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Gender Perceptions of Generative AI in Higher Education

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Gender Perceptions of Generative AI in Higher Education

Abstract

Purpose: This study explored the themes and sentiments of online learners regarding the use of Generative Artificial Intelligence (AI) or "generative AI" technology in higher education. **Method:** English-language tweets were subjected to topic modelling and sentiment analysis. Three prevalent themes were identified and discussed: curriculum development opportunities, lifelong learning prospects, and challenges associated with generative AI use. **Findings:** The results also indicated a range of topics and emotions toward generative AI in education, which were predominantly positive but also varied across male and female users. **Values:** The findings provide insights for educators, policymakers, and researchers on the opportunities and challenges associated with the integration of generative AI in educational settings. This includes the importance of identifying AI-supported learning and teaching practices that align with gender-specific preferences to offer a more inclusive and tailored approach to learning.

Keywords: *Gender; Higher Education; AI; Generative AI; Social Network Analysis*

1. Introduction

Deep learning and reinforcement learning algorithms have emerged as effective tools in higher education, which facilitate the analysis, structuring, and reasoning of diverse information types (e.g., text, images, audio, and video) (Hemachandran et al., 2022). Generative AI tools, such as ChatGPT, exemplify this trend by utilizing unsupervised pre-training and supervised fine-tuning to generate human-like responses to queries and provide expert-like insights (Uc-Cetina, Navarro-Guerrero, Martin-Gonzalez, Weber, & Wermter, 2023). These tools found widespread use among students and educators across various learning scenarios. Despite their popularity, gender biases in the formation of generative AI models have attracted the attention of many scholars and have sought to influence users' perceptions and use of the tools (Gross, 2023; Sun et al., 2024). In this study, it is argued that responses generated from using generative AI tools can differently influence male and female learners. For example, male users may perceive technology as more efficient and effective in learning due to their inclination towards problem-solving and technology-related fields. On the other hand, female users may perceive technology as less intuitive and less human-centred, as they may prioritize social and emotional aspects of learning (Park, Kim, Cho, & Han, 2019). Moreover, gender biases in technology can influence individuals' sentiments and emotions toward it (Chauhan et al., 2024; Mouronte-López, Ceres, & Columbrans, 2023). In addition, the specific needs and experiences of online learners, particularly regarding gender dynamics, have not been explored. This study aims to bridge this gap in knowledge by using topic modelling and sentiment analysis approaches to characterize how male and female learners perceive the use of generative AI in learning.

2. Gender and learner perceptions

In a learning context, gender has been widely studied as one of the potential predictors of technology success, which is why more studies are considering it as an influencing factor. A recent study by Strzelecki and ElArabawy (2024) reported the limited evidence of gender role in driving students' intention to use ChatGPT. AI gender biases and discrimination have also been addressed in the literature as influential factors shaping users' perceptions of technology (Mourelatos et al., 2024). For example, Nyaaba, et al. (2024) identified a significant gender disparity in the use ofGAI tools with male showing a higher intention to use compared to female. This can be linked to the interdisciplinary nature of generative AI tools, which encompass nuanced biases in their model generation. Researchers like Gross (2023) suggested that male and female users might approach AI tools differently based on how the results align with their gender identity. Previous studies (e.g., Lee, Guo, & Nambudiri, 2022; Xia, Chiu, & Chai, 2023) have also described how gender biases in AI-powered learning content generation can lead to different perceptions among learners, thereby revealing a layer of hegemonic gendering and gender biases that require further exploration. Ofosu-Ampong (2023) argued that gender can play a key role in shaping students' use of AI-based tools in education. The author found disparity in the overall levels of perceived innovation characteristics based on gender. This was supported by Nouraldeen (2023), who revealed that males tend more to adopt AI than females, and that gender moderates the associations between technology readiness, usefulness, ease of use, and adoption of AI.

Therefore, this study asked the following questions: 1) What are the main themes and topics associated with the use of AI generative in higher education? 2) How do male and female users perceive the use of generative AI in higher education? and 3) What are the sentiments towards the use of generative AI among these users? Answering these questions can help reveal essential information on the use of technology in education from a wider perspective, specifically addressing the identified gaps in gender dynamics and the experiences of online learners.

3. Method

Figure 1 shows the main steps followed in this study.

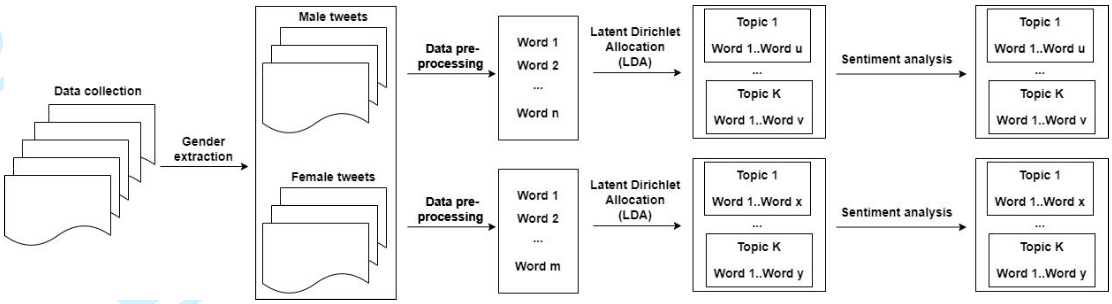

Figure 1: Stages of the research process

3.1 Data collection

English tweets were retrieved using the Twitter API and then saved in a CSV file. To ensure their relevance to our research objectives, we obtained the tweets using predetermined keywords such as ‘ChatGPT*’ OR ‘Generative AI*’ OR ‘Conversational AI*’ OR ‘Chatbot’ AND ‘higher education' OR ‘Universit*’, OR ‘postgraduates’, excluding retweets. We searched tweets from December 1, 2022, to April 30, 2023, as this was the period where ChatGPT attracted users’ attention worldwide. We followed Twitter research ethical guidelines when collecting the data.

