private	Medium
28	University of California, Santa Barbara	Santa Barbara	California	Public	Large
29	University of North Carolina at Chapel Hill	Chapel Hill	North Carolina	Public	Large
30	University of Southern California	Los Angeles	California	Private	Large
31	Boston University	Boston	Massachusetts	Private	Large
32	University of Minnesota	Minneapolis	Minnesota	Public	Large
33	Purdue University West Lafayette	West Lafayette	Indiana	Public	Large
34	University of California, Irvine	Irvine	California	Public	Large
35	Vanderbilt University	Nashville	Tennessee	Private	Medium
36	Ohio State University	Columbus	Ohio	Public	Large
37	Emory University	Atlanta	Georgia	Private	Medium
38	University of Maryland, College Park	College Park	Maryland	Public	Large
39	Michigan State University	East Lansing	Michigan	Public	Large
40	Texas A&M University	College Station	Texas	Public	Large
41	Rice University	Houston	Texas	Private	Small
42	Penn State	State College	Pennsylvania	Public	Large
43	University of Massachusetts	Amherst	Massachusetts	Public	Large
44	University of Florida	Gainesville	Florida	Public	Large
45	University of Rochester	Rochester	New York	Private	Medium
46	University of Colorado Boulder	Boulder	Colorado	Public	Large
47	University of Pittsburgh-Pittsburgh campus	Pittsburgh	Pennsylvania	Public	Large
48	University of Arizona	Tucson	Arizona	Public	Large
49	Dartmouth College	Hanover	New Hampshire	Private	Small

Table 1 (continued)

Rank	Name	City	State	Type	Size
50	Case Western Reserve University	Cleveland	Ohio	Private	Medium

On average, each document contains 1,093.57 words and 44.06 sentences. This corpus provided the opportunity for a thorough descriptive analysis using Term Frequency (TF) and Term Frequency-Inverse Document Frequency (TF-IDF). The objective of this research was to measure the frequency of words inside individual documents (TF) and evaluate the significance of terms across the full collection of documents (IDF). By using these measures, we successfully determined both the most often used phrases and the terms that had particular significance in certain documents. This provided us with first insights into the specialized issues within the wider collection of guidelines and policies regarding generative AI in higher education institutions.

Step 2: topic modeling

In Step 2, we used feature extraction and optimized Latent Dirichlet Allocation (LDA) to identify the main topics. This step focused on thoroughly cleaning the documents by removing unnecessary characters and standardizing the text formats. Additionally, normalization techniques such as lowercasing, stemming, and lemmatization were applied to bring different word forms to their base and dictionary entries. To find the important patterns we were looking for, we eliminated stop words that may potentially cloud the data with linguistic noise. By using tokenization, we divided the text into discrete units of analysis, such as words or concepts, which facilitated the creation of a structured representation of the data. This step was crucial for organizing our data in a way that is suitable for LDA analysis. This process extended beyond just identification of the most frequent or significant words using TF or TF-IDF. Rather, we aimed to use the capabilities of LDA to identify the latent themes present in the corpus. Next, we performed the critical task of determining the structure of topics. We determined the ideal number of subjects by combining statistical validation and domain knowledge.

Step 3: sentiment analysis

In Step 3, we performed sentiment analysis to examine sentiment trends and analyzed the connection between sentiment analysis and topic areas. We computed sentiment scores by utilizing the Sentiment Intensity Analyzer from the Natural Language Toolkit (nltk). This analyzer is part of the VADER (Valence Aware Dictionary and Sentiment Reasoner) lexicon, which is specifically designed for analyzing sentiments expressed in social media. However, it can also be effectively adapted for academic texts. The Sentiment Intensity Analyzer calculates a compound score that combines the overall sentiment expressed in a text, ranging from −1 (indicating a very negative feeling) to + 1 (indicating a highly positive mood). By using these scores, we conducted a comparison of the differences in emotional expression across the chosen documents. This analysis offers valuable insights on the predominant in each document's discussions about GenAI use. In addition to evaluating individual documents, we computed the average

of these sentiment scores by institution to identify patterns and trends across different types of institutions.

Step 4: qualitative thematic analysis

After completing the LDA analysis, it was necessary to further analyze the GenAI guidelines to gain more detailed and contextual understanding. After an initial review of all selected guidelines, we decided to analyze the guidelines separately by target audience (faculty, all stakeholders, students, researchers, and staff/administrators). Thematic analysis methods were used to inductively code guidelines for emerging themes (Miles et al., 2014). To increase reliability, two researchers coded a subset of the guidelines individually, then compared and discussed the identified themes to reach a consensus.

Results

In Table 2, we present distinct characteristics of the 214 documents selected for this study. Following text preprocessing, we extracted 235,118 words from these documents. Subsequently, we calculated their TF and TF-IDF, as detailed in Table 3.

The TF analysis reveals that 'AI' (TF = 4945) and 'tool' (TF = 2609) are the most frequently occurring terms. These terms are closely followed by 'generative' (TF = 2071) and 'ChatGPT' (TF = 1037). The TF-IDF analysis reveals that 'AI' (TF-IDF = 49.004809) and 'tool' (TF-IDF = 26.548032) are not only frequent but also crucial in delineating the thematic content of the documents. Their high TF-IDF scores highlight their central roles in discussions. Similarly, terms like 'generative' (TF-IDF = 24.520669) and 'ChatGPT' (TF-IDF = 11.984026) underscore the critical focus on generative AI and specific AI applications.

