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CHATBOTS IN HIGHER EDUCATION: A SCOPING REVIEW OF SOCIO-AFFECTIVE ASPECTS

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ABSTRACT

The growing integration of chatbots in higher education has revealed that their effectiveness extends beyond instructional performance, involving emotional, motivational, and relational dimensions. This study explores how socio-affective variables influence learning experiences mediated by conversational agents and identifies the main research trends addressing this phenomenon; A scoping review was conducted following the PRISMA-ScR guidelines. Articles were retrieved from Scopus, Web of Science, ERIC, and ScienceDirect. The analysis included studies that examined socio-affective variables in chatbot-mediated higher education contexts. Data were categorized by type of chatbot, socio-affective variable assessed, and research design; Findings indicate that motivation, behavioral engagement, trust, satisfaction, and anxiety reduction are the most frequently studied variables. Chatbots designed with empathetic language, adaptive feedback, and emotional recognition features positively impact student motivation, confidence, and well-being. However, significant methodological fragmentation persists, with limited standardization in the measurement of socio-affective outcomes; Socio-affective factors play a decisive role in students' acceptance and sustained engagement with chatbots. Integrating emotional intelligence and empathy into chatbot design enhances learning experiences and humanizes digital education. Future research should develop standardized instruments and hybrid models combining cognitive, emotional, and ethical dimensions of interaction

KEYWORDS: Chatbot; Higher Education; Sociocognitive.

1. INTRODUCTION

Over the last decade, higher education has undergone a transformation driven by artificial intelligence (AI) that is changing the way students learn. AI, specifically chatbots, are applications designed to interact with humans. One of the features of these applications that most appeals to students is their ability to engage in natural conversations (NLP) with users, offering personalized assistance, virtual support, and immediate feedback in various academic contexts.

The NLP possessed by chatbots allows machines to analyze and understand human language while processing large volumes of information.

This phenomenon has sparked a series of debates about the human dimensions that affect learning. Although a large body of research (Dhakal, 2025; Filippone et al., 2025; Nozhovnik et al., 2023; Yin et al., 2021) is concerned with determining the effectiveness of learning in terms of acquiring information, it is pertinent to consider that, as it is a process that involves the human factor, human dimensions should be taken into account.

In particular, these human dimensions underlie the socio-affective characteristics of the student, which, in principle, intervene in the comprehension, effectiveness, and memorization of the content learned (Bravo & Cruz-Bohorquez, 2024; Eltahir & Babiker, 2024).

The debate over the importance of understanding the relationship between technology and affective factors applied to education is not new. In 1954, B.F. Skinner first introduced the concept of educational technology, although even before that, there were references to radio being used as a technological aid in classrooms (UNESCO, 2025).

Since then, socio-affective impact has been a variable that determines students' access to learning when they use technological tools. The rapid evolution of these tools has renewed scientific interest in understanding the influence of artificial agents in the fields of deep learning (D. Ali et al., 2024; Peng & Li, 2025; Roveta et al., 2025).

Although most research (Almaiah et al., 2021; Ting et al., 2022; J. Wang et al., 2022) has focused on satisfaction and motivation as intervening affective factors, the truth is that several studies (Córdova-Esparza, 2025; Delello et al., 2025; Urzúa et al., 2025) suggest that other variables could play a decisive role in the learning experience, namely distress, stress, and demotivation.

For example, the presence of a virtual agent that responds with empathy can adapt its discourse to the student's emotional state or, by showing more affective social recognition, can significantly modify academic commitment and willingness to engage in autonomous learning (Ackermann et al., 2025).

Other studies have demonstrated the usefulness of establishing socio-affective variables in the implementation of different language models in artificial intelligence, whether these be intrinsic motivation (Karataş et al., 2024; Yin et al., 2021), confidence (Haqbeen et al., 2024), academic anxiety (Hsu et al., 2023; Mrabet et al., 2024), and emotional engagement (Huang, Hui-Wen; Chang, 2025; Xie, 2025).

In a comparative study in Canada that used virtual assistants as a surgical training mechanism, students with positive aspects (happiness, hope, and gratitude) maintained their aspects throughout the study, while students with negative aspects (confusion and anxiety) were able to change their states to positive aspects from the first intervention, and both groups significantly improved their academic practice scores (Fazlollahi et al., 2022). Chernenko's (2024) research also coincided with this data. In his study on improving educational quality using chatbots as tools for the development of verbal and logical reasoning, it was found that the implementation of large language models such as ChatGPT reduces anxiety and increases students' motivation to succeed.

The relevance of addressing this issue is based on the growing incorporation of chatbots in universities around the world, both in administrative processes and in academic support. Understanding the socio-affective dynamics generated in interaction with these tools will not only optimize their pedagogical design but also ensure ethical, empathetic use oriented toward student well-being (Deep et al., 2025; Devassy et al., 2023).

In an educational context characterized by accelerated virtualization and the diversification of student profiles, the socio-affective approach offers a humanizing perspective that complements technological efficiency with emotional sensitivity, becoming a key pillar of contemporary digital education (O. Ajlouni et al., 2023).

The present study aims to conduct a scoping review with a socio-affective approach on the use of chatbots in higher education, in order to identify the main trends, analytical categories, and gaps in the scientific literature.

Although systematic review studies have focused their efforts on determining the impact of socio-affective variables on the use of chatbots in higher education (Ansari et al., 2024; Gökçearslan et al., 2024; Klekovkina & Denié-Higney, 2022), there are dimensions that remain to be resolved, such as the citation score of publications, the type of population involved, and the types of chatbots used.

Therefore, this research contributes to the existing scientific body by systematizing the global evidence that helps us understand the impact of chatbots in higher education, viewed from a socio-affective approach, closing the possible thematic gaps that exist to date.

1.1. RESEARCH QUESTIONS

The possible categories that may be aligned with the research questions have been rigorously analysed (as shown in Table 1). The following questions will guide this study:

1. Who is the research being conducted on?
2. What topics and technologies do it focus on?
3. What research design do you use?
4. What socio-affective variables are used?
5. What are the most cited publications?
6. What are the future research approaches?

Table 1: Relationship between Research Question and Search Dimensions.

Relationship between research questions and search dimensions.	Dimensions
Who is the research being conducted on?	Region where the research was conducted - Genders of participants
What topics and technologies does it focus on?	Technological focus - Academic discipline
What research design do you use?	Primary research design
What socio-affective variables are used?	Socio-affective variable
What are the most cited publications?	Frequency of citations
What are the future research approaches?	Lines of research to be covered - Year of publications

2. MATERIALS AND METHODS

Due to the complexity of evaluating chatbots in higher education, this review used the PRIMA-ScR methodology (Tricco et al., 2018).

A search strategy was designed to identify relevant studies across multiple databases. A set of inclusion and exclusion criteria was developed to select studies that specifically addressed the research questions.

A rigorous selection process was implemented, including independent peer review.

To assess reliability, the selection was evaluated using an inter-rater reliability matrix.

In cases of reviewer disagreement, a third author intervened to determine the inclusion or exclusion of the document.

This study focused on articles to outline the empirical processes related to chatbots in higher education over the past five years.

2.1. Search Strategy

The search was conducted from April to July of 2025.

A strategy was developed to ensure the collection of studies was comprehensive and impartial.

A review was conducted across multiple high-impact academic databases to ensure reliable results.

The databases used included Scopus, Web of Science, ERIC (Education Resources Information Center), and PubMed.

To identify current priorities and facilitate a large-scale review, the search was limited to articles published in Spanish and English between 2020 and 2025.