Our initial search returned a total of 10,403 tweets, which we screened to ensure their relevance to this study. During our preliminary check of the tweets, we were able to detect several irrelevant ones. This was because some of the terms we used, such as ‘conversational AI*’ and ‘Chatbot’ were frequently used for non-learning or teaching purposes, such as marketing, customer service, and satisfaction surveys. Consequently, some of the tweets discussed the use of conversational AI and Chatbot in facilitating individuals' satisfaction with general services, with little or no relation to the context of higher education. Based on this, two authors reviewed the search options by carefully excluding a selection of terms that had led to non-meaningful tweets in all cases (e.g., -customer, -service, -client, -fees, -IT support, -relation, -job, -algorithm, -representative, -local, -contact). After implementing these revisions to the search, we retrieved 8,403 tweets. A further manual inspection of the new tweets revealed a relevant mix of views and opinions that were more consistent with the topic of this investigation.

3.2 Gender extraction

We determined the gender of Twitter users by analysing their account information using a list of gendered first names obtained from the Genderize.io AI. The gender of a specific name was identified using the genderizeR package in R. The tool determines the gender of a name based on whether it has been used by a particular gender at least 90% of the time. We categorized the tweets posted by users as either male or female based on whether the first part of their username or first name matched either of the two lists of male or female names (Thelwall, Thelwall, & Fairclough, 2021). To improve the accuracy of our predictions, we used the localization function provided by the API, which included the 'country_id' parameter to match the usernames to the list of names for a specific country. In addition, we found that some of the retrieved tweets (n: 451) were created by users who did not disclose their gender identity in their bio or username. This is because some of these users were created to represent specific companies, associations, or personal accounts. We also identified 153 cases where names were used for both genders (e.g., Jackie, Andy, etc.). A further examination was conducted by obtaining a list of unisex names or nicknames and manually searching for cases of disagreement between the pronoun (if provided) and the first name for accuracy. As a result, we were only able to verify the gender of 24 users, and the remaining users and their associated tweets were removed from the corpus. These measures left us with 4,982 tweets for data analysis. Finally, a manual examination of 100 random tweets were conducted by the first and second authors to ensure that names are correctly classified into male/female. We found that the gender classification was consistent with the users' wider bio information.

3.3 Data pre-processing

In order to extract the relevant words, we used tokenization by splitting tweets into words. These words were then used to generate a dictionary serving as the foundation of our main corpus. The weight of each word was assigned a specific weight using term frequency–inverse document frequency based on the recommendations of Bhattacharjee, Srijith and Desarkar (2019). This allowed us to obtain a set of tweets-related words (features) which we further refined by removing the mention symbol (@), URLs, and hashtags, keeping only the essential tweet content and ensuring high consistency (refer to Table 1 for the detailed breakdown figure). We also replaced contractions (e.g., “won’t” and “don’t”) with their expanded forms (“will not” and “do not”). All tweets-related words were then converted to lowercase form to standardize their format across the dataset. We then removed special characters such as punctuation marks (e.g., !%$#& ∗?,/.;”\ ) using regular expression techniques and eliminated non-essential words using the Stopwords list technique (pre-defined set of words which we to exclude commonly used and irrelevant words). After these steps, our corpus contained a total of 5,562 tweets.

3.4 Topic modelling

We extracted the topics that Twitter users discussed in their tweets using the Latent Dirichlet Allocation (LDA) algorithm where topics are represented by a distribution over words, and words are represented by a distribution over topics. To select and retain the best output, we followed two steps: (i) examining the coherence and exclusivity of each topic, and (ii) manually inspecting the model output to ensure interpretability. In this context, the first and second authors provided independent opinions on each topic by reading topic-related tweets. Then, appropriate labels/themes (see section 4.1) were assigned to the identified group of topics. We utilized probabilistic inference from topic modelling to uncover the underlying labels in the text and interpret the topics. The probability of a given topic was determined by the proportion of terms attributed to that topic across the entire corpus. Then a measure of topic coherence and exclusivity was employed to select and retain the best model. To assess the validity of our labelling, we utilized the kappa statistic method to evaluate the level of agreement (e.g., agree and disagree) among three external evaluators in the field of educational technology. The evaluators were provided with 200 randomly selected tweets for labelling purposes. The validation results revealed an 87% agreement among the evaluators, indicating a high level of agreement.

3.5 Sentiment analysis

To discern the embedded sentiments of users within the collected tweets, a lexicon-based approach was employed by utilizing the " NRC Emotion Intensity Lexicon" and "SentiStrength" techniques. This was carried out using the Waikato Environment for Knowledge Analysis (WEKA) tool as described by previous studies. The polarity of the collected and processed tweets was examined using the "SentiStrength" method to identify two types of tweet polarity (positive and negative) using numerical values ranging from -1 (not negative) to -5 (extremely negative) and 1 (not positive) to 5 (extremely positive).

4. Results

Table 1 presents the primary attributes of the study corpus, while Figure 2 shows the distribution of the tweets worldwide. Based on these, it is evident that the concentration of topics was predominantly observed among users from the USA, UK, Canada, and Australia. Furthermore, the proportion of male tweets (60.3%) was higher compared to female tweets (39.7%).

