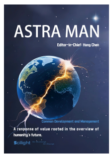
Scilight

ASTRA MAN
https://www.sciltp.com/journals/astm



Article

Public Sentiment and Social Cognition toward Generative AI in Education: A Comparative Analysis of ChatGPT and DeepSeek in Sina Weibo Discourse

Han Huang, Qiong Wei, Zicheng Wang, Kang Liu and Min Yuan *

School of Health Management, Anhui Medical University, Hefei 230032, China
* Correspondence: myuan@ustc.edu.cn

How To Cite: Huang, H.; Wei, Q.; Wang, Z.; et al. Public Sentiment and Social Cognition toward Generative AI in Education: A Comparative Analysis of ChatGPT and DeepSeek in Sina Weibo Discourse. *ASTRA MAN* **2026**, *1*(1), 3.

Received: 18 June 2026
Revised: 8 July 2026
Accepted: 9 July 2026
Published: 16 July 2026

Abstract: With the rapid development of generative artificial intelligence (GenAI) technologies, their application in the field of education has gradually become a focal topic of interest for both academia and the public. However, research on emotional responses and social cognition regarding the educational applications of GenAI based on social media data analysis remains limited. Based on public Weibo posts and comments related to ChatGPT and DeepSeek, this study combines BERT-based sentiment classification, BERTopic topic modeling, dynamic topic analysis, and representative-text validation to examine sentiment patterns and negative discourse themes in education-related discussions. Social cognitive theory is used as a discourse-oriented interpretive framework to organize negative topics into perceived competence, perceived risk, and value-related concerns. The results show that ChatGPT-related negative discourse was mainly associated with uncertainty about AI use and human competence, academic integrity, teacher substitution, reduced independent thinking, and classroom effectiveness. DeepSeek-related negative discourse was more closely related to children's learning dependence, output reliability, employment pressure, humanities learning, traditional cultural education, and teacher roles. Overall, public responses to GenAI in education vary across model-specific, temporal, and sociocultural contexts. The study contributes context-specific evidence on GenAI-related public discourse in China and suggests that GenAI literacy, output verification, academic integrity, teacher professional development, and value-sensitive implementation should receive greater attention in future empirical research and educational practice.

Keywords: generative artificial intelligence; education; social cognitive theory; social media discourse; technical challenge

1. Introduction

With the rapid development of generative artificial intelligence (GenAI) technologies, social structures and modes of operation have undergone profound transformations [1]. The organization and implementation models within the field of education also experienced significant changes [2,3], which promoted widespread discussions on various aspects such as teaching practices, learning methods, assessment systems, and academic ethics [4]. Among them, the new generation of large language models represented by ChatGPT released by OpenAI and DeepSeek developed in China are applied to multiple teaching and learning scenarios, such as schoolwork writing, language translation, automatic question answering, and educational content generation. Due to their convenience and intelligence, these tools have brought a technological revolution to education [5], while also triggering concerns in the public and academic circles about their risks, limitations, and ethical boundaries [6,7].

Existing research has mainly focused on the functional applications of GenAI in education, such as curriculum support, lesson planning, and assignment generation [8]. However, studies on user emotional attitudes, cognitive preferences, and socio-psychological mechanisms during the use of these tools remain limited. Unlike internal investigations conducted within universities, public discourse on social media tends to be more immediate, emotional, and socially embedded. It reflects user emotional responses, social comparisons, and psychological expectations [9]. Therefore, by analyzing large volumes of comments and discussions on social platforms, it is possible to gain a more comprehensive and objective understanding of public attitudes and perceptions regarding the application of GenAI in education.

Research on GenAI has primarily approached the topic from the perspectives of educational technology, instructional assessment, or ethical regulations [10,11], with an emphasis on tool design and policy orientation. In contrast, this study focuses on user subjective experiences and discourse production, emphasizing the mechanisms behind the formation of public attitudes. Particularly in the Chinese context, DeepSeek represents a localized technological exploration in GenAI and serves as a cultural and technological counterpart to ChatGPT. Based on data collected from the Sina Weibo (Weibo) platform, this study crawled public user comments related to the use of ChatGPT and DeepSeek in educational settings. Sentiment analysis techniques were applied to classify user emotional expressions, followed by topic clustering of negative sentiment texts to identify major public concerns. Applying social cognitive theory (SCT) to the analysis of social media discourse helps to understand public perceptions of GenAI in education from the perspective of psychological mechanisms.

This study contributes to the literature on GenAI in education by providing a model-comparative analysis of ChatGPT- and DeepSeek-related public discourse in the Chinese Weibo context. Unlike studies that examine GenAI perceptions in general, this study focuses on a globally prominent GenAI system and a Chinese-developed GenAI system generated negative discourse themes during their respective diffusion stages. Methodologically, it integrates supervised sentiment classification, BERTopic-based topic modeling, dynamic topic analysis, and representative-text validation to connect large-scale discourse patterns with interpretable textual evidence. Theoretically, it uses social cognitive theory as a discourse-oriented interpretive framework to organize negative topics into perceived competence, perceived risk, and value-related concerns.

2. Literature Review

2.1. Generative Artificial Intelligence and Education

GenAI has become an important topic in educational technology research and practice. Large language models such as ChatGPT and DeepSeek can generate, summarize, translate, and reorganize natural-language content, making them relevant to writing support, teaching-material preparation, feedback generation, question answering, and personalized learning assistance [12–14]. These applications have encouraged growing interest in how GenAI may improve instructional efficiency, expand access to learning resources, and support more flexible forms of learning.

At the same time, GenAI has raised concerns about educational quality, academic integrity, and the changing role of teachers. Because GenAI systems can generate complete essays, explanations, and learning materials, they may complicate the evaluation of students' original work and increase the difficulty of detecting inappropriate assistance or academic misconduct [15]. In assessment contexts, recent research has also questioned whether AI-based grading can achieve sufficient validity, reliability, and fairness compared with human raters [16]. In addition, inaccurate outputs, biased representations, and overreliance on generated content may affect students' critical thinking, independent learning, and trust in educational information [17]. These issues suggest that GenAI adoption in education cannot be evaluated only through technical capability or efficiency.

Existing research has mainly examined GenAI in education from the perspectives of teaching practice, learning support, assessment design, and institutional response. These studies provide important evidence about the potential benefits and risks of GenAI-supported education. However, less is known about how these opportunities and concerns are expressed in public social media discourse, especially in the Chinese platform context. This study therefore focuses on public Weibo discourse about ChatGPT and DeepSeek in education-related contexts.

2.2. Social Media Responses to GenAI and Emerging Technologies

Social media has evolved from a communication tool to a platform for public engagement with emerging technologies, shaping emotional attitudes and discourse [18]. Since GenAI gained public attention, platforms like Weibo, Twitter, and Reddit have seen a surge in real-time discussions [19]. These platforms, supported by algorithmic recommendation systems, play a crucial role in GenAI governance [20].

In the GenAI context, existing work has explored public attitudes toward ChatGPT and related tools, showing that online discussions often involve optimism, ethical concerns, fairness, transparency, and perceived social impact [21,22]. These studies demonstrate the value of social media data for understanding how emerging AI systems are received and debated outside formal educational or institutional settings.

