Contents

1 Introduction

As Charles Darwin once said, "It is not the strongest of the species that survive, nor the most intelligent, but the one most responsive to change." We are all living in an ever-changing world. No matter how much we wish to hold on to the familiar and comfortable environment around us, life always pushes us onto new and exciting journeys. Sometimes, we may find it hard to get used to a new environment and want to find helpful tools to help us adapt.

One such tool is the sentiment-aware chatbot. When embedded in a campus context, such a chatbot could not only provide timely information about the campus with high accuracy, but also provide suitable emotional support for users. This combination of sentimental analysis and campus context chatbot deserves deeper exploration. Therefore, this review investigates the landscape of campus chatbots and the sentiment analysis technology. To guide our systematic review, we constructed the following research questions:

- RQ1: What is the current state of chatbots in campus contexts?
- RQ2: What are the current technical approaches to sentiment analysis?
- RQ3: What are the impacts of sentiment-aware chatbots on user experience?

To attain a focused and manageable scope for this literature review, we set the inclusion criteria for studies. Studies were considered for inclusion if they were peer-reviewed journal articles or full conference papers published between 2014 and 2024, written in any language (with priority given to English), and directly focused on chatbot or conversational-agent technologies and/or sentiment-analysis techniques. We excluded abstracts, posters, dissertations, theses, commentaries, editorials, letters to the editor, and review articles, as well as studies that only presented theoretical frameworks. Papers focusing on applications outside the scope of conversational agents or sentiment analysis, such as purely predictive analytics in finance, healthcare, or other non-conversational domains–were also excluded.

2 Landscape of Campus Chatbots

In order to gain an in-depth understanding of the current state of chatbots in universities, we have been conducting a comprehensive analysis of academic literature. Particular emphasis has been placed on research findings that are dedicated to chatbots in the university context. Research indicates that chatbots have the potential to revolutionize campus technology, which frequently lags behind the times. Additionally, they can confer multiple advantages to the overall academic ecosystem, benefiting both students and faculty members alike (Dibitonto, Leszczynska, Tazzi, & Medaglia, 2018).

With the rapid development of artificial intelligence and natural language processing technologies, educational chatbots have evolved into a diverse range of specialized tools in academic settings. Modern educational chatbots can be roughly classified based on their core functions and technical foundations. These categories include teaching chatbots for academic assistance, emotional support chatbots for promoting student well-being, and campus service chatbots for facilitating campus interactions.

2.1 Academic Assistance Chatbots

The traditional teaching approach based on master classes or techniques, which places students in a passive position, has been proven to be an inefficient method in the learning process. The application of technology in universities helps to foster student interest, and enhance their engagement in their own educational development. For this reason, the application of chatbots has been brought into consideration. These techniques simulate the human thought process by leveraging structures that encapsulate the knowledge and experience of human experts (Villegas-Ch, Arias-Navarrete, & Palacios-Pacheco, 2020). One example of academic assistance chatbot is EDUBOT. EDUBOT is an educational chatbot developed by Sathyabama Institute of Science and Technology in India, aiming to address the issue of the lack of teacher guidance during the online learning of primary and secondary school students during the COVID-19 pandemic. The system is built on the Google Dialogflow platform for semantic understanding, combined with RNN models for language processing, and deployed on the web via the Flask framework, supporting integration with mainstream social platforms such as Telegram and Messenger. EDUBOT offers question-and-answer services, a math calculator, demonstration videos, and the ability to save history records. It is designed to be simple and user-friendly, targeting students from grades 1 to 5, and provides 24-hour self-service answers (Sophia & Jacob, 2021).

2.2 Emotional Support Chatbots

In Japan, due to COVID-19, the number of college students encountering challenges has been on the rise. However, despite the availability of on-campus counseling services, many students hesitate to use them. This reluctance is primarily attributed to psychological barriers associated with seeking help (Yasuda et al., 2021). This highlights the essential role that emotional support chatbots can play on campus, providing a low-barrier means for students to cope with mental health challenges. Yin, Chen, Zhou, and Yu (2019) proposed Evebot, an innovative sequence-to-sequence (Seq2Seq) based generative conversational system designed for detecting negative emotions and preventing depression through positively framed responses. The system integrates several deep learning components, including a Bi-LSTM model for identifying negative user emotions, a psychological counseling corpus, an anti-language Seq2Seq network, and a maximum mutual information (MMI) model to enhance dialogue relevance.

