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Exploring Emotional and Content Influences on ChatGPT's Educational Usability Within the Field of Human–Computer Interaction

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ABSTRACT

This empirical study analyzes 26,399 education-focused user reviews of ChatGPT from the Google Play Store to investigate factors shaping perceptions of educational usability. Using quantitative methods including feature engineering, sentiment analysis, and ordinary least-squares regression, we examine how emotional sentiment, content quality, and review scores influence usability perceptions. Results reveal a counterintuitive emotional pattern: while surprise and anticipation enhance perceived usability, joy and disgust are associated with lower usability perceptions. Overall sentiment emerges as the strongest predictor of usability (coefficient = 0.8565, $p \leq 0.001$), with content quality also exerting a significant positive effect (coefficient = 0.0334, $p \leq 0.001$). In contrast, review scores show a small but significant negative relationship with usability (coefficient = −0.0210, $p \leq 0.001$). Trust exhibits a slight negative effect, whereas fear, anger, and sadness show no significant associations. These findings highlight the critical role of emotional factors in educational AI usability, suggesting that developers should prioritize both high-quality content and positive emotional engagement. This research contributes to HCI and educational technology by providing a replicable framework for analyzing user perceptions of AI tools while emphasizing the importance of affective dimensions in technology adoption.

1 | Introduction

The rapid advancement of artificial intelligence (AI) technologies has profoundly transformed various sectors, and education is no exception. Generative AI models, such as ChatGPT, have emerged as powerful tools in educational settings, offering personalized learning experiences, supporting teachers, and assisting students with a range of academic tasks. The transformative potential of AI in education is increasingly recognized, with studies highlighting its capacity to enhance educational processes, support creativity, and facilitate innovative problem-solving [1, 2]. However, despite the increasing adoption of such tools, understanding the underlying factors that shape users' perceptions of these AI models remains crucial. Emotional responses and perceptions of content quality play significant roles in determining how users engage with ChatGPT, particularly in educational contexts.

While much attention has been paid to the technical performance and utility of AI in education, less emphasis has been

placed on the emotional and affective dimensions of user interactions. Emotions, such as trust, fear, joy, and anger, have been shown to profoundly influence users' experiences [3] with technology and can directly impact their satisfaction, engagement, and overall perceptions of a tool's usability [4, 5]. These emotional responses can either enhance or hinder user engagement, making it essential to examine how they affect the use of AI tools like ChatGPT in educational settings. For instance, a positive emotional experience can lead to greater trust and continued use, while negative emotions, such as frustration or anxiety, may result in disengagement and reduced effectiveness [6]. As such, understanding the emotional dynamics that shape users' perceptions of ChatGPT's usability in education is critical for maximizing its educational potential. In addition to emotional factors, another critical element influencing user perceptions is perceived content quality. The value of ChatGPT as an educational tool is not only determined by its ability to generate responses but also by the quality and relevance of the content it produces. In an educational context, perceived content quality refers to how users assess the usefulness, accuracy, clarity, and relevance of the information provided by the AI model. High-quality content enhances the perceived utility of ChatGPT, fostering trust, engagement, and positive emotional responses from users [2, 5]. Conversely, low-quality content can lead to frustration, confusion, and a lack of trust in the tool, which ultimately undermines its effectiveness in supporting learning activities. Therefore, understanding how perceived content quality influences users' emotional reactions and overall satisfaction is vital to improving the design and performance of ChatGPT in educational environments. The interaction between emotional factors and perceived content quality is especially important when considering how users perceive the usability of ChatGPT in education. Emotional responses to ChatGPT—whether positive or negative—are often tied to the content it generates. Positive emotions such as joy, trust, and surprise may arise when users find the content helpful and engaging, while negative emotions like fear, sadness, and anger may result from poor content quality or perceived inaccuracies in the responses [4]. For instance, a student might feel joy when ChatGPT provides a clear and relevant explanation of a complex concept, but frustration or sadness may arise if the content is vague or inaccurate. By examining the ways in which emotional factors and content quality intersect, this study aims to offer a more nuanced understanding of how ChatGPT's usability can be improved in the educational context.

This study seeks to explore how various emotional and sentiment-driven factors, including sentiment scores, trust, fear, anger, surprise, anticipation, joy, sadness, disgust, and perceived content quality, shape users' perceptions of ChatGPT's usability for educational purposes. Sentiment scores, which quantify the emotional tone of user interactions, are particularly important as they provide insights into users' general feelings about the tool. Positive sentiment scores often correlate with higher user satisfaction and engagement, while negative sentiment can indicate frustration or dissatisfaction with the AI's performance [5]. Trust, a key emotion in human–computer interaction, is another critical factor, as users must feel confident that ChatGPT will provide accurate and helpful responses. When users trust the system, they are more likely to engage with it regularly and rely on it as a learning tool [1]. On the other hand, emotions such as fear and anger, which may arise from negative experiences with the tool, can discourage continued use and reduce the effectiveness of ChatGPT in education [6]. In addition to these emotions, surprise and anticipation also play important roles in shaping users' perceptions of ChatGPT's utility. Positive surprise, which occurs when the tool provides unexpected yet valuable information, can enhance user satisfaction and trust in the system. Similarly, anticipation—users' expectations of the tool's performance—can motivate engagement when those expectations are met, or result in disappointment when they are not. The emotions of joy and sadness are equally significant, as they reflect the overall satisfaction with the learning experience. Joy is often associated with positive experiences, such as discovering helpful content, while sadness may stem from dissatisfaction or a sense of unmet expectations [4]. Finally, disgust, though a less common response, can occur if users encounter inappropriate or irrelevant content, potentially leading to disengagement and diminished trust in the tool [1].

Perceived content quality serves as an important mediator in this emotional landscape. The quality of the content generated by ChatGPT has a direct influence on users' emotional responses. High-quality content fosters trust, engagement, and positive emotions, while low-quality responses can lead to frustration, anger, and reduced satisfaction. This dynamic is crucial for ensuring that ChatGPT remains an effective and reliable educational tool. Understanding the role of AI tools like ChatGPT in educational contexts can help developers refine performance, ensuring that it supports both content delivery and user interaction effectively [2]. The objectives of this study are to investigate how sentiment scores, trust, fear, anger, surprise, anticipation, joy, sadness, disgust, and perceived content quality influence users' perceptions of ChatGPT's usability for educational purposes. By exploring these emotional factors, we aim to gain insights into how users engage with ChatGPT, how they assess its content quality, and how these elements shape their overall satisfaction with the tool. Ultimately, this study seeks to provide recommendations for improving the design of ChatGPT to better align with users' emotional needs and enhance its effectiveness as an educational tool.

Additionally, feature engineering techniques have become increasingly popular in extracting valuable customer insights from raw data, particularly in the context of analyzing user reviews [7]. In our study, we utilized these techniques to better understand user perceptions of the usability and content quality of the ChatGPT app in educational contexts. By transforming the unstructured review text into structured data, we were able to capture meaningful insights about how users evaluate the app's performance. Specifically, we employed keyword-based feature extraction to assess perceptions related to usability and content quality. These features allowed us to classify reviews into categories, reflecting positive or negative user experiences (UXs), aligned with sentiment analysis. We also incorporated emotional sentiment analysis to capture the emotional tone of user feedback, further enriching our understanding of user sentiment. By leveraging feature engineering techniques, we were able to extract actionable insights that contribute to a deeper understanding of customer behavior, helping to inform the design and improvement of the ChatGPT app for educational purposes. These methods are increasingly crucial in extracting meaningful

patterns from complex textual data and provide an essential tool for gaining customer insights [7].

Moreover, as generative AI tools like ChatGPT become increasingly integrated into educational settings, it is essential to consider not only their technical capabilities but also the emotional dynamics that shape users' interactions with these tools. By exploring how emotional responses and perceived content quality influence user perceptions of usability, this study aims to contribute to a deeper understanding of how AI can be optimized to support learning and engagement. By addressing both the emotional and cognitive dimensions of UX, the findings of this study will help inform the future development of AI tools in education, ensuring that they are both effective and emotionally resonant with their users [4, 5]. Methodologically, this research contributes a transparent framework for analyzing educational AI tools that bridges HCI, educational technology, and data science. By combining LLM-assisted feature engineering with comprehensive sentiment analysis, we offer a replicable approach for extracting nuanced insights from large-scale user feedback. This framework enables future researchers to systematically evaluate user perceptions of emerging educational technologies through scalable, domain-specific analytical techniques. We test these relationships through a computational analysis of 26,399 education-related user reviews collected from the Google Play Store.