Table 1: characteristics of the corpus of tweets

Variables		
Date of search	Earliest 01/12/2022 Latest 30/04/2023	
Hashtags (#) no.		1219
Mentions (@) no.		803
Retweets no.		1905
Retweets no. (per tweet)		• min = 0 • max = 10761 [not included in the final analysis]
Width (characters)		• min = 5 • average = 169.61 • max = 11630
Favourites count		• min = 0 • average = 4.45 • max = 2388
Processed Male tweets no.		56.3 %
Processed Female tweets no.		43.7 %

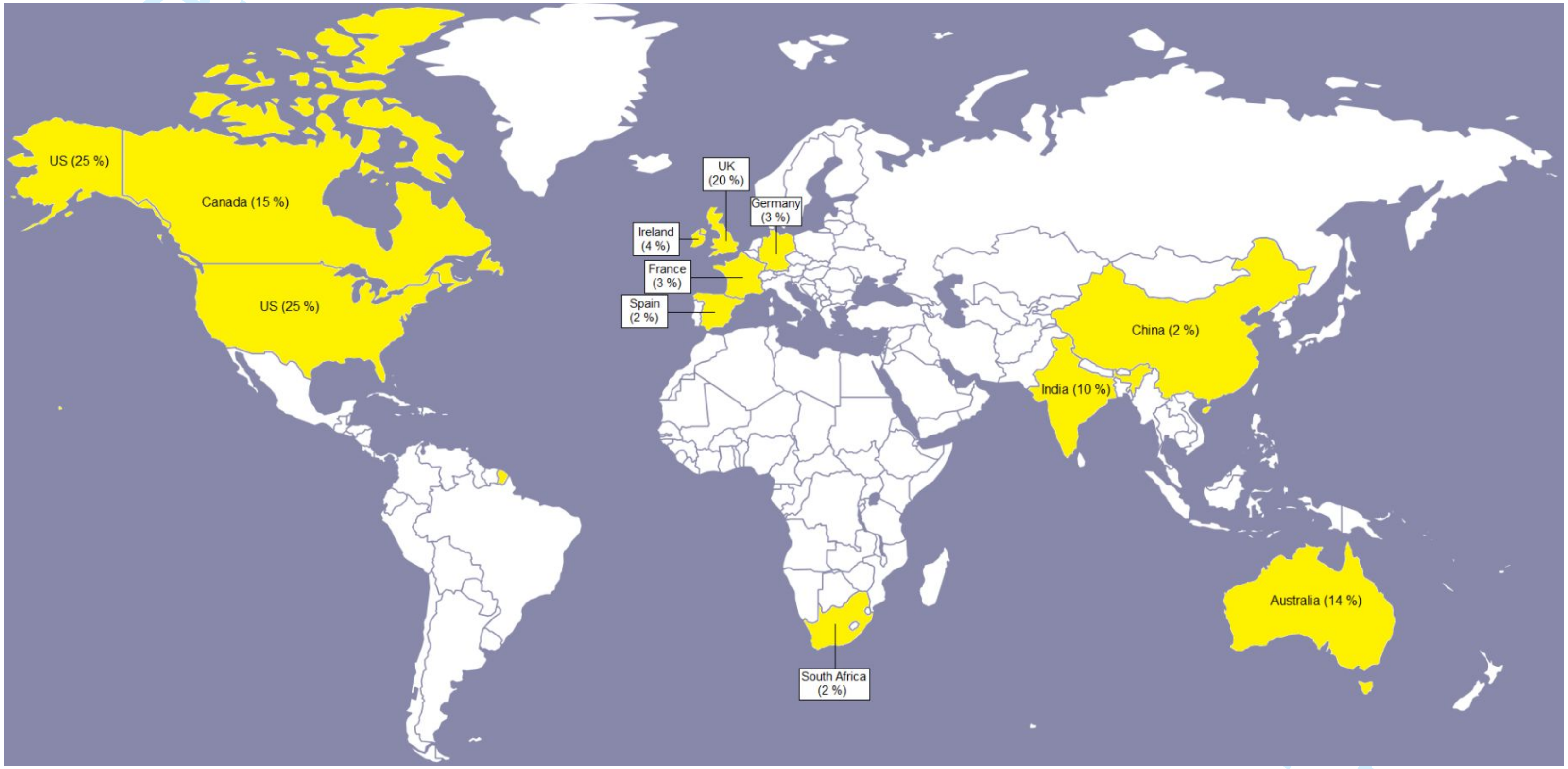

Figure 2: Geographic distribution of tweets

4.1 Topic modelling results

Figure 3 illustrates the most frequently occurring words (occurring more than 10 times) observed within the tweet corpus. We used mean exclusivity to estimate the degree to which words within a specific topic are exclusive to that topic and not shared with other topics. After analysing the results, we concluded that a three-topic model, characterized by a mean exclusivity across topics of 14.05 and a normalized mean exclusivity of 0.21, provided the most suitable representation of the corpus. This model effectively balanced word exclusivity, topic consistency, and interpretability, leading us to choose it for further analysis and interpretation. The identified themes were as follows: (i) Curriculum development opportunities, (ii) Lifelong learning opportunities, and (iii) Challenges associated with the use of generative AI. Table 2 presents a summary of the main topic probabilities for the top related words in each theme.