Given that adolescents often avoid expressing negative emotions in face-to-face settings, traditional methods of emotional support may be ineffective. Therefore, Evebot leverages virtual platforms to identify early signs of depression or anxiety, manage emotional states, and prevent the escalation of mental health issues. In a one-month field study conducted on a campus platform, the system demonstrated superior effectiveness in improving users' emotional well-being compared to public chatbot baselines.

2.3 Campus Service Chatbots

Colleges invest a great deal of time and resources in optimizing their websites to more effectively convey the key information about the institution and campus resources. The institution's website functions as its "virtual image," projecting the specific face it wishes to present to the online community, including prospective and current students, faculty and staff, parents, and general users. Although these websites provide comprehensive information, they lack the capability to offer personalized responses to users' inquiries. For example, when a prospective student needs to learn the specifics of submitting ACT scores, wishes to ascertain tuition and fee amounts, or is uncertain about which parent's information to include in the FAFSA application, they must navigate through multiple web pages to locate the answers. This process often takes a considerable amount of time. However, sometimes due to unclear information or the lack of personal interaction, users' questions remain unanswered (Neupane et al., 2024). Therefore, a chatbot can be a useful and effective solution for students, providing them with immediate and up-to-date information. "Lisa" is one example of a campus service chatbot. "Lisa" is a chatbot designed to help students solve problems in their campus life by providing information and services, answering questions 24 hours a day.

Information provided by campus service chatbots is often generic, such as details about university facilities, admissions processes, and course offerings. However, chatbot assistants can be utilized in various contexts throughout the academic year to address specific student needs. For instance, during the application process, a chatbot can assist prospective students by guiding them through enrollment procedures. The primary goal is to enable students to access information quickly and efficiently, eliminating the need to search through multiple web pages for answers to frequently asked questions. A chatbot serves as a shortcut for obtaining information in a more accessible and natural manner. It functions not only as an excellent guide for newcomers navigating the initial steps into the university environment but also as a valuable resource throughout students' entire campus experience (Dibitonto et al., 2018).

Many students do not attend classes every day. For them, it is very important to be able to access updated information remotely. This information can be either response-based (replies to specific requests) or push-based, such as relevant updates and notifications to remind students of upcoming deadlines. Response-based information typically provided by chatbots includes university facilities, upcoming events, and academic information (Ranoliya, Raghuwanshi, & Singh, 2017). In essence, Campus Service Chatbots function as intuitive, always-available digital assistants that enhance students' access to institutional support throughout their academic journey.

3 Technical Approaches to Sentiment Analysis

Sentiment analysis, or opinion mining, is an active area of study in the field of natural language processing that analyzes people's opinions, sentiments, evaluations, attitudes, and emotions via the computational treatment of subjectivity in text. In this section, we will discuss the technical approaches to sentiment analysis by looking into three common methods.

3.1 Lexicon Methods

Lexicon methods use a precompiled "sentiment lexicon" plus linguistic rules to assign an overall sentiment score to a sentence or document. A sentiment lexicon is a list of lexical features (e.g., words) which are generally labeled according to their semantic orientation as either positive or negative. Although one of the most reliable ways to create a sentiment lexicon is to create it manually, it is also one of the most time-consuming. Therefore, most of the research on sentiment analysis relies heavily on pre-existing lexicons. Two main kinds of lexicons exist currently: Polarity-based lexicons and Valence-based lexicons (Hutto & Gilbert, 2014).