The strategy consisted of two parts. First, in April 2025, a preliminary search was conducted using the categorical variables "socio-affective" and "higher education" to generate specific results.

This yielded only 83 articles combined across Scopus and Web of Science.

In mid-April, additional search terms were selected to identify all relevant articles about chatbots and higher education in a learning approach.

The following categories were applied: "chatbot*" OR "virtual assistant*" OR "conversational agent*" OR "AI tutor*" AND "higher education" OR "university" OR "tertiary education" OR "college" OR "undergraduate" OR "postgraduate" AND "teaching" OR "learning" OR "education" OR "pedagogy" OR "student support" AND "impact" OR "effectiveness" OR "evaluation" OR "challenges" OR "perception").

This resulted in 5,296 documents across the four aforementioned databases. The search parameters were adjusted according to each database's requirements. See the PRISMA-ScR diagram for more details (as shown in Figure 1).

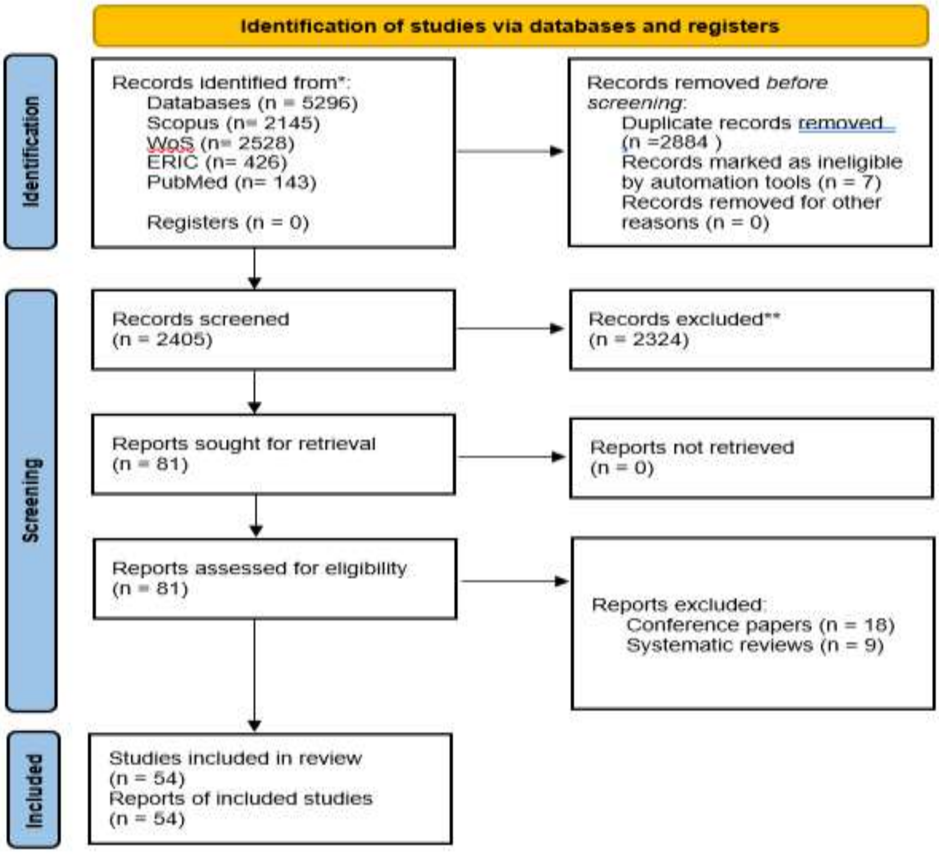

Figure 1: PRISMA Scr Diagram.

2.2. *Inclusion and Exclusion Criteria*

The key inclusion criteria are as follows:

Table 2: Scheme for Inclusion and Exclusion Categories of the Study.

Criteria	Statement
Publication date?	January 2020 - June 2025
Language	English
Type of publication	Peer-reviewed book, book chapter, journal article, conference proceedings
Learning context	It must contain original empirical data on practices or perceptions of chatbot use in Higher education. Qualitative, quantitative, and mixed-methods studies Were included. Experimental and laboratory-based methods were included when it was clear that the studies examined the chatbot in higher learning Contexts and reported socio-affective data. Systematic reviews and articles with study Designs lacking data were excluded.
Use of digital media technology	Any type of chatbot-type AI
Methodology Quality	Publications must provide sufficient detail and clarity for analysis, be peer-reviewed, and meet basic academic publishing Standards for their field.

The following exclusion criteria were applied to sharpen the focus and ensure the empirical foundation of this scoping review:

1. Gray literature (e.g., theses, reports, white papers) was excluded to concentrate on peer-reviewed research that has undergone academic scrutiny, ensuring a consistent

standard of methodological quality.

2. Systematic reviews and meta-analyses were excluded to avoid duplication of evidence and to focus the synthesis on primary, empirical data.
3. Articles lacking sufficient methodological detail or empirical results were excluded to enable a robust analysis of socio-affective outcomes.
4. Studies not conducted in higher education learning contexts or that did not involve higher education students were excluded to maintain the relevance of the findings to the target educational level.
5. Studies whose primary aim was to validate or test a specific theoretical model (e.g., Technology Acceptance Model - TAM, Self-Determination Theory - SDT) without a primary focus on reporting broad empirical data on socio-affective outcomes in learning were excluded. The objective of this review was to map the landscape of reported socio-affective evidence, rather than to evaluate the explanatory power of particular theoretical frameworks.
6. Studies related to interface design or collaborative design were excluded because they did not allow us to evaluate the impact of the socio-affective variables used.

The results of this search were exported to Mendeley. "Tags" were applied to code the publications according to the aforementioned elements, and duplicates were removed. Then, the results were uploaded to the Rayyan Systems Inc. platform for author screening. In an effort to minimize potential biases and errors in study selection, two professors from participating universities, who possess postgraduate degrees and specializations in digital tools for education, participated in the review process. The lead author served as the third author to reach a final decision in instances of reviewer disagreement. External researchers (reviewers) were informed, via a Zoom meeting, about the project's objective, as well as the study's inclusion and exclusion criteria. The subjects submitted their informed consent forms via email. Prior to the commencement of the study review, a sample of 300 articles was selected to measure inter-reviewer consistency. The reviewers received a single day of training. The data were recorded in an improvised concordance matrix (as shown in Table 3). The Cohen's Kappa coefficient was then applied to the data in the concordance matrix using the following formula: According to the methods outlined by Rau and Shih (2021), the Kappa coefficient is calculated as follows:

Kappa = (Po – Pe) / (1 – Pe)

In this equation, Po represents the observed proportion of agreement, while Pe denotes the proportion of agreement that would be expected by chance. For Rau and colleagues, Cohen's common interpretation is as follows: 0.01–0.20 (slight), 0.21–0.40 (fair), 0.41–0.60 (moderate), 0.61–0.80 (substantial), and 0.81–1.00 (nearly perfect).

First, we calculate the point of intersection (Po) as follows:

Po = (a + d) / (N) = (160 + 131) / 300 = 0.97

Then, we calculate the point of agreement (Pe) as follows:

Pe = [((a + b) × (a + c)) + ((c + d) × (b + d))] / N^2 = 0.50462

Finally, we calculate the kappa index (K) as follows:

K = (Po – Pe) / (1 – Pe) = (0.97 – 0.50462) / (1 – 0.50462) = 0.9394

Table 3: Inter-Reviewer Agreement Matrix.

	Reviewer 2 (include)	Reviewer 2 (exclude)	Total
Reviewer 1 (include)	160	3	163
Reviewer 1 (exclude)	6	131	137
Total	166	134	300

Kappa = 0.9394

4. RESULTS

Due to the diversity of study designs and outcome measures, we employed the following results analysis structure based on responses to the research questions. This structure provides a clear, organized way to describe the findings and allows us to explore, explain, and relate the selected studies.