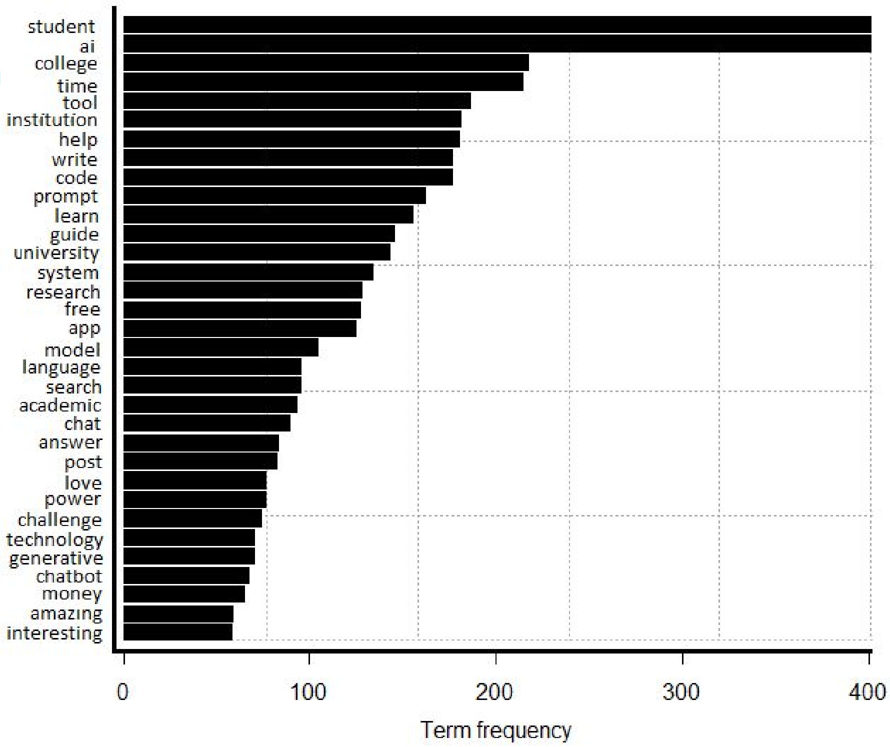

Figure 3: Most frequent words (> 10) observed in the tweet corpus

Figure 4 illustrates the network model of top bigrams, offering insights into word relationships and patterns across the entire corpus. The width of the connecting lines in the figure represents the frequency of co-occurrences between words, with thicker lines indicating more frequent word co-occurrences.

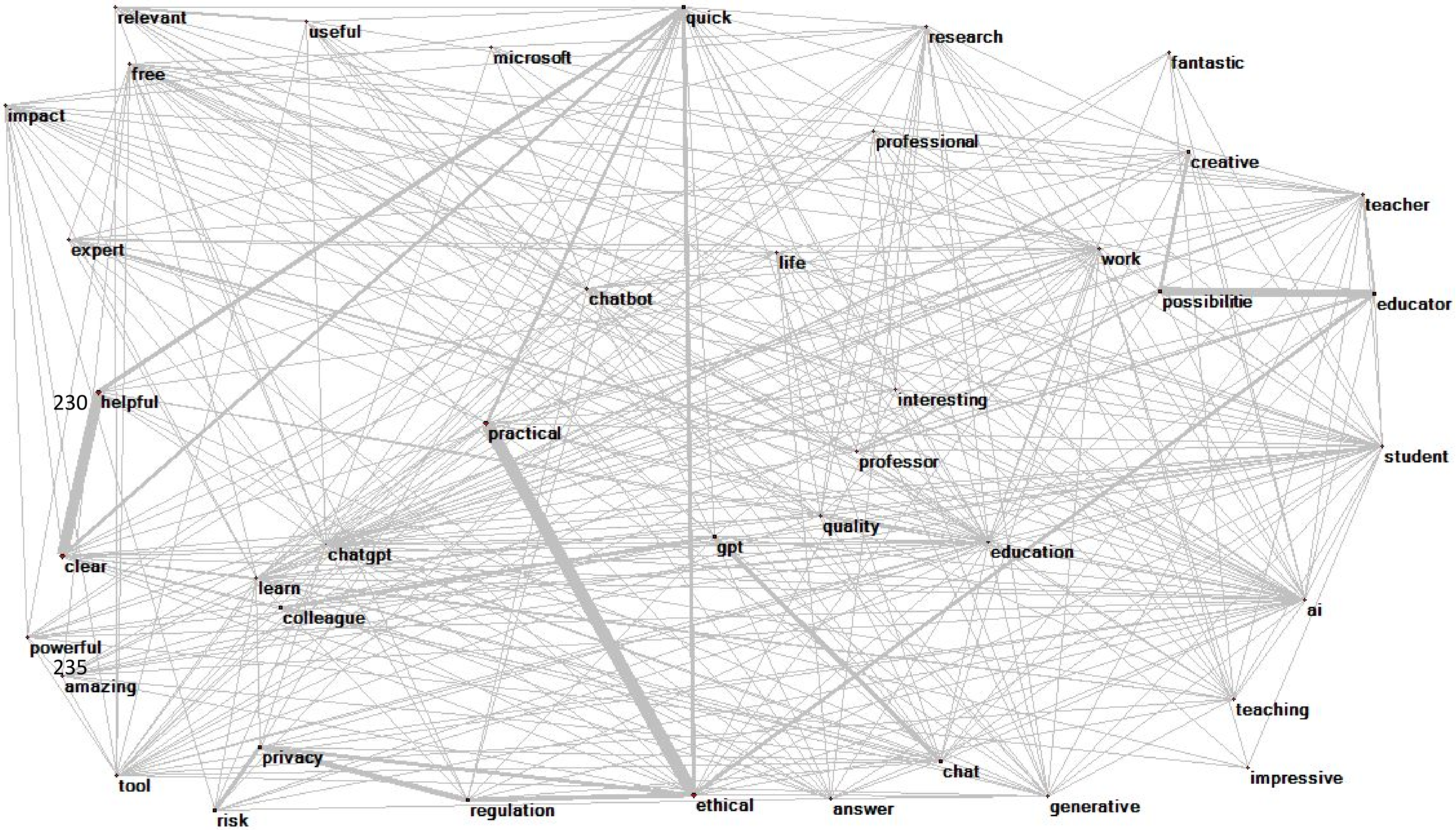

Figure 4: Network model of relations between words (bigrams) from the entire corpus

Given the difficulty of attributing opinions on a specific topic to specific demographic characteristics, this study aimed to offer a broad perspective on how male and female users perceived the use of generative AI in higher education. The sentiment analysis results were interpreted based on the opinions expressed by both genders. It is also worth noting that topics with mean topic probability of 0.5 and below were not discussed in this work. In addition, while some opinions were shared by both males and females, others were specific to each gender. This approach was followed to present the study findings. The subsequent subsections applied this understanding. Figure 5 shows the percentage of discussion intensity for each theme over the data collection period.