The analysis also addresses additional significant terms such as 'academic' (TF-IDF = 10.393287) and 'assignment' (TF-IDF = 10.110615), which reflect the educational and research orientation of the corpus. The presence of terms like 'instructor' (TF-IDF = 8.876741), 'research' (TF-IDF = 7.844217), and 'integrity' (TF-IDF = 6.185632) further supplement our understanding of the academic settings, indicating extensive engagement with pedagogical methods, research activities, and ethical considerations.

Table 2 Document Characteristics of the Selected Universities

Characteristic		Count
Institution Type	Public	116
	Private	98
Institution Size	Small	11
	Medium	42
	Large	161
Tool	Generative AI	201
	ChatGPT	13
Audience	All	65
	Faculty	93
	Students	36
	Researchers	12
	Staff/administrators	8
Total		214

Table 3 TF and TF-IDF

Rank	TF		TF-IDF		Rank	TF		TF-IDF	
	Term	Frequency	Term	Frequency		Term	Frequency	Term	Frequency
1	AI	4945	AI	49.004809	11	Research	523	Research	7.844217
2	Tool	2609	Tool	26.548032	12	Technology	513	Technology	6.902252
3	Generative	2071	Generative	24.520669	13	Write	457	Genai	6.349428
4	Chatgpt	1037	Chatgpt	11.984026	14	Resource	427	Integrity	6.185632
5	Work	901	Academic	10.393287	15	Intelligence	424	Resource	6.074821
6	Academic	782	Assignment	10.110615	16	Artificial	416	Prompt	5.998587
7	Policy	777	Work	9.811413	17	Model	399	Intelligence	5.995653
8	Learn	733	Policy	9.412308	18	Create	399	Write	5.990069
9	Assignment	703	Instructor	8.876741	19	Help	386	Artificial	5.909094
10	Instructor	602	Learn	8.765141	20	Integrity	383	Model	5.787168

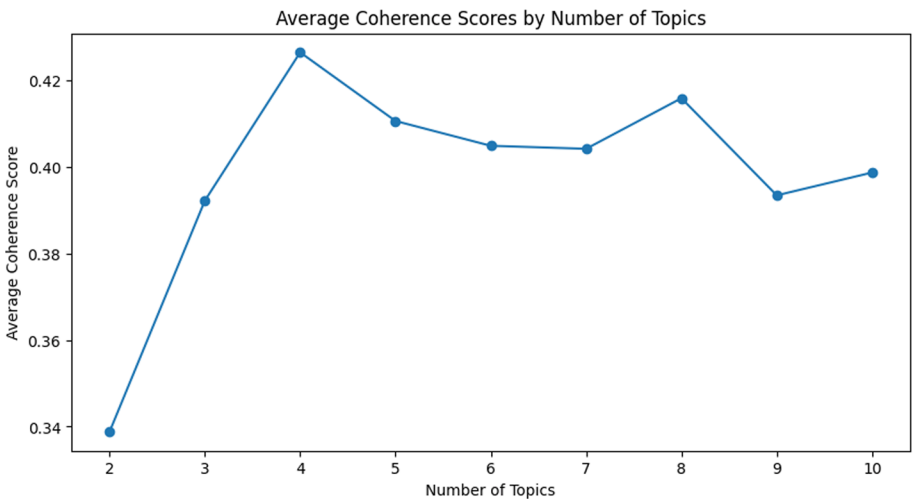

Fig. 2 Coherence scores by number of topics

Results (RQ1): what topics are most prevalent in the GenAI guidelines issued by the top 50 U.S. universities?

Guided by coherence scores, we identified four potential topics (see Fig. 2). These scores are important for evaluating topic quality within models such as LDA, where high coherence scores indicate strong semantic associations among words in a topic, enhancing its meaningfulness and interpretability (Liu et al., 2020; Syed & Spruit, 2017).

The intertopic distance map shown in Fig. 3, utilizing multidimensional scaling, visually represents the relationships between the identified topics. The proximity of the circles indicates the degree of relationship between the topics they represent. The LDA algorithm has assigned numerical labels to each topic.