4.1. Who Is the Investigation Being Conducted On?

4.2. Region

The publications were coded according to the region in which the study was conducted (as shown in Figure 2). If the study was conducted in multiple countries, it was coded for each region. As determined by the heat map, Asia (n = 28) had the highest level of scientific output in the subject area, followed by Europe (n = 7), the Americas (n = 6), Australia (n = 1), and Africa (n = 2).

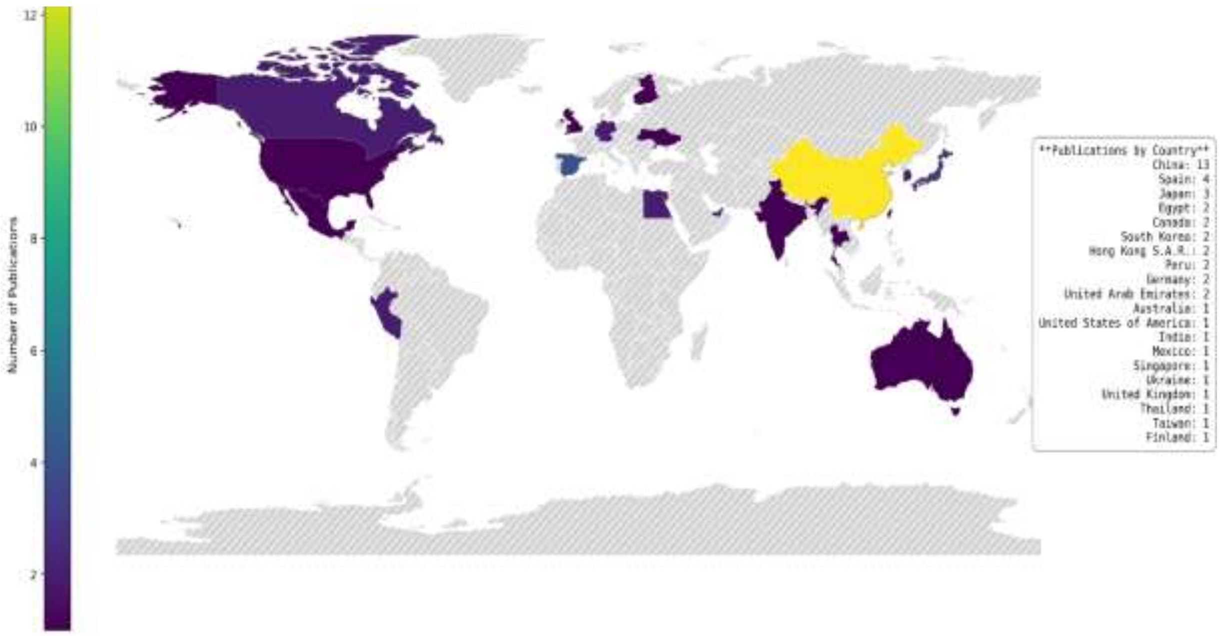

Figure 2: Global Distribution of Research.

The continent that provides the strongest government support for technological development tops the list of countries implementing chatbots in higher education.

4.3. Gender

The publications were coded according to the gender of all participants (as shown in Figure 3). We used this coding to determine whether current studies are considering the gender diversity that exists today. The value "Other" was assigned when articles reported non-binary or other genders. Only three studies (Fang et al., 2025; Gruenhagen et al., 2024; Ortega-Ochoa et al., 2024) reported having students with diverse genders. Similarly, the high percentage of figures in the unspecified section reflects the considerations of the collected studies. The reason why the 23 studies with the highest sample sizes did not specify the genders of the participants is unknown.

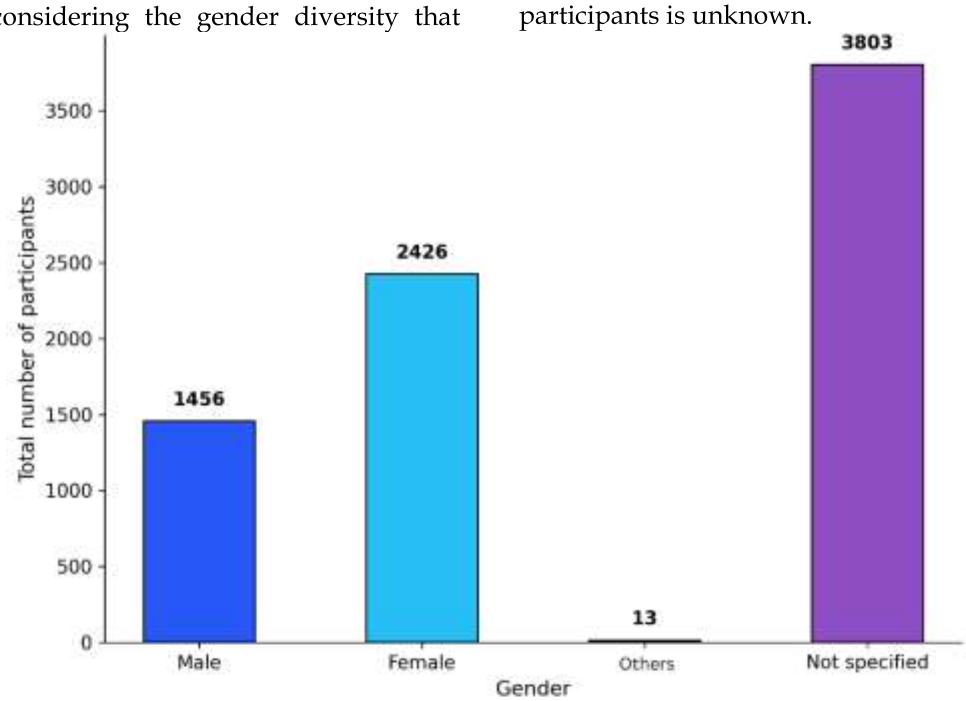

Figure 3: Distribution Of the Total Sample Sizes of The Studies by Gender.

4.4. Who Is the Investigation Being Conducted On?

4.5. Topics

Studies that reported the use of chatbots for more than one purpose were recorded as having more than one subject. In studies where subjects were not reported, coding was justified according to the faculty or program in which the samples were located. The most prevalent areas were found in education (n = 14), where conversational agents were applied to several subjects and recorded as academic programs. Eleven subject categories were analyzed in which chatbots were used as higher-level learning tools (as shown in Figure 4).

