How the Public Views AI in Vocational Education in China: Topic Modelling and Sentiment Analysis on Bilibili

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Abstract: The rapid development of generative artificial intelligence (GenAI) technologies has injected new momentum into the field of vocational education. This study analyses 55,913 standard comments collected from Bilibili between January 2023 and March 2025, using text mining, topic modelling, and sentiment analysis to examine public perceptions of AI in vocational education in China. Public discourse clusters around five thematic categories: technological applications and tools, educational content and competency development, social impacts and employment concerns, application scenarios and practices, and public sentiments and attitudes. Controversies centre on issues such as technological reliability, the boundaries of human-AI collaboration, and the impact on employment. The results show that overall public sentiment toward AI in vocational education is positive, though it exhibits periodic fluctuations. Based on these findings, we propose optimization strategies from four aspects: policy regulation, educational practice, technology development, and ethical governance, to promote the deep integration and sustainable development of AI and vocational education.

Keywords: Artificial Intelligence; Data Mining; Social Media; Vocational Education

1 Introduction

Vocational training plays a significant role in equipping individuals with the skills necessary for sustainable development and inclusive growth [3, 23]. In China, vocational education has become a strategic national priority, serving not only to expand employment opportunities but also to support the country's ongoing economic transformation and industrial upgrading [5]. With over 30 million students enrolled in secondary and higher vocational institutions, China operates one of the largest vocational education systems in the world, making it a critical arena for examining the impact of emerging technologies [29].

Artificial intelligence (AI), as a transformative technology, not only significantly impacts vocational education but also helps align educational practices with evolving industry standards and workforce demands [3,4,21,25]. By facilitating personalized instruction, adaptive learning, and data-driven skills assessment, AI enhances both the efficiency and effectiveness of vocational training, particularly in practice-oriented domains where access to equipment and real-world scenarios is often limited [7, 24, 37]. Beyond the classroom, AI's integration into vocational education reshapes institutional management and policy planning [6, 19]. Predictive analytics can identify students at risk, optimize resource allocation, and support competency-based certification, while AI-driven labor market insights ensure that training programs remain aligned with current and emerging industry needs [22]. These developments suggest that AI has the potential to transform traditional pedagogical approaches while also reshaping the skill requirements of future work environments [4]. However, the extent to which these benefits can be realized in practice depends not only on institutional readiness but also on the transformative potential of AI in vocational education being met with broad societal acceptance and informed public engagement.

Understanding how the public perceives AI in vocational education is critical to its sustainable implementation [14, 34]. Public attitudes, expressed through social media platforms like Twitter, YouTube, and Bilibili, reflect not only enthusiasm for AI-enabled learning but also public concerns regarding ethical risks, job displacement, and the reliability of AI technologies [2]. Examining these perceptions provides insights into societal acceptance, potential barriers to adoption, and areas requiring policy guidance [2, 10]. Nevertheless, existing research on public perceptions of AI in education has focused predominantly on higher education or general K-12 contexts, with vocational education receiving comparatively little at-

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tention. This is notable given vocational education's distinct institutional pressures, employment orientation, and rapid digital transformation, particularly in the Chinese context [5]. The few studies that do examine vocational contexts tend to focus on learners' or educators' attitudes within institutional settings, rather than capturing the broader public discourse that shapes policy legitimacy and societal acceptance.

To address this gap, this study aims to analyze large-scale public discourse on Bilibili regarding AI in vocational education in China, employing topic modelling and sentiment analysis to uncover dominant themes, focal concerns, and evolving sentiments. By doing so, it contributes to both theoretical understanding and practical guidance for the deep integration of AI in vocational education, ensuring that technological innovation supports equitable, effective, and industry-aligned skill development.

2 Literature Review

2.1 AI in Vocational Education

Within vocational education, AI serves two core functions. First, it represents part of the content of learning: as industries increasingly adopt AI technologies, learners must develop AI literacy and applied competencies to remain employable in technology-rich workplaces [31]. This includes understanding how to collaborate with intelligent systems, interpret data, and adapt to evolving occupational standards [31]. Second, AI operates as a pedagogical tool. Institutions are leveraging AI tools to improve instructional quality, provide personalized learning support, and streamline management [24]. In this sense, AI is simultaneously shaping what vocational learners study and how they acquire and demonstrate their competencies.

Studies have examined diverse applications of AI in vocational settings e.g., [23, 27]. For instance, researchers have investigated the use of intelligent tutoring systems and adaptive platforms that deliver personalized instruction in technical subjects, as well as AI-driven assessments such as automated grading of practical tasks. Others have highlighted the role of AI-powered analytics in supporting institutional governance and aligning training with labor market demands. Tsai et al. [27] extended on this by designing and evaluating a SPOC-AIoT model course for vocational senior high schools. Their study not only established a framework for cross-domain AIoT learning but also validated a context-specific learning scale, finding that a structured approach effectively guided students in mastering AIoT knowledge.