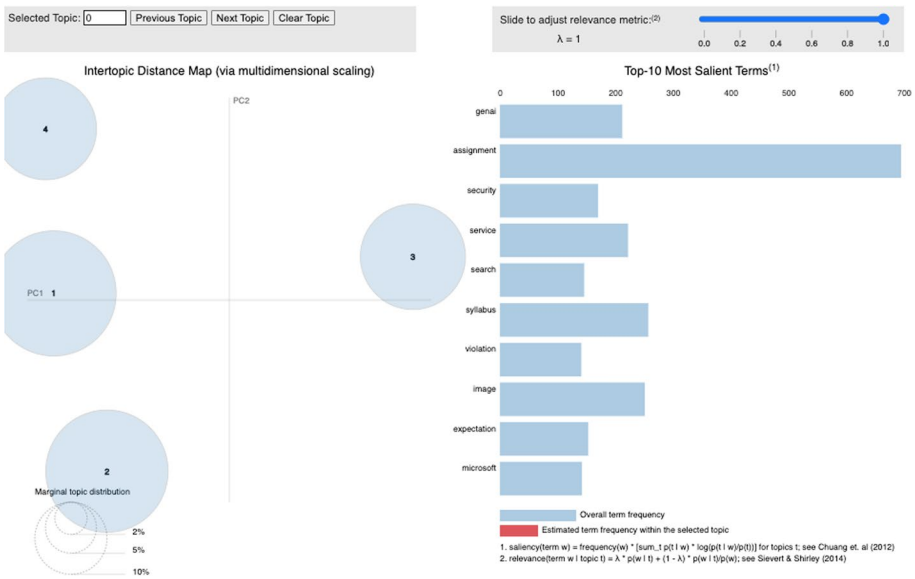

Fig. 3 4 Topic Model

Table 4 LDA Results

Topic	Count	Most Important Terms
1. Integration of GenAI in Learning and Assessment	60	assignment* (0.017), prompt* (0.011), learning (0.01), llm (0.008), link (0.008), assessment (0.008), class* (0.008), design (0.007), high (0.007), article (0.006)
2. GenAI in Visual, Interactive, and Multimodal Media	43	genai (0.019)*, image (0.013), prompt* (0.012), search (0.011), google (0.01), microsoft (0.009), free (0.008), chatbot (0.008), source (0.008), code* (0.007)
3. Security and Ethical Considerations in GenAI	59	service (0.015), security (0.013), guidance (0.013), privacy (0.011), human (0.009), risk (0.009), copyright (0.008), community (0.007), responsible (0.007), ensure (0.007)
4. GenAI in Academic Integrity	53	assignment* (0.026), syllabus (0.013), statement (0.011), class* (0.01), writing (0.009), violation (0.009), expectation (0.008), code* (0.008), submit (0.007), permit (0.007)

*Words specific to the subject are indicated with an asterisk

Topic 1, representing 30% of the tokens, is the largest circle on the map, indicating that it is the most dominant theme within the data. Topics 2 and 3, representing 28.8% and 21.3% of the tokens respectively, are depicted by moderately sized circles, showing significant prevalence but slightly less dominance compared to Topic 1. In contrast, Topic 4, which comprises 20% of the tokens, is the smallest circle on the map, indicating a lower frequency in the data corpus. Table 4 presents the LDA results, characterizing the identified four topics using the most representative terms.

Topic 1: integration of GenAI in learning and assessment

Topic 1 centers on the integration of GenAI tools in learning environments and assessment practices. The high probability of 'assignment' and 'prompt' indicates a significant

focus on using GenAI for academic tasks and assignments. Terms like 'learning,' 'llm' (large language models), and 'assessment' highlight discussions around GenAI's role in enhancing learning processes and assessments. The inclusion of 'class' and 'design' suggests considerations of how GenAI can be integrated into classroom settings and course design. The terms 'link' and 'high' indicate the connections GenAI creates within educational content and its potential to raise academic standards. The mention of 'article' reflects the dissemination of knowledge and research related to GenAI in these contexts.

Topic 2: GenAI in visual, interactive, and multimodal media

Topic 2 highlights the use of GenAI in visual, interactive, and multimodal media. 'Image' and 'prompt' point to significant discussions about GenAI's capabilities in image processing and prompt generation. Terms such as 'search,' 'google,' and 'microsoft' highlight the integration of GenAI with major tech platforms and search engines. The inclusion of 'free' and 'chatbot' suggests the accessibility and conversational features of GenAI tools. The term 'source' points to the origins of data and information used by GenAI, while 'code' pertains to the programming and development aspects of GenAI applications. This topic underscores the diverse applications of GenAI beyond text, including its role in enhancing visual media, interactive experiences, and multimodal content.

Topic 3: security and ethical considerations in GenAI

Topic 3 revolves around the security and ethical considerations related to GenAI usage. The prominent terms 'service' and 'security' indicate a strong focus on ensuring the secure deployment of GenAI services. 'Guidance' and 'privacy' highlight the need for clear guidelines and the protection of personal information. Terms like 'human' and 'risk' point to the human factors and potential risks associated with GenAI. The inclusion of 'copyright' and 'community' suggests discussions on intellectual property rights and the impact of GenAI on communities. The terms 'responsible' and 'ensure' emphasize the importance of responsible GenAI usage and the measures needed to ensure compliance with ethical standards.

Topic 4: GenAI in academic integrity

Topic 4 highlights the role of GenAI in upholding academic integrity. The high probabilities of 'assignment' and 'syllabus' underscore the significant impact GenAI has on academic assignments and course syllabi. The terms 'statement' and 'class' reflect the integration of GenAI guidelines within academic statements and classroom settings. 'Writing' and 'violation' indicate discussions on GenAI's impact on writing practices and potential policy violations. Terms such as 'expectation' and 'code' point to the standards and ethical codes enforced applied in academic contexts. The inclusion of 'submit' and 'permit' indicates procedural elements related to assignment submissions and permissions associated with GenAI use.

Results (RQ2): how do sentiments in the GenAI guidelines from the selected universities vary based on institution characteristics and target audience?

The sentiment scores were analyzed across various variables of the documents collected, including institution type, institution size, document purpose, specific tools

mentioned, and target audience. The average sentiment scores for both private (mean = 0.945355) and public institutions (mean = 0.963464) were highly positive, indicating a generally favorable tone towards GenAI across all types of institutions (see Table 5). To test for significant differences in sentiment scores between private and public institutions, the normality test was first performed, yielding a statistic of 0.2202 (p = 0.0000), indicating non-normal distribution. Subsequently, the Mann–Whitney U test was conducted, resulting in a statistic of 5664.5000 (p = 0.9664). These results indicate no statistically significant differences in sentiment scores between private and public institutions.