Nevertheless, several gaps remain. First, much existing social media research on GenAI focuses on English-language platforms or on single-model cases, especially ChatGPT. Second, studies of GenAI in education often emphasize teachers, students, or institutional adoption, while less attention has been paid to broader public discourse surrounding education-related use. Third, few studies compare global GenAI systems with Chinese-developed systems within the same Chinese social media environment. By examining ChatGPT- and DeepSeek-related Weibo discourse, this study provides a model-comparative analysis of how GenAI in education is discussed in a specific national and platform context.

2.3. Social Cognitive Theory and Technology Acceptance

Research on technology acceptance has often used models such as the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology to explain adoption through constructs such as perceived usefulness, perceived ease of use, performance expectancy, and effort expectancy [23,24]. These models are useful for explaining individual intention to use technology, especially in survey-based studies. However, this study does not aim to predict individual adoption intention. Instead, it examines how public comments express concerns about competence, anticipated consequences, and socially observed experiences of GenAI in education. For this purpose, SCT provides a suitable interpretive framework.

SCT is widely used in psychology and educational research, positing that behavior results from dynamic interactions between cognition, environment, and behavior [25]. It emphasizes three key factors: self-efficacy, outcome expectations, and observational learning. Self-efficacy refers to one's confidence in using technology to complete tasks; outcome expectations relate to the anticipated consequences of using it; and observational learning involves forming attitudes based on others' actions and outcomes. SCT is therefore appropriate for interpreting Weibo discourse on GenAI in education because the comments are not only evaluations of technical tools, but also public expressions of perceived capability, anticipated risk, and socially shared judgments. Existing studies on AI and educational technology adoption have shown that perceived usefulness, trust, social support, and self-efficacy can influence users' engagement with GenAI and related technologies [26,27]. In family and educational contexts, guidance from parents, teachers, and peers may also shape learners' confidence and technology-related behavior [28]. These findings support the relevance of social and cognitive processes in understanding GenAI adoption.

3. Methods

Figure 1 presents the data processing and analysis workflow of this study. Weibo was used as the data source, and comments and posts related to ChatGPT and DeepSeek in educational contexts were collected using keyword-based web scraping. After data cleaning and preprocessing were completed, text mining methods were applied to conduct sentiment analysis and topic modeling. This approach aimed to identify user attitudes toward GenAI in educational settings and to trace the evolution of their negative cognitive focal points.

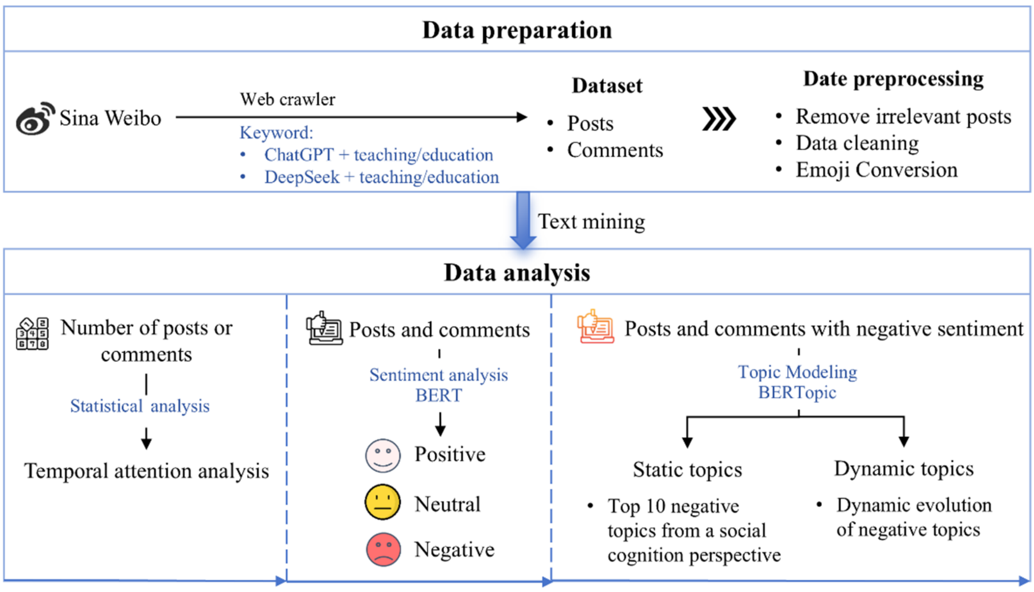


Figure 1. Data processing and analysis workflow.

3.1. Data Collection and Processing

This study focused on ChatGPT and DeepSeek because they represent two prominent GenAI systems in Chinese public discourse. ChatGPT serves as the globally recognized reference model that initiated large-scale public discussion of GenAI in education, whereas DeepSeek represents a Chinese-developed counterpart and provides a meaningful case for examining localized public responses.

Weibo was selected as the data source because it is one of the most widely used public social media platforms in China and provides a suitable setting for observing public responses to emerging technologies in everyday discourse. The dataset consisted of public posts and user comments related to the educational use of ChatGPT and DeepSeek. No private messages and non-public posts were collected. Specifically, from 30 November 2022 to 15 May 2025, a keyword search combining the terms ChatGPT with teaching or education (ChatGPT + 教学; ChatGPT + 教育) yielded 7395 posts. From 2 November 2023, to 15 May 2025, a similar search combining DeepSeek with teaching or education (DeepSeek + 教学; DeepSeek + 教育) yielded 13,505 posts. The time range was determined based on the release dates of the models and the need for data comparability.

A relevance screening procedure was then applied at the keyword and record-validity levels. Posts were retained when they contained the target model name and an education-related search term and could be interpreted as part of public discourse on GenAI and education. Posts were removed when they were exact duplicates or texts without interpretable semantic content. After screening, 5101 ChatGPT-related posts and 9184 DeepSeek-related posts were retained. User comments were then collected from the retained posts through the Weibo comment interface. The crawler first retrieved root comments and then collected available nested replies under each root comment. The comment hierarchy was recorded using parent comment IDs. On this basis, there were 39,741 user comments related to ChatGPT and 97,127 related to DeepSeek. Finally, the study used the emoji library in Python to convert emoji symbols into recognizable text and conducted data cleaning procedures, including the removal of hyperlinks, special characters, and other noise elements.

3.2. Sentiment Analysis

Sentiment analysis, a key task in natural language processing, aims to identify emotions and attitudes in text. It is often divided into binary sentiment classification (positive or negative) or multi-class emotion recognition. Sentiment analysis has evolved from rule-based and shallow machine learning methods to deep learning models, such as BERT, which automatically learn text representations, improving accuracy and generalizability [29]. More recently, large language models like ChatGPT and Claude have been applied to sentiment analysis, offering strong contextual modeling and supporting zero-shot or few-shot tasks [30]. However, challenges remain, such as high computational costs and weak output controllability, especially in domain-specific, high-precision tasks.

To ensure the reliability of sentiment classification, a manually annotated corpus was constructed before model training. A total of 15,000 Weibo comments were annotated into three balanced sentiment categories: neutral, negative, and positive. The annotation followed unified guidelines: neutral comments referred to factual statements, news sharing, technical descriptions, or texts without a clear emotional orientation; negative comments expressed concern, criticism, anxiety, or perceived risks; and positive comments expressed support, approval, expectation, or perceived usefulness. Annotators were trained using the same guidelines, and disagreements were resolved through discussion. Inter-annotator agreement was assessed using Cohen's kappa, yielding a value of 0.83, which indicates strong annotation consistency.