While such studies demonstrate the potential of AI to enrich vocational teaching and learning, existing research has largely focused on classroom-level integration and learners' experiences. This body of work, however, tells us little about how the broader public understands and evaluates AI in vocational education, a question that has begun to attract attention in the adjacent literature on public discourse and social media.

2.2 Public Perceptions and Social Discourse on AI in Education

Beyond the classroom-level applications reviewed above, public attitudes play a critical role in shaping the broader trajectory of AI in education [4]. Previous studies have examined how learners, educators, and the general public perceive both the promises and risks of AI, highlighting concerns over privacy, algorithmic bias, the displacement of teachers, and overreliance on technology e.g., [4, 39]. Social media platforms such as Twitter and YouTube provide valuable spaces where these attitudes are expressed and debated in real time, reflecting a spectrum from enthusiasm to skepticism [10]. Theoretical frameworks such as the Technology Acceptance Model (TAM) have been applied to explain individual-level adoption attitudes, though their extension to collective, platform-mediated discourse remains limited [5]. In the Chinese context, where platform ecology and cultural dynamics differ substantially from Western social media [26], dedicated studies have begun to map public sentiment on AI in education. In the context of China, Zhou and Zhang [39] examined public perceptions of GenAI in education through large-scale social media discourse. Based on over 40,000 comments from major Chinese platforms (e.g., Bilibili, Weibo, and Douyin), the study used LDA topic modelling and sentiment analysis to identify dominant themes and affective orientations. Results revealed four key themes, i.e., career development, school education, intelligent futures, and higher education, with overall attitudes toward intelligent futures being more positive than negative, while negative sentiments clustered around concerns about employment and schooling concerns.

Nevertheless, this body of research reveals a persistent gap: public discourse specifically surrounding AI in vocational education remains largely unexamined. Existing studies either treat vocational education as a peripheral subcategory within broader educational AI discourse, or focus exclusively on institutional actors rather than the general public. Given the scale and employment-centrality of China's vocational education system, and the rapid pace of its AI integration, this gap is both empirically significant and practically consequential [6, 34].

The present study therefore takes Bilibili as its empirical site to examine how the Chinese public constructs, debates, and evaluates AI in vocational education through large-scale online discourse. The research questions are as follows:

RQ1: What are the public's key concerns regarding AI in vocational education?

RQ2: What are the most discussed topics in public discourse about AI in vocational education?

RQ3: What is the public's sentiment toward AI in vocational education? How does it change over time?

3 Methods

To capture large-scale public discourse, this study adopts a big-data methodology to examine societal perceptions of AI in vocational education. Techniques such as Latent Dirichlet Allocation (LDA) topic modelling are used to identify dominant themes across large corpora [12, 16], while sentiment analysis measures affective orientations such as optimism, anxiety, or resistance [32]. These approaches have been applied in diverse educational contexts and policy debates, offering insights into stakeholders' concerns and attitudes e.g., [4, 39]. Given the scale and dynamics of online discussions about AI in vocational education, topic modelling and sentiment analysis provide a systematic means to uncover key issues, frame public concerns, and track shifts in sentiment over time.

3.1 Context

Bilibili.com was selected for this study because of its diverse user demographics and distinctive interaction features, which provide valuable insights into public sentiment e.g., [20, 33]. Founded in 2009, Bilibili has grown into one of China's most influential video platforms and a leading community for younger generations [1]. While originally centered on anime, manga, and gaming culture, it has since expanded to include a wide range of content, including educational and language learning resources. The platform is also notable for its highly participatory user culture, with "UP" (content creators) and viewers engaging in dynamic exchanges.

Bilibili supports two distinct forms of user-generated text interaction: danmu (bullet screen comments), which overlay real-time scrolling text across videos and capture in-the-moment reactions; and standard comments, which are posted below videos in a conventional threaded format and tend to reflect more considered, substantive opinions. While danmu is a widely recognized hallmark of Bilibili's participatory culture, the present study analyzed standard comments exclusively, as these are systematically retrievable via the platform API and offer the kind of extended, interpretable text suited to topic modelling and sentiment analysis. This choice is consistent with prior research on Bilibili discourse e.g., [33, 36], which has similarly prioritized standard comments for computational text analysis. As of March 31, 2023, Bilibili reported an average of 315 million monthly active users, including 276 million on mobile devices [30].