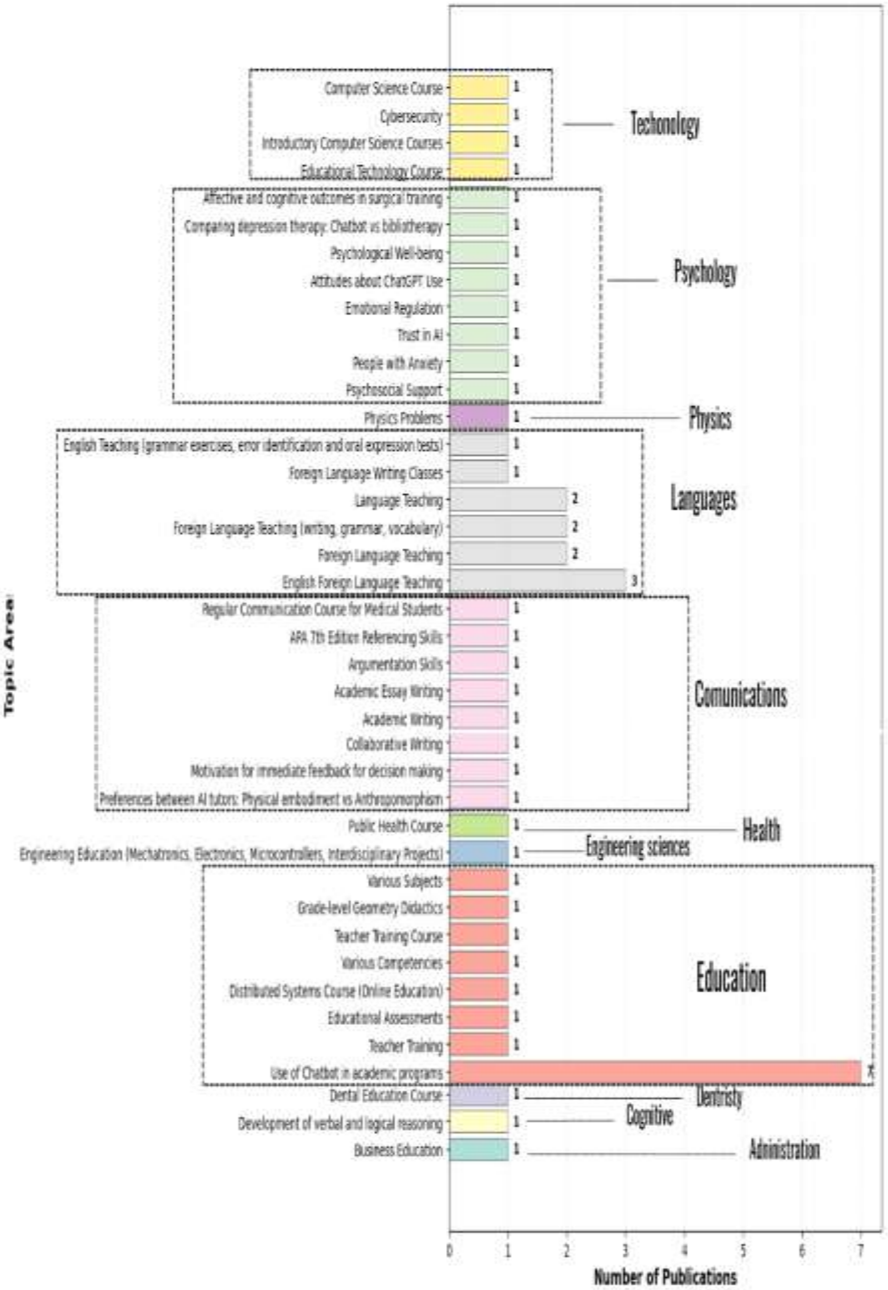

Figure 4: Distribution of the Total Sample Sizes of The Studies by Gender.

4.6. Technologies

The next category, "Chatbot Type" (as shown in Figure 5), was created to identify and classify the various technological and functional configurations of conversational agents used in the reviewed studies. This category was included to understand how chatbots influence interaction with students and directly impact reported socio-affective outcomes. Since not all chatbots have the same dialogue, personalization, and emotional response capabilities, recognizing their differences is essential for contextualizing the findings on motivation, self-efficacy, anxiety, and social engagement.

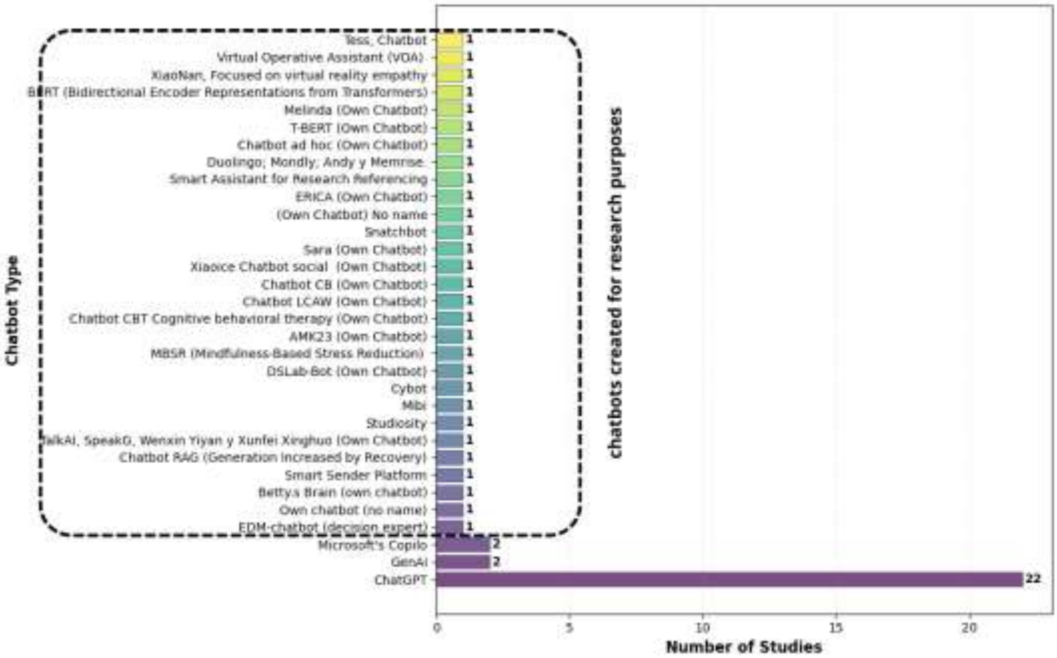

Figure 5: Types Of Chatbots Used as Educational Tools in Higher Education.

Thanks to increased access to information, the code for creating chatbots is now open source and publicly available. This has enabled 29 research projects to develop chatbots tailored to students' educational and social characteristics, while another 22 research groups use OpenAI's ChatGPT.

4.7. Who Is the Investigation Being Conducted On?

The reported research design appears to be moderately balanced. This variable was coded as quantitative, qualitative, or mixed when the research design indicated it as such. In cases where this was not reported, the variable was coded according to the instrument and data analysis (as shown in Figure 6).

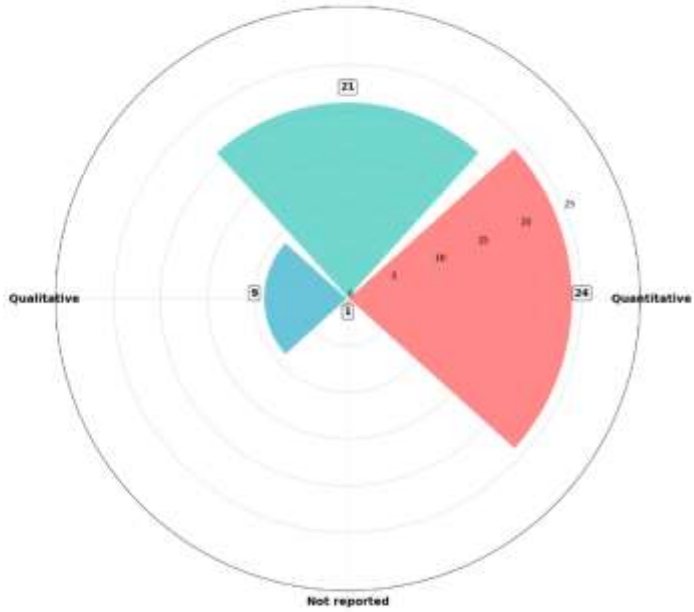

Figure 6: Distribution Of Types of Documented Research.

Of the total publications (n = 55), a significant proportion of studies favored a quantitative approach (n = 24), while 21 studies primarily employed a qualitative approach. A smaller group (n

= 9) reported using a mixed-methods approach.