When examining institution size, small institutions exhibited the highest average sentiment score (mean = 0.975273), followed by medium (mean = 0.961407) and large institutions (mean = 0.952171). This trend implies that smaller institutions might be more optimistic and possibly more agile in adopting GenAI technologies, whereas medium and large institutions also show very positive sentiment, reflecting widespread support across different sizes. A normality test indicated a statistic of 0.2202 (p = 0.0000), suggesting non-normal distribution. The Kruskal–Wallis test was then applied, producing a statistic of 1.9726 (p = 0.3730). This indicates no statistically significant differences in sentiment scores based on institution size.

The sentiment scores also varied across different target audiences. Documents intended for administrators had the highest average sentiment score (mean = 0.996750), indicating a highly positive and supportive tone towards GenAI. Faculty-targeted documents also showed strong positive sentiment (mean = 0.976451), reflecting an encouraging attitude towards integrating GenAI in teaching practices. In contrast, documents aimed at researchers (mean = 0.898900) and students (mean = 0.910272) had lower average sentiment scores, suggesting a more cautious and regulatory approach, potentially addressing concerns and risks

Table 5 Sentiment analysis results

Variable	Group	Mean Sentiment Score	Kruskal–Wallis Test	Mann–Whitney U Test	Post-Hoc Dunn's Test
Institution Type	Private	0.945355	N/A	5664.5000 (p = 0.9664)	N/A
	Public	0.963464			
Institution Size	Small	0.975273	1.9726 (p = 0.3730)	N/A	N/A
	Medium	0.961407			
	Large	0.952171			
Document Purpose	Guideline	0.966138	7.8684 (p = 0.0196)	N/A	No significant pairwise differences
	Guideline/Policy	0.9998			
	Policy	0.857927			
Document Tool	Generative AI	0.956236	N/A	1670.5000 (p = 0.0929)	N/A
	ChatGPT	0.9387			
Document Audience	Administrators	0.99675	22.7987 (p = 0.0004)	N/A	Significant difference between Faculty and Students (p = 0.000460)
	All	0.955788			
	Faculty	0.976451			
	Researchers	0.8989			
	Staff	0.986733			
	Students	0.910272			

associated with GenAI usage in these groups. The normality test produced a statistic of 0.2202 ($p = 0.0000$), indicating non-normal distribution. The Kruskal–Wallis test was then applied, resulting in a statistic of 22.7987 ($p = 0.0004$), indicating statistically significant differences in sentiment scores across different audience categories. Post-hoc analysis with Dunn's test revealed significant divergence between documents intended for faculty versus students ($p = 0.000460$). Other pairwise comparisons, such as administrators vs. all audiences, faculty vs. researchers, and staff vs. students, showed no significant differences, with p-values all above 0.05.

Interestingly, documents referring to "GenAI" had a higher positive sentiment (mean = 0.956236) compared to those focusing on "ChatGPT" (mean = 0.938700). This suggests that the broader concept of GenAI is perceived more favorably than the specific application of ChatGPT. A normality test showed a statistic of 0.2202 ($p = 0.0000$), indicating non-normal distribution. The Mann–Whitney U test was then conducted, resulting in a statistic of 1670.5000 ($p = 0.0929$). These results indicate a trend towards significance, though not conclusive, warranting further analysis to explore these trends.

Results (RQ3): what specific themes do these leading U.S. universities address for different stakeholders (faculty, students, researchers, staff, and administrators) in their GenAI guidelines?

The guidelines were separately analyzed for each target audience. Table 6 summarizes the key themes in the guidelines for each target audience group.

Guidelines for faculty: key themes

Almost all the universities (47 out of 50 institutions) provided their faculty with some guidelines for the use of generative AI. Seven major themes were identified from the guidelines for faculty: (1) Syllabus statements for GenAI use, (2) setting and communicating course policy regarding the use of GenAI, (3) redesigning assignments and assessments, (4) what is GenAI?, (5) using AI detection tools, (6) incorporating GenAI in teaching, and (7) ethical use of GenAI.

Syllabus statements for GenAI use. More than half of the universities (56%) provided their faculty with guidance for syllabus statements on the use of GenAI tool. For example, Stanford University provided template syllabus statements for GenAI use in three categories: (1) AI tools permitted freely, (2) AI usage permitted with limitations, and (3) no AI usage permitted. Similarly, the University of Chicago provided examples of syllabus statements on the use of AI tools in four categories: (1) use prohibited in all situations, (2) use with prior permission, (3) use with proper citations, and (4) free use with no citation required.

Setting and communicating course policy regarding the use of GenAI. Twenty-seven universities (54%) advised their faculty to set their own policies related to GenAI and communicate the policy to their students. They emphasized the importance of clear communication of expectations regarding what is and is not allowed around AI use, pointing out that many students are using AI without clear directions from instructors.