2 | Literature Review

2.1 | Psychological and Interactive Factors Influencing AI Tool Engagement in Education

The integration of AI tools, such as ChatGPT, into educational contexts has garnered significant attention in recent years. As AI technology continues to evolve, understanding the factors that drive user engagement and satisfaction with these tools is becoming increasingly important. One key framework for exploring user engagement is gratification theory, which posits that individuals engage with media and technology to satisfy their specific needs or desires [8]. In the case of educational tools like ChatGPT, this theory suggests that user engagement is influenced by the tool's ability to fulfill educational, emotional, and social needs. Research has shown that factors such as content quality, emotional sentiment, and perceived usefulness significantly shape user satisfaction and continued usage, particularly in educational settings [9, 10]. The role of these factors in shaping the usability of AI tools like ChatGPT in education remains an important area of inquiry, as they may determine whether such tools are accepted and used effectively in learning environments. One of the key aspects influencing user engagement with ChatGPT is content quality. Research has consistently emphasized the importance of high-quality content in determining user satisfaction and engagement with educational technologies [9]. In the context of AI, content quality refers not only to the relevance and accuracy of the information provided but also to its ability to engage and maintain user interest. Alhassan et al. [10] found that when users perceive a tool as useful, accurate, and engaging, they are more likely to continue using it. Similarly, studies on AI educators have shown that systems with higher autonomy—those that can assess and respond to user needs—are more likely to increase engagement [9]. In the case of ChatGPT, the perceived quality of the content generated by the tool plays a critical role in shaping users' perceptions of its utility in an educational context. If the responses provided by ChatGPT are accurate, relevant, and clear, users are more likely to perceive the tool as valuable for their learning needs.

In addition to content quality, emotional sentiment also plays a crucial role in shaping user engagement with AI tools. The emotional responses elicited by interactions with educational technologies like ChatGPT can influence users' satisfaction and future usage intentions [11]. Research has shown that positive emotional sentiment—such as satisfaction, joy, and encouragement—can increase user engagement and satisfaction with AI-driven tools [12]. In contrast, negative emotional responses, such as frustration or confusion, can lead to disengagement and decreased satisfaction [13]. The role of emotions in shaping user engagement is particularly relevant in education, where learners' emotional experiences can directly impact their motivation, retention, and overall satisfaction with digital learning tools [14]. In the case of ChatGPT, ensuring that the tool evokes positive emotional responses—such as feelings of clarity, support, and helpfulness—may be key to fostering continued engagement and use in educational settings. Another important factor influencing user engagement is the role of user feedback and review scores. Studies have shown that positive feedback from other users—through mechanisms like star ratings and reviews—can influence individuals' perceptions of a tool's quality and usability [15]. For instance, research on user-generated content in online platforms has shown that high ratings and favorable reviews are often associated with greater perceived usefulness and satisfaction [16]. In the case of ChatGPT, users' perceptions of the tool's usability in education may be shaped by the feedback and reviews shared by others who have already interacted with the platform. As Hussain et al. [17] found in their study on YouTube engagement with ChatGPT-related content, positive feedback from other users can significantly influence new users' adoption of the tool. When users perceive that others have had positive experiences with ChatGPT, they may be more likely to trust the tool and continue using it for their educational needs.

The role of human–computer interaction (HCI) in shaping user engagement with AI tools is another key consideration in understanding the usability of ChatGPT in education. HCI research has shown that factors such as usability, interactivity, and system responsiveness are critical in determining user satisfaction and engagement with educational technologies [18]. For example, studies have highlighted how well-designed AI systems that prioritize ease of use and responsiveness can lead to higher levels of user satisfaction and engagement [12]. Similarly, emotional engagement plays a significant role in shaping users' perceptions of educational technology. Saini et al. [19] emphasized that emotional states—whether positive or negative—can significantly impact users' interactions with digital platforms. For educational AI tools like ChatGPT, the ability to recognize and respond to users' emotional cues may enhance engagement and satisfaction, ultimately improving the tool's perceived usability [14].

While existing studies provide valuable insights into content quality, emotional sentiment, and user feedback, there is a gap in understanding how these factors interact to shape users' overall perceptions of ChatGPT's usability in education. This study

examines the combined influence of these elements by analyzing user reviews, categorizing them based on keyword presence and sentiment. By systematically identifying patterns in user perceptions, this research provides insights into how ChatGPT is perceived as an educational tool and its potential impact on learning experiences.

2.2 | Gratification Theory to Understand User Engagement With ChatGPT in Education

Gratification theory provides a valuable framework for understanding user engagement with ChatGPT, particularly in an educational context. This theory posits that individuals actively seek out media and technology that fulfill their specific needs or desires, which in turn influences their continued use and satisfaction [8]. When applied to ChatGPT, gratification theory can help explain how the tool's content quality, emotional sentiment, and perceived usefulness impact user engagement, particularly for educational purposes. Studies on AI and education emphasize the critical role that content quality plays in user satisfaction. Niu et al. [9] found that AI educators with greater autonomy, particularly in sensing, thought, and action, positively influenced students' engagement through their ability to meet students' needs. Similarly, for ChatGPT, the quality of content provided—whether accurate, relevant, and engaging—can influence users' perceptions of the tool's utility. As Alhassan et al. [10] suggest, user attitude, shaped by factors like usefulness and ease of use, plays a key role in fostering continued use. If users find ChatGPT to be highly useful and engaging, it may enhance their satisfaction and increase their likelihood of continued use. Users may be more inclined to rely on ChatGPT for future educational inquiries if they believe it will offer useful and accurate responses that meet their learning needs.

Beyond content quality, emotional sentiment also plays a key role in shaping user engagement with ChatGPT. Users' emotional reactions to ChatGPT's responses—whether they feel satisfied, frustrated, or confused—are critical to understanding how they engage with the tool. Al-Khalifa et al. [11] highlighted that sentiment analysis of user interactions with AI tools reveals important insights into UX and satisfaction. In an educational setting, positive emotional sentiments associated with ChatGPT's helpfulness, clarity, and reliability will likely increase users' perceived value of the tool. Conversely, negative emotions stemming from poor-quality responses or misunderstandings may reduce engagement. Therefore, ensuring that ChatGPT evokes positive emotional responses is essential for sustaining its usage in educational contexts. Additionally, review scores and user feedback further shape perceptions of ChatGPT's educational utility. As Hussain et al. [17] demonstrated in their study on YouTube engagement with ChatGPT-related content, positive feedback from other users can influence how new users approach the tool. If ChatGPT receives high ratings or positive reviews from users who highlight its educational effectiveness, new users may be more likely to adopt and continue using it for their learning needs. The influence of social validation, particularly through review scores, can act as an extrinsic motivator for users, guiding their decision-making process and fostering greater interaction with the AI.

Gratification theory also suggests that users engage with technology to fulfill social interaction and information-seeking needs. In the case of ChatGPT, users may seek out the tool not only for factual information but also for interactive and conversational engagement. By offering dynamic, contextually relevant responses, ChatGPT can facilitate a more interactive learning experience, fulfilling the user's desire for social interaction in an educational setting. This is consistent with Hussain et al. [17], who noted that content related to new and innovative technologies like ChatGPT draws more engagement, in part because users are motivated by a desire for novelty and social connection through shared learning experiences. Moreover, applying gratification theory to ChatGPT's educational engagement provides a framework to explore how emotional sentiment, content quality, and review scores influence users' perceptions of the tool. Users are more likely to engage with ChatGPT if it satisfies their educational needs, evokes positive emotions, and is validated by others' experiences. These factors collectively determine the usability of ChatGPT in education, shaping both short-term engagement and long-term adoption. By focusing on these gratification factors, our study seeks to uncover the drivers of user satisfaction and continued use of ChatGPT as an educational tool.

2.3 | AI in HCI for Education

HCI has become an essential area of research in understanding how technology, particularly AI, affects UXs in education. The integration of AI-driven tools like ChatGPT into educational environments offers new opportunities to enhance learning experiences through improved engagement, personalized feedback, and real-time communication. Research has highlighted the importance of HCI factors in determining the effectiveness of educational technology. For instance, AL-Sayid and Kirkil [18] explored how students' web-based activities moderated the relationship between HCI factors such as usability, interactivity, and content quality on their success and acceptance of e-learning systems during the COVID-19 pandemic. The study showed that engaging with the course system and its content quality significantly influenced perceived usefulness and ease of use, which ultimately led to higher academic performance. These insights underscore the relevance of designing user-centered AI systems that consider the emotional and interactive needs of learners.

Moreover, emotional factors play a crucial role in user engagement and satisfaction with educational technology. For instance, Saini et al. [19] emphasized the emotional exhaustion experienced by healthcare workers during the pandemic, which affected their overall job satisfaction. The emotional state of users, whether positive or negative, can influence their interaction with AI-based educational tools. This emotional aspect is equally important in education, where learners' emotional states can affect their engagement and satisfaction with digital learning platforms. Additionally, studies have highlighted the importance of AI's ability to detect and respond to user emotions. Li et al. [14] studied how emotions like fear of missing out (FoMO) interact with social media use, suggesting that emotional responses can influence behavior in digital environments. Similar dynamics can be observed in educational AI systems, where emotional responses to learning experiences can shape students' continued use and satisfaction with these tools. AI systems in education also benefit from creating an experience that resonates emotionally with users. Research by Wu et al. [12] on the Macau gaming industry demonstrated that experiential quality—such as fun,

surprise, and engagement—positively influenced future engagement intentions. By enhancing the emotional quality of educational AI tools like ChatGPT, developers can foster greater user satisfaction and commitment to continued use. Ultimately, understanding the intersection of emotional engagement, system usability, and AI capabilities in education is crucial for optimizing HCIs. The findings from these studies suggest that AI tools in educational settings must not only be functionally effective but also emotionally responsive to create meaningful and enduring user engagement. Through thoughtful integration of HCI and emotional considerations, AI systems can play a pivotal role in enhancing educational experiences, improving user satisfaction, and encouraging the continued use of AI-driven tools like ChatGPT.