The annotated dataset was used to fine-tune a BERT-based sentiment classifier. On the test set, the best-performing model achieved an overall accuracy of 86.50%, with a macro-F1 score of 85.36% and a weighted-F1 score of 86.43%. Specifically, the F1-scores for neutral, negative, and positive comments were 81.88%, 89.75%, and 84.44%, respectively. These results indicate that the model achieved relatively balanced performance across the three sentiment categories, although neutral comments were slightly more difficult to classify than negative and positive comments. The fine-tuned model was then applied to the full comment corpus.

3.3. Topic Modeling

This study explores public concerns about GenAI in education by analyzing negative sentiment through topic modeling, using a social cognition perspective. Topic models automatically identify latent semantic structures in large-scale text data, helping to uncover cognitive pathways behind emotional responses [31]. While traditional methods like Latent Semantic Analysis and Latent Dirichlet Allocation are widely used, they often miss contextual dependencies and require manual specification of topics, making them sensitive to parameter settings. To address these limitations, we used BERTopic, which incorporates BERT-based semantic embeddings, capturing contextual relationships between words and improving topic accuracy [32]. BERTopic also supports dynamic topic modeling, tracking topic evolution over time.

Topic modeling was conducted separately for the ChatGPT-related and DeepSeek-related negative comment corpora. Before topic modeling, Chinese texts were cleaned, segmented using Jieba (version 0.42.1), and processed with a stop-word list to remove high-frequency function words and semantically uninformative terms. Sentence embeddings were generated using the 'sbert-chinese-general-v2-distill' model, which was selected to support Chinese semantic representation. The same BERTopic settings were used for both corpora. Specifically, the model was implemented with unigram keywords, a minimum topic size of 40, and the top 10 keywords retained for each topic. The nr_topics parameter was set to auto, allowing BERTopic to generate and reduce the number of topics based on the semantic clustering structure of each corpus. No seed topic list or zero-shot topic list was used.

To enhance topic validity, topic labels were assigned through a manual validation procedure, in which two researchers independently reviewed the top keywords and representative original comments generated by BERTopic for each topic, descriptively assigning labels based on the shared semantic meaning between these elements and resolving discrepancies through discussion until consensus was reached. Following this labeling procedure, social cognitive theory (SCT) was employed as a sensitizing framework to organize these descriptive topics into broader interpretive dimensions: topics pertaining to anticipated harms, uncertainty, academic integrity, employment pressure, or educational disruption were interpreted as reflecting perceived risks and negative outcome expectations; topics concerning users' ability to understand, control, or effectively apply GenAI tools were interpreted in relation to self-efficacy and perceived competence; and topics involving educational values, human agency, fairness, cultural identity, or the perceived displacement of human learning were treated as value-related concerns shaped partly by social observation and public discourse.

4. Results

This section presents the temporal distribution of Weibo user discussions on GenAI in educational contexts, emotional attitudes, and the topic clustering results based on negative sentiment texts. Through static and dynamic topic modeling, the analysis further reveals the types of content that constitute public concerns and the evolution of these concerns over time. These findings provide data-driven support for understanding the cognitive structures and behavioral tendencies of users.

4.1. Temporal Attention Analysis

Figure 2 illustrates the changes in the volume of discussions surrounding two major GenAI models, ChatGPT and DeepSeek, in the context of education. ChatGPT reached its peak in discussion volume in 2023, with a significant increase in both original posts and comments. However, as time progressed, the volume of discussion gradually declined in 2024 and 2025. In contrast, DeepSeek entered the educational domain at a later stage, but in 2025, the number of related original posts and comments rose sharply. Overall, the popularity of discussions about ChatGPT in education peaked in 2023, whereas discussions about DeepSeek experienced an explosive surge in 2025.

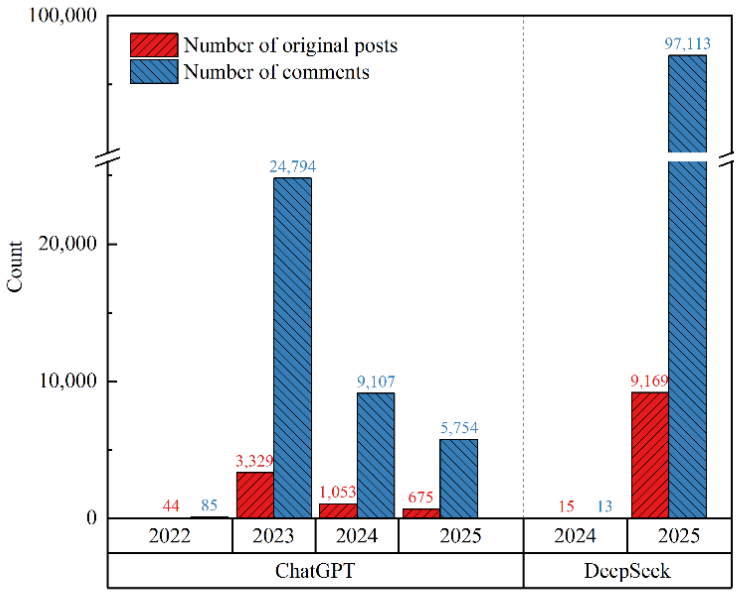


Figure 2. Volume of discussions on GenAI in education on Weibo.

4.2. Sentiment Analysis Results

Figure 3 focused on the distribution of sentiment categories and the change in sample sizes for ChatGPT and DeepSeek in the field of education. For ChatGPT, the number of negative sentiment samples in original posts was relatively low (705), while the proportion in comments was much higher (11,226). The number of neutral sentiment samples was moderate (16,039). Although the number of positive sentiment samples in original posts was small (663), the number in comments was substantially higher (16,209). For DeepSeek, the number of negative sentiment samples was relatively low (1080), but the number of corresponding comments was high (16,421). Neutral sentiment had a large number of samples (28,730), and positive sentiment samples were extremely high, especially in the comments section (58,412), indicating a strong positive evaluation from users regarding the application of DeepSeek in education.

Category of GenAI	Sentiment category	Representative example description	Sample size	Sample size
ChatGPT	Negative	Original post: Doing it this way ruins everything. The brain just stops working.	705	11,931
		Comment: AI awakening and the extinction of humanity.	11,226	
	Neutral	Original post: A step-by-step method for instructing ChatGPT to generate descriptive prompts for image synthesis.	3,733	16,039
		Comment: Understood.	12,306	
	Positive	Original post: Whatever others say, I've really enjoyed working with ChatGPT lately, and I'm very thankful it taught me how to code.	663	16,872
		Comment: To be honest, after many conversations, it feels like it truly understands me.	16,209	
DeepSeek	Negative	Original post: While helping a colleague's child with a reading comprehension assignment, we encountered a multiple-choice question. The AI from Homework Help suggested option B, whereas DeepSeek analyzed the passage and selected A, C, and D. I genuinely don't understand what these AI systems are trying to do.	1,080	17,501
		Comment: The accuracy of the mathematical solutions is questionable.	16,421	
	Neutral	Original post: DeepSeek for homework tutoring and education.	6,436	28,730
		Comment: The future integrated with technology.	22,294	
	Positive	Original post: DeepSeek is too good! Homework with the kid? Super easy now!	1,668	60,080
		Comment: Not bad at all!	58,412	

Figure 3. The distribution of sentiment categories.