Table 2: Summary of topic modelling

No.	Mean topic probability	Top related words	Main theme
1	Overall: 0.76 Male: 0.79% Female: 0.65%	responsive instruction, assessment, education, theoretical teaching, work, ideation, research, helpful, design, evaluation, mapping, engaging, speed, quality, centered	Curriculum development opportunities
2	Overall: 0.71 Male: 0.61% Female: 0.69%	motivation, creative, work, impact, powerful, impressive, interesting, expert, helpful, colleague, flexible, clear, practical, professional, examples, imagination, skills, mindset, inspiration	Lifelong learning opportunities
3	Overall: 0.73 Male: 0.76% Female: 0.70%	ethics, professional, education, tool, generative, risk, delay, colleague, misuse, possibilities, quality, relevant, privacy	Challenges associated with the use of generative AI

Curriculum development opportunities

The first theme was labelled "curriculum development opportunities," where male users expressed interest in two main topics: the use of generative AI in offering a personalized learning experience (mean: 0.81) and in problem-solving (mean: 0.77). These topics were commonly associated with relevance, ideation, and self-reflection. Male users perceived the practical application of generative AI in developing knowledge-building process skills acquired during their studies. Students also expressed a positive perception of the responsiveness of generative AI in supporting their problem-solving experience. However, female users discussed the potential of using generative AI for providing a learner-centred curriculum design capable of enhancing students' engagement (mean: 0.65).

In addition, three main topics were identified among male and female users. The first topic focused on the use of generative AI tools as foundational learning support tools (mean: 0.85) that can be utilized across different disciplines. One important aspect discussed was the need for students to have a basic understanding of AI concepts and how to effectively utilize them based on their individual learning needs and situations. For example, online users perceived generative AI as a valuable opportunity for non-English speakers to improve their grammar skills without spending additional time in traditional lectures. The second topic focused on empowering lecturers to design concise and easily understandable learning materials (mean: 0.74).

This viewpoint was not specific to any particular discipline, but topics associated with this view were predominantly related to social sciences and humanities. This may be because students in these fields often place greater emphasis on theoretical elements in their learning journey, leading them to perceive generative AI as a means to simplify the understanding of complex theories. The third topic centred around utilizing generative AI tools to streamline the assessment and evaluation of students' work (mean: 0.70). This involved leveraging technology to review and evaluate the content, structure, and coherence of written texts.

Lifelong learning opportunities

Male users expressed self-motivation to explore learning concepts from different perspectives with generative AI (mean: 0.61). A small segment of male users (21%) reported that the tools allowed them to provoke questions related to their research or learning topic. However, female users were more concerned about the use of generative AI to enhance learning flexibility and enable learners to achieve higher competence in their studies (mean: 0.69). Upon reviewing specific tweets related to this topic, we discovered several noteworthy aspects. For instance, a considerable portion of female users (40%) regarded generative AI as a tool to foster a challenge-seeking approach, enabling them to independently compare and validate their knowledge on a given topic. Female users (23%) also discussed how generative tools might facilitate self-evaluation of various examples, aiding in their comprehension of the learning content.

The results revealed two common topics shared among male and female users. The first topic (mean: 0.77) encompassed users' perspectives on the practicality of generative AI in supporting their professional development. A significant aspect of this viewpoint was the potential of generative tools to enhance students' writing skills by providing valuable suggestions for improving the quality of written texts, such as research papers, and offering feedback on grammar, sentence structure, and word choice. The second topic (mean: 0.64) reflected a shared interest among users of both genders in utilizing generative AI to access explanations or resources that aid their comprehension of complex concepts related to their studies. This includes enhancing problem-solving skills by guiding students through logical steps to tackle learning challenges across various subjects, as well as assisting them in grasping fundamental concepts and methodologies in ways that align with their learning styles and needs.

Challenges associated with the use of generative AI

Both male and female users expressed four concerns regarding the use of generative AI tools in higher education. The first concern raised was related to the reliability of the linguistic model utilized in most text generative AI tools (mean: 0.83), particularly in handling idioms and generating content that lacks real connection to the searched topic. It is believed that this limitation could reduce the ability of generative tools to differentiate between figurative and literal information.

The second topic pertained to misinformation (mean: 0.61). The majority of female users (n: 43%) reported that heavy reliance on generative tools may lead to situations where misinformation is generated due to the low reliability of these tools in classifying or detecting false sources. This limitation can lead to the dissemination of false knowledge to learners, particularly among those who place high trust in technology. Male users (n: 21%) also shared their personal experiences of unknowingly consuming misleading or inaccurate information, which had a negative impact on their understanding and knowledge acquisition.

The third concern examined the ethical use of generative tools in learning (mean: 0.78). Users expressed concerns about the feasibility of using generative tools for cheating or attempting to rewrite previously published content as if it were produced by the learner. Other concerns related to answering exam questions (particularly take-home exams) and duplicating other people's work were frequently mentioned in the analysis of both male and female users' tweets. Ethical considerations regarding generative AI have been a primary focus since the technology was first introduced. Various educational bodies have published guidelines to guide students and academics in the best practices of using AI. However, it is important to note that not all students may be aware of or adhere to these practices.

The fourth topic covered concerns about the decline of creativity among online users (mean: 0.70). Female users expressed their concerns about the impact of continuous use of generative AI on the development of creative thinking skills. They highlighted how these tools are often used to complete assignments or tasks, resulting in a reliance on AI-generated ideas and solutions rather than engaging in independent creative thinking. On the other hand, male users showed a more optimistic view regarding the role of generative AI in facilitating their work on difficult and specific goals. They considered it as an external source of time pressure and evaluation rather than an internal form of regulation.