3.2 Data Collection

Standard comments from Bilibili were collected using a Python API wrapper, which offers a streamlined interface for interacting with Bilibili's API. After securing the required API credentials, we extracted comments from targeted posts by specifying the target video ID and comment thread. Throughout the process, we followed the platform's API usage guidelines to ensure ethical and compliant data collection.

Search keywords included artificial intelligence, AI, AIGC, and intelligence, combined with terms such as vocational education, higher vocational, secondary vocational, and vocational undergraduate. For each matched video, the fields collected included the video title, uploader (UP) name, comment text, and comment timestamp. As of March 2025, after data cleaning, a total of 55,913 valid entries were obtained, covering the period from January 2023 to March 2025.

3.3 Data Analysis

This study employed Python-based tools and applied both text analysis and content analysis to examine comment texts related to the application of AI in vocational education [16]. All collected comments first underwent preprocessing, including removal of punctuation, special characters, and URLs, conversion to lowercase, and elimination of stop words. Preliminary analysis and visualization were then conducted with Python libraries. The Jieba tokenizer was used to extract high-frequency keywords and calculate their weights, which were then visualized through word clouds and semantic network diagrams.

LDA was applied to extract key thematic features from the preprocessed comment texts. To determine the optimal number of topics, we evaluated models across a range of k values (e.g., k = 5 to 20). Model selection was guided by two complementary metrics: perplexity, which measures the model's ability to generalize to unseen data (lower values indicate better fit), and topic coherence (CV score), which assesses the semantic interpretability of the resulting topics (higher values indicate more coherent topics). Based on these evaluations, k = 10 was selected as it yielded the lowest perplexity and highest coherence score, while producing thematically distinct and interpretable topics without excessive redundancy. The resulting topics and associated keywords were visualized in word clouds and tables to identify public concerns and perceptions, thereby addressing RQ1 and RQ2.

Sentiment analysis was performed to explore users' attitudes, emotions, and opinions toward AI in vocational education (RQ3). Following preprocessing, a sentiment analysis toolkit was used to classify comments as positive, neutral, or negative. The results were then visualized in distribution charts to present overall sentiment tendencies over time.

3.4 Ethical Considerations

Ethical approval for this study was obtained from the corresponding author's Institutional Review Board (IRB) in mainland China, which determined that informed consent was not required given the publicly accessible nature of the online comments. To uphold ethical standards, all data were anonymized, and any personal identifiers were removed.

4 Results

4.1 The Public's Key Concerns Regarding AI in Vocational Education

Based on the Jieba segmentation results, the WordCloud library was used to visualize the segmented keywords (Fig. 1). Combined with the word cloud and the table of high-frequency keywords with their TF-IDF weights (Table 1), it can be observed that public perceptions toward the application of AI in vocational education are diverse, covering areas such as AI technologies, employment opportunities, and career development.

Quarter	English	TF-IDF Weight	Quarter	English Translation	TF-IDF Weight
2023Q1	AI	0.1095	2024Q1	AI	0.1069
2023Q1	Claim	0.1659	2024Q1	Video	0.0534
2023Q1	Design	0.0419	2024Q1	Generate	0.0523
2023Q2	AI	0.0754	2024Q2	AI	0.1133
2023Q2	Job	0.0322	2024Q2	Thesis	0.0528
2023Q2	AFA	0.036	2024Q2	Video	0.0261
2023Q3	AI	0.0791	2024Q3	AI	0.0885
2023Q3	AIGC	0.0551	2024Q3	Game	0.0509
2023Q3	Video	0.033	2024Q3	Video	0.031
2023Q4	AI	0.0484	2024Q4	AI	0.0419
2023Q4	Vocational High School	0.0461	2024Q4	Job	0.0522
2023Q4	Video	0.0269	2024Q4	Thanks	0.0536

Table 1. Top 5 High-frequency keywords and their TF-IDF Weights by quarter (Selected)

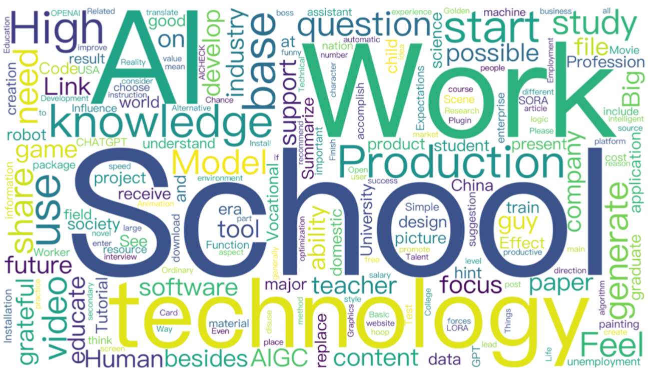

Figure 1. Word cloud of comment texts on AI vocational education

4.2 Semantic Network Analysis

By further constructing a semantic network diagram, we can clearly visualize the weight distribution of keywords and capture the semantic associations between them, thus uncovering deeper structural relationships, as shown in Fig. 2. It can be observed that keywords such as "AI", "learning", "work", "tool", "problem", and "sharing" are located at the core layer, representing topics of general public concern regarding AI in vocational education. Meanwhile, keywords that reflect the unique culture of the Bilibili community, such as "practical tips", "UP" (content creators), and "tutorial", are situated on the outer layer, still retaining the platform's distinctive thematic characteristics.