4.8. What Socio-Affective Variables Are Used?

We analyzed the "socio-affective variable" (as shown in Figure 7) category to identify the emotional, motivational, and relational components included in studies analyzing the interaction between students and chatbots in higher education contexts. This category is essential for understanding the human-related characteristics currently being evaluated in conversational, agent-mediated learning. This is based on the understanding that educational experiences are achieved not only through the transfer of information, but also through socio-affective elements that influence attention, willingness to learn, and academic retention.

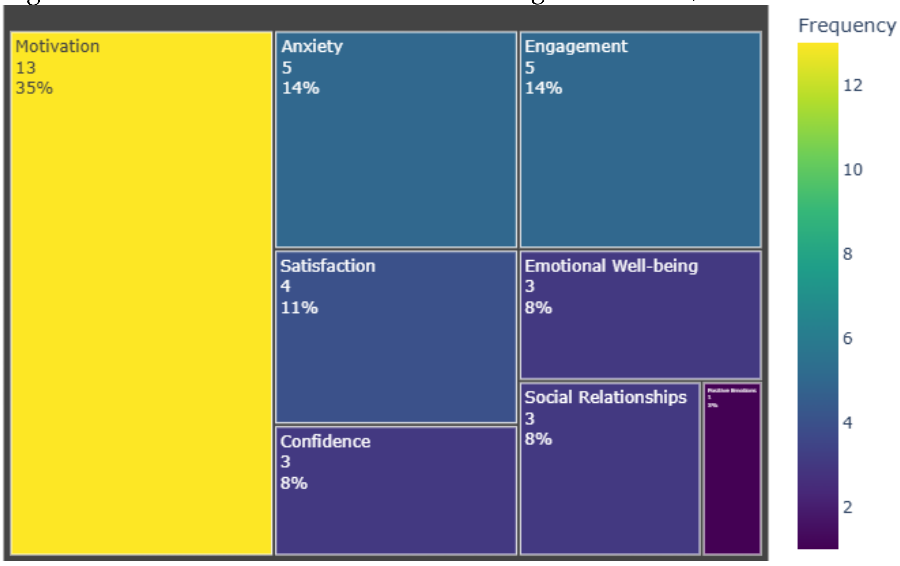

Figure 7: Socio-Affective Distribution of Studies.

We can emphasize the variety of socio-affective variables examined in the literature and their connection to pedagogical results. The most frequently studied variables in the reviewed studies are motivation (35%), anxiety and engagement (14%), and satisfaction (11%). Similar percentages were found for emotional well-being, confidence, and social relationships (n = 8%). Each analyzed variable offers a perspective on students' emotional behavior when interacting (or not interacting) with a chatbot (Vanichvasin, 2022; Hsu et al., 2023). Analyzing these variables reveals which affective dimensions have been prioritized by recent research and which remain underexplored, thus highlighting gaps in our comprehensive understanding of the phenomenon. Only 1% of publications (Fazlollahi et al., 2022) categorize the variable "happiness" when using chatbots in surgical learning processes with medical students in Canada.

4.9. Most Frequently Reported Dimensions

A cognitive or technological perspective alone is insufficient for chatbot-mediated learning in higher education. To give meaning to the educational experience, it requires considering emotions, motivations, and human interactions. From a socio-affective perspective, the relationship between students and chatbots is a space of symbolic mediation where rational and affective processes intertwine. Thanks to this perspective, emotional variables become determining factors in engagement, persistence, and learning quality. The selected studies were therefore grouped according to their reported socio-affective characteristics and presented in a table to improve the clarity of the analysis.

4.10. Anxiety

The first variable analyzed is the reduction of anxiety and stress. In higher education, where personalized learning is a pedagogical strategy, students commonly use digital tools to complete assignments or fill learning gaps. These actions can lead to negative emotional states that affect academic performance and the willingness to learn (Estrada-Araoz et al., 2024; Y. Li et al., 2025; Puente et al., 2024). Students may experience cognitive overload, uncertainty, or fear of making mistakes. Our data (as show in Table 4) shows that chatbots primarily function as support agents rather than evaluators of learning outcomes (F. Ali et al., 2024; Hopman et al., 2023; Moldt et al., 2022). Thus, chatbots function as emotional mediators, reducing tension and solving negative socio-affective issues (Klos et al., 2021;

Trappey et al., 2022)

Table 4: Studies With Anxiety Variable.

ID	Title	Socioemotional Varible	Results
1	Effects of Incorporating an Expert Decision-Making Mechanism into Chatbots on Students' Achievement, Enjoyment, and Anxiety	Anxiety	Improvement significant in academic achievement and enjoyment of learning, reduction of Anxiety
15	Educational innovation in the information age: AI tutoring and micro-learning	Anxiety	Significant improvement in writing quality and anxiety management
25	Investigating the attitude of university students towards the use of ChatGPT as a learning resource	Anxiety	a) Predominantly middle-level attitude, enjoyment of use as a learning tool. b) Increase in basic skills
27	Chatbot-Based Mindfulness-Based Stress Reduction Program for University Students With Depressive Symptoms: Intervention Development and Pilot Evaluation	Anxiety	a) Significant improvements in the reduction of depressive symptoms; b) Academic motivation is recorded
29	Development of a Chatbot Powered by Artificial Intelligence to Diagnose and Improve Stress and Anxiety Levels in University Students	Anxiety	High usability (SUS scores 82.13), promising reduction of stress and anxiety levels
36	Social Chatbot: My Friend in My Distress	Anxiety	Social interaction anxiety increases compulsive chatting
45	A Digital Coach to Promote Emotion Regulation Skills	Anxiety	a) Increased intention to use emotional regulation strategies
51	Assessing medical students' perceived stress levels by comparing a chatbot-based approach to the Perceived Stress Questionnaire (PSQ20) in a mixed-methods study	Anxiety	a) Reduces pandemic stress levels; b) Reduced pandemic worries
52	Development of an Empathy-Centric Counseling Chatbot System Capable of Sentimental Dialogue Analysis	Anxiety	Decreased stress levels and improved psychological sensitivity
55	Artificial intelligence based chatbot for anxiety and depression in university students: Pilot randomized controlled trial	Anxiety	a) Significant decrease in ingroup anxiety symptoms; b) promising results in usability and acceptance; c) Increased interaction with the chatbot.

The chatbot offers a safe space for practice by allowing students to rehearse answers without direct judgment from a teacher or peers, which reduces anxiety associated with public exposure or fear of failure. According to data collected based on value-control theories, anxiety decreases when students perceive greater control over the task and receive supportive feedback. A conversational agent designed for this purpose can provide both of these conditions.

4.11. Confidence

Trust (as shown in Table 5) is another fundamental socio-affective pillar. In interactions with intelligent systems, trust means believing in the chatbot's technical competence. This trust develops progressively based on the student's experience as they evaluate the system's coherence, truthfulness, and empathy (Haqbeen et al., 2024; Nour et al., 2024). Tossell et al. (2024) found that students had little trust in ChatGPT for writing academic essays in the initial tests (pretest). However, trust increased when ChatGPT was used as a collaborative resource under the professor's supervision as the course content matured.

Increased credibility is reported when the interaction is perceived as transparent and human. Similarly, the willingness to follow suggestions, share information, and maintain sustained use of the tool depends on trust as a socio-affective variable

(Devassy et al., 2023).

Table 5: Studies with Confidence Variable.