4.3. Static Topic Modeling Results

4.3.1. ChatGPT

This section applied the BERTopic model to extract topics from negative social media comments related to ChatGPT and education. Outlier topic −1 was excluded from substantive interpretation, yielding a total of 39 public concern topics. Table 1 reports the ten largest substantive topics, which together accounted for 68.2%, excluding the outlier category.

Table 1. Key negative topics in ChatGPT-education discourse.

ID	Top Keywords	Label	Label Basis	SCT Interpretive	Representative Text and Translation
0	cannot, feel, unable, no, AI, ChatGPT	Uncertainty about AI Use and Human Competence	The topic links GenAI progress with human replacement and competence uncertainty.	Perceived competence	A few years ago, when AlphaGo had just defeated humans and DeepMind had just become popular…… Now Diffusion has emerged, ChatGPT has also emerged, and the wheels of history have proven that it is our group of gravity bound humans who should be eliminated. 早几年AlphaGo刚战胜人类，DeepMind刚热起来的时候……现Diffusion出来了，ChatGPT也出来了，历史的车轮证明，该被淘汰的是我们这群被重力束缚的人类。
1	ChatGPT, education, China, nation, history, not simple	AI Substitution in Teaching and Coursework	The topic concerns AI substitution, teacher roles, and adaptation to technological change.	Perceived risk	#Chatgpt will replace 90% of teachers' jobs # Expert: Teachers' responsibilities need to shift to preaching and teaching students to establish values. #Chatgpt将取代90%教师的工作# 专家：教师职责要转变为传道和教学生树立三观。
2	music, domestic, engineers, garbage, article, teacher	Satirical Reactions to Teaching and AI	The topic uses criticism and irony to discuss teachers' responses to ChatGPT.	Value-related concern	No wonder the teacher said what nonsense I wrote. There's high technology. 怪不得老师说我写的什么狗屎。有高科技啊。
3	ChatGPT, USA, education, China, learning, ability	Educational Disruption and Academic Integrity Concerns	The topic links ChatGPT to academic misconduct, thesis writing, and possible displacement of language-related teaching roles.	Perceived risk	The dean said that the emergence of ChatGPT, especially, is a disaster for humanities students. As for writing papers, the student union will become even more arrogant in copying them. English teachers may be the first to be eliminated, as simultaneous translation is already very mature and there may be more convenient technologies in the future. 院长说特别是ChatGPT出现对文科学生是灾难，就写论文一事，学生会抄得更嚣张。最先被淘汰的可能是英语老师，因为同声翻译已经非常成熟，未来可能还有更便捷的技术出现。
4	domestic, no, not good, India, return, USA	Domestic AI Capability and International Comparison	The topic compares domestic AI education and technological capability with foreign models.	Value-related concern	I don't understand, but I understand what the pedestrian said. It requires massive data resources to accumulate, and there is no other company in China that has this ability. No chance in the short term. 看不明白，听懂行人讲它需要海量数据资源积累，国内还没有那一家有这个能力。短时间没戏。
5	crying, raise hand, sadness, sobbing, male celebrity, baby	Platform-specific Emotional Expressions	This theme mainly captures emotions and platform specific expressions, with a majority of comment texts.	-	Will I become unemployed? [crying emoji]. 我会不会失业[泪泪]。

Table 1. *Cont.*

ID	Top Keywords	Label	Label Basis	SCT Interpretive	Representative Text and Translation
6	bitterness, poor, help, sad, calculate, teach me	Emotional Distress and Help-seeking	The topic reflects help-seeking and difficulty in using AI effectively, with a majority of comment texts.	Perceived competence	I feel like this thing doesn’t work well when doing homework, and I don’t even know if the things I write have a passing level [bitter bitterness]. 我感觉这玩意写作业也不好使啊，写的东西都不知道有没有及格水平[苦涩苦涩]。
7	don’t need, whatever, worry, exhausting, pressure, uninterested	Reduced Thinking and Academic Misuse Concerns	The topic links AI use to reduced thinking, academic dependence, and cheating.	Perceived risk	Without thinking, one will eventually be enslaved by AI. 不用大脑思考，迟早被AI奴役。
8	don’t want, back to school, censorship, privacy, comments	Access Cost and Reluctance to Use ChatGPT	The topic reflects hesitation, access cost, and reluctance to adopt ChatGPT.	Perceived competence	$20, struggling with whether to open a chatgpt plus and experience a gpt-4.0, but it’s a bit expensive and there’s no educational discount yet. 纠结要不要开个ChatGPT体验一把，GPT-4.0小贵，还没教育优惠。
9	teacher, school, curriculum, class, teaching, application	Teacher Role and Classroom Effectiveness Concerns	The topic questions whether AI can replace teachers and emphasizes classroom effectiveness.	Value-related concern	ChatGPT is amazing. I was thinking, do I still need to give a lecture. ChatGPT太厉害了。我在想，那还需要我讲课吗。

(1) Perceived competence: uncertainty, help-seeking, and access barriers

This dimension includes Topic 0, Topic 6, and Topic 8. Topic 0 reflects uncertainty about human competence in the face of rapid GenAI development. The representative comment connects AlphaGo, Diffusion, and ChatGPT with the possible elimination of humans, indicating a perceived decline in human agency and competence. Topic 6 captures emotional distress and help-seeking in educational use, especially when users cannot judge whether AI-generated homework reaches an acceptable standard. Topic 8 further shows that perceived competence is also shaped by access barriers, such as subscription cost and the absence of education discounts. Together, these topics suggest that negative attitudes toward ChatGPT are partly related to users' uncertainty about whether they can understand, evaluate, and effectively use GenAI tools.

(2) Perceived risks and negative outcome expectations: substitution, misconduct, and reduced thinking

This dimension includes Topic 1, Topic 3, and Topic 7. Topic 1 focuses on AI substitution in teaching, especially the claim that ChatGPT may replace a large proportion of teachers' work and force a shift in teachers' professional responsibilities. Topic 3 highlights concerns about educational disruption and academic integrity, particularly the risk that students may use ChatGPT to copy essays or complete academic tasks without sufficient effort. Topic 7 extends this concern to reduced thinking and dependence on AI, as reflected in comments warning that users who stop thinking independently may eventually become controlled by AI. These topics indicate that negative discourse around ChatGPT is strongly linked to anticipated harms in teaching, learning, and academic practice.

(3) Value-related concerns: satire, national comparison, and teacher roles

This dimension includes Topic 2, Topic 4, and Topic 9. Topic 2 captures satirical reactions to teaching and AI-assisted writing, where users use informal criticism to discuss the relationship between teachers, student writing, and technological intervention. Topic 4 reflects value-related concerns about domestic AI capability and international comparison, especially doubts about whether domestic institutions have sufficient data resources and technical capacity to develop ChatGPT-like systems. Topic 9 focuses on teacher roles and classroom relevance, with teachers questioning whether they are still needed when ChatGPT appears capable of supporting instruction. These topics show that ChatGPT-related negative discourse is not only about technical use, but also about professional identity, educational value, and the perceived position of domestic AI development.