Polarity-based lexicons are lexicons in which words are categorized into binary classes according to their context-free semantic orientation. They are straightforward to implement and enables low computational complexity. At the same time, they cannot distinguish between degrees of positivity–for example, they would score 'excellent' and 'good' equally–and they require great effort to maintain (Ravi & Ravi, 2015). Some representative Polarity-based lexicons are LIWC (Linguistic Inquiry and Word Count), GI (General Inquirer) and Hu-Liu04. Valence-based lexicons are lexicons in which words are associated with valence scores for sentiment intensity. By capturing fine-grained differences in sentiment intensity by assigning each entry a continuous numerical score, they allow models to distinguish between 'excellent' and 'good'. Moreover, for multi-meaning words, lexicons like SentiWordNet score each separately, ensuring that a word's positive or negative intensity reflects its specific sense in context. However, Valence-based lexicons also have the disadvantage of being difficult to maintain (Yadollahi, Shahraki, & Zaiane, 2017) and ambiguous scoring in continuous context. Some representative Valence-based lexicons are ANEW (Affective Norms for English Words), SentiWordNet, SenticNet and NRC VAD (Mohammad, 2018).

VADER (Valence Aware Dictionary for sEntiment Reasoning) is a sentiment analysis tool that is able to capture both the polarity and intensity of sentiment. Research has shown that the VADER lexicon performs exceptionally well in the social media domain. Comparison of VADER with LIWC, GI, ANEW, SWN, SCN, WSD and more tools shows that VADER performs better than those eleven highly-regarded sentiment analysis tools (Hutto & Gilbert, 2014).

3.2 Machine-Learning Methods

To address the time-consuming and hard-to-maintain issue of Lexicon methods, we turn to Machine-Learning methods. Rather than relying on a manually created list of sentiment-bearing words and complex linguistic rules, Machine-Learning approaches build predictive models directly from labeled data. These methods train classifiers–such as SVM or Naive Bayes–on labeled data using features like n-grams and word embeddings, learning patterns that correspond to positive, negative, and neutral sentiments. Once trained, the model assigns sentiment scores to new texts without requiring manual lexicon updates.

The benefits of applying machine learning are obvious. It is capable of learning semantic features automatically and is better at capturing emotions in a long context. However, its training demands high computational resources (e.g., GPU/TPU) (Young, Hazarika, Poria, & Cambria, 2018) and it struggles to capture long-distance dependencies and contextual meanings, and cannot automatically extract deep semantic information (Ribeiro, Singh, & Guestrin, 2016).

3.3 Deep-Learning Methods

Different from Machine-Learning Methods which rely on manually crafted features and shallow architectures, Deep-Learning Methods utilize multilayer neural networks to automatically learn hierarchical representations from raw text data. These neural networks are inspired by the structure of the biological brain. Similar to the learning process of a biological brain, neural networks can learn by adjusting the connection weights between neurons, which are information processing units organized in layers (LeCun, Bengio, & Hinton, 2015).

Based on network topologies, neural networks can generally be categorized into feedforward neural networks, recurrent or recursive neural networks and the combination of the two. In feedforward neural networks, data flows from the input layer through one or more hidden layers to the output layer, with no recurrent or feedback connections in between (Heaton, 2017). Typical types of feedforward neural networks are CNN (Convolutional Neural Network), MLP (Multilayer Perceptron) and Autoencoder. Recurrent neural networks (RNN) and recursive neural networks introduce a recurrent connection in the hidden layer between time step t and t-1, so that the network can retain the previous time step's state, enabling it to model sequential data.

Emerging as a powerful machine-learning technique and producing extraordinary results in many application domains, deep learning has also shown great results when applied to sentiment analysis, which includes learning automatically without manual feature engineering and handling more complex sentence structures such as negation and contrast better (Yang et al., 2016). On the other hand, due to the black-box nature of deep learning models, interpretability is reduced, making it difficult to identify which words or sentence segments the model focuses on internally.

4 Sentiment Analysis and Personalization Strategies in Educational Chatbots

4.1 Overview

In recent years, the application of sentiment analysis technology in educational chatbots has gradually become a research hotspot, especially with the development of multimodal sentiment recognition systems, which have significantly improved AI's ability to understand learners' emotional states. Traditional sentiment recognition primarily relies on textual information, which has limitations in accurately identifying complex emotions, making it difficult to achieve precise emotional adaptation in educational settings.