ID	Title	Socioemotional Varible	Results
22	Cybot: A Chatbot for Teaching and Testing Cybersecurity Courses	Confidence	a) Positive feedback as an effective and supportive study partner; b) Effectiveness in the use of chatbots in education.
28	Facilitation chatbots enhance student confidence in learning platforms	Confidence	Chatbots induced effective learning
38	Student Perceptions of ChatGPT Use in a College Essay Assignment: Implications for Learning, Grading, and Trust in Artificial Intelligence	Confidence	Increase trust by being recognized as a collaborative resource, with human oversight, technical aptitude, and subject matter expertise.
42	Development of immersive learning framework (ILF) in achieving the goals of higher education: measuring the impact using a pre–post design	Confidence	a) Significant improvement in well-being; b) reliability; c) willpower; d) altruism and independence

The absence of this variable can cause the interaction to become mechanical and superficial, severely limiting the chatbot's pedagogical potential. Therefore, the affective component of trust is crucial for internalizing and generalizing educational content.

4.12. Empathy and Sense of Belonging Variable

Furthermore, the chatbot's perceived empathy (as shown in Table 6), expressed through affective language, messages of understanding, and emotional recognition, enhances the human connection in digital interactions. This empathy reduces the isolation often associated with virtual learning environments (Fuentes et al., 2024; Zaky, 2023). This perception of closeness is associated with a sense of belonging—another key factor influencing student retention and academic engagement.

Table 6: Studies with Empathy and Sense of Belonging Variables.

ID	Title	Socioemotional Varible	Results
2	Physical Embodiment and Anthropomorphism of AI Tutors and Their Role in Student Enjoyment and Performance	Empathy	Physical presence related to greater enjoyment initial, sociability negatively related to performance.
32	Understanding the Attitude of Teacher Education Students Toward Utilizing ChatGPT as a Learning Tool: A Quantitative Analysis	Sense of belonging	Moderately positive results in the use of ChatGPT as a learning tool
47	Chatbot Positive Design to Facilitate Referencing Skills and Improve Digital Well-Being	Empathy	a) Significant increase in benchmark skills; b) Improvement in digital well-being
48	Using chatbots for English language learning in higher education	Sense of belonging	a) Positive experience; b) social isolation as a driving factor;
53	Using AI chatbots to provide self-help depression interventions for university students: A randomized trial of effectiveness	Empathy	a) More effective treatment; b) lower degree of anxiety; c) higher levels of empathy

When students feel that the chatbot "understands" or "supports" them, their relationship with the educational institution changes, strengthening their social integration and commitment to the academic community. Furthermore, positive feelings during interaction facilitate solid learning. Emotionally pleasant experiences promote attention, curiosity, and information retention, creating a cycle of pleasure, motivation, and persistence (Annamalai et al., 2023; Liu et al., 2022).

4.13. Engagement

Behavioral engagement (as shown in Table 7) is the observable manifestation of a student's involvement in their learning process. It is expressed through the frequency of interaction with the chatbot, consistency in completing activities, and willingness to maintain effort over time (Civit et al., 2024; Hu et al., 2025; Xie, 2025).

Table 7: Studies with Engagement Variable.

ID	Title	Socioemotional Varible	Results
6	Human-AI Interactions in Teacher Education: Examining Social Presence and Friendship	Engagement	Chatbots provide practical benefits but lack deep emotional connections.
7	Enhancing student engagement in online collaborative writing through a generative AI-based conversational agent	Engagement	Significant improvement in cognitive engagement, with no impact on behavioral or emotional engagement
11	Will you help AI? A longitudinal study on the relationship between interacting with chatbots and altruistic willingness towards AI	Engagement	Positive correlation between frequency of interaction and altruistic disposition in virtual company scenarios
13	Class integration of ChatGPT and learning analytics for higher education	Engagement	Greater acceptance of chatGPT compared to traditional methodologies
18	Using AI-driven chatbots to foster Chinese EFL students' academic engagement: An intervention study	Engagement	a) More effective treatment; b) lower degree of anxiety; c) higher levels of empathy a) Positive influence on academic engagement: behavioral, cognitive and emotional; b) Significant increase in academic participation.
19	The Influence of Artificial Intelligence Tools on Student Performance in e-Learning Environments: Case Study	Engagement	a) Significant differences in academic performance between the groups; b) knowledge retention and improvements in critical thinking
20	A Chatbot Won't Judge Me: An Exploratory Study of Self-disclosing Chatbots in Introductory Computer Science Classes	Engagement	a) Chatbot promotes self-disclosure of learning challenges; b) Helps students feel less alone; c) Significant results in computer science
41	Exploring the use of chatbot to promote online EFL students' behavioral, cognitive, and emotional engagements	Engagement	a) Chatbot promotes self-disclosure of learning challenges; b) Helps students feel less alone; c) Significant results in computer science

According to contemporary models of academic engagement, this variable is the behavioral expression of deeper motivational processes. Its development depends on the chatbot's ability to sustain attention, provide immediate feedback, and establish a dialogic relationship that fosters continued learning (Eltahir & Babiker, 2024; Y. Wang & Xue, 2024). Immediate responses, task personalization, and recognition of progress serve as positive reinforcers that encourage active participation (Goddard et al., 2024; Luo et al., 2023; Xinyi, 2023).

4.14. Motivation

Intrinsic commitment is closely related to motivation (as shown in Table 8) which is defined as the internal energy that drives and maintains action toward learning (Bravo & Cruz-Bohorquez, 2024; Chernenko, 2024; Nozhovnik et al., 2023; Ryong et al., 2024). According to Self-Determination Theory (Deng et al., 2024; Renfeng et al., 2025), motivation increases when the psychological needs for autonomy, competence, and relatedness are met (H. Li et al., 2025; Renfeng et al., 2025; Yin et al., 2021). In this sense, chatbots can facilitate motivation if they promote student autonomy through choice options, reinforce competence with formative feedback, and foster relationships through empathetic discourse (Gruenhagen et al., 2024; Guo & Li, 2024; Hmoud et al., 2024).

Table 8: Studies with Motivation Variable.

ID	Title	Socioemotional Varible	Results
4	Conversation Technology with Micro-Learning: The Impact of Chatbot-Based Learning on Students' Learning Motivation and Performance	Motivation	Intrinsic motivation significativamente greater; performance comparable al traditional learning
5	Chatbot Gamified and Automated Management of L2 Learning Process Using Smart Sender Platform	Motivation	Increase in Motivation, English proficiency and Engagement, large effect size
9	The Motivational Impact of GenAI Tools in Language Learning: a Quasi-Experiment Study	Motivation	Significant improvement in autonomous motivation to basic psychological needs
10	Artificial Intelligence in Physics Courses to Support Active Learning	Motivation	Greater student engagement and problem-solving skills in learning with chatbots vs. traditional ones
12	The rapid rise of generative AI and its implications for academic integrity: Students' perceptions and use of chatbots for assistance with assessments	Motivation	The frequency of chatbot use increased, students felt increased motivation, engagement and satisfaction.
14	Incorporating AI in foreign language education: An investigation into ChatGPT's effect on foreign language learners	Motivation	Positive effects on learning experiences, especially in writing, grammar and vocabulary
16	Understanding EFL students' use of self-made AI chatbots as personalized writing assistance tools: A mixed methods study	Motivation	a) Positive impact on writing motivation: clearer goals, greater confidence, and a positive attitude; b) Students created their own chatbots; c) Proficiency in argumentative writing
17	The Effectiveness of Integrating Artificial Intelligence into Traditional Educational Management Methods to Enhance the Educational Process Quality	Motivation	It has a favorable impact on educational quality, the development of verbal-logical reasoning, and the reduction of anxiety.
21	Engineering Education in the Age of AI: Analysis of the Impact of Chatbots on Learning in Engineering	Motivation	a) Chatbots increase initial engagement and motivation; b) Chatbots can take on the roles of tutor, companion, or support assistant.
23	AI-supported Authentic Communication with Native Speakers: Exploring EFL Learners' Willingness to Communicate and Emotional Changes	Motivation	a) Positive results in the WTC, emotional changes from negative to positive. b) Improvement in verbal communication processes in English.
24	The effectiveness of empathic chatbot feedback for developing computer competencies, motivation, self-regulation, and metacognitive reasoning in online higher education	Motivation	a) The empathic chatbot has significantly better results than human teacher feedback in Motivation and self-regulation; b) It does not differ significantly in academic performance compared to