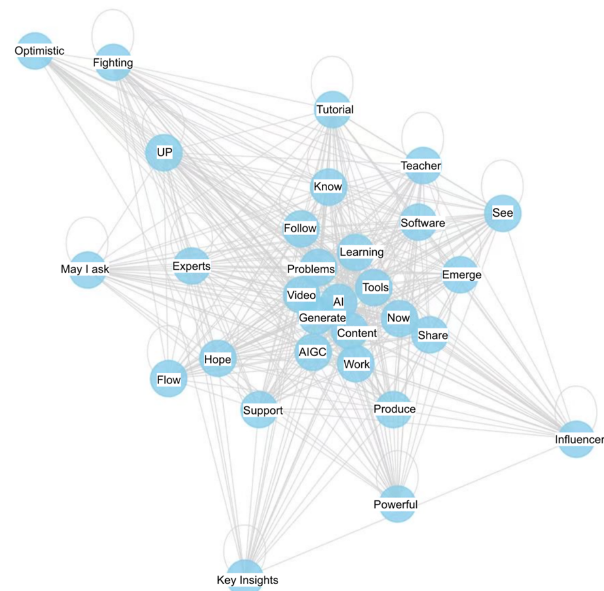

Figure 2. Semantic network of comment texts related to AI in vocational education

4.3 Public Perceptions of AI in Vocational Education

An LDA topic model was applied to analyze the public's perceptions of AI in vocational education (see Table 2). The results reveal five main areas of concern:

Technological applications and tools (Topic 1, 23.7%; Topic 2, 15.3%; Topic 4, 9.6%). This category covers the application of intelligent technologies, tool usability, and the use of open-source resources. Relevant keywords include AI, tools, models, algorithms, technical theory, open source, links, code, software, robots, and knowledge base.

Educational content (Topic 3, 11.0%; Topic 7, 7.4%). This includes skill enhancement, curriculum design, knowledge acquisition, and career development. Keywords include education, skills, courses, knowledge, learning, competence, positions, careers, and productivity.

Social impacts (Topic 5, 9.1%). Concerns focus on unemployment risks, changes in job skill requirements, and industry trends. Keywords include unemployment, positions, risks, problems, expectations, capabilities, and industries.

Application scenarios and practices (Topic 9, 6.2%; Topic 10, 6.2%). This covers design, product development, project management, and other practical uses. Keywords include videos, design, images, products, code, painting, projects, and companies.

Public sentiments and attitudes (Topic 6, 11.0%; Topic 8, 9.1%). This includes concerns about technology misuse, data privacy, attitudes toward technology, and expectations for the future. Keywords include gratitude, support, expectation, success, ethics, and risk.

Topics	Translation of the Top-10 Most Relevant Terms	Percentage
1	AI, AIGC, not/without, technology, content, human, tool, training, development, representative	23.7%
2	model, not/without, plugin, school, effect, ChatGPT, things, installation, may I ask, data	15.3%
3	education, occupation, work, major, kids, PowerPoint, vocational high school, society, digital artist, position	11%
4	video, AI, generate, learning, crying emoji, image, world, GPT, USA, address	9.6%
5	company, bad, China, unemployment, replace, senior female student, salary, industry, environment, era	9.1%
6	really, like, support, claim, not / without, university, student, things (colloquial), material, carrot (Carrot Fantasy)	7.4%
7	software, feel/feeling, UP (uploader, content creator, esp. on Bilibili), tutorial, teacher, link, fighting, training, course, AMD	7.4%
8	Done the triple (like, coin, favorite), UP, knowledge base, share, thank you, gratitude, asking repeatedly (colloquial), AFA, graduation, city	6.3%
9	game, material, work, download, follow, smile emoji, comment, want, prompt, NOTION	6.2%
10	not ok/can't, eyes, document, robot, communication, take a look, register, QQ (Chinese instant messenger), bro/dude, struggle, mistakes	4%

Table 2. LDA topic modeling results on public key concerns regarding AI in vocational education

4.4 Public Sentiment toward AI in Vocational Education

By plotting the sentiment distribution proportions (Fig. 3), it is evident that positive sentiments consistently maintained a relatively high level, indicating broad public recognition and support for the development of AI in vocational education. Notably, the first quarter of 2023 recorded the highest proportion of positive sentiment at 57.1%. Subsequently, positive sentiment stabilized between 46.3% and 52.6%, which may suggest that public expectations toward AI in vocational education practices have gradually become more moderate. Meanwhile, the persistent presence of neutral and negative sentiments reflects ongoing challenges in the development of AI in vocational education, stemming from unresolved concerns over technological reliability, practical applicability, and ethical governance.