According to Heilala, Araya, and Hämäläinen (2024), current educational chatbots still primarily rely on text-generation models for sentiment analysis, such as ChatGPT or similar large language models for interaction, while research on integrating multimodal information such as speech, images, and physiological signals remains limited. However, multimodal information (such as voice tone, facial expressions, and behavioral responses) can enhance AI's ability to understand, but its application in the educational field is still in its early stages. The study emphasizes that multimodal emotion recognition will be an important direction for the future development of educational AI, but its implementation still faces challenges such as model complexity and the difficulty of data collection and integration.

Kovacevic, Holz, Gross, and Wampfler (2024) further implemented a multimodal emotion recognition framework based on text, audio, and visual data in an actual system to enhance emotion recognition capabilities in human-computer interaction. The results showed that the system significantly improved the accuracy of chatbots in recognizing user emotions and dynamically adjusted response strategies based on emotional signals from different modalities. Such systems are highly adaptable to educational scenarios, such as building virtual teachers with emotional perception capabilities or question-answering robots, thereby enhancing the personalization and humanization of learning interactions.

In summary, research on emotion analysis in educational chatbots is evolving from single-text modalities toward multimodal fusion. Multimodal emotion recognition not only helps improve the understanding of deeper emotional states but also provides technical support for the implementation of personalized teaching strategies, signalling the development of educational AI toward smarter and more human-centric directions.

4.2 Emotion Recognition Usages in Chatbots

With the development of artificial intelligence technology, chatbots in the education field have gradually gained the ability to dynamically adjust teaching strategies based on learners' emotional states.

Ma, Dou, Zhu, Zhong, and Wen (2021) proposed a method for automatically constructing implicit user profiles based on historical dialog data. This method uses a Transformer model to learn users' language styles and preferences from their historical responses and construct dynamic user profiles. By introducing a key-value memory network, the system can process current input.

In addition to processing users' real-time emotions and providing flexible responses, higher-level strategies include combining users' historical learning records to generate more customized responses. After analyzing the learning capabilities of users' multi-round dialog data, the system can generate an AI profile of the user, storing changes in the user's learning state as "long-term memory" to predict their potential behavior, preferences, and psychological state, thereby providing more customized responses.

According to Baradari, Kosmyna, Petrov, Kaplun, and Maes (2025), the NeuroChat system is a neuro-adaptive AI tutor, which combines real-time electroencephalogram (EEG) monitoring with generative AI technology. The system uses wearable EEG devices to monitor learners' cognitive levels in real time and dynamically adjust the complexity and pace of instructional content based on cognitive levels, thereby achieving a personalized learning experience. Experimental results show that the NeuroChat system has a significant effect on improving learners' cognitive and subjective engagement levels.

4.3 The Role and Challenges of Emotion Recognition Chatbots in Educational Settings

As artificial intelligence technology continues to mature, emotion recognition chatbots are increasingly being applied in educational settings, demonstrating significant value as teaching aids. According to Vistorte et al. (2024), artificial intelligence emotion recognition technology holds promising application prospects in learning environments, enabling real-time monitoring and assessment of learners' learning states, thereby providing more personalized support and intervention for the learning process. The integration of this technology helps enhance learners' motivation, emotional regulation abilities, and ultimately their learning outcomes.

4.3.1 Advantages of Chatbots in the Educational Field

Specifically, emotion recognition chatbots have three significant advantages. First, Davar, Dewan, and Zhang (2025) point out that such systems can serve as virtual tutoring assistants, providing learners with immediate feedback and cognitive support through real-time dialog to enhance learning initiative.

Secondly, by continuously recording and analyzing learners' emotional states during interactions through AI systems, teachers can adjust teaching methods and pacing to achieve personalized instruction.

Thirdly, AI chatbots can maintain learners' learning pace without teacher intervention, thereby enhancing their self-directed learning abilities and persistence.