			traditional learning.
30	L2 vocabulary learning with an AI chatbot: From linguistic, affective, and cognitive perspectives	Motivation	Vocabulary learning outcomes improved.
31	The effects of generative AI usage in EFL classrooms on the l2 motivational self-system	Motivation	a) Higher levels in all motivational factors; b) Significant improvements in the L2 Self Ideal and Ought-to L2 Self Experience study program
33	ChatGPT's Motivational Effects on Japanese University EFL Learners: A Qualitative Analysis	Motivation	a) Students felt more motivated; b) less anxious when no false responses were detected; c) less confident if teachers didn't teach how to use it; d) significant improvements in learning.
34	The influence of GenAI on the effectiveness of argumentative writing in higher education: evidence from a quasi-experimental study in China	Motivation	a) Significant improvement in writing performance; b) Increased motivation
39	Chatbot's Complementary Motivation Support in Developing Study Plan of E-Learning English Lecture	Motivation	Increases self-efficacy, enjoyment, and intention to continue.
43	Higher Education Students' Task Motivation in the Generative Artificial Intelligence Context: The Case of ChatGPT	Motivation	Significant results in all motivation categories (Enjoyment, Satisfaction, Curiosity and Anxiety)
44	Effects of chatbot-assisted in-class debates on students' argumentation skills and task motivation	Motivation	a) They improve the organization and structure of the arguments but no significant effects were observed.
46	Students' Attitudes Towards Using ChatGPT as a Learning Tool: The Case of the University of Jordan	Motivation	a) High level of positive attitude
54	Effect of artificial intelligence tutoring vs expert instruction on learning simulated surgical skills among medical students a randomized clinical trial	Motivation	Significant improvement in virtual and real-life practice compared to lecture-based instruction.

Chatbots that are perceived as supportive rather than evaluative foster sustained intrinsic motivation, which is essential for deep and self-regulated learning (Huang & Mizumoto, 2025; S.-M. Lee, 2024; Ortega-Ochoa et al., 2024; Yamaoka, 2024).

4.15. Satisfaction

Similarly, satisfaction (as shown in Table 9) is defined as the student's overall emotional evaluation of their interaction with the chatbot. It incorporates perceptions of usefulness, ease of communication, relevance of feedback, and emotional tone of responses (Amaro et al., 2024; Chen, 2025).

Table 9: Studies with Satisfaction Variable.

ID	Title	Socioemotional Varible	Results
3	Impact of Chatbots on Student Learning and Satisfaction in the Entrepreneurship Education Programme in Higher Education Context	Satisfaction	Positive impact in learning and Satisfaction, very high perceived appropriateness
8	Improving English semantic learning outcomes through AI chatbot-based ARCS approach	Satisfaction	Significant improvement in semantic achievement and self-efficacy, increased satisfaction.

35	Artificial Intelligence (AI)-driven dental education: Exploring the role of chatbots in a clinical learning environment	Satisfaction	Significant improvement in student learning and engagement
37	Believe in Artificial Intelligence? A User Study on the ChatGPT's Fake Information Impact	Satisfaction	Significant difference in trust and satisfaction
40	Analysis of artificial intelligence chatbots and satisfaction for learning in mathematics education	Satisfaction	a) High level of satisfaction with AI creations; b) improved digital competence
49	Perceived satisfaction of university students with the use of chatbots as a tool for self-regulated learning	Satisfaction	a) Improves perceived satisfaction

Satisfaction reflects both the system's functional effectiveness and the quality of the symbolic bond that students establish with conversational agents. When the interaction is perceived as fluid, empathetic, and relevant, satisfaction increases. This, in turn, favors continued use and recommendation of the tool. This emotional component is a key indicator of academic well-being and an important predictor of technological loyalty in university settings (Moral-Sánchez & Rey, 2023; Sáiz-Manzanares et al., 2023).

4.16. Self-Efficacy

Alongside the main variables, other complementary socio-affective dimensions enrich our comprehensive understanding of the phenomenon. Self-efficacy, defined as a student's belief in their ability to complete academic tasks, is strengthened when the chatbot mediates between difficulty and achievement (as shown in Table 10). By providing immediate guidance and positive reinforcement, the system helps students build mastery experiences that boost confidence in their abilities. Similarly, the chatbot's perceived empathy, expressed through emotional language, understanding, and recognition, enhances the human connection in digital interactions and reduces the isolation often associated with virtual learning environments (Bejarano, 2025).

Table 10: Studies with Self-Efficacy Variable.

ID	Title	Socioemotional Varible	Results
26	Intelligent Tutoring Systems as A Solution to Emotional and Academic Challenges in Higher Education: Analysis of a Survey from Instituto Politécnico Nacional	Self-efficacy	a) 47.7% emotional problems; b) 70.4% are unaware of available mentoring figures
50	Impacts of an AI-based chabot on college students' after-class review, academic performance, self-efficacy, learning attitude, and motivation	Self-efficacy	a) Improvement of academic performance, Self-efficacy and Learning Attitude and Motivation

This perception of closeness is associated with a sense of belonging—another key factor influencing student retention and academic engagement. When students feel that the chatbot "understands" or "supports" them, their relationship with the educational institution changes, strengthening their social integration and commitment to the academic community.

These variables form a dynamic network that influences the emotional, social, and motivational components of learning mediated by conversational artificial intelligence. Interacting with the chatbot is not merely an instrumental exchange; it is a relational process that can stimulate autonomy, reduce anxiety, increase confidence, and generate satisfaction with the educational process. Understanding this socio-affective framework is essential for designing more humane, empathetic, and ethically responsible educational chatbots that can contribute to higher education, which recognizes emotions as an essential driver of knowledge, not just an accompaniment to the cognitive process (Y.-F. Lee et al., 2022).

4.17. What Are the Most Cited Publications?

This category recognizes studies that have had the greatest academic impact on the socio-affective approach to chatbot use in higher education. The results of this dimension (as shown in Figure 8) allow us to identify the intellectual influences that have guided the theoretical development of the topic and understand the most relevant approaches, methodologies, and results for the global scientific community. Within the context of systematic reviews, this type of analysis establishes the conceptual foundations that support the state of the art of the compiled studies, determining the core areas of knowledge that are legitimate and recognized within the field.