2.4 | ChatGPT's Impact on Education

The integration of AI tools like ChatGPT into education has sparked considerable interest, with varying views on its potential and challenges. Lo [20] conducted a rapid review of the literature, examining ChatGPT's performance across several subject domains during its initial months of release. The study found that ChatGPT performed outstandingly in economics, satisfactorily in programming, and unsatisfactorily in mathematics. This variation highlighted its potential as a teaching assistant in some fields while exposing its limitations in others, particularly concerning the accuracy of its generated content. Lo's study emphasized the need for caution, especially regarding the potential generation of incorrect or fake information and the risk of bypassing plagiarism detectors. Similarly, Strzelecki [21] explored the factors influencing students' acceptance of ChatGPT in higher education using the Unified Theory of Acceptance and Use of Technology (UTAUT2) model. The study revealed that habit, performance expectancy, and hedonic motivation were significant predictors of students' behavioral intentions to use ChatGPT, which ultimately influenced their actual usage. This research highlights the importance of understanding students' attitudes and readiness to adopt AI tools in educational settings, as their engagement with such technologies is shaped by perceived usefulness and enjoyment. Cooper [22] examined ChatGPT's potential in science education, noting its usefulness in generating course materials, quizzes, and rubrics. However, Cooper cautioned that ChatGPT's tendency to present itself as an epistemic authority—offering answers without sufficient grounding in evidence—could be problematic. The author recommended that educators critically evaluate AI-generated content and use it in conjunction with fostering critical thinking among students. This reflects broader concerns raised by Tlili et al. [23], who explored ethical issues in the use of ChatGPT in education. Their study emphasized the need for clear guidelines and training for both students and educators to ensure responsible use of AI tools.

In the context of higher education, Ivanov and Soliman [24] focused on the impact of ChatGPT on tourism education and research, proposing that ChatGPT could disrupt traditional practices by enabling students and researchers to generate texts for assignments and research papers more efficiently. They called for a re-evaluation of teaching and assessment strategies to accommodate AI-generated content, which could revolutionize the academic landscape. Fütterer et al. [6] further examined global reactions to ChatGPT in education, using sentiment analysis of social media data. They found a mixed reception, with some praising ChatGPT as an intelligent learning partner, while others raised concerns about its role in cheating and the spread of misinformation. This division of opinion suggests that the integration of ChatGPT in education is far from straightforward and may be influenced by broader societal attitudes toward AI technologies. Moreover, Wang et al. [25] investigated AI readiness among teachers, emphasizing that educators' knowledge and vision about AI are crucial for successful implementation in classrooms. Teachers who perceived AI as a tool for innovation were more likely to adopt AI technologies like ChatGPT, which, in turn, enhanced their job satisfaction. This suggests that teacher training and professional development are essential to ensure that educators are equipped to use AI tools effectively and ethically in their teaching practices.

While existing studies highlight various aspects of ChatGPT's potential in education, there remains a gap in understanding how emotional sentiment, perceived content quality, and review scores influence users' perceptions of its usability in educational settings. Much of the literature has focused on ChatGPT's applications, benefits, and ethical considerations, such as its role in supporting research, enhancing student services, and improving teacher readiness [21, 23, 24]. However, limited research has examined how users' emotional responses to AI-generated content—whether they find it helpful, engaging, or frustrating—shape their overall evaluation of ChatGPT as an educational tool. Similarly, while content quality is widely recognized as a critical factor in AI adoption, there is little research specifically analyzing how the coherence, accuracy, and clarity of ChatGPT-generated content influence user trust and engagement. Additionally, while review scores and user feedback are commonly used to assess technology adoption, their impact on perceptions of ChatGPT's usability in education remains largely unexplored. Our study addresses this gap by systematically analyzing ChatGPT reviews using feature keyword search engineering. We generated 50 education-related, 50 usability-related, and 50 content quality-related keywords using structured prompts in ChatGPT to identify relevant user perceptions. By categorizing reviews based on keyword presence and sentiment analysis, we examine how these factors collectively influence perceptions of ChatGPT's usability in educational contexts. Through this approach, our study provides empirical insights into the interplay between emotional sentiment, perceived content quality, and user feedback in shaping ChatGPT's role in education. While existing studies provide valuable insights into content quality, emotional sentiment, and user feedback, there remains a methodological gap in systematically analyzing these factors through scalable, reproducible frameworks. This study addresses this gap by introducing a comprehensive analytical approach that combines feature engineering with multidimensional sentiment analysis, providing both empirical findings and methodological innovation for the field.

3 | Hypotheses Development

3.1 | Users' Sentiment and Perceptions of ChatGPT's Usability for Education

The reviewed prior studies provide valuable insights into the relationship between sentiment and usability perceptions, which can be applied to understanding users' perceptions of ChatGPT's usability for education. The study by Theodorou et al. [26] demonstrates the importance of sentiment analysis in evaluating the UX with assistive technologies. Positive user sentiment was associated with higher

usability perceptions, highlighting that favorable sentiment enhances user acceptance and satisfaction. Grimalt-Álvaro and Usart [27] discuss the underexplored use of sentiment analysis in educational contexts but suggest that positive sentiment generally leads to more favorable usability experiences. Al-Wesabi et al. [28] emphasize the role of sentiment analysis in low-resource language processing tasks, where positive sentiment improved the overall perception of usability, even in challenging settings. White et al. [29] highlight that while mothers generally had positive sentiments toward the Milk Man mobile app, negative sentiment was more associated with usability issues rather than the app's overall acceptability or content. Finally, Haoues et al. [30] highlight that positive user feedback in mHealth applications correlates with better usability perceptions. These findings collectively suggest that sentiment plays a significant role in shaping how users perceive the usability of a technology. Thus, based on this evidence, we propose the hypothesis:

H1: Users' sentiment toward ChatGPT significantly influences their perceptions of its usability for education.

3.2 | Users' Provided Star Rating and Perceptions of ChatGPT's Usability for Education

There is a significant body of research indicating that user-generated star ratings can influence their perceptions of an application's usability. For instance, Pashchenko et al. [15] explore the relationship between emotional aspects of customer reviews and their corresponding star ratings in the context of hotel and travel services, showing that users' feelings toward a service directly impact the star rating they provide. Similarly, Wilks et al. [31] find a correlation between the star ratings of dialectical behavior therapy (DBT) apps and their usability scores, suggesting that a higher star rating is often associated with a more positive evaluation of an app's usability. Lee and Lee [16] further highlight the role of user ratings in the selection of mHealth apps, where higher star ratings reflect better perceived usability and impact on users' healthcare needs.

In the context of WeChat app analysis, Chen et al. [32] confirm that star ratings have a significant impact on app downloads, which in turn is influenced by user perceptions of usability, performance, and functional needs. This suggests that the star rating system provides valuable feedback that directly correlates with users' evaluations of an app's functionality and ease of use. Furthermore, Nemirovsky et al. [33] show that in educational applications, such as the SICKO surgical simulation app, high ratings are linked to positive perceptions of the app's usability and educational value. Collectively, these studies underscore the importance of star ratings as a key indicator of perceived usability across different types of applications. Based on this evidence, we propose the following hypothesis:

H2: The star rating (score) provided by users for ChatGPT significantly influences their perceptions of its usability for education.

3.3 | Perceived Content Quality and Perceptions of ChatGPT's Usability for Education

Building on the findings from the prior studies, it is evident that the quality of content provided by educational platforms or applications plays a crucial role in shaping users' perceptions of usability and overall satisfaction. For instance, Alqurni [34] highlights that the usability of e-learning software is significantly influenced by various factors, including content quality, which impacts student satisfaction and performance. Shilbayeh and Ismail [35] further support this by showing that user satisfaction with an mHealth application is driven by factors like presentation quality, which can be seen as a component of content quality in educational contexts. Additionally, Chen et al. [32] note that tools designed for online collaborative writing improve student engagement when they present useful and relevant content, underlining the importance of content quality in promoting usability. Similarly, Tao et al. [37] observe that the perceived quality of content in MOOCs is a strong mediator in students' acceptance and intention to use the platform, reinforcing the idea that quality content directly impacts perceived usability. Furthermore, AL-Sayid and Kirkil [18] find that students' activities and interactions with the system's content are crucial in moderating their perceptions of usability, emphasizing the pivotal role that content quality plays in driving educational success. In light of these findings, we propose the following hypothesis:

H3: Users' perceived content quality of ChatGPT significantly influences their perceptions of its usability for education.