4.3.2 Disadvantages of Chatbots in the Educational Field

However, this technology still faces significant challenges in educational practice. According to Vistorte et al. (2024), the accuracy of emotion recognition is one of the core technical challenges in current applications. Complex emotional states are often difficult to accurately identify using single-modal data. While multimodal fusion has improved accuracy, it remains constrained by the generalization capabilities of algorithms. Additionally, the literature highlights that the collection of personal data such as facial, voice, and physiological information inevitably raises privacy protection and ethical concerns, particularly in educational applications involving adolescents, where caution is essential.

Davar et al. (2025) further point out that AI chatbots lack the ability to handle high-complexity teaching tasks and cannot fully replace human teachers' instructional judgment and emotional care. Meanwhile, over-reliance on AI technology may weaken social interaction between teachers and students, affecting students' learning emotions and thereby having a negative impact on their learning motivation.

In summary, emotional recognition chatbots, as an important branch of educational AI, have demonstrated positive effects in areas such as personalized teaching, dynamic feedback, and learning state recognition. However, to achieve widespread adoption in educational settings, continuous optimization is needed in dimensions such as recognition accuracy, data security, and ethical regulation.

4.4 Feedback Adjustment Post-Emotion Recognition in Education

With the development of artificial intelligence technology, chatbots in the field of education have gradually acquired the ability to recognize learners' emotional states and adjust feedback forms accordingly, thereby enhancing user satisfaction and learning effectiveness.

According to Yin, Xu, Pan, and Hu (2025), educational chatbots can effectively reduce learners' negative emotions during interactions and enhance their learning motivation by providing metacognitive feedback. The study employed an experimental design to compare differences in emotional responses and learning initiative between students receiving metacognitive feedback and those receiving neutral feedback. The results showed that students in the metacognitive feedback group exhibited higher levels of learning interest and motivation.

Additionally, Han, Park, and Lee (2022) found in a study targeting nursing students that educational programs incorporating chatbots with personalized feedback capabilities significantly improved students' learning interest and self-directed learning abilities. Although no significant differences were observed in knowledge mastery levels or clinical skills, students expressed high satisfaction with the feedback provided by the chatbot, believing it enhanced their learning experience. In summary, the application of emotion recognition technology in educational chatbots not only enhances user satisfaction but also boosts learning motivation and self-directed learning abilities, thereby improving overall learning outcomes.

5 Conclusion

5.1 Answers about Research Questions

- **RQ1: Current State of Campus Chatbots**
  Campus chatbots are evolving into three key categories: academic assistance (e.g., EDUBOT for Q&A and learning support), emotional support (e.g., Evebot for mental health monitoring), and campus services (e.g., Lisa for administrative queries). However, most remain rule-based or FAQ-driven, lacking adaptive emotional intel-

ligence.

- **RQ2: Sentiment Analysis Techniques**
  Core techniques span lexicon-based (e.g., VADER for social media), machine learning (e.g., SVM for labeled data), and deep learning (e.g., Bi-LSTM/Transformer for context-aware modeling). Multimodal fusion (text + audio + visual) now enhances accuracy but still faces algorithmic generalization limits.

- **RQ3: Impact on User Experience & Learning**
  Emotion-aware chatbots significantly improve satisfaction and outcomes. Examples include:

  – Metacognitive feedback reducing negative emotions.

  – EEG-driven tutors (e.g., NeuroChat) adapting content to cognitive states.

5.2 Recommendations

1. **For researchers**:
   Prioritize the construction of culturally diverse datasets to reduce bias in emotion recognition.

2. **For educators**:
   Adopt hybrid deployment: chatbots for routine queries like admissions and human instructors for complex mentoring.

3. **For developers**:
   Design modular architectures like Rasa/Dialogflow, enabling seamless integration of sentiment analysis modules with campus systems.