4.3.2. DeepSeek

This section applied the BERTopic model to extract topics from negative social media comments related to DeepSeek and education. Outlier topic −1 was excluded from substantive interpretation, yielding a total of 89 public concern topics. Table 2 reports the ten largest substantive topics, which together accounted for 41.6% excluding the outlier category.

Table 2. Key negative topics in DeepSeek-education discourse.

ID	Top Keywords	Label	Label Basis	SCT Interpretive	Representative Text and Translation
0	thinking, still, feel, unable, AI, humanities	Limits of AI Thinking in Humanities Learning	The topic concerns the perceived limits of AI reasoning in Chinese and humanities learning.	Value-related concern	There are some things in humanities that AI cannot replace thinking. 人文的有些东西ai还是不能替代思考的。
1	not good, too difficult, very difficult, employment, feel, job hunting	Employment Pressure and Learning Difficulty	The topic links educational background, job-market pressure, and difficulty adapting to changing skill demands.	Perceived risk	The employment environment for liberal arts students is really not good. 就业环境文科还真的不行。
2	children, parents, education, students, learning, AI, DeepSeek, primary school	Children's Learning and Parental Concerns	The topic focuses on parental concerns about children's homework, learning ability, and dependence on AI.	Perceived risk	DeepSeek doesn't charge anymore, parents might cry! If children use DeepSeek to understand problem-solving ideas, it is indeed a good tool, but the reality is—they don't even look at the process, they just copy the answers, and their hands are faster than AI! If this continues, children's thinking and learning abilities will be lost, and they will increasingly rely on AI instead of using their own brains to solve problems in the future. What's even more terrifying is that the younger the child, the more enthusiastic they are about using it. Starting from elementary school, they rely on AI to "do things for them". What independent thinking ability can they expect from them in the future? DeepSeek再不收费，家长们怕是要哭了！……如果孩子用DeepSeek来理解解题思路，那确实是个好工具，可现实是——他们根本不看过程，直接抄答案，手速比AI还快！这样下去，孩子的思考能力、学习能力都被废掉了，未来只会越来越依赖AI，而不是自己动脑筋解决问题。更恐怖的是，年龄越小的孩子，用得越起劲，从小学就开始靠AI"代劳"，以后还能指望他们有什么独立思考能力？
3	no, not working, unable, useless, thinking, no thought	Output Inconsistency and Reasoning Reliability	This topic expresses doubts about the value of DeepSeek's functionality.	Perceived competence	I'm so confused. The logical chain of thought earlier didn't mention this point at all. When the result was output, it suddenly popped up, and I doubted if it was the result of human intervention. 好懵逼，前面的思考逻辑链完全没提到这一点，结果输出时突然蹦出来，我都怀疑是不是人为干预的结果。

Table 2. *Cont.*

ID	Top Keywords	Label	Label Basis	SCT Interpretive	Representative Text and Translation
4	do not want, cannot, cultural education, rupture, comment, unable	Traditional Cultural Education and AI Use	The topic links AI-generated cultural content with concerns about weakened traditional cultural education.	Value-related concern	The rupture of traditional cultural education has led to the emergence of such "poetry", and perhaps some people will still praise it… Deepseek wrote it, what does the teacher think? 传统文化教育断裂，就出现这样的“诗”，也许还会有人叫好吧……deepseek写的，老师觉得如何？
5	crying, burst into tears, tears, daughter, sadness, emotional expression	Platform-specific Emotional Reactions	The topic mainly captures platform-specific emotional expressions related to education-related events.	-	I firmly believe that over a decade of happy education has gone bankrupt [crying emoji]. 我深信十几年的快乐教育破产了[泪泪]
6	goodgood, coffee, celebrities, internet, Two Sessions, entertainment	Platform-specific Entertainment Expressions	The topic is dominated by platform-specific entertainment expressions.	-	With it, what else do we need to do? [good good] 有了它，还要我们干什么[good good]
7	nothing, no problem, bitterness, no, unable, it is okay	Poor functional tuning	The topic expresses general dismissal of DeepSeek's educational usefulness and weak confidence in its current application.	Perceived competence	DeepSeek is completely ineffective... educating it is a long and arduous task. DeepSeek完全不行啊…教育它任重而道远。
8	doge, college, salary, Tsinghua, wages, education	Education Status and Job-market Valuation	The topic concerns university hierarchy, education status, and job-market valuation.	Perceived risk	You may become unemployed first. [doge doge] 可能你会先失业[doge doge]
9	liberal arts, teacher, professor, DeepSeek, value, class, AI	Humanities Education and Teacher Role Concerns	The topic concerns humanities education, teachers' classroom work, and the changing role of instructors under AI use.	Value-related concern	DeepSeek has caused a silent earthquake in the workplace. During university classes, several teachers suggested that we can use DeepSeek to self-study theory #DeepSeek引来悄无声息的职场地震#是这样大学上课的时候好几个老师说我们可以用deepseek自学理论

(1) Perceived competence: functional uncertainty and weak confidence in AI use

This dimension includes Topic 3 and Topic 7. Topic 3 reflects doubts about DeepSeek's reasoning reliability, as users questioned why the final output contained information not supported by the preceding reasoning chain. This concern points to uncertainty about whether users can understand, verify, and trust AI-generated responses. Topic 7 further captures weak confidence in DeepSeek's educational usefulness, with users describing the system as ineffective and suggesting that it still requires substantial improvement. Together, these topics indicate that negative perceptions of DeepSeek are partly shaped by limited perceived control over AI outputs and uncertainty about its functional reliability in educational contexts.

(2) Perceived risks: employment pressure, learning dependence, and job displacement

This dimension includes Topic 1, Topic 2, and Topic 8. Topic 1 links DeepSeek-related discourse with employment pressure, especially among liberal arts students facing a difficult job market. Topic 2 focuses on children's learning and parental concerns. Although DeepSeek may help students understand problem-solving processes, users worried that children might skip the learning process, copy answers directly, and become dependent on AI from an early age. Topic 8 also reflects perceived risk, but at the level of employment insecurity, as the representative comment suggests that AI development may lead to job displacement. These topics show that negative discourse around DeepSeek is closely related to anticipated harms in learning autonomy, educational development, and future employment.

(3) Value-related concerns: humanities thinking, cultural education, and teacher roles

This dimension includes Topic 0, Topic 4, and Topic 9. Topic 0 emphasizes the perceived limits of AI in humanities learning, suggesting that some forms of humanistic thinking cannot be replaced by AI. Topic 4 extends this concern to traditional cultural education, where AI-generated poetry is interpreted as a sign of weakened cultural understanding. Topic 9 focuses on humanities education and teacher roles, with users noting that university teachers encouraged students to use DeepSeek for self-learning theoretical content. These topics indicate that negative perceptions of DeepSeek involve not only technical performance, but also broader concerns about humanistic value, cultural continuity, and the changing role of teachers.