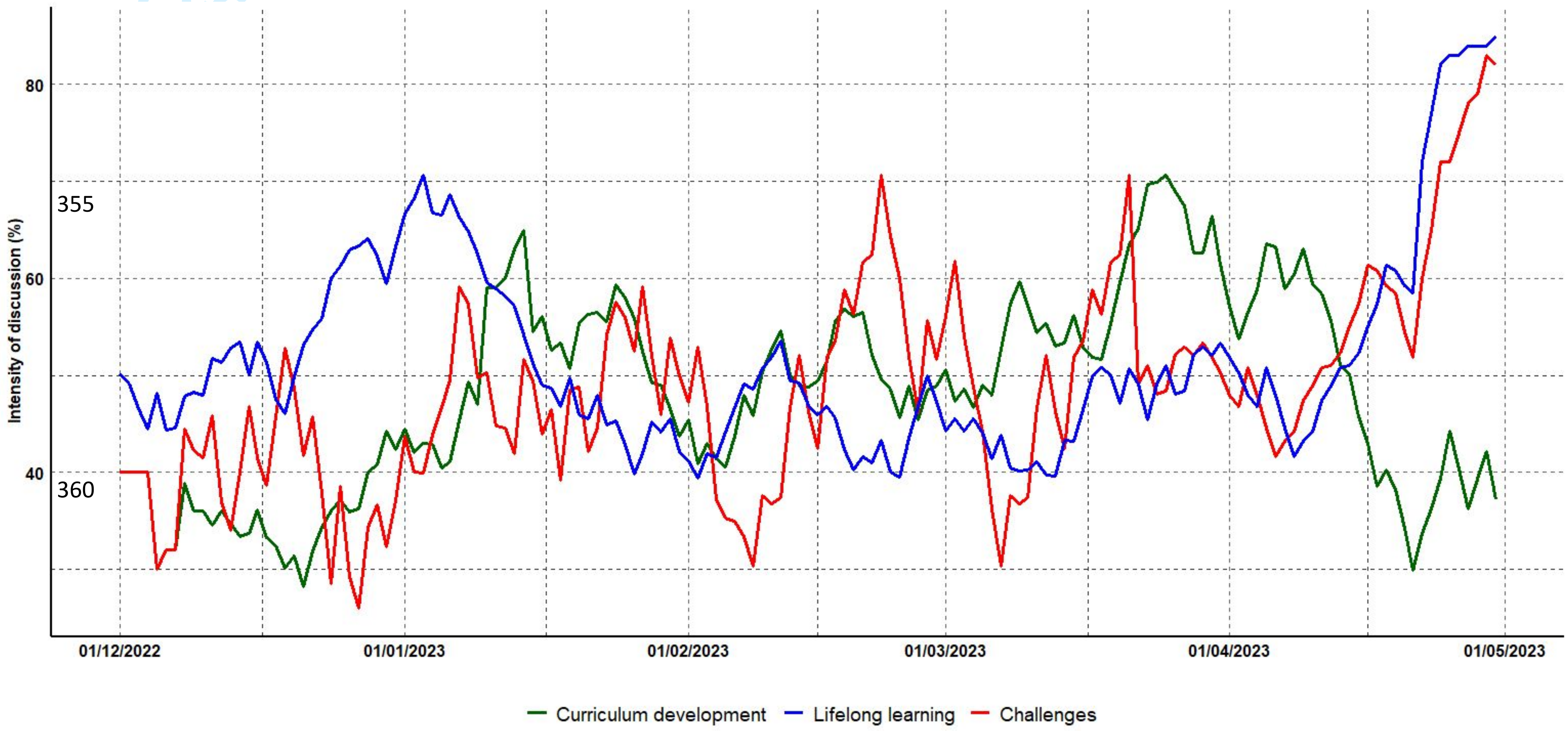

Figure 5: Discussion intensity percentage for each theme during data collection

4.2 Sentiment analysis results

Figure 6 (A) presents the results of the sentiment analysis, indicating that trust was the most prevalent sentiment in the corpus (90 %), followed by anticipation (65 %) and joy (49 %). The combination of these emotions resulted in an overall prevalence of positive sentiment, as depicted in Figure 6 (B). Less common sentiments observed were disguise (15 %), surprise (22 %), sadness (25 %), anger (26 %), and fear (33 %), which are believed to contribute to the overall negative sentiment regarding the use of generative AI in higher education. Figure 7 shows the corpus positive and negative keywords associated with users' use of generative AI in higher education.