Emotion-aware campus chatbots are becoming a key tool in promoting personalized education. Not only can they answer academic questions and provide guidance on campus life details like an 'all-weather learning partner,' but they can also act as guardians, sensing students' level of knowledge acquisition and emotional fluctuations caused by academic pressure, and providing timely comfort, encouragement, or resource guidance. This ability to deeply understand and proactively care for students allows technology to truly serve their growth, rather than merely conveying information.

References

Baradari, D., Kosmyna, N., Petrov, O., Kaplun, R., & Maes, P. (2025). *Neurochat: A neuroadaptive ai chatbot for customizing learning experiences.* Retrieved from https://arxiv.org/abs/2503.07599

Davar, N. F., Dewan, M. A. A., & Zhang, X. (2025, 3). AI chatbots in education: challenges and opportunities. *Information*, *16*(3), 235. Retrieved from https://doi.org/10.3390/info16030235 doi: 10.3390/info16030235

Dibitonto, M., Leszczynska, K., Tazzi, F., & Medaglia, C. M. (2018). Chatbot in a campus environment: Design of lisa, a virtual assistant to help students in their university life. In M. Kurosu (Ed.), *Human-computer interaction. interaction technologies* (pp. 103–116). Cham: Springer International Publishing. Retrieved from https://link.springer.com/chapter/10.1007/978-3-319-91250-9_9

Han, J.-W., Park, J., & Lee, H. (2022, 12). Analysis of the effect of an artificial intelligence chatbot educational program on non-face-to-face classes: a quasi-experimental study. *BMC Medical Education*, *22*(1). Retrieved from https://doi.org/10.1186/s12909-022-03898-3 doi: 10.1186/s12909-022-03898-3

Heaton, J. (2017, 10). Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning. *Genetic Programming and Evolvable Machines*, *19*(1-2), 305–307. Retrieved from https://doi.org/10.1007/s10710-017-9314-z doi: 10.1007/s10710-017-9314-z

Heilala, V., Araya, R., & Hämäläinen, R. (2024, 9). Beyond Text-to-Text: An overview of multimodal and generative artificial intelligence for education using topic modeling. *arXiv (Cornell University)*. Retrieved from http://arxiv.org/abs/2409.16376 doi: 10.48550/arxiv.2409.16376

Hutto, C., & Gilbert, E. (2014, 5). VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. *Proceedings of the International AAAI Conference on Web and Social Media*, *8*(1), 216–225. Retrieved from https://doi.org/10.1609/icwsm.v8i1.14550 doi: 10.1609/icwsm.v8i1.14550

Kovacevic, N., Holz, C., Gross, M., & Wampfler, R. (2024, 11). On multimodal emotion recognition for human-chatbot interaction in the wild. In *Proceedings of the 26th international conference on multimodal interaction* (p. 12-21). Retrieved from https://doi.org/10.1145/3678957.3685759 doi: 10.1145/3678957.3685759

LeCun, Y., Bengio, Y., & Hinton, G. (2015, 5). Deep learning. *Nature*, *521*(7553), 436–444. Retrieved from https://doi.org/10.1038/nature14539 doi: 10.1038/nature14539

Ma, Z., Dou, Z., Zhu, Y., Zhong, H., & Wen, J. (2021). One chatbot per person: Creating personalized chatbots based on implicit user profiles. *CoRR*, *abs/2108.09355*. Retrieved from https://arxiv.org/abs/2108.09355

Mohammad, S. (2018, July). Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 English words. In I. Gurevych & Y. Miyao (Eds.), *Proceedings of the 56th annual meeting of the association for computational linguistics (volume 1: Long papers)* (pp. 174–184). Melbourne, Australia: Association for Computational Linguistics. Retrieved from https://aclanthology.org/P18-1017/ doi:

10.18653/v1/P18-1017

Neupane, S., Hossain, E., Keith, J., Tripathi, H., Ghiasi, F., Golilarz, N. A., ... Rahimi, S. (2024). *From questions to insightful answers: Building an informed chatbot for university resources.* Retrieved from https://arxiv.org/abs/2405.08120