3.4 | Users' Emotional Aspect and Perceptions of ChatGPT's Usability for Education

Previous research has established the significant role that emotions play in shaping users' perceptions of various experiences, including those in educational contexts. For instance, Saini et al. [19] explored emotional exhaustion among healthcare workers during the COVID-19 pandemic, suggesting that emotional exhaustion can diminish the intensity of negative emotions such as fear. This can influence how individuals evaluate their work environment and job satisfaction, which is relevant when considering how emotional states might impact the perception of usability in educational tools. Similarly, Li et al. [14] found that negative emotions, like anxiety stemming from a "fear of missing out" (FoMO), could drive problematic social media use, highlighting how emotions can steer engagement and the perceived effectiveness of a platform. Moreover, Wu et al. [12] examined the impact of experiential quality in the Macau gaming industry, concluding that emotional engagement (via fun and surprise) directly influenced users' satisfaction and future engagement. This finding can be extended to educational platforms, where emotional satisfaction through engaging content may enhance users' perception of a tool's usability. Griessmair et al. [38] similarly argued that positive emotional responses, such as being moved by kindness, could increase loyalty and satisfaction with services. This suggests that positive emotional experiences within educational tools may also elevate users' perceptions of usability.

On the other hand, studies also highlight the detrimental effects of negative emotions. For instance, Masorgo et al. [13] demonstrated that negative emotional responses, such as frustration, significantly impacted customer satisfaction and repurchase intentions. Such emotions may hinder the positive perception of an educational tool's usability, particularly if users encounter barriers or frustrations within the platform. Eniayejuni [39] revealed that negative emotions like fear and anger could drive collective actions in protest movements, emphasizing how negative emotions can influence decision-making processes. Similarly, negative emotional experiences in education may

diminish users' engagement and overall perception of the platform's usability. Additionally, Akca et al. [40] emphasized the importance of positive emotions such as joy and compassion in fostering job satisfaction, and Cheshin et al. [41] demonstrated that overly intense emotions could negatively impact trust and satisfaction. In educational settings, appropriate emotional engagement—such as positive feedback and encouragement—could enhance users' trust in the tool and boost their satisfaction, leading to a more favorable usability perception. Furthermore, Ng et al. [12] explored how emotional satisfaction in the workplace could mediate life satisfaction, suggesting that emotional experiences in education—whether positive or negative—could also mediate users' perceptions of usability. Building on these insights, the following hypothesis is proposed:

H4: Users' emotional aspects, including trust (H4a), joy (H4b), surprise (H4c), fear (H4d), anger (H4e), sadness (H4f), disgust (H4g), and anticipation (H4h), significantly influencing their perceptions of the usability of educational tools.

4 | Method

4.1 | Data Collection and Preprocessing

On January 1, 2025, data were collected from the official ChatGPT application page on the Google Play Store using the open-source Google Play Scraper Python library within a Google Colab environment. This tool enables systematic retrieval of publicly available app metadata and user reviews while ensuring compliance with Google Play's terms of service and maintaining user anonymity through the exclusion of personally identifiable information. The initial dataset comprised 391,816 reviews spanning from the application's initial release period through December 31, 2024, providing comprehensive temporal coverage of UXs.

Following data collection, the dataset was downloaded to a local computer for analysis using a Jupyter Notebook with essential Python packages including pandas for data manipulation, regular expressions for text processing, NRCLex for emotional sentiment analysis, and statsmodels, seaborn, and matplotlib for statistical analysis and visualization. A comprehensive preprocessing pipeline was implemented involving the removal of duplicate entries, elimination of NaN values, stripping of emojis and nonessential symbols, and text standardization by retaining only letters, digits, punctuation, and spaces to ensure data quality and analytical consistency.

4.2 | Feature Engineering and Educational Review Identification

The primary objective of this study was to evaluate education-related reviews through a systematic feature engineering approach. We employed keyword search techniques, generating 50 unique education-related keywords using structured prompts with ChatGPT to ensure comprehensive domain coverage. This methodology, validated in similar research contexts [7], leverages large language models' capability to efficiently produce domain-specific terminology while maintaining methodological transparency. The complete keyword set is detailed in Table A1.

Application of these education-related keywords to the preprocessed dataset resulted in a refined analytical sample of 26,399 education-focused reviews spanning from July 25, 2023, to December 31, 2024, covering 526 unique dates. Further, to enable a multidimensional analysis of user perceptions, we generated two additional keyword sets using structured prompts with ChatGPT. The first set comprised 50 usability-related keywords designed to capture how users describe ChatGPT's usefulness for educational activities, such as studying, learning, teaching, and interacting with educational tools or processes. The second set consisted of 50 content quality-related keywords intended to reflect users' evaluations of the clarity, accuracy, usefulness, engagement, comprehensiveness, and overall value of the educational content provided. Both keyword sets are systematically documented in Table A1. This methodological framework provides a replicable approach for extracting domain-specific insights from large-scale user feedback datasets.

4.3 | Multilayered Sentiment and Emotional Analysis

We implemented a comprehensive sentiment analysis framework combining multiple approaches to capture both explicit and implicit user perceptions. The primary sentiment classification followed established methodologies in app review analysis [7, 15], categorizing reviews based on provided scores: scores of 4 or higher as positive sentiment, scores of 3 as neutral sentiment, and scores of 2 or lower as negative sentiment. As presented in Table 1, positive sentiment accounted for the majority of reviews (24,550 reviews, 93.00%), with neutral and negative sentiment comprising 859 (3.25%) and 990 (3.75%) reviews, respectively. Table 2 further details the score distribution, showing 21,229 five-star reviews (80.42%) and 3321 four-star reviews (12.58%).

For enhanced emotional granularity beyond basic sentiment classification, we employed the NRCLex library to compute intensity scores for eight basic emotions from the NRC Emotion Lexicon: trust, fear, anger, surprise, anticipation, joy, sadness, and disgust. This approach significantly improves upon conventional sentiment analysis by capturing nuanced emotional

TABLE 1 | Number of reviews with percentage toward each sentiment class.

Sentiment	Number	Percentage
1 (Positive)	24,550	93.00
0 (Neutral)	859	3.25
−1 (Negative)	990	3.75
Total	26,399	100

TABLE 2 | Number of reviews with percentage toward each score.

Score	Number	Percentage
5	21,229	80.42
4	3321	12.58
3	859	3.25
2	329	1.25
1	661	2.50
Total	26,399	100.00

responses in user feedback, providing a more comprehensive understanding of UXs with educational AI tools. The emotional analysis processed each review text to extract normalized emotion intensity scores, enabling quantitative analysis of emotional dimensions alongside traditional sentiment metrics.

4.4 | Perception Classification Framework

User perceptions of usability and content quality were systematically classified using our keyword-based feature engineering approach. Reviews containing usability-related keywords were classified as 1, indicating positive usability perception, while absence of keywords resulted in classification as 0. For reviews with negative sentiment, positive classifications were converted to −1 to capture negative perceptions, with the same methodology applied to content quality perceptions. Similar methods have been successfully applied in prior research to detect nuanced user satisfaction from textual reviews [43]. This classification incorporated advanced negation handling, scanning for negation terms within a three-word window of keywords to accurately capture contextual meaning and avoid misclassification.

The resulting distributions, presented in Tables 3 and 4, reveal that 96.25% of reviews indicated positive usability perception (25,409 reviews) and 3.75% showed negative usability perception, while content quality perceptions showed 69.07% neutral (18,235 reviews), 30.00% positive (7920 reviews), and 0.92% negative (244 reviews). These classifications formed the foundation for our comprehensive analysis of how users perceive ChatGPT's educational utility across multiple dimensions.

4.5 | Statistical Analysis and Temporal Modeling

To assess the comprehensive impact of emotional, sentiment, and content factors on usability perceptions, we conducted ordinary least-squares (OLS) regression analysis with usability perception as the dependent variable. The independent variables included sentiment scores, review scores, content quality perceptions, and the eight emotional dimensions. Variance inflation factor (VIF) calculations ensured analytical robustness by evaluating multicollinearity among predictors, with all values below established thresholds indicating minimal multicollinearity concerns.

Temporal analysis was conducted by converting review timestamps to chronological format, enabling examination of daily averages and trends across key metrics including usability, sentiment, content quality, and emotional dimensions. Figure 1 presents a word cloud visualization generated from the text of the 26,399 education-related reviews. This graphic highlights the most frequently used words and phrases, providing an immediate visual summary of the predominant themes in user feedback regarding ChatGPT's educational use. Additionally, daily changes in key metrics were calculated by differencing daily averages, enabling analysis of perception stability and variability over time and offering a dynamic perspective on the evolution of UXs throughout the study period.