> *Establish a policy for your course around the use of AI-based tools (e.g., ChatGPT) and communicate this with students through the syllabus and/or assignment*

Table 6 Key Themes of GenAI Guidelines

Target Audience	Key Themes	Sample Guidelines
Faculty	Syllabus statements for GenAI use	Stanford University provided template syllabus statements for GenAI use in three categories: (1) AI tools freely permitted, (2) AI tools permitted with limitations, or (3) AI tools not permitted
	Setting and communicating course policy	Faculty at the University of Washington are advised to establish clear policies on GenAI use in syllabi and assignment prompts and communicate them to students
	Redesigning assignments and assessments	Faculty can use authentic assessments (e.g., real-world tasks or projects) or process-oriented evaluations (e.g., drafts, oral exams, portfolios) to reduce reliance on GenAI
	What is GenAI?	Provide faculty with basic knowledge about GenAI capabilities, risks, and examples of tools like ChatGPT, DALL-E, or Microsoft Copilot
	Using AI detection tools	Universities like Princeton and Northwestern discourage reliance on tools like Turnitin due to their unreliability and bias. Faculty are advised not to use these tools for detecting AI-generated content
	Incorporating GenAI in teaching	The University of North Carolina at Chapel Hill suggests using GenAI for interactive teaching activities but emphasizes that "AI should help you teach, not teach for you."
	Ethical use of GenAI	Follow MIT's guidance to avoid entering confidential data into public AI tools and ensure compliance with institutional data privacy policies
All Stakeholders	Privacy and security	Ensure data compliance with privacy regulations, such as FERPA, by avoiding sharing sensitive or confidential information with GenAI tools
	Limitations and risks of GenAI	Carefully review outputs for accuracy and bias, as emphasized by the University of Texas at Austin. Educate users on implicit bias inherent in AI models
	What is GenAI?	Provide a basic overview of GenAI, including its capabilities, limitations, and GenAI tools
	Academic integrity	The University of Chicago explicitly explained that the use of information obtained from an outside source is considered plagiarism if the source of the information is not disclosed
	Disclosure and transparency	When using GenAI, always disclose promptly, or reference the use of GenAI tools and application plug-ins, as applicable
Students	Academic integrity	Follow university guidelines like Northwestern's: Disclose and cite the use of GenAI when it is authorized and clarify that unauthorized use is considered plagiarism
	Checking with instructors	Students are advised to consult course syllabi and instructors before using GenAI tools to understand course-specific policies, as recommended by Michigan State University
	Limitations of GenAI	Evaluate the reliability of GenAI outputs critically, as tools like ChatGPT may generate biased or fictitious information

Table 6 (continued)

Target Audience	Key Themes	Sample Guidelines
Researchers	Limitations and risks of GenAI	Critically evaluate GenAI outputs for outdated or inaccurate information. Confirm alignment with journal and funding agency policies (e.g., NSF, NIH)
	Recommendations for ethical use in research	Cornell University's guidelines outline responsible GenAI use across research stages, including research conception, dissemination, and funding compliance
	Staying up to date with GenAI uses and guidelines	Regularly review policies from funding agencies (e.g., NSF) and adopt evolving best practices for responsible AI use in research
Staff & Administrators	Privacy and data protection	Ensure sensitive institutional data is not inputted into public GenAI tools. Implement policies to secure administrative workflows
	Capabilities of GenAI	Use GenAI for administrative tasks like presentations, communications, and resource allocation, as outlined by the University of North Carolina
	Limitations of GenAI	Recognize the potential for inaccuracies and biases in GenAI outputs and validate information used in administrative decisions

prompts. Discuss how you will proceed if you discover that a student has turned in AI-generated work. (University of Washington)
Many students are exploring AI tools, some unknowingly. They use AI for spellchecking, coding, math, citations, and online shopping. Some students have never heard of ChatGPT while others are already creating AI applications or earning money through AI-driven content… Remember that students' experiences differ, and guidelines on AI use may vary across classes. Take time to clarify with your students what the parameters of AI use are in your class–and why. (University of Arizona)

Redesigning assignments and assessments. A little less than half of the universities (48%) advised their faculty to redesign course assignments and assessments. Specifically, authentic assessments (e.g., real-world tasks, projects), process-oriented assessments (e.g., low-stakes writing, drafts, presentations, oral exams, portfolios), and assignments requiring higher-order thinking were commonly recommended in adjusting assignments and assessments in the era of GenAI. In addition, AI literacy and citing generative AI were addressed in the guidelines.

What is GenAI? Twenty-one universities (42%) provided faculty with basic information about GenAI, including definitions of GenAI and related concepts, its capabilities and limitations, its impact on higher education, and examples of GenAI tools.

Using AI detection tools. Addressing the limitations of current AI detection tools (e.g., unreliable, biased), 19 universities (38%) stated that they did not recommend using those detection tools as shown in the following quotes. Some universities even informed faculty that they had decided to turn Turnitin off.

We believe that detection and surveillance tools are not an effective means to identify or deter the use of generative AI. They're not reliable, and they appear to be biased. We don't recommend that faculty use these tools. (Princeton University)

> *Instructors may be familiar with Turnitin, Northwestern's anti-plagiarism software. Turnitin piloted an AI Writing Indicator from April to August 2023, but after a series of consultations, Northwestern has decided to turn it off. We do not recommend using this detection tool as the basis for reporting a suspected case of academic dishonesty. (Northwestern University)*

Incorporating GenAI in teaching. Sixteen universities (32%) provided their faculty with guidelines and recommendations for incorporating GenAI in teaching. For example, the University of North Carolina at Chapel Hill provided principles for using GenAI in teaching, such as "AI should help you teach, not teach for you," "You are 100% responsible for your teaching materials, "Facilitate and encourage critical thinking," "Ensure that AI use is inclusive." Some universities, such as Columbia University, provided faculty with examples across disciplines.