4.4. Dynamic Topic Modeling Results

Figure 4 illustrates the temporal evolution of major negative topics related to ChatGPT and DeepSeek in education-related Weibo discourse. Figure 4a shows the dynamic trends of ChatGPT-related negative topics. Topic 0, Uncertainty about AI Use and Human Competence, was the most frequent topic and showed a sharp peak shortly after ChatGPT entered public discussion in late 2022. Its frequency exceeded 1000 at the initial peak and then declined rapidly during 2023. This pattern suggests that early negative discourse around ChatGPT was strongly associated with uncertainty about human competence, replacement, and adaptation to GenAI. Other ChatGPT-related topics were less frequent but showed more sustained low-level fluctuations. Topic 3, Educational Disruption and Academic Integrity Concerns, rose during the early diffusion period and then remained visible across the observation window, reflecting continued concern about academic misconduct, learning disruption, and changes to educational practice. Topic 1, AI Substitution in Teaching and Coursework, and Topic 9, Teacher Role and Classroom Effectiveness Concerns, also appeared mainly in relation to perceived changes in teachers' professional roles. Topic 4, Domestic AI Capability and International Comparison, and Topic 2, Satirical Reactions to Teaching and AI, remained comparatively limited but indicated that part of the negative discourse connected ChatGPT with broader evaluations of technological capability and educational criticism. Overall, ChatGPT-related negative discourse was concentrated in the early stage, with later discussions becoming more dispersed and lower in frequency.

Figure 4b presents the temporal evolution of DeepSeek-related negative topics. DeepSeek-related negative discourse was concentrated within a shorter period in early 2025 and showed several topic peaks between February and March. Topic 2, Children's Learning and Parental Concerns, rose early and remained prominent before March, indicating concern about children's homework, learning dependence, and reduced independent thinking. Topic 0, Limits of AI Thinking in Humanities Learning, increased sharply in March and became the most frequent topic at its peak, suggesting that negative discourse increasingly focused on whether DeepSeek could support humanities learning and humanistic reasoning. Topic 1, Employment Pressure and Learning Difficulty, also peaked in March, linking DeepSeek-related discussion with job-market pressure and adaptation difficulties, especially in liberal arts contexts. Topic 3, Output Inconsistency and Reasoning Reliability, followed a similar temporal pattern, reflecting doubts about the reliability and interpretability of DeepSeek's reasoning process. Topic 4, Traditional Cultural Education and AI Use, remained at a lower but visible level, indicating concern about AI-generated cultural content and the continuity of traditional cultural education. Topics 5 and 6 were mainly associated with platform-specific emotional or entertainment expressions and were therefore interpreted cautiously. Overall, DeepSeek-related negative discourse was more temporally compressed and thematically dispersed, with prominent concerns around children's learning, humanities reasoning, employment pressure, and output reliability.

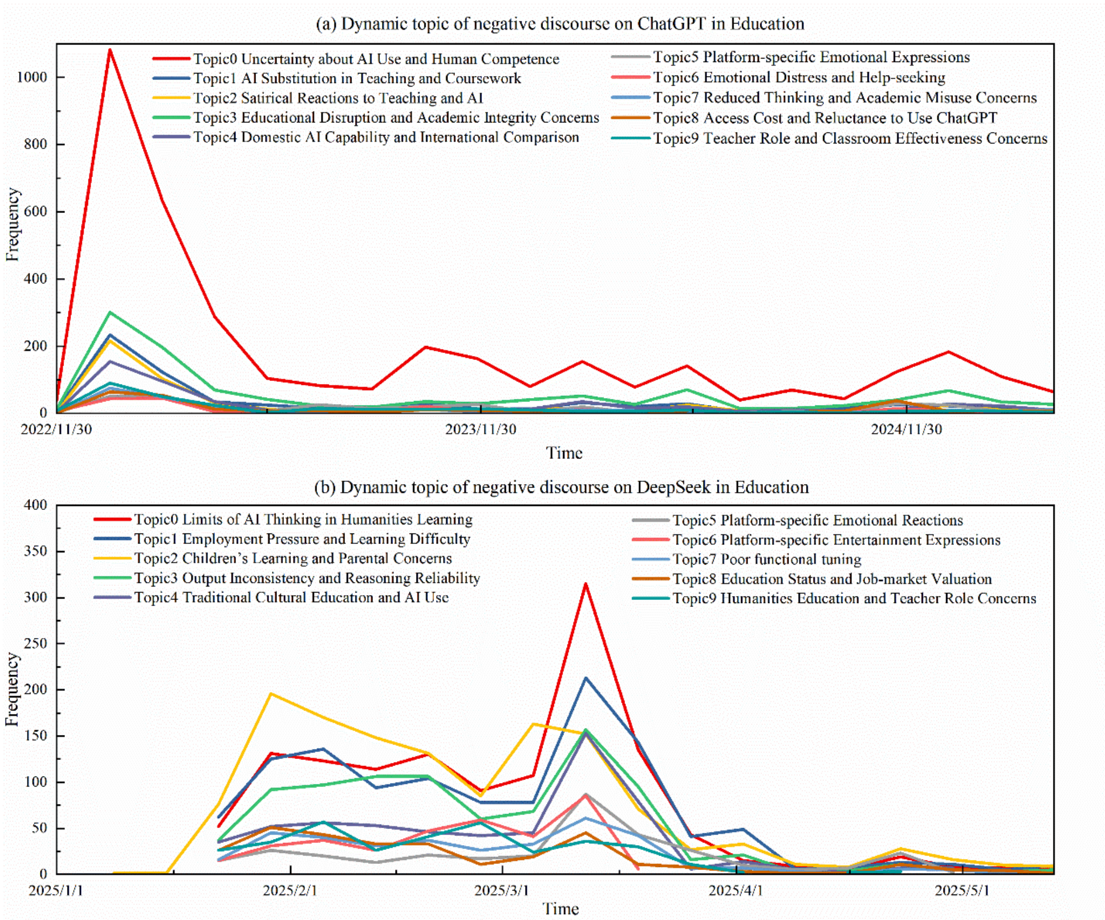


Figure 4. Dynamic topic of negative discourse on GenAI in education.

5. Discussions

This study examined public sentiment and negative discourse toward ChatGPT and DeepSeek in education-related Weibo discussions. The findings show that negative discourse on GenAI in education was not limited to technical dissatisfaction. Users also expressed concerns about the ability to understand, evaluate, and trust AI outputs, the risks of academic misuse and learning dependence, and the value implications of AI-supported education. Existing studies have mainly emphasized the potential of GenAI to support personalized learning, instructional efficiency, and access to educational resources [12,33]. The present study complements this literature by showing that public discourse also contains recurring concerns about reliability, controllability, educational appropriateness, and value alignment. In this sense, the study shifts attention from the functional affordances of GenAI to the public concerns that accompany its educational diffusion.

Capability-related concerns appeared in both ChatGPT- and DeepSeek-related discourse. In the ChatGPT corpus, users discussed uncertainty about AI use, human competence, help-seeking, and barriers to adoption. In the DeepSeek corpus, users questioned output consistency, reasoning reliability, and functional effectiveness. These findings are consistent with the relevance of self-efficacy in social cognitive theory, which emphasizes the role of perceived capability in shaping human action [34]. The risk-related topics further show that public concerns about GenAI in education extend beyond operational difficulty. ChatGPT-related discourse included concerns about teacher substitution, academic integrity, reduced independent thinking, and classroom effectiveness. DeepSeek-related discourse placed greater emphasis on children's learning dependence, employment pressure, and job displacement. These findings complement previous research on GenAI-supported learning by showing that public responses are shaped not only by perceived usefulness [35,36], but also by negative outcome expectations regarding learning behavior, academic norms, and future employability. Accordingly, GenAI literacy should include not only technical operation, but also output verification, academic integrity, and strategies for preventing uncritical dependence on AI-generated content.