This comprehensive methodological framework provides a replicable approach for analyzing educational AI tools through transparent feature engineering, multilayered sentiment analysis, and rigorous statistical modeling, contributing both empirical findings and methodological innovation to the field of educational technology research. For future studies, researchers may consider combining AI-generated keyword sets with a small human review process to further enhance classification accuracy and domain specificity. Additionally, while this study focuses on the "usefulness" aspect of usability, future work could expand to include other usability dimensions, such as ease of use or learnability, to provide a more holistic evaluation of educational AI tools. These approaches would strengthen the methodological framework and support even more nuanced analyses of user perceptions.

TABLE 3 | Number of reviews with percentage toward users' perception regarding usability.

Value	Number	Percentage
1 (Positive)	25,409	96.24986
−1 (Negative)	990	3.750142
Total	26,399	100

TABLE 4 | Number of reviews with percentage toward users' perception regarding content quality.

Value	Number	Percentage
0 (Neutral)	18,235	69.07459
1 (Positive)	7920	30.00114
−1 (Negative)	244	0.924277
Total	26,399	100

5 | Finding and Discussion

Table 5 presents the mean values of the study variables for each usability class (positive usability, indicated by 1, and negative usability, indicated by −1). For the negative usability class (−1), the mean sentiment score is −1, signifying a negative sentiment, while the mean review score is 1.33, indicating a low level of user satisfaction. The emotional aspects also reflect this negativity, with higher values in trust (1.10) and fear (0.39), suggesting that users with negative usability perceptions tend to experience a combination of trust and mild fear. Other emotions such as anger (0.34), surprise (0.28), and anticipation (0.69) are also present but at relatively moderate levels. Negative emotions like sadness (0.59) and disgust (0.26) have notable values, indicating the presence of negative emotional responses from users who perceive poor usability. In contrast, the positive usability class (1) shows a mean sentiment score of 0.97, which leans toward a neutral to positive sentiment, and a significantly higher mean review score of 4.80, reflecting high user satisfaction. Positive emotions are more prominent in this group, with high values in trust (0.94), anticipation (0.48), and joy (0.66). This suggests that users perceiving high usability also feel more trust and positive emotions like joy and anticipation. On the other hand, negative emotions such as fear (0.16), anger (0.06), sadness (0.08), and disgust (0.03) are much lower, indicating that positive usability perceptions are linked to less negative emotionality. Overall, the table clearly demonstrates that users with positive usability perceptions tend to express more positive emotions and satisfaction, while users with negative usability perceptions tend to experience more negative emotions and lower satisfaction.

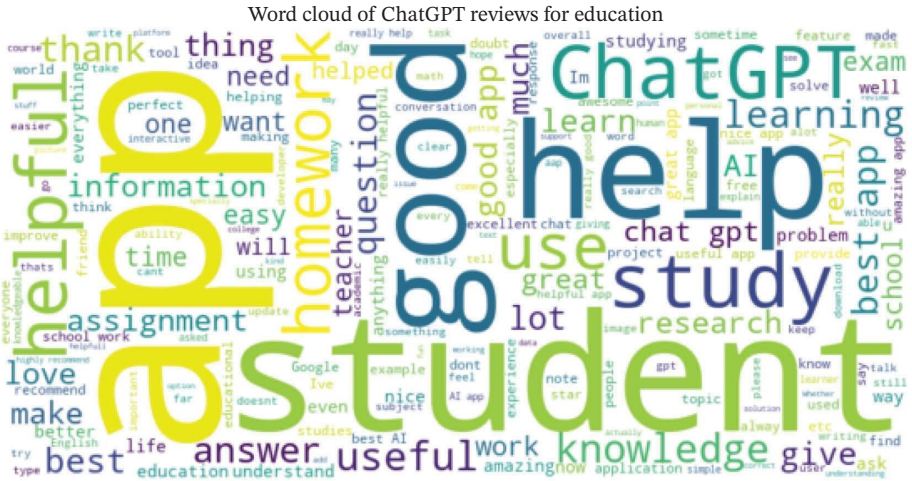

FIGURE 1 | Word cloud of education-related reviews.

Additionally, to know the impact of emotional sentiment, perceived content quality, and review scores on users' perceptions of ChatGPT's usability for education, OLS regression has been conducted. Table 6 presents the results of the regression analysis, which aims to understand how these variables influence users' overall perceptions of the usability of ChatGPT apps in educational contexts. The OLS regression results provide insights into the factors influencing users' perceptions of ChatGPT's usability. The constant term, with a coefficient of 0.2510 and a t-value of 26.621 ($p \leq 0.001$), suggests that when all independent variables are zero, the baseline usability perception is 0.2510. Sentiment emerges as a significant predictor, with a positive coefficient of 0.8565 and a t-value of 148.298 ($p \leq 0.001$), indicating that higher sentiment correlates strongly with a higher perception of usability. On the other hand, review scores show a slight negative effect, with a coefficient of −0.0210 and a t-value of −7.179 ($p \leq 0.001$), suggesting that higher review scores are associated with a small decrease in perceived usability. Content quality has a positive relationship with usability perceptions, with a coefficient of 0.0334 and a t-value of 14.459 ($p \leq 0.001$). Trust, while slightly negative (−0.0032), is statistically significant ($p = 0.012$), indicating a slight reduction in usability perceptions with increased trust. Emotions such as fear (−0.0011, $p = 0.691$) and anger (−0.0004, $p = 0.922$) do not show significant effects on usability perception. In contrast, surprise (0.0151, $p \leq 0.001$) and anticipation (0.0077, $p \leq 0.001$) both have positive effects on perceived usability. Joy, with a negative coefficient of −0.0076 ($p \leq 0.001$), suggests a slight reduction in usability perception when joy is present. Sadness shows a marginally insignificant effect, with a coefficient of −0.0070 and a t-value of −1.867 ($p = 0.062$). Finally, disgust has a significant negative impact on usability perception, with a coefficient of −0.0264 and a t-value of −4.783 ($p \leq 0.001$). These findings highlight that while many emotional factors influence usability perception, some, such as trust, surprise, and disgust, stand out as significant contributors. To further interpret these results, we note several nuanced patterns. Trust exhibited a slight negative association with usability, which may occur because users with higher trust in the platform can experience greater frustration when errors arise, leading to more critical usability evaluations. Joy, despite being a positive emotion, showed a negative effect; this may reflect users' amusement with ChatGPT rather than appreciation of its practical utility for educational tasks. Regarding review scores, very high ratings (5-stars) often reflect general praise, while detailed feedback regarding usability is more frequently observed in 4-star reviews, which may explain the small negative coefficient observed for score.

Additionally, hypotheses results are shown in Table 7. The results of the hypotheses testing provide valuable insights into the various factors influencing users' perceptions of the usability of ChatGPT for educational purposes, with a combination of positive and negative effects observed across different variables. H1, which posited that users' sentiment toward ChatGPT significantly influences their perceptions of its usability for education, was accepted. The positive coefficient for sentiment (0.8565) with a statistically significant p-value ($p \leq 0.001$) indicates that higher sentiment correlates with a more favorable perception of usability in educational contexts. Essentially, as users' sentiment improves, so does their perception of the tool's usability, emphasizing the importance of positive emotional responses in enhancing user engagement and interaction with educational technology. H2, which suggested that the star rating (score) provided by users for ChatGPT significantly influences their perceptions of its usability for education, was also accepted. However, the coefficient for score was negative (−0.0210), meaning that higher ratings were associated with a slight decrease in perceived usability. This result implies that users with higher expectations based on the ratings might become more critical, leading to a lower perception of usability. This suggests that higher user expectations may not always align with their overall satisfaction or perceived usability of the tool. H3, which proposed that users' perceived content quality of ChatGPT significantly influences their perceptions of its usability for education, was accepted. A positive coefficient (0.0334) and a significant p-value ($p \leq 0.001$) showed that higher content quality positively impacted users' perceptions of usability. This confirms that clear, accurate, and engaging content can enhance the perceived usefulness of educational tools like ChatGPT, making content quality a key factor in the UX. H4, which hypothesized that users' emotional aspects, including trust, joy, surprise, fear, anger, sadness, disgust, and anticipation, significantly influence their perceptions of the usability of educational tools, was partially accepted. Several emotions demonstrated

TABLE 5 | Mean values of study variables for each usability class.