Ethical use of GenAI. Twelve universities (24%) emphasized the importance of data privacy and provided guidance on the ethical use of GenAI, as evidenced in the following quote.

> *As a general rule, and in accordance with MIT's Written Information Security Policy, you should never enter any data or input that is confidential or sensitive into publicly accessible generative AI tools. This includes (but is not limited to) individual names, physical or email addresses, identification numbers, and specific medical, HR, financial records, as well as proprietary company details and any research or organizational data that are not publicly available. (Massachusetts Institute of Technology)*

Guidelines for All stakeholders: key themes

Almost 70% of the universities (34 out of 50 institutions) had guidelines for all stakeholders without specifying a specific group. Five major themes were identified from the guidelines for all stakeholders: (1) privacy and security, (2) limitations and risks of GenAI, (3) What is GenAI?, (4) academic integrity, and (5) disclosure and transparency.

Privacy and security. Half of the universities (50%) had guidelines outlining privacy and security concerns. Specifically, the universities emphasized the importance of protecting personal and private information and provided guidelines for protecting data when using GenAI tools. For example, the University of California, Berkley made the distinction that personal, confidential, and proprietary information must be protected to ensure FERPA compliance.

Limitations and risk of GenAI. Emphasizing the limitations and risks of GenAI (e.g., inaccurate content, hallucinations, biases, etc.), 19 universities (38%) encouraged the community to carefully review and fact-check the outputs of GenAI tools. The universities also warned about the potential biases and stereotypes reproduced by GenAI tools, as shown in the following quote.

> *Because humans train them, generative AI output has both explicit and implicit biases baked into it, including stereotypes. It won't be possible to entirely avoid bias in generative AI, just as it is not possible to avoid it in the real world, but a few small tips can help you engage with greater awareness. Educate yourself on the nature of*

implicit bias. Be aware that because humans train the models, they will reproduce our biases. Be skeptical and avoid overreliance on the models for any project. When you observe output from AI that is clearly biased or laced with stereotypes, report it to the vendor of the app you are using. (The University of Texas at Austin)

What Is GenAI? Fourteen universities (28%) provided definitions of GenAI and related terms in their guidelines for all stakeholders. Along with the definitions, they provided basic overview of GenAI, including its capabilities, limitations, and GenAI tools. Among the tools listed are ChatGPT, Google Gemini, DALL-E, Microsoft Copilot, and Zoom AI Companion.

Academic integrity. Thirteen universities (26%) included policy information or guidelines about academic integrity. For example, the University of Chicago explicitly explained that the use of information obtained from an outside source is considered plagiarism if the source of the information is not disclosed.

Disclosure and transparency. Eleven universities (22%) emphasized the importance of transparency and disclosure, recommending that users communicate their use of AI tools and specify which tools were used. The discussions focused on the significance of disclosure, proper citation of AI tools, and avoiding plagiarism. The following quotes convey university guidelines about disclosure and transparency:

When using GenAI, always disclose promptly, or reference the use of GenAI tools and application plug-ins, as applicable. This transparent disclosure ensures that others are aware when GenAI was used to generate content and reduces misunderstandings regarding the source of information, potentially limiting claims of academic dishonesty or plagiarism. (California Institute of Technology)

Guidelines for students: key themes

Twenty-one out of 50 universities (42%) provided guidelines for students on the use of GenAI. Three major themes were identified from the student guidelines: (1) academic integrity, (2) checking with instructors, and (3) limitations and risks of GenAI.

Academic integrity. The guidelines for students from 14 universities addressed academic integrity policy and related issues, such as consequences of AI misuse and how to cite generative AI. The following quotes show a few examples of academic integrity policies on the use of GenAI.

Unauthorized use of ChatGPT or other Generative AI tools is considered cheating and/or plagiarism in Academic Integrity: A Basic Guide. However, different professors may allow limited use of Generative AI tools for brainstorming, and/or with proper citation, and/or accept its use on a case-by-case basis. (Northwestern University)

Unless your instructor specifically authorizes the use of generative AI as a learning tool (for example, to summarize information on a topic), using these tools could constitute a violation under Penn State's academic integrity policy, which prohibits "accessing or using unauthorized or prohibited materials, information, tools, technologies, or study aids." (Penn State University)

Along with academic integrity policy, several universities provided guidance on how to cite ChatGPT in different formats including APA and MLA styles.

Checking with instructors. The guidelines for students from 12 universities consistently recommended that students read their course syllabi and check with their instructors before using GenAI tools. Since different courses have different policies, students were advised to consult their instructors for each course to find out the course policy and follow their instructors' guidance on how GenAI tools can be used for their course or assignments.