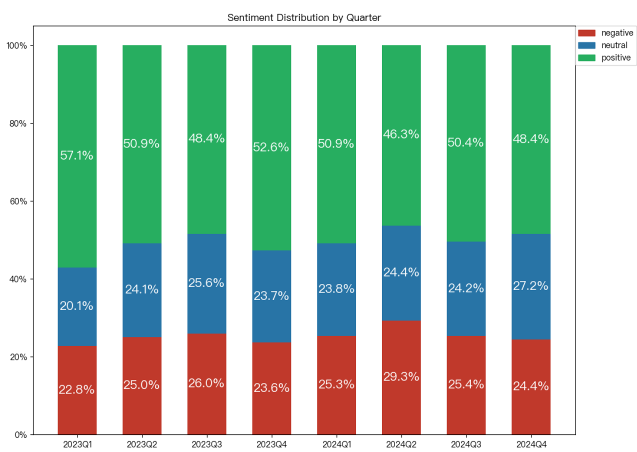

Figure 3. Sentiment distribution proportion chart

The sentiment distribution histogram, as shown in Fig. 4 and Fig. 5, reveals that positive sentiment comments are more prevalent, and the overall public emotional distribution remains relatively stable. From 2023 to 2024, the right peak representing positive sentiment gradually rose, indicating increasingly positive public attitudes toward AI in vocational education.

Conversely, the left peak representing negative sentiment fluctuates, suggesting that negative emotions are influenced by various factors and show periodic changes. The bimodal distribution in the histogram indicates an emotional divide among the public regarding AI in vocational education. Those with positive attitudes may view AI in vocational education as bringing new models and employment opportunities, while those with negative attitudes may perceive issues with the technology's application and curriculum design. This divergence likely stems from differences in experience, cognition, and expectations across different groups.

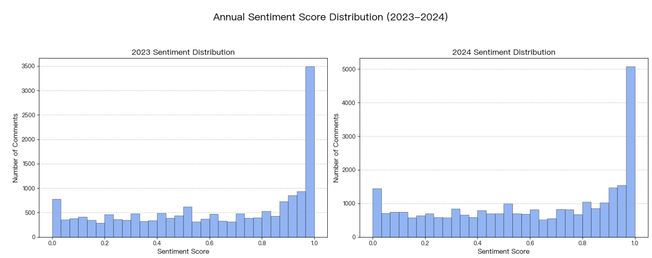

Figure 4. Sentiment distribution histogram by year

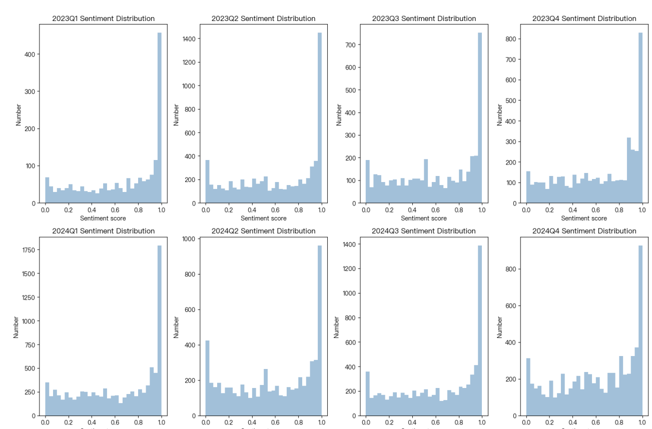

Figure 5. Sentiment distribution histogram by quarter

By plotting a fluctuation chart, the trend of sentiment scores over time can be visualized, as shown in Fig. 6 and Fig. 7. In 2023, public sentiment exhibited alternating peaks and troughs, first rising and then falling. This pattern may reflect the early-stage development of AI in vocational education, where successive new technologies and policies exerted notable influence. Compared with 2023, the year 2024 marked a period of sustained growth in AI in vocational education. Public attention to AI in vocational education gradually entered a relatively stable phase, with an overall positive trajectory, though still subject to the impact of emerging technologies and newly introduced plans.