Usability	Sentiment	Score	Content_quality	Trust	Fear	Anger	Surprise	Anticipation	Joy	Sadness	Disgust
−1	−1	1.332323	−0.24647	1.10303	0.392929	0.338384	0.281818	0.692929	0.593939	0.452525	0.259596
1	0.966193	4.801684	0.311701	0.937502	0.163564	0.059113	0.269275	0.47802	0.662128	0.080956	0.032823

a clear impact on usability perception, while others did not. Trust (H4a) had a negative effect (coefficient = −0.0032), suggesting that higher trust in the tool was associated with a slight reduction in perceived usability. This may indicate that users with greater trust in the platform could become more discerning, expecting greater functionality or transparency, and therefore perceiving a slight decline in usability. Joy (H4b) also showed a negative effect (coefficient = −0.0076), which was surprising. Despite the positive emotion, joy did not enhance usability perceptions; it may suggest that users in a joyful state do not focus as much on the functional aspects of the tool, leading to a lower usability rating. Surprise (H4c), on the other hand, had a positive effect (coefficient = 0.0151), meaning that elements of surprise within the educational tool can positively influence users' perceptions of usability. This indicates that surprise can add novelty and engagement, making users perceive the tool as more usable. Fear (H4d) was rejected, showing no significant impact on usability perceptions (coefficient = −0.0011). Fear may reduce engagement with the tool, but it was not strong enough to influence usability perception significantly. Anger (H4e) also had a negligible effect (coefficient = −0.0004), indicating that while anger might influence UX, it does not significantly affect usability perceptions. Sadness (H4f) was marginally rejected (coefficient = −0.0070), showing a slight negative effect but not statistically significant ($p = 0.062$), suggesting that sadness might slightly detract from usability perception but its impact is not decisive. Disgust (H4g) had a strong negative effect (coefficient = −0.0264), indicating that disgust significantly reduces usability perceptions. Users experiencing disgust are likely to perceive the tool as less usable, highlighting the importance of avoiding negative emotional responses such as disgust in educational technology design. Anticipation (H4h), on the other hand, had a positive effect (coefficient = 0.0077), suggesting that users who experience excitement or anticipation in their interactions with the tool perceive it as more usable. This aligns with the idea that engagement and curiosity improve usability perceptions. Moreover, the findings reveal the complexity of emotional influences on usability perceptions. Positive emotions like sentiment, surprise, and anticipation enhance usability perceptions, while negative emotions like trust, joy, and disgust can detract from them. Some emotions, such as fear, anger, and sadness, had minimal or no effect, indicating that these emotions are not significant in shaping usability perceptions in educational contexts. These results offer actionable insights for developers to optimize UXs by focusing on emotional engagement, content quality, and platform trust.

The R-squared value of 0.819 indicates that approximately 81.9% of the variance in users' perceptions of usability is explained by the variables included in the model, such as sentiment, score, content quality, and emotions like trust, fear, and anger. This strong fit suggests that the model effectively captures a substantial portion of the variation in usability perceptions. Additionally, the adjusted R-squared value of 0.818 accounts for the number of predictors in the model, ensuring that the explanatory power is not inflated by overfitting, further supporting the model's adequacy. The F-statistic of $1.082e + 04$ and its associated $p \leq 0.001$ indicate that the overall model is statistically significant, meaning that the independent variables, including sentiment, score, content quality, and emotions, collectively have a significant impact on users' perceptions of usability.

TABLE 6 | OLS regression results.

	Coef	Std err	t	$P > \|t\|$	(0.025)	(0.975)
const	0.2510	0.009	26.621	≤ 0.001	0.233	0.269
sentiment	0.8565	0.006	148.298	≤ 0.001	0.845	0.868
score	−0.0210	0.003	−7.179	≤ 0.001	−0.027	−0.015
content_quality	0.0334	0.002	14.459	≤ 0.001	0.029	0.038
trust	−0.0032	0.001	−2.501	0.012	−0.006	−0.001
fear	−0.0011	0.003	−0.397	0.691	−0.006	0.004
anger	−0.0004	0.004	−0.098	0.922	−0.009	0.008
surprise	0.0151	0.003	5.795	≤ 0.001	0.010	0.020
anticipation	0.0077	0.002	3.980	≤ 0.001	0.004	0.011
joy	−0.0076	0.002	−3.935	≤ 0.001	−0.011	−0.004
sadness	−0.0070	0.004	−1.867	0.062	−0.014	0.000
disgust	−0.0264	0.006	−4.783	≤ 0.001	−0.037	−0.016

To assess the presence of multicollinearity among the predictor variables, we have computed the VIF for each variable. VIF measures how much the variance of the estimated regression coefficients is inflated due to collinearity with other predictors. Generally, a VIF value above 10 indicates high multicollinearity. In Table 8, the VIF results suggest that multicollinearity is not a major concern in the model, as the values are generally below the threshold.

The temporal analysis presented in Figures 2 and 3 provides valuable insights into the dynamics of user perceptions. Figure 2 illustrates the daily average values of key variables, while Figure 3 tracks their daily changes, revealing how different factors fluctuate and interact over time. The analysis shows that content quality, surprise, and disgust exhibit the highest fluctuation levels, indicating that these variables are particularly sensitive to changes in UXs with ChatGPT. This pattern likely reflects shifts in content perception and emotional reactions, suggesting that targeted improvements in content quality and management of surprising or negative elements could significantly influence usability perceptions.

In contrast, usability, sentiment, score, trust, and joy experience moderate fluctuations, suggesting that these aspects of UX are more stable but still subject to variation. This is important because it implies that, while these factors are important, they are less volatile and may reflect more consistent perceptions of usability, influenced by longer-term or more gradual changes in user interactions with the system. Lastly, fear, anger, and sadness show the lowest levels of fluctuation, which may imply that users' emotional responses related to these feelings are more stable over time. This is significant because it suggests that these emotions might not have as strong an impact on users' perceptions of ChatGPT's usability, or they may not change as frequently, providing insights into how these emotions influence overall perceptions in a more subdued or static manner. Moreover, these fluctuations help identify which variables are more volatile and which are more stable, providing guidance on where improvements could have the most noticeable impact on users' perceptions of ChatGPT's usability for education. Understanding the dynamics of these variables over time is crucial for optimizing the system's design and enhancing the UX.

Beyond the empirical findings, this study demonstrates the value of our methodological framework for educational technology evaluation. The combination of feature engineering with emotional sentiment analysis proved particularly effective in capturing nuanced user perceptions that might be missed through conventional analysis methods. This approach offers researchers a replicable template for studying UXs with AI educational tools, emphasizing the importance of both functional and emotional dimensions in usability assessment.

6 | Applications

6.1 | Theoretical Applications

This study has several important theoretical applications. Firstly, it contributes to usability theory by emphasizing the dominant role of sentiment in shaping users' perceptions of usability. The findings indicate that sentiment is the most influential predictor, reinforcing the notion that usability should not be viewed solely in terms of task efficiency but also through the lens of emotional engagement and user perception. This challenges traditional usability models that focus primarily on functionality and task completion. Secondly, the study enriches UX theory by providing a more nuanced understanding of how specific emotions shape user interactions. The results show that surprise and anticipation enhance usability perceptions, while joy and disgust negatively affect usability. Contrary to expectations, trust has a small but negative effect, and emotions like fear, anger, and sadness do not exhibit significant relationships with usability. These findings suggest that UX design must account for both positive and negative emotional influences, as not all traditionally "positive" emotions lead to improved usability. Thirdly, the research extends HCI theory by illustrating how emotional sentiment and content quality influence user interactions with educational technologies. The results indicate that higher content quality improves usability perceptions, suggesting that AI-driven learning environments should be designed to provide high-quality, contextually relevant content to enhance user engagement. Additionally, review scores show a small but significant negative effect, indicating that users may develop usability perceptions based on personal experience rather than aggregated external ratings. These insights underscore the need for HCI

TABLE 7 | Hypothesis testing and decision outcomes.

Hypothesis	Significant influence	Decision
H1: Users' sentiment towards ChatGPT significantly influences their perceptions of its usability for education.	Yes	Accepted
H2: The star rating (score) provided by users for ChatGPT significantly influences their perceptions of its usability for education.	Yes	Accepted
H3: Users' perceived content quality of ChatGPT significantly influences their perceptions of its usability for education.	Yes	Accepted
H4: Users' emotional aspects, including trust (H4a), joy (H4b), surprise (H4c), fear (H4d), anger (H4e), sadness (H4f), disgust (H4g), and anticipation (H4h), significantly influence their perceptions of the usability of educational tools.	Yes (partial acceptance)	Partially Accepted
- H4a: Trust	Yes	Accepted
- H4b: Joy	Yes	Accepted
- H4c: Surprise	Yes	Accepted
- H4d: Fear	No	Rejected
- H4e: Anger	No	Rejected
- H4f: Sadness	No (marginal)	Rejected
- H4g: Disgust	Yes	Accepted
- H4h: Anticipation	Yes	Accepted

TABLE 8 | VIF.

	Variable	VIF
0	const	89.540025
1	sentiment	5.74362
2	score	5.677632
3	content_quality	1.210186
4	trust	2.335395
5	fear	1.533756
6	anger	1.83791
7	surprise	1.897318
8	anticipation	2.384559
9	joy	2.950567
10	sadness	1.865587
11	disgust	1.641267

frameworks to integrate emotional responses and content quality considerations when designing AI-based learning platforms. Fourthly, the study strengthens educational technology theory by demonstrating that content quality is a key driver of usability in AI-powered learning platforms. The findings suggest that fostering positive emotional experiences, particularly through surprise and anticipation, can enhance usability perceptions, which in turn may increase engagement and learning outcomes. This underscores the importance of designing educational technologies that not only provide high-quality content but also create emotionally engaging learning experiences. Lastly, this study informs future research in affective computing and emotional design by highlighting the complex role of emotions in usability perceptions. The findings suggest that AI-driven educational tools capable of recognizing and responding to user emotions could enhance engagement and satisfaction. By emphasizing the role of sentiment and content quality in usability assessments, this study offers new perspectives for integrating affective computing principles into educational AI systems and highlights opportunities for improving user-centered design in AI-assisted learning.