> *It is your responsibility to read the syllabus for each course you take so that you understand the particular expectations of each of your instructors. If you are unsure of expectations, you are encouraged to ask for clarification before you use specific resources in completing assignments. (University of Washington)*
> *Ask before you use AI and check your syllabus and assignment guidelines. Many instructors are providing specific guidance about appropriate use of generative AI in their courses. If you do not know whether your use of generative AI is appropriate to the outcomes in your course or research activities, tell your instructor or supervisor what you are considering and ask for guidance. Do this well in advance of your deadlines, not after you have submitted your work. (Michigan State University)*

Limitations and risks of GenAI. The guidelines for students from 9 universities emphasized the importance of understanding the limitations and risks of GenAI. Since the output of GenAI models may be inaccurate, misleading, biased, and even fictitious, the guidelines advised students to think critically about GenAI and carefully evaluate, fact check, and verify the information from GenAI.

Guidelines for researchers: key themes

Only 9 out of 50 universities (18%) included guidelines for researchers on the use of GenAI in research. Three major themes were identified from the guidelines for researchers: (1) limitations and risks of GenAI, (2) recommendations for the responsible and ethical use of GenAI in research, and (3) staying up to date with GenAI uses and guidelines.

Limitations and risks of GenAI. Five out of 9 guidelines for researchers communicated the limitations of risks of GenAI, such as outdated information, inaccurate or fictitious information, biases, and privacy risks. Researchers were advised to critically evaluate and corroborate information obtained from GenAI.

Recommendations for the responsible and ethical use of GenAI in research. Five out of 9 guidelines for researchers included recommendations and best practices for the responsible and ethical use of GenAI in research. A few universities provided specific guidelines for the use of GenAI across research stages. For example, Cornell University addressed the use of generative AI at four stages of the research process, including research conception and execution stage, research dissemination stage, research translation stage, and research funding and compliance stage.

Staying up to date with GenAI uses and guidelines. Emphasizing that AI tools and guidelines are constantly evolving, the guidelines advised researchers to stay informed about emerging AI tools and adhere to the specific policies of journals and funding agencies regarding AI use. Several universities, including Michigan State University

and University of Rochester, included the National Science Foundation (NSF) and the National Institutes of Health (NIH) policies regarding the use of GenAI in the grant review process.

> *It is a shared responsibility to stay informed about relevant developments surrounding generative AI. Both the technical capabilities of generative AI tools, as well as the rules and norms surrounding their use, are constantly evolving, and responsible research requires an up-to-date awareness of changes in AI technology and best practices within specific fields of research and scholarship. Everyone involved in research should make efforts to stay informed about relevant emerging AI tools, research studies, and ethical guidelines, and should take advantage of professional development opportunities to enhance their AI integration skills. (University of North Carolina)*

Guidelines for staff and administrators: key themes

Seven out of 50 universities (14%) had guidelines specifically targeting staff and administrators. Three major themes were identified from the guidelines for staff and administrators: (1) privacy and data protection, (2) capabilities of GenAI, and (3) limitations of GenAI.

Privacy and data protection. All seven universities discussed privacy and data protection guidelines and concerns. They advised staff and administrator not to enter any confidential or sensitive information into GenAI tools.

Capabilities of GenAI. Six of the seven universities outlined uses and capabilities of GenAI and encouraged their staff and administrators to explore the capabilities of new technologies. The University of North Carolina, for example, described how GenAI tools could be used for specific administrative tasks, such as administrative presentations, communications, data analysis and reporting, and resource allocation.

Limitations of GenAI. Five of the seven universities described the limitations of generative AI, which focused on inaccuracies and biases more than other limitations.

Discussion and conclusion

This study investigated the emerging institutional guidelines and policies regarding the use of GenAI in higher education through text mining, sentiment analysis, and qualitative thematic analysis. While previous studies focused on guidelines for assessments (Luo, 2024; Moorhouse et al., 2023), this study examined all GenAI-related guidelines for all stakeholders, including faculty, students, researchers, staff, and administrators. The findings from the comprehensive reviews revealed interesting insights into how higher education institutions are navigating the opportunities and challenges presented by GenAI.

The topic modeling identified four core topics driving the GenAI discourse in higher education institutions: Integration of GenAI in Learning and Assessment, GenAI in Visual, Interactive, and Multimodal Media, Security and Ethical Considerations in GenAI, and GenAI in Academic Integrity and Policy Enforcement. These findings are consistent with Adıgüzel et al. (2023) and Bahroun et al. (2023), who emphasized the transformative potential of AI in educational settings. The dominance of topics related to learning

and assessment suggests that institutions are prioritizing GenAI tools to enhance pedagogical practices and outcomes, highlighting a proactive approach to educational innovation (Smolansky et al., 2023). However, the distinct focus on security and ethical considerations underscores ongoing concerns about GenAI's impact on privacy and academic integrity, echoing the warnings in recent literature on AI ethics (Schiff, 2022). This concern is particularly relevant as educational institutions grapple with balancing the benefits of GenAI with the potential risks. Holmes et al. (2022) emphasized the importance of explicitly considering issues such as fairness, accountability, transparency, bias, autonomy, agency, and inclusion in AI in education (AIED).