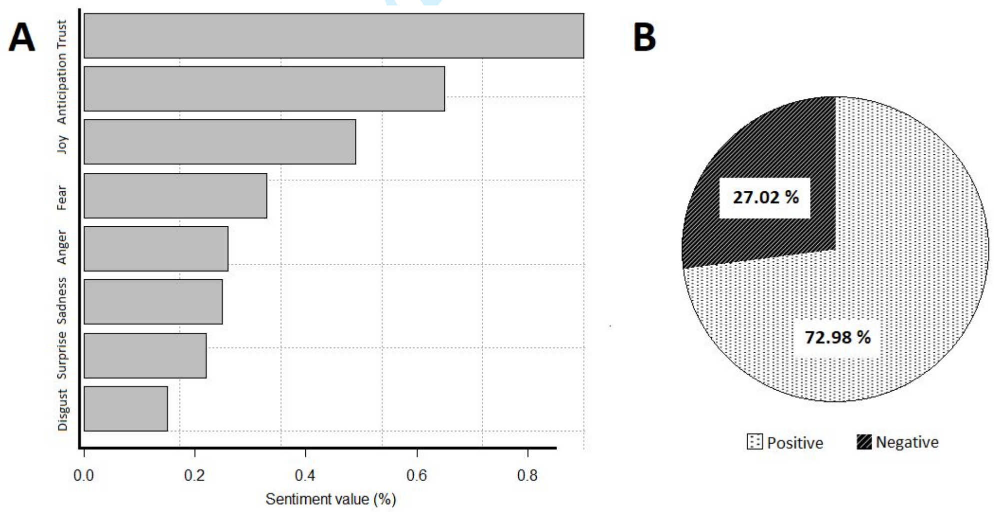

Figure 6: Sentiment analysis of the entire tweet corpus

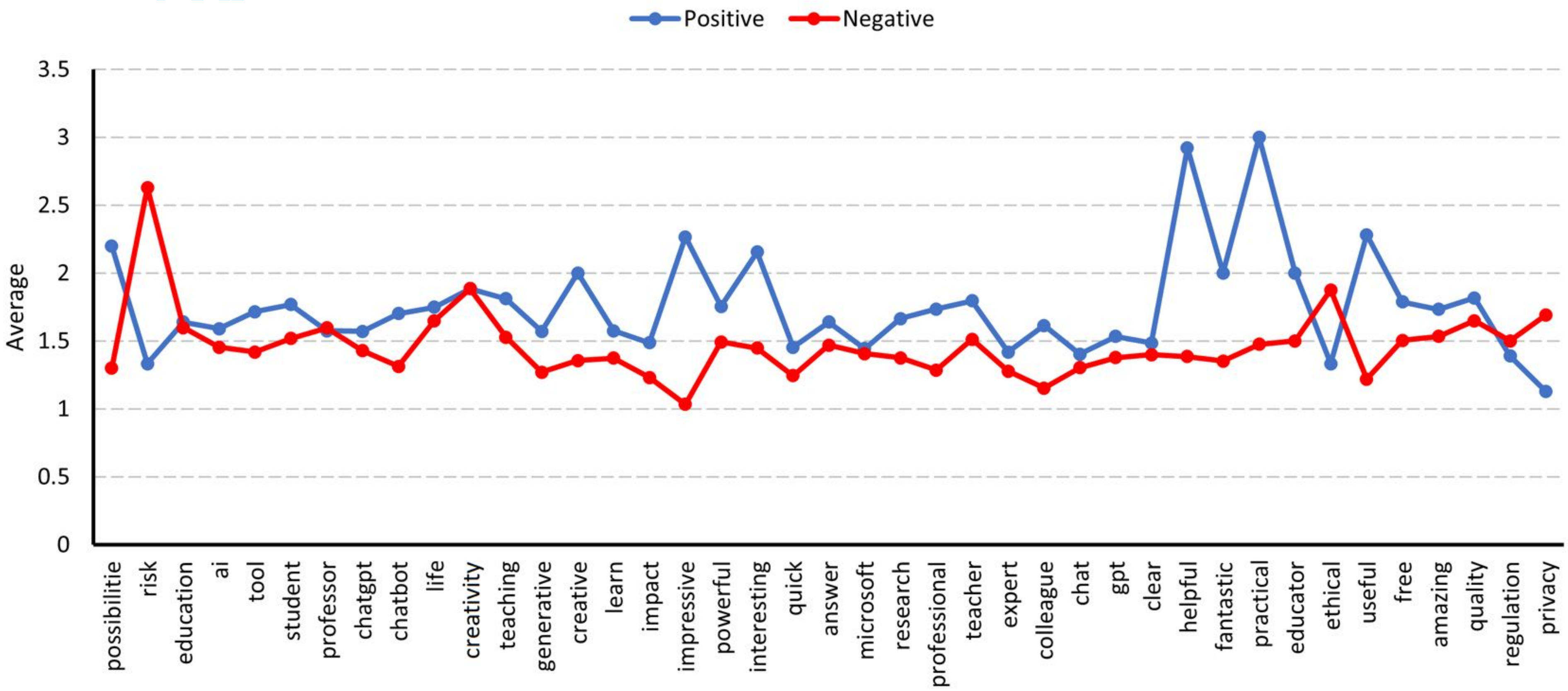

Figure 7: Emotion spikes per keywords in association with established network model of the overall corpus

5. Discussion

This study found positive sentiment among male and female users in relation to the use of generative AI in curriculum development based on its role in providing personalized learning experience, supporting students' problem-solving experience, and providing learner-centred curriculum design. The sentiment of male users was predominantly welcoming the integration of generative AI into their teaching and learning practices. Some previous studies (e.g., Vázquez-Cano, Meneses, & García-Garzón, 2017) suggested that male learners are more inclined to support technology integration in learning compared to female users. The results showed the potential of using generative AI to provide foundational learning support, empowering lecturers to design learning materials, and streamline the assessment and evaluation. Most of the tweets in relation to this topic pointed to how generative AI tools can be used for tasks such as proofreading, editing, providing feedback, and generating writing examples. By facilitating these practices, users expressed their hope for reduced inequality in higher education, which extends previous works (e.g., Bozkurt et al., 2023; Ibrahim et al., 2023) on the possibility of generative tools in increasing access to information and services among non-English speaking countries. However, it remains unclear to what extent online users were actually using or considering using generative AI tools in this manner. This aligns with recent studies on the use of AI in assessment, such as the work by Olga et al. (2023), which explores the potential of generative

AI in reviewing and assessing complex student work. Providing future instructions on how to use generative AI to summarize student texts according to the assessment rubric can be viewed as a potential step towards revitalizing the higher education curriculum.