6.2 | Practical Applications

The findings of this study provide several actionable insights for improving the design and usability of AI-driven educational technologies. Sentiment emerges as the strongest predictor of perceived usability ($\beta = 0.8565$, $p \leq 0.001$), highlighting the importance of fostering positive emotional engagement. Designers should prioritize features that enhance anticipation ($\beta = 0.0077$, $p \leq 0.001$) and surprise ($\beta = 0.0151$, $p \leq 0.001$), as these emotions are associated with higher usability perceptions. For example, to leverage surprise, an AI educational platform could occasionally provide helpful study tips or novel learning prompts that the user did not explicitly request, creating moments of engagement and delight. Conversely, joy ($\beta = -0.0076$, $p \leq 0.001$) and disgust ($\beta = -0.0264$, $p \leq 0.001$) negatively affect usability, suggesting that designers should carefully manage elements that might amuse users without supporting educational objectives or trigger frustration. Content quality also plays a significant role ($\beta = 0.0334$, $p \leq 0.001$), emphasizing the need for accurate, clear, and engaging materials to improve user satisfaction. Interestingly, review scores show a small negative association ($\beta = -0.0210$, $p \leq 0.001$), which may indicate that users with higher expectations provide critical feedback despite giving high star ratings. Trust exhibits a slight negative effect ($\beta = -0.0032$, $p = 0.012$), potentially reflecting that highly trusting users become more discerning and notice usability issues more critically. Fear, anger, and sadness show no significant influence on usability, suggesting that these emotions are less relevant for shaping user perceptions in educational contexts. Finally, the methodological framework presented in this study can be used to continuously track user feedback over time, allowing developers to monitor changes in sentiment, emotional responses, and

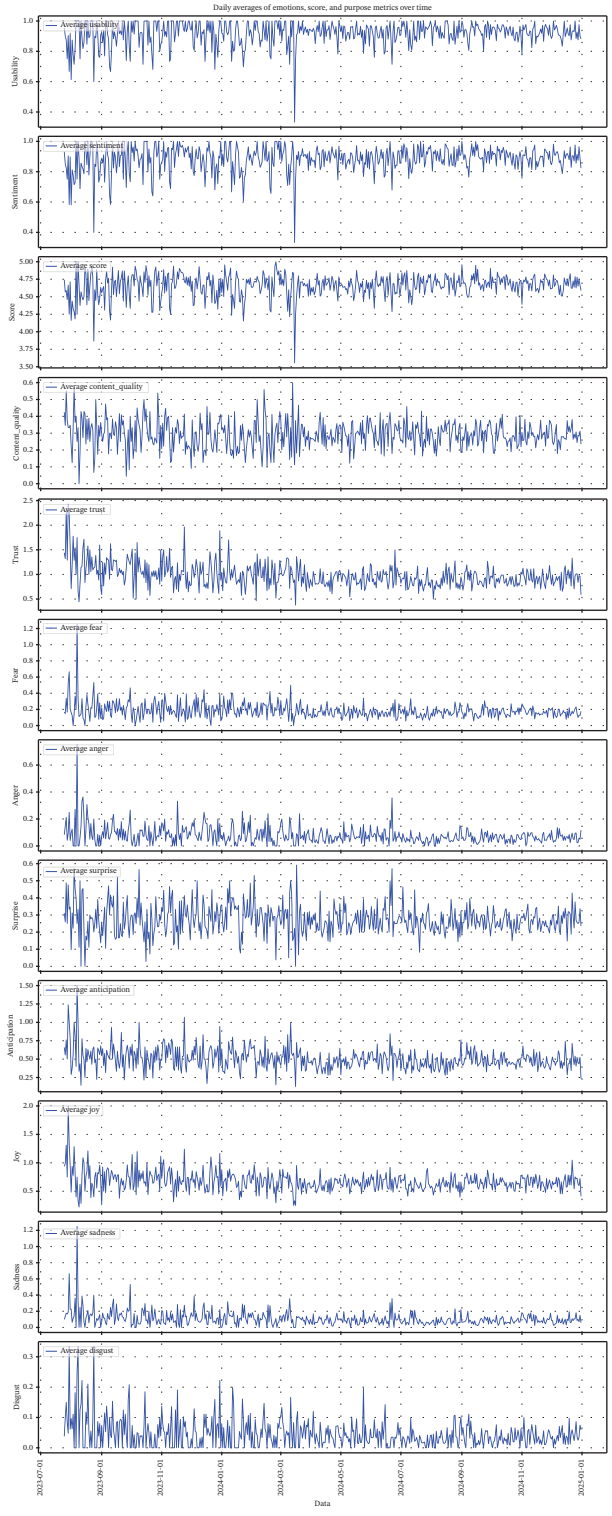

FIGURE 2 | Daily average value.

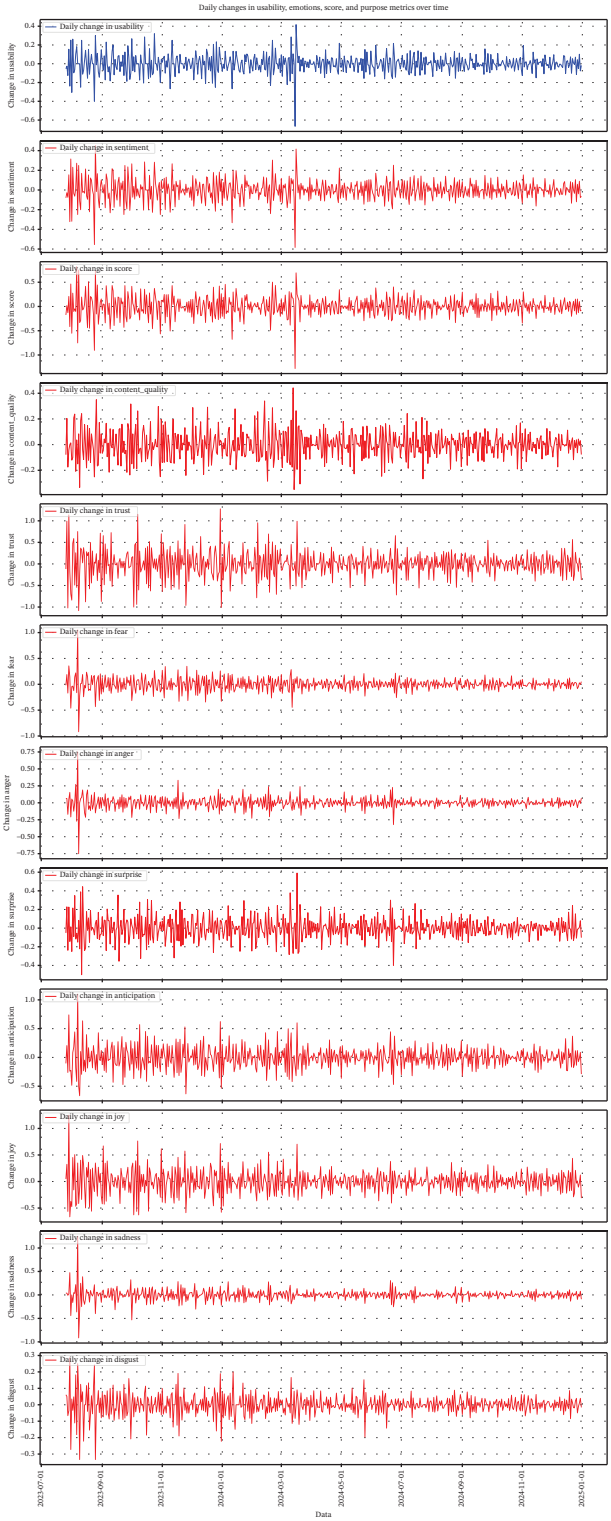

FIGURE 3 | Daily changes of values.

content quality after app updates. By incorporating these insights, developers can design AI educational tools that not only provide high-quality content but also foster positive emotional experiences, such as surprise and anticipation, while minimizing negative emotional responses, thereby supporting adaptive, user-centered experiences that enhance engagement, satisfaction, and overall learning outcomes.