Sentiment analysis revealed highly positive sentiments towards GenAI across all institution types. This collective optimism mirrors the findings of Stracqualursi and Agati (2024), who analyzed public opinions and sentiments regarding various AI applications in e-learning, such as ChatGPT, virtual and augmented reality, microlearning, mobile learning, adaptive learning, and gamification. Through a two-step sentiment analysis and LDA model, they identified that 'trust' and 'joy' were the most common positive emotions, while 'fear' was the predominant negative emotion. Notably, the negative sentiments included concerns about the ethical implications of GenAI and its impact on future job security in artistic and intellectual fields. Conversely, positive topics centered on the trust and hope in GenAI tools to improve job efficiency and educational outcomes. The significant divergence in sentiments between GenAI guidelines intended for faculty and those for students suggests a nuanced communication strategy. Universities appear to promote GenAI's benefits among faculty, who are instrumental in educational delivery and innovation, while adopting a more cautious tone with students to mitigate risks of misuse (Cotton et al., 2023). This differentiation indicates an understanding of the distinct roles and responsibilities of these groups within the academic ecosystem.

Qualitative thematic analysis was conducted to gain more detailed and contextual understanding. Most universities (94%) had GenAI guidelines for their faculty, which shows a big difference from previous finding by Moorhouse et al. (2023) who reported that less than half of the institutions developed publicly available guidelines. Qualitative analysis of the faculty guidelines revealed that faculty were advised to set their own policies related to GenAI and communicate the policies to their students through the course syllabi and other channels. This finding is consistent with previous studies (Jin et al., 2024; Moorhouse et al., 2023). In accordance with faculty guidelines, the student guidelines emphasized that different courses have different policies and that it is students' responsibility to understand and follow the expectations of each of their instructors. Students were consistently advised to read their course syllabi and check with their instructors before using GenAI tools. Although many universities provided suggested syllabus statements, guidance for redesigning assignments and assessments, and ideas for incorporating GenAI into teaching, faculty might need more specific guidelines or training to set their own policies regarding the use of GenAI in their courses.

Academic integrity was one of the major recurring themes. Overall, unauthorized use of GenAI was considered plagiarism. Similarly, Luo (2024) found that students' use of GenAI was mainly framed as a concern of plagiarism or academic misconduct in policy documents. Luo (2024) argued that such problem representation fails to recognize how GenAI further complicates what it means by originality in an era where knowledge

production is increasingly collaborative and mediated by technology. As she suggested, universities might need to develop a more inclusive approach to address the originality of students' work and academic integrity in the GenAI era. Another interesting finding was that faculty were discouraged to use AI detection tools, which is in line with recommendations from researchers (Dalalah & Dalalah, 2023; Kohnke et al., 2023; Lodge et al., 2023; McDonald et al., 2024; Moorehouse et al., 2023).

While most universities had guidelines for faculty and students, less than 20% of the universities provided GenAI guidelines for researchers. Similarly, only 14% of the universities had guidelines specifically targeting staff and administrators. Overall, guidelines for researchers suggested a more cautious approach, and researchers were advised to stay informed about emerging AI tools as well as the rules and policies around their use. Privacy and data protection was emphasized in the staff guidelines as well as the guidelines for all stakeholders. Everyone was advised not to enter any confidential or sensitive information into GenAI tools. This study suggests that universities continue developing customized guidelines for different groups to address their unique needs.

Researchers have emphasized the need for GenAI guidelines and policies to remain flexible and continually updated to keep pace with technological advancements (Ghimire & Edwards, 2024; McDonald et al., 2024; Moorhouse et al., 2023). Similarly, universities must evaluate the risks associated with the implementation and use of Generative AI, ensuring they make informed decisions and navigate responsibly to avoid unintended harm (Baeza-Yates & Fayyad, 2024). Aligned with this, many universities in this study noted that their guidelines and policies would constantly evolve as the technology develops. The evolving nature of GenAI guidelines and policies presents both a challenge and an opportunity for researchers, as well as all higher education stakeholders. The importance of communicating the updates and changes in the GenAI guidelines and policies cannot be overemphasized.

Limitations and Future Research

This study has several limitations. First, the data reviewed only included publicly available guidelines extracted from the websites of the top 50 universities in the United States. The universities may have guidelines that are not publicly accessible. Also, the findings of the study may not be consistent with guidelines in other universities in the United States or those in other countries. Future research should explore GenAI guidelines in different countries and examine how GenAI guidelines in diverse contexts are similar and different. Cross-cultural studies examining GenAI guidelines in diverse contexts could offer valuable insights into the similarities and differences in how institutions around the world navigate the opportunities and challenges of GenAI. Further, future research could examine guidelines offered through different communication channels, including social media (Jin et al., 2024).

Second, the number of guidelines targeted staff and administrators was relatively small. Researchers should explore the underdeveloped guidelines for researchers, staff, and administrators, identifying gaps and proposing strategies to address their unique needs. Third, the data were collected during a certain period (Spring 2024). Considering the evolving nature of GenAI guidelines, future research should examine how GenAI guidelines and policies evolve over time. Longitudinal studies are essential to track how

institutional policies evolve over time as AI technology advances. Finally, investigating the impact of GenAI guidelines on pedagogy, student outcomes, and faculty development would provide valuable insights into the effectiveness of these policies.

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Author contributions
YA and JY contributed to the study conception and design. YA conducted a literature review, collected data, conducted qualitative thematic analysis, and prepared a manuscript draft. JY performed the topic modeling and sentiment analysis and contributed to writing the manuscript. SJ contributed to data collection and analyzed a subset of the data.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request. All the data used to create the datasets are publicly available online through each university's website and can be directly accessed via their public domains.

Declarations

Competing interests
The authors declare that they have no competing interests.

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