Ranoliya, B. R., Raghuwanshi, N., & Singh, S. (2017). Chatbot for university related faqs. In *2017 international conference on advances in computing, communications and informatics (icacci)* (p. 1525-1530). Retrieved from https://doi.org/10.1109/ICACCI.2017.8126057 doi: 10.1109/ICACCI.2017.8126057

Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: Tasks, approaches and applications. *Knowledge-Based Systems*, *89*, 14-46. Retrieved from https://doi.org/10.1016/j.knosys.2015.06.015 doi: 10.1016/j.knosys.2015.06.015

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "why should i trust you?": Explaining the predictions of any classifier. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (p. 1135-1144). New York, NY, USA: Association for Computing Machinery. Retrieved from https://doi.org/10.1145/2939672.2939778 doi: 10.1145/2939672.2939778

Sophia, J., & Jacob, T. (2021). Edubot-a chatbot for education in covid-19 pandemic and vqabot comparison. In *2021 second international conference on electronics and sustainable communication systems (icesc)* (p. 1707-1714). Retrieved from https://doi.org/10.1109/ICESC51422.2021.9532611 doi: 10.1109/ICESC51422.2021.9532611

Villegas-Ch, W., Arias-Navarrete, A., & Palacios-Pacheco, X. (2020). Proposal of an architecture for the integration of a chatbot with artificial intelligence in a smart campus for the improvement of learning. In (Vol. 12). Retrieved from https://www.mdpi.com/2071-1050/12/4/1500 doi: 10.3390/su12041500

Vistorte, A. O. R., Deroncele-Acosta, A., Ayala, J. L. M., Barrasa, A., López-Granero, C., & Martí-González, M. (2024, 6). Integrating artificial intelligence to assess emotions in learning environments: a systematic literature review. *Frontiers in Psychology*, *15*. Retrieved from https://doi.org/10.3389/fpsyg.2024.1387089 doi: 10.3389/fpsyg.2024.1387089

Yadollahi, A., Shahraki, A. G., & Zaiane, O. R. (2017, May). Current state of text sentiment analysis from opinion to emotion mining. *ACM Comput. Surv.*, *50*(2). Retrieved from https://doi.org/10.1145/3057270 doi: 10.1145/3057270

Yang, Z., Yang, D., Dyer, C., He, X., Smola, A., & Hovy, E. (2016, June). Hierarchical attention networks for document classification. In K. Knight, A. Nenkova, & O. Rambow (Eds.), *Proceedings of the 2016 conference of the north American chapter of the association for computational linguistics: Human language technologies* (pp. 1480–1489). San Diego, California: Association for Computational Linguistics. Retrieved from https://aclanthology.org/N16-1174/ doi: 10.18653/v1/N16-1174

Yasuda, K., Shiramatsu, S., Kawamura, I., Matsunaga, Y., Murakami, T., & Aoshima, H. (2021). Designing a chatbot system for recommending college students to counseling and collecting dialogue data. In *Proceedings of the 9th international conference on human-agent interaction* (p. 358-363). New York, NY, USA: Association for Computing Machinery. Retrieved from https://doi.org/10.1145/3472307.3484655 doi: 10.1145/3472307.3484655

Yin, J., Chen, Z., Zhou, K., & Yu, C. (2019). A deep learning based chatbot for campus psychological therapy. *CoRR*, *abs/1910.06707*. Retrieved from http://arxiv.org/abs/1910.06707

Yin, J., Xu, H., Pan, Y., & Hu, Y. (2025, April). Effects of different AI-driven Chatbot feedback on learning outcomes and brain activity. *npj Science of Learning*, *10*(1), 17. Retrieved from https://doi.org/10.1038/s41539-025-00311-8 doi: 10.1038/s41539-025-00311-8

Young, T., Hazarika, D., Poria, S., & Cambria, E. (2018). Recent trends in deep learning based natural language processing [review article]. *IEEE Computational Intelligence Magazine*, *13*(3), 55-75. Retrieved from https://doi.org/10.1109/MCI.2018.2840738 doi: 10.1109/MCI.2018.2840738