A second theme was found to cover topics related to lifelong learning opportunities. Self-motivation to continue learning with the support of generative AI was found to be directly associated with the development of students' creative thinking process, mainly among males. According to Cooper (2023), this process is believed to be supported through inquiry-based learning which generative AI provided to students. Yet, it was difficult to assess the practicality of generative tools in allowing student to develop critical thinking except for their role in increasing awareness and facilitating experiential learning. Despite this, facilitating experiential learning with generative AI has been less investigated/explored in the literature in which little evidence found to support this claim. Female users also attributed the use of generative AI to achieving higher competence in their studies, supporting previous findings like those of Yilmaz and Yilmaz (2023), who stated that generative AI has the potential to increase students' computational thinking skills, programming self-efficacy, and motivation for the lesson. However, this result does not align with the experiences of male users, which might be attributed to generative AI biases. This aspect is supported by Yilmaz and Yilmaz (2023), who investigated biases in the generative art AI pipeline and how this might influence users' perceptions of art creation. Both male and female users found generative AI to be a valuable tool for supporting their professional development and accessing resources that aid their comprehension of complex concepts. This finding aligns with recent studies (e.g., Baidoo-Anu & Owusu Ansah, 2023) that have demonstrated the potential of generative tools in supporting the learning progress of university students. It is also assumed that generative AI might perpetuate old and non-inclusive understandings of gender (Gross, 2023), which can influence students' perceived learning experiences.

Challenges associated with the use of generative AI were reported in relation to the generation of inaccurate content and outdated information. Some previous studies (e.g., Ahuja et al., 2023; Korzynski et al., 2023) have partially discussed the needs for improving the multilingual performance of generative models. This concern highlights the importance of ensuring the linguistic accuracy and relevance of generative AI tools to enhance their usability and effectiveness in educational settings. Chan and Lee (2023) reported that current language models need to provide a comprehensive list of all potential mitigations for combating misinformation to ensure accurate responses. The results also indicated that ethical issues may arise from using generative AI in learning. Previous studies have argued that this might be linked to how AI models are constructed, which often exhibit a centric bias (Singh, 2024). Creativity-related concerns were also identified among female users regarding the constant use of generative AI in learning. The heavy reliance on generative tools in learning may reduce users' exposure to experiences that directly contribute to their creative thinking skills. This finding is supported by the work of Doshi and Hauser (2023), who stated that ideas retrieved from generative AI are more similar to each other than stories created solely by humans, which can hinder the production of a creative output.

Based on these findings, gender biases in generative AI can impact students' educational experiences differently. In many non-English speaking countries, gender roles and expectations still heavily influence educational and career choices. If not carefully designed, generative AI tools may unintentionally reinforce these expectations by providing gender-biased examples and feedback, perpetuating existing gender imbalances in various professions. In addition, access to AI-driven educational resources varies significantly across genders in non-English speaking contexts. Female students may encounter additional barriers, such as lower levels of digital literacy or limited access to technology, which can hinder their ability to effectively utilize generative AI tools. This digital divide can further widen the educational gap between male and female students. Therefore, it's crucial to design AI tools that not only deliver accurate and relevant information but also consider these gender gaps and biases.

6. Implications

The findings of this study offer timely insights and guidance for policy makers, educators, researchers, and curriculum developers regarding the perception and utilization of generative AI in a higher education setting. For example, our findings gained from the curriculum development aspect shed light on the role of both male and female users in adapting these tools for learning. This includes identifying AI-supported learning and teaching practices that align with gender-specific preferences, offering a more inclusive and tailored approach to learning. Generative AI has been perceived to be effective in offering a broad range of practical applications in higher education across different subjects and settings. For instance, in language learning, learners described how generative AI can provide interactive translation and tutoring opportunities by offering contextual explanations for difficult concepts. Similarly, in science-related disciplines, generative AI can help solve learning problems and simplify students' conceptual understanding of complex concepts. In literature and other social science subjects, generative AI can be used to encourage students to develop their creative writing skills with prompts and feedback. These examples highlight how generative AI has the potential to enhance learning in various educational contexts.

In addition, outcomes from this study can inform policy-making in higher education on how best to promote gender equality in the use of technology for learning or research. The comparison of general themes and topics identified in this study holds significant value for educational decision makers who aim to reshape the learning and research culture within a university context. Moreover, the identified challenges can contribute to a deeper understanding of the conditions that must be considered when incorporating generative AI tools in educational settings. This information, in our opinion, is valuable for educational technologists and practitioners, providing them with insights into potential obstacles and considerations that can enhance the effective use of these tools in teaching and learning environments.

7. Limitations and future works

Despite the valuable findings presented in this study, there are several limitations that should be taken into account for future research. Firstly, this study relied on data obtained from a single social media site to capture users' opinions on generative AI in higher education. While Twitter has been widely utilized by researchers as the primary platform for extracting user opinions, future research could explore the possibility of combining data from multiple sources to provide a more comprehensive and diverse view of users' opinions. Users' perceptions of generative AI were based on English tweets, which may restrict the generalizability of the conclusions to specific countries and practices. It is recommended that future studies consider extracting and analysing tweets in other languages to ensure a more inclusive representation of user perspectives. Other limitations in name classification might influence the identification of gender in this study. Therefore, future studies should consider using self-reported gender data instead of relying solely on names, as was done in this study. It is also worth mentioning that this study did not delve into how generative AI has precisely influenced online learners' learning or examine the reasons behind learners' use of the technology in their learning. We believe this is another limitation that can be further explored in the future by employing additional data collection methods such as interviews to correlate the findings from topic modelling and sentiment analysis with specific students' data.

8. Conclusion

This study found three significant themes related to the use of generative AI in higher education: curriculum development opportunities, lifelong learning opportunities, and challenges associated with the use of generative AI. We also compared and examined the associated topics within these themes among male and female users, providing valuable insights into the role of gender in shaping perceptions and preferences related to generative AI in education. The findings highlighted the need for gender-specific considerations in the design and implementation of AI-supported learning and teaching practices, promoting inclusivity and equity. This study contributes to the existing knowledge by providing a comprehensive analysis of users' perceptions and experiences with generative AI tools in higher education.

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