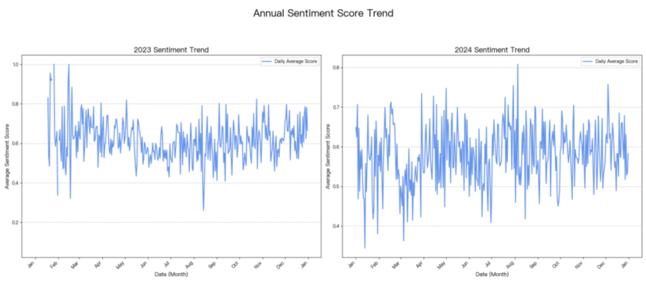

Figure 6. Sentiment score fluctuation by year

Figure 7. Sentiment score fluctuation by quarter

A review of the comment sections identified three types of challenges that readily trigger negative public sentiment. The first is technical challenges, as AI technologies may not necessarily facilitate the development of students' vocational skills. For example, in the case of news writing, generative AI can quickly produce news articles, but unlike professional journalists, it struggles to conduct in-depth investigation and analysis. As a result, the generated content may lack accuracy and remain superficial. The second is practical challenges, since intelligent technologies may not always align with workplace contexts. In medical and nursing education, for instance, AI can suggest surgical plans or provide diagnostic assistance, but in real clinical environments, doctors must rely on their professional expertise and experience to respond accurately and flexibly to emergencies. The third is ethical challenges, including issues of data privacy, algorithmic bias, misinformation, and intellectual property. Examples include companies over-collecting users' personal information, discriminatory practices in recruitment based on gender or ethnicity, and the misuse of AI to imitate the writing style of renowned authors to create novels that mislead the public.

5 Discussion

5.1 The Public's Key Concerns Regarding AI in Vocational Education

The findings suggest that public discourse on Bilibili does not merely react to AI-enabled vocational education; rather, it actively constructs interpretive frames through which "AI in vocational education" becomes understandable, desirable, or contestable. Drawing on the five topic categories identified in the LDA analysis, four recurrent interpretive frames emerge: instrumental utility and tool adoption (derived primarily from Topics 1, 2, and 4 on technological applications and tools); employment anxiety and labor-market disruption (Topic 5 on social impacts); ethical governance demands (Topic 8 on public sentiments and attitudes); and equity and implementation concerns (Topics 3 and 9 on educational content and application scenarios). These frames demonstrate that AI in vocational education is perceived as a socio-technical project, where expectations of efficiency coexist with anxieties about disruption and governance.

First, the discourse is strongly instrumental and practice-oriented. Technology-related terms (e.g., AI, tool, generate, design) occupy a central position in high-frequency and semantic network analyses, indicating that many users evaluate AI in vocational education primarily through workable utility, whether AI can concretely enhance teaching efficiency, produce usable learning materials, and support practice-oriented training. This aligns with the TAM, in which perceived usefulness and perceived ease of use shape favorable attitudes [5]. Importantly, what TAM captures here is not only individual adoption but also collective evaluation: Bilibili users publicly test, review, and recommend tools, thereby turning "usefulness" into a socially negotiated criterion. This community-based evaluation echoes prior research showing that social media often functions as a public arena for assessing AI's potential in education [4, 10].

Second, optimism is consistently entangled with employment anxiety. One salient topic cluster centers on jobs, unemployment, risks, and positions, reflecting strong concern about labor-market disruptions. This duality, AI as both an upskilling resource and a displacement threat, forms a central contradiction in public perceptions [39]. In vocational education, where training is explicitly tied to employability, AI becomes a particularly sensitive symbol: it promises competitiveness while simultaneously destabilizing occupational futures. This finding is consistent with global discussions about AI-induced job restructuring, yet its prominence in vocational discourse suggests that employment implications are not peripheral but constitutive of how intelligent vocational education is judged.

Third, ethical concern operates as a governance demand rather than abstract reflection. Users express sensitivity to privacy, misinformation, intellectual property, and the moral boundaries of human-machine collaboration. These concerns appear not as isolated complaints but as calls for clearer rules and accountability, indicating that publics increasingly treat educational AI as requiring institutional governance rather than private experimentation. This pattern resonates with recent findings that public attitudes toward GenAI in education contain an "ethical turn", where legitimacy depends on transparency and safeguards [4]. In other words, ethical discourse is not separate from adoption: it conditions trust and long-term acceptance.

Finally, equity and implementation concerns reveal a layered digital divide within vocational education. The discussion reflects both structural concerns (whether AI will exacerbate resource stratification) and concrete implementation issues (access to tutorials, links, tools, and usable guidance). Here, Van Dijk's [28] framework is particularly relevant: inequality is not only about access but also about capability and outcomes, forming a multi-level divide. Notably, Bilibili users address this divide in a distinctive way, through platform-based mutual aid. In this sense, discourse becomes not only perception but also practice: users share resources and tutorials to compensate for institutional gaps, indicating the emergence of a "grassroots support ecology" that is especially visible on participatory platforms.