6.3 | Methodological Contributions

This study makes several significant methodological contributions that advance research practices in educational technology, HCI, and AI evaluation. Beyond the empirical findings, our research provides a comprehensive and replicable framework

that can be readily adopted and adapted by other researchers studying UXs with AI educational tools. The primary methodological contribution lies in the development of a holistic evaluation framework that effectively bridges qualitative user insights with rigorous quantitative analysis. This framework integrates three complementary components that together provide a more nuanced understanding of UXs than conventional approaches. First, our LLM-assisted feature engineering approach demonstrates how structured prompts with large language models can generate domain-specific keyword sets, offering a scalable and efficient alternative to traditional manual codebook development. This method is particularly valuable for studying emerging technologies where established categorization schemes may not yet exist. Second, our multilayered sentiment analysis methodology combines traditional rating-based classification with NRCLex emotional analysis, capturing both explicit and implicit user perceptions that would be missed by conventional sentiment analysis methods. Third, our temporal perception tracking approach provides a dynamic perspective on how UXs evolve over time, moving beyond static snapshot analyses to reveal patterns in perception stability and variability.

A key strength of our methodological approach is its emphasis on reproducibility and adaptability. The complete analytical pipeline—from ethical data collection using the Google Play Scraper library through systematic preprocessing and comprehensive statistical modeling—is designed to be transparent and replicable. The systematic preprocessing protocol, including duplicate removal, text normalization, and advanced negation handling, ensures consistency across studies while maintaining the nuanced meaning of user feedback. The adaptable keyword generation process, using structured prompts that can be easily modified for other educational technologies or domains, provides researchers with a flexible tool for domain-specific analysis. The integration of OLS regression with VIF analysis and temporal tracking offers a robust statistical template for analyzing complex user perception data across multiple dimensions.

Our methodology represents a significant advancement in educational technology assessment methods by addressing several limitations in current evaluation approaches. The framework enables the analysis of large-scale user feedback while preserving the nuanced understanding of individual UXs, balancing scalability with depth of insight. By systematically incorporating eight distinct emotions beyond basic positive/negative sentiment, we provide a more comprehensive approach to understanding the emotional dimensions of user engagement. The negation-aware keyword classification system accounts for contextual language use, significantly reducing misclassification common in simpler keyword-based approaches and capturing the subtle ways users express mixed or qualified opinions about educational technologies. From a practical implementation perspective, our methodological approach offers concrete guidance for researchers seeking to conduct similar studies. The structured prompt templates for keyword generation can be readily adapted for other domains by modifying the core question structure. The clear documentation of preprocessing steps, including specific techniques for handling emojis, special characters, and negation patterns, provides a practical roadmap for ensuring data quality. The integration of multiple analytical techniques—from feature engineering through emotional analysis to statistical modeling—demonstrates how researchers can triangulate findings to develop a comprehensive understanding of UXs. This methodological contribution is particularly valuable for the growing community of researchers studying AI in education, providing them with a robust, transparent, and adaptable framework for evaluating how users perceive and interact with increasingly sophisticated educational technologies.

7 | Conclusion

This study provides a comprehensive examination of the factors influencing users' perceptions of ChatGPT's usability in educational contexts, with particular emphasis on the underexplored dimensions of emotional sentiment and content quality. Our analysis of 26,399 education-focused reviews reveals that usability in AI-driven educational tools extends far beyond traditional metrics of functional efficiency and task completion. The findings demonstrate that emotional sentiment emerges as the most powerful predictor of perceived usability, significantly outweighing the influence of other factors and challenging conventional usability frameworks that prioritize functionality over affective experience. The research uncovers the nuanced and sometimes counterintuitive roles of specific emotions in shaping usability perceptions. While surprise and anticipation positively influence usability perceptions—suggesting that elements of novelty and engaged curiosity enhance UXs—joy exhibits an unexpected negative relationship, potentially indicating that pure enjoyment may distract from functional assessment or raise expectations unrealistically. The strong negative impact of disgust underscores the critical importance of avoiding content or interactions that users find objectionable, while the complex relationship with trust suggests that trusted tools are held to higher standards of performance. Meanwhile, content quality maintains its fundamental importance, serving as a foundational element that users consistently associate with positive usability experiences.

This research makes significant contributions across theoretical, practical, and methodological domains. Theoretically, it advances usability theory by integrating emotional dimensions as central components rather than peripheral considerations, thereby enriching UX theory and HCI frameworks for educational technologies. The findings challenge the assumption that all positive emotions uniformly enhance usability and demonstrate the need for more nuanced emotional design principles in educational AI systems. Practically, the study offers actionable guidance for developers, educators, and instructional designers. The evidence suggests that optimizing ChatGPT for educational use requires a dual focus: maintaining high standards of content quality while deliberately designing for specific emotional experiences. Developers should prioritize generating accurate, relevant content while incorporating elements that foster anticipation and positive surprise, implementing safeguards against experiences that might evoke disgust, and recognizing that building trust requires consistent performance excellence. Methodologically, this research contributes a replicable analytical framework that combines feature engineering with multilayered sentiment analysis, providing researchers with a robust approach for studying user perceptions of educational technologies at scale. The integration of LLM-assisted keyword generation, NRCLex emotional analysis, and comprehensive statistical

modeling offers a template that can be adapted for studying diverse educational technologies and learning environments.

8 | Limitations and Future Research Directions

While this study provides valuable insights into the factors shaping users' perceptions of ChatGPT's usability in education, several limitations should be considered. Firstly, the study relies on ChatGPT to generate keywords, retaining only the top 50 for each category. Since ChatGPT may produce different keywords depending on the prompt, the results might vary based on keyword selection. Future research could explore alternative keyword generation methods and assess the impact of varying keyword sets on analysis outcomes. Secondly, the study focuses specifically on ChatGPT in educational settings, which may limit the generalizability of findings to other AI-powered platforms or different use cases, such as corporate training or recreational learning. Future research could examine whether emotional and usability dynamics remain consistent across various educational technologies. Thirdly, the study does not fully examine the role of cultural and demographic differences in shaping users' emotional responses and usability perceptions. Since users from diverse backgrounds may experience AI-powered educational tools differently, future research could explore how factors like age, educational level, or geographic region influence their experiences. Additionally, this study used sentiment as a proxy for negative usability to simplify analysis, though manually capturing nuanced negative expressions—such as "useless," "not useful," or words with negative prefixes like "dis-" and "un-"—could provide more precision. Our VIF results indicate no serious multicollinearity, but overlap between sentiment and usability should be considered. Future research could develop more refined methods to detect negative usability. Finally, this study captures a snapshot of user perceptions but does not address how these perceptions evolve with continued platform use. Future longitudinal research could explore how emotional engagement and usability assessments change over time, providing deeper insights into sustained UX and adaptation. By addressing these limitations, future research can enhance the understanding of emotional and usability factors in AI-driven educational tools, ultimately improving their effectiveness and UX [44].

Author Contributions

Peng Sun: conceptualization, data curation, formal analysis, investigation, methodology, software, visualization, writing–original draft, and writing–review and editing.

Md. Ziaul Haque: conceptualization, data curation, formal analysis, investigation, methodology, validation, and writing–review and editing.

Le Li: conceptualization, software, visualization, resources, supervision, and writing–review and editing.

Md. Shamim Hossain (Corresponding author): conceptualization, data curation, formal analysis, investigation, methodology, project administration, supervision, software, visualization, writing–original draft, writing–review and editing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

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

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Appendix 1

TABLE A1 | Featured engineering keywords.

Education_keywords (total 50)	Usability_keywords (total 50)	Content_quality_keywords (total 50)
"learn", "teaching", "study", "education", "homework", "exam", "school", "college", "university", "course", "tutoring", "classroom", "training", "practice", "knowledge", "student", "lectures", "assignment", "curriculum", "syllabus", "notes", "teacher", "professor", "instructor", "quiz", "assessment", "certificate", "scholarship", "degree", "e-learning", "MOOC", "mentor", "guidance", "presentation", "discussion", "workshop", "seminar", "online class", "interactive", "education app", "learning app", "revision", "educational", "learning resources", "self-study", "academic", "research", "knowledge sharing", "pedagogy", "exam preparation"	"self-study", "exam preparation" "educational" "learn", "online class", "teaching", "quiz", "education", "homework", "exam", "workshop", "research", "scholarship", "school", "university", "course", "tutoring", "college", "classroom", "training", "practice", "knowledge", "student", "seminar", "interactive", "education app", "lectures", "study", "assessment", "assignment", "curriculum", "syllabus", "notes", "teacher", "learning app", "certificate", "degree", "e-learning", "professor", "instructor", "MOOC", "mentor", "academic", "knowledge sharing", "learning resources" "revision", "guidance", "pedagogy", "presentation", "discussion",	"clear", "detailed", "accurate", "informative", "relevant", "useful", "helpful", "high-quality", "good explanation", "understandable", "concise", "engaging", "well-written", "reliable", "coherent", "comprehensive", "structured", "insightful", "well-researched", "organized", "thorough", "in-depth", "effective", "consistent", "practical", "educational", "focused", "logical", "original", "intelligible", "evidence-based", "succinct", "approachable", "expert", "convincing", "correct", "meaningful", "accurate information", "well-explained", "valid", "engaging content", "high-standard", "reliable source", "relevant data", "clear explanation", "well-organized", "easy to follow", "easy to understand", "well-supported", "coherent argument"