The findings also indicate that negative discourse on GenAI in education involves value-related concerns. In the ChatGPT-related discourse, users discussed teacher roles, classroom effectiveness, domestic AI capability, and broader judgments about educational change. In the DeepSeek-related discourse, users raised concerns about humanities learning, traditional cultural education, teacher roles, and the legitimacy of AI-supported learning. These topics suggest that GenAI is evaluated not only as a technical tool, but also as a technology embedded in educational values, professional identities, and cultural expectations. This finding is consistent with prior research suggesting that GenAI in education raises ethical, cultural, and pedagogical questions beyond efficiency and performance [37,38]. Therefore, educational institutions should be cautious about treating GenAI adoption as a purely technical reform; teacher professional development and curriculum design should also address pedagogical judgment, cultural sensitivity, and the appropriate boundaries of AI-supported learning.

6. Conclusions and Limitations

This study examined public sentiment and negative discourse toward ChatGPT and DeepSeek in education-related Weibo discussions. By combining BERT-based sentiment classification with BERTopic topic modeling, the study identified how public concerns about GenAI in education were expressed across two model-specific discourse contexts. The results show that negative discourse was not limited to technical dissatisfaction. Users also raised concerns about AI output reliability, human competence, academic integrity, learning dependence, employment pressure, teacher roles, humanities education, and the value implications of AI-supported learning. ChatGPT-related negative discourse was more closely associated with early uncertainty about AI use, teacher substitution, academic misconduct, and classroom effectiveness. DeepSeek-related negative discourse showed stronger links to children's learning dependence, output reliability, employment pressure, humanities learning, and traditional cultural education.

This study has several limitations. First, the dataset was constructed from keyword-filtered public Weibo discourse and should not be interpreted as representative of all Chinese users or all educational stakeholders. In particular, this study did not conduct bot filtering, institutional-account identification, or coordinated-behaviour detection. The findings may still be affected by platform-specific visibility, user activity, promotional content, and topic amplification mechanisms. Second, this study focused solely on ChatGPT and DeepSeek in education, excluding other GenAI tools, which may limit the generalizability of the findings. Additionally, while sentiment analysis and topic modeling were based on social media data, these discussions may not fully capture the experiences of educators and learners in real classroom settings. Future research should expand the scope to include more GenAI tools, multiple platforms, and additional educational contexts. Mixed-method approaches, such as interviews, surveys, classroom observations, or case studies, would also help validate the psychological and educational interpretations derived from social media data.

Author Contributions

M.Y.: Funding acquisition. H.H.: Conceptualization, Methodology, Data curation, Writing—original draft, Writing—review & editing. Q.W.: Writing—review & editing. Z.W.: Data processing. K.L.: Data processing. All authors have read and agreed to the published version of the manuscript.

Funding

This study is supported by Anhui Provincial Quality Engineering Professional Construction Project (2024xjzlts010).

Institutional Review Board Statement

This study used publicly accessible Weibo posts and involved no direct interaction with users, intervention, or collection of private information. Formal institutional review was not required because the study relied solely on publicly available online materials. Data collection and analysis complied with relevant platform terms and ethical principles for public social media research. We did not store or report user IDs, profile names, avatars, location information, follower counts, or other identifiable profile metadata. Only textual content needed for sentiment analysis and topic modelling was retained. Representative examples were anonymised and, where necessary, paraphrased to reduce re-identification risk. All findings are reported in aggregate form, and no attempt was made to identify, contact, or profile individual users.

Informed Consent Statement

This research does not involve human participants, and therefore, no informed consent was required. All data used in the study were obtained from publicly available online sources and were fully anonymized prior to analysis.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author, Min Yuan, upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

References

1. Krakowski, S. Human-AI Agency in the Age of Generative AI. *Inf. Organ.* **2025**, *35*, 100560. https://doi.org/10.1016/j.infoandorg.2025.100560.
2. Kim, H.; Hwang, J.; Kim, T.; et al. Impact of Generative Artificial Intelligence on Learning: Scaffolding Strategies and Self-Directed Learning Perspectives. *Int. J. Hum. Comput. Interact.* **2026**, *42*, 2965–2987. https://doi.org/10.1080/10447318.2025.2531267.
3. Ortega-Mohedano, J. Impact of Artificial Intelligence and Other Emerging Technologies on Education and Media. *Educ. Media Int.* **2024**, *61*, 345–351. https://doi.org/10.1080/09523987.2024.2436735.
4. Liang, E.S.; Bai, S. Generative AI and the Future of Connectivist Learning in Higher Education. *J. Asian Public Policy* **2025**, *18*, 329–351. https://doi.org/10.1080/17516234.2024.2386085.
5. Francis, S.P.; Kolil, V.K.; Pavithran, V.; et al. Exploring Gender Dynamics in Cybersecurity Education: A Self-Determination Theory and Social Cognitive Theory Perspective. *Comput. Secur.* **2024**, *144*, 103968. https://doi.org/10.1016/j.cose.2024.103968.
6. Bewersdorff, A.; Hartmann, C.; Hornberger, M.; et al. Taking the next Step with Generative Artificial Intelligence: The Transformative Role of Multimodal Large Language Models in Science Education. *Learn. Individ. Differ.* **2025**, *118*, 102601. https://doi.org/10.1016/j.lindif.2024.102601.
7. Liu, Y.; Du, Y. The Effect of Generative AI Ethics on Users' Continuous Usage Intentions: A PLS-SEM and fsQCA Approach. *Int. J. Hum. Comput. Interact.* **2025**, *41*, 12831–12842. https://doi.org/10.1080/10447318.2025.2465861.
8. Cai, H.; Han, B.; Sun, J.; et al. Harnessing AI for Teacher Education to Promote Inclusive Education: Investigating the Effects of ChatGPT-Supported Lesson Plan Critiques on the Development of Pre-Service Teachers' Lesson Planning Skills. *Internet High. Educ.* **2025**, *67*, 101022. https://doi.org/10.1016/j.iheduc.2025.101022.
9. Huang, H.; Sun, K.; Long, R. Navigating Sentiment Dynamics in Social Media: The Role of Information Characteristics in Promoting Green Consumption across Multiple Domains. *Environ. Impact Assess. Rev.* **2025**, *112*, 107840. https://doi.org/10.1016/j.eiar.2025.107840.
10. Li, H.; Wang, Y.; Luo, S.; et al. The Influence of GenAI on the Effectiveness of Argumentative Writing in Higher Education: Evidence from a Quasi-Experimental Study in China. *J. Asian Public Policy* **2025**, *18*, 405–430. https://doi.org/10.1080/17516234.2024.2363128.
11. Xia, Q.; Zhang, P.; Huang, W.; et al. The Impact of Generative AI on University Students' Learning Outcomes via Bloom's Taxonomy: A Meta-Analysis and Pattern Mining Approach. *Asia Pac. J. Educ.* **2025**, 1–31. https://doi.org/10.1080/02188791.2025.2530503.
12. Chiu, T.K.F. A Classification Tool to Foster Self-Regulated Learning with Generative Artificial Intelligence by Applying Self-Determination Theory: A Case of ChatGPT. *Educ. Technol. Res. Dev.* **2024**, *72*, 2401–2416. https://doi.org/10.1007/s11423-024-10366-w.
13. Uğraş, H.; Uğraş, M.; Papadakis, S.; et al. ChatGPT-Supported Education in Primary Schools: The Potential of ChatGPT for Sustainable Practices. *Sustainability* **2024**, *16*, 9855. https://doi.org/10.3390/su16229855.
14. Uğraş, H.; Uğraş, M.; Papadakis, S.; et al. Innovative Early Childhood STEM Education with ChatGPT: Teacher Perspectives. *Technol. Knowl. Learn.* **2025**, *30*, 809–831. https://doi.org/10.1007/s10758-024-09804-8.
15. Rasul, T.; Nair, S.; Kalendra, D.; et al. Enhancing Academic Integrity among Students in GenAI Era:A Holistic Framework. *Int. J. Manag. Educ.* **2024**, *22*, 101041. https://doi.org/10.1016/j.ijme.2024.101041.