5.2 The Most Discussed Topics among the Public Regarding AI in Vocational Education

Beyond thematic concerns, the topic structure shows that Bilibili discourse is characterized by highly actionable participation, centered on "how-to" knowledge, peer learning, and tool experimentation.

First, public discourse centers on the application and evaluation of AI tools. Users discuss specific AIGC software, large language models, and algorithms, with particular attention to their performance in vocational tasks such as design, video production, code generation, and painting. In this process, Bilibili functions not only as a discussion space but also as an evaluative arena, where tools are demonstrated, tested, and reviewed through videos and comment interactions [26, 33]. This pattern represents a technology-driven form of collective knowledge sharing, in which users explore the practical boundaries of intelligent technologies via peer exchange and hands-on experimentation [35]. Such practices reflect a community logic of learning-by-doing and peer scaffolding: UP creators translate technical advances into accessible demonstrations, while viewers contribute questions, feedback, and resource sharing. These dynamics resemble innovation diffusion, as early adopters and opinion leaders accelerate tool awareness and uptake. More broadly, the discourse exemplifies a participatory learning culture [13, 15], where knowledge is collaboratively produced and socially validated through interaction.

Second is the transformation and reshaping of vocational skills. Discussions closely revolve around education, skills, courses, and learning to ensure adaptability to the intelligent era. The public focuses on which professions and positions AI is creating or reshaping, what new elements the future competency system includes, such as human-machine collaboration skills, and how the existing curriculum system should be reformed to cultivate this competitiveness [11].

Finally, there is community learning and cultural practice. Bilibili's unique community culture profoundly shapes discussion topics [33]. UP hosts, as content creators and key nodes, produce and lead discussions on practical tips and tutorials. Users construct a distributed learning community around AI in vocational education through sharing, thanking, and supporting behaviors [35]. The discussion here is not only information exchange but also a form of social interaction and cultural practice. Such practices render discourse on AI in vocational education concrete and actionable, embodied in a case library and experience set co-created, verified, and disseminated by community members. This crowdsourcing mode of knowledge production, combined with Bilibili's unique secondary creation culture, forms what Jenkins [13] described as participatory culture, greatly enriching the practical ecosystem of AI in vocational education.

5.3 Public Sentiment toward AI in Vocational Education over Time

Beyond the thematic and topical dimensions examined above, sentiment analysis reveals a temporal dimension to public engagement with AI in vocational education, showing that overall sentiment is predominantly positive while demonstrating periodic fluctuations. This pattern suggests that AI in vocational education is perceived as a promising innovation, yet one whose legitimacy remains contingent upon technological reliability, contextual applicability, and ethical trust.

First, regarding the dominant positive sentiment and its roots, data show that positive sentiment has always dominated and shown a steady upward trend between 2023 and 2024. This reflects broad recognition and support for AI in vocational education. Its roots lie in three factors: (1) technological novelty and perceived utility. The public is excited and optimistic about the new possibilities and efficiency improvements brought by AI [2, 17]; (2) community reinforcement on Bilibili, where positive sharing stimulates group sentiment [36]; and (3) expectations for career development, as many users view AI literacy as a pathway to personal competitiveness. This is consistent with the conclusion of a stable proportion of positive sentiment observed in Feng et al. [8] and fits the mechanism in the TAM, where perceived usefulness drives positive attitudes.

Second, stable negative sentiment and its triggering mechanisms require attention. Although accounting for a relatively low proportion, negative sentiment persists and shows fluctuations and a bimodal distribution, indicating a stable skeptical group whose sentiments are easily influenced by external events. Comment analysis reveals three major triggering mechanisms: technological defects, such as superficial output; practical disconnection, including mismatch with real work scenarios; and ethical conflicts, like privacy infringement. Any news reports, policy changes, or personal experiences involving these aspects can trigger peaks of negative sentiment, closely related to the public's ongoing scrutiny of technological risks [4, 38, 39]. Lian et al. [18] also found a similar phenomenon of attitude differentiation, partly attributed to public concerns arising from technology reliability and ethical issues.