16. Zacharis, G.; Papadakis, S. Can AI Grade Like a Human? Validity, Reliability, and Fairness in University Coursework Assessment. *Educ. Process Int. J.* **2025**, *19*, e2025591. https://doi.org/10.22521/edupij.2025.19.591.
17. Yang, H.; Markauskaite, L. Fostering Language Student Teachers' Transformative Agency for Embracing GenAI: A Formative Intervention. *Teach. Teach. Educ.* **2025**, *159*, 104980. https://doi.org/10.1016/j.tate.2025.104980.
18. Yujie, Z.; Al Imran Yasin, M.; Alsagoff, S.A.B.S.; et al. The Mediating Role of New Media Engagement in This Digital Age. *Front. Public Health* **2022**, *10*, 879530. https://doi.org/10.3389/fpubh.2022.879530.
19. So, H.-J.; Jang, H.; Kim, M.; et al. Exploring Public Perceptions of Generative AI and Education: Topic Modelling of YouTube Comments in Korea. *Asia Pac. J. Educ.* **2024**, *44*, 61–80. https://doi.org/10.1080/02188791.2023.2294699.
20. Napoli, P.M.; Adi, S. On Moving Fast and Breaking Things…Again: Social Media's Lessons for Generative AI Governance. *Inf. Commun. Soc.* **2026**, *29*, 1912–1928. https://doi.org/10.1080/1369118X.2025.2513668.
21. Cohen, M.; Khavkin, M.; Davidow, D.M.; et al. ChatGPT in the Public Eye: Ethical Principles and Generative Concerns in Social Media Discussions. *New Media Soc.* **2026**, 28, 5–31. https://doi.org/10.1177/14614448241279034.
22. Qi, W.; Pan, J.; Lyu, H.; et al. Excitements and Concerns in the Post-ChatGPT Era: Deciphering Public Perception of AI through Social Media Analysis. *Telemat. Inform.* **2024**, *92*, 102158. https://doi.org/10.1016/j.tele.2024.102158.
23. Venkatesh, V.; Morris, M.G.; Davis, G.B.; et al. User Acceptance of Information Technology: Toward A Unified View1. *MIS Q.* **2003**, *27*, 425–478. https://doi.org/10.2307/30036540.
24. Davis, F.D. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Q.* **1989**, *13*, 319–340. https://doi.org/10.2307/249008.
25. Bandura, A. Social Cognitive Theory: An Agentic Perspective. *Asian J. Soc. Psychol.* **1999**, *2*, 21–41. https://doi.org/10.1111/1467-839X.00024.
26. Ma, X.; Huo, Y. Are Users Willing to Embrace ChatGPT? Exploring the Factors on the Acceptance of Chatbots from the Perspective of AIDUA Framework. *Technol. Soc.* **2023**, *75*, 102362. https://doi.org/10.1016/j.techsoc.2023.102362.
27. Shata, A.; Hartley, K. Artificial Intelligence and Communication Technologies in Academia: Faculty Perceptions and the Adoption of Generative AI. *Int. J. Educ. Technol. High. Educ.* **2025**, *22*, 14. https://doi.org/10.1186/s41239-025-00511-7.
28. Jin, B.; Zhang, D. Linking Parental Restrictive Mediation to Adolescents' Science Achievement: A Social Cognitive Theory Perspective. *Learn. Individ. Differ.* **2022**, *98*, 102187. https://doi.org/10.1016/j.lindif.2022.102187.
29. Huang, H.; Long, R.; Chen, H.; et al. Examining Public Attitudes and Perceptions of Waste Sorting in China through an Urban Heterogeneity Lens: A Social Media Analysis. *Resour. Conserv. Recycl.* **2023**, *199*, 107233. https://doi.org/10.1016/j.resconrec.2023.107233.
30. Chandan, M.K.; Mandal, S. A Comprehensive Survey on Sentiment Analysis: Framework, Techniques, and Applications. *Comput. Sci. Rev.* **2025**, *58*, 100777. https://doi.org/10.1016/j.cosrev.2025.100777.
31. Özmantar, M.F.; Gökdağ, K.; Hangül, T.; et al. Research Themes and Trends in the Field of Teacher Educators: A Topic Modelling Study. *Teach. Teach. Educ.* **2024**, *148*, 104696. https://doi.org/10.1016/j.tate.2024.104696.
32. Grootendorst, M. BERTopic: Neural Topic Modeling with a Class-Based TF-IDF Procedure. *arXiv* **2022**, arXiv:2203.05794.
33. Francis, N.J.; Jones, S.; Smith, D.P. Generative AI in Higher Education: Balancing Innovation and Integrity. *Br. J. Biomed. Sci.* **2025**, *81*, 14048. https://doi.org/10.3389/bjbs.2024.14048.
34. Woreta, G.T.; Zewude, G.T.; Józsa, K. The Mediating Role of Self-Efficacy and Outcome Expectations in the Relationship Between Peer Context and Academic Engagement: A Social Cognitive Theory Perspective. *Behav. Sci.* **2025**, *15*, 681. https://doi.org/10.3390/bs15050681.
35. Amzalag, M. When Professions Meet GenAI: Patterns of Self-Regulated Learning. *Educ. Sci.* **2026**, *16*, 416. https://doi.org/10.3390/educsci16030416.
36. Chung, J.; Henderson, M.; Slade, C.; et al. The Use and Usefulness of GenAI in Higher Education: Student Experience and Perspectives. *Comput. Educ. Open* **2026**, *10*, 100347. https://doi.org/10.1016/j.caeo.2026.100347.
37. Cheah, Y.H.; Lu, J.; Kim, J. Integrating Generative Artificial Intelligence in K-12 Education: Examining Teachers' Preparedness, Practices, and Barriers. *Comput. Educ. Artif. Intell.* **2025**, *8*, 100363. https://doi.org/10.1016/j.caeai.2025.100363.
38. García-López, I.M.; Trujillo-Liñán, L. Ethical and Regulatory Challenges of Generative AI in Education: A Systematic Review. *Front. Educ.* **2025**, *10*, 1565938. https://doi.org/10.3389/feduc.2025.1565938.