Finally, sentiment rationalization and its evolution across development stages warrant attention. The dramatic fluctuations in sentiment in 2023 vividly depict the early stage of the technology hype cycle. Public sentiment rose and fell sharply with the continuous release of new technologies and policies, manifesting as initial enthusiasm followed by a trough of disillusionment. Entering 2024, sentiment stabilized and became optimistic, indicating that public expectations for AI in vocational education are shifting from initial idealized fervor to a more rational and mature optimism [39]. The public is beginning to view this technology with a more balanced attitude, recognizing its long-term potential while accepting its imperfections during development, marking the field's gradual entry into a mature application stage. This evolutionary trajectory perfectly fits the typical stages described by the Gartner Hype Cycle, including Technology Trigger, Peak of Inflated Expectations, Trough of Disillusionment, Slope of Enlightenment, and Plateau of Productivity [9]. Currently, public sentiment is transitioning from the Trough of Disillusionment to the Slope of Enlightenment, suggesting that applying AI to vocational education is about to enter a new phase of more pragmatic and deeper integration.

5.4 Limitations and Future Research Directions

This study's examination of public perceptions of AI in vocational education via Bilibili has several limitations that suggest avenues for future research.

First, the data source is limited to a single social media platform, Bilibili. While the platform offers rich interactions and a young, engaged user base, it may not fully represent broader public opinion, including older learners, vocational educators, or other stakeholders. Future studies could incorporate additional platforms such as Weibo or TikTok to capture a more diverse set of perspectives.

Second, the study focuses exclusively on Chinese-language comments, which introduces a language and cultural bias. This focus may overlook non-Chinese-speaking viewpoints on AI in vocational education. Future research should consider multilingual and cross-cultural analyses to provide a more comprehensive understanding of public attitudes toward AI in vocational education globally.

Third, the study is constrained by temporal scope, analyzing comments collected during a specific period. Given the rapid pace of AI adoption and policy developments in vocational education, public perceptions may shift quickly. Longitudinal studies would allow researchers to track changes over time and capture the evolution of attitudes and concerns.

Fourth, the study relies primarily on computational text analysis methods, such as topic modelling and sentiment analysis, which may not capture nuanced opinions or the reasoning behind users' perceptions. Integrating qualitative methods, such as interviews or focus groups with learners, educators, and policymakers, could complement big-data approaches and provide deeper insights into the motivations, experiences, and expectations underlying public discourse.

Finally, the study focuses on aggregate public discourse without differentiating among specific demographic groups such as students, teachers, and vocational trainers, whose perceptions and needs may differ substantially. Future research could investigate these subgroups to develop more targeted theoretical accounts of how different stakeholders engage with and evaluate AI in vocational education. Ethical and policy considerations, including privacy, algorithmic fairness, and the impact of AI on employment and skill development, also warrant focused attention as AI technologies continue to evolve.

6 Conclusion

Against the backdrop of China's rapidly digitalizing vocational education system, this study investigated public perceptions of AI in vocational education by analyzing large-scale discourse on Bilibili through topic modelling and sentiment analysis. The findings reveal that public concerns are multidimensional, encompassing pragmatic expectations of technological efficacy, anxieties about employment and job security, scrutiny of ethical and governance risks, and inquiries into educational equity and practical implementation. Discussions are highly practice- and community-oriented, focusing on technological tools, the transformation of vocational skills, and the role of online learning communities. Public sentiment toward AI in vocational education is predominantly positive and increasingly rational, moving from initial enthusiasm to more balanced expectations as the technology matures.

These findings offer both theoretical and practical contributions. Theoretically, the study enriches research on AI in vocational education by integrating perspectives from technology acceptance, risk society, and participatory culture. It highlights how public discourse reflects not only perceptions of technological utility but also deeper societal concerns about equity, ethics, and governance.

Practically, the results provide guidance for policymakers, educators, and technology developers in promoting the sustainable integration of AI into vocational education. Strategies should emphasize four areas: policy regulation to ensure equity and accountability, pedagogical innovation to support adaptive and competency-based learning, technological development aligned with real-world practice, and ethical governance to safeguard trust and fairness. As China pursues large-scale modernization of its vocational education system, understanding and responding to public perceptions is crucial for fostering acceptance and ensuring that technological innovation contributes to inclusive and industry-aligned skill development. More broadly, the study underscores the need for ongoing dialogue between stakeholders, integrating public voices into the design and governance of AI in vocational education. By doing so, the integration of AI into vocational education can move beyond institutional experimentation toward a publicly informed, equitable, and sustainably governed transformation of skill development in China.

7 Declarations

7.1 Ethics approval and consent to participate

Ethical approval for this study was obtained from the corresponding author's Institutional Review Board (IRB) in mainland China, which determined that informed consent was not required given the publicly accessible nature of the online comments. To uphold ethical standards, all data were anonymised, and any personal identifiers were removed.

7.2 Conflict of interest

No potential conflict of interest was reported by the authors.

7.3 Data availability

The data that support the findings of this study are available on request from the corresponding author.

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