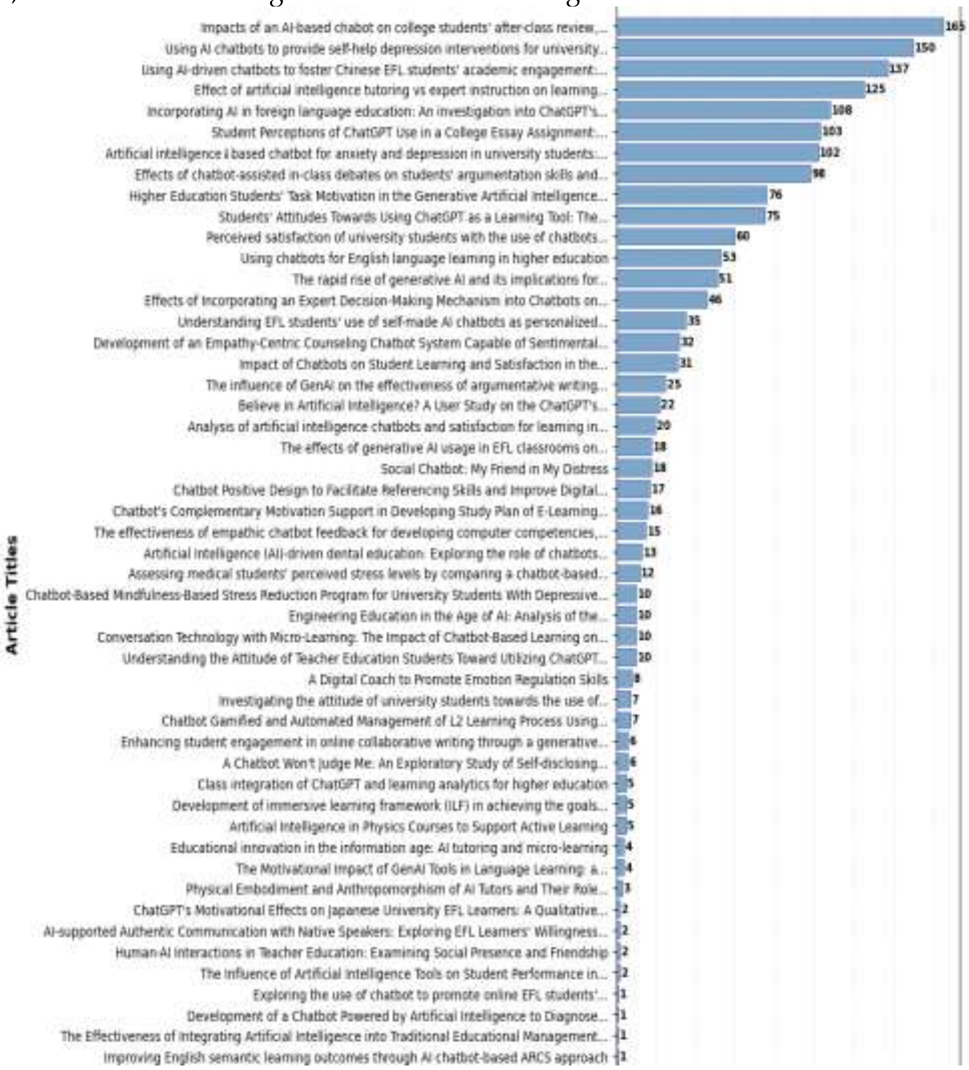

Figure 8: Most Cited Studies in the Last 5 Years.

The most frequently cited works often serve as structural references or foundational texts that define the interpretive frameworks of the phenomenon being studied. Analyzing their content and frequency of appearance provides a historical view of the evolution of scientific interest in the socio-affective dimension of chatbot-mediated environments. For instance, Lee et al.'s (2022) study, with 165 citations in Scopus, suggests using chatbots linked to review or academic support systems to help students' complete assignments after school.

The study evaluates various perspectives to strengthen the educational process. It assesses learning performance, acquired knowledge, retained knowledge, self-efficacy, motivation, and attitude toward learning.

Similarly, the study by Liu et al. (2022) compares traditional pedagogical therapy and academic therapy for resolving classroom problems using a chatbot called "XiaoNan." The study has received 150 citations in Scopus. The study also considers socio-affective variables, such as academic depression and empathy for classmates, when performing an augmented reality simulation task. The results of this research indicate that students have a high ability to solve academic problems with the help of AI. Furthermore, the researchers report high levels of empathy, reduced depression, and increased altruism among university students.

4.18. What Are the Future Research Approaches?

As shown in Figure 9 shows that 2024 had the highest production of studies related to the socio-affective approach.

It is important to note that, as of the cutoff date for this study (July 2025), only six articles had been coded. To determine a decrease in scientific production, it will be necessary to consider future studies that begin their search in August 2025.

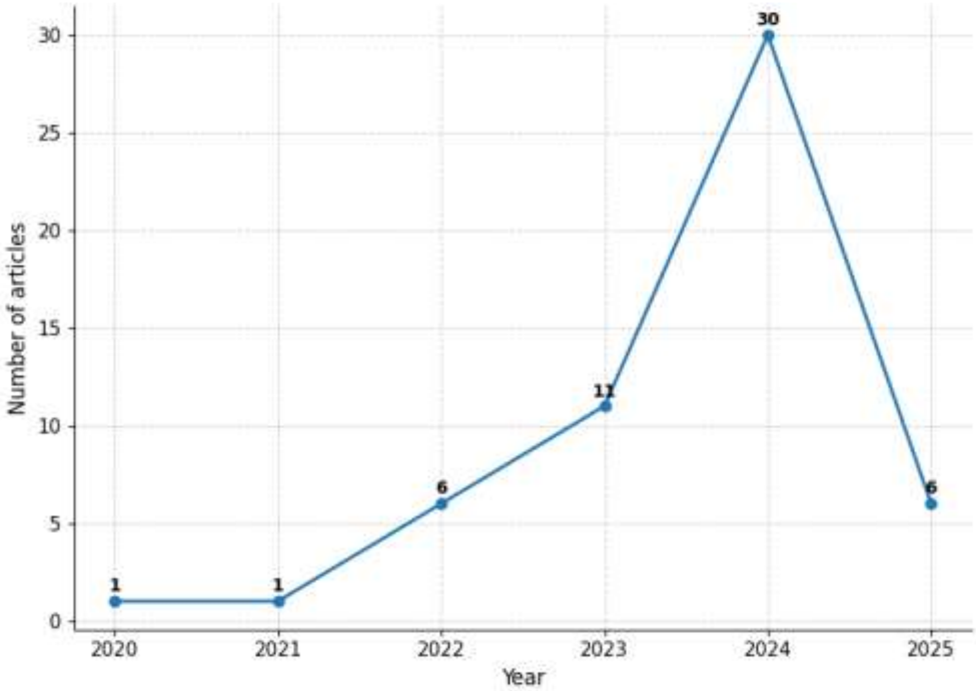

Figure 9: Number of Articles per Year.

5. DISCUSSIONS

The results of the scoping review confirm that the socio-affective approach is a key dimension for understanding the educational impact of chatbots in higher education. The evidence gathered indicates that learning mediated by conversational agents cannot be explained solely by technological efficiency or the accessibility of digital resources. Rather, it is explained by the way these systems build symbolic and emotional connections with students, shaping their educational experience.

A critical observation from the reviewed literature is the predominant reliance on self-reported measures (e.g., surveys, questionnaires) to capture socio-affective states such as motivation, satisfaction, and anxiety. While these instruments are valuable for accessing students' subjective perceptions, they represent a single methodological lens. Fewer studies incorporated behavioral indicators—such as log data on chatbot interaction frequency, persistence in task completion, or objective measures of academic persistence—which could provide a more holistic and objective view of engagement and affective states. This methodological predominance of self-report data, while informative, underscores a significant gap. It limits our ability to draw causal inferences and to discern whether reported affective improvements translate into sustained behavioral change. Future research would benefit from a multimodal approach that triangulates self-report data with behavioral analytics to build a more robust understanding of the socio-affective impact of chatbots.

Several of the reviewed studies agree that motivation and self-efficacy are the most frequently cited socio-affective variables in the literature. Studies such as those by Karataş et al. (2024) and Robledo-Rella, Victor, and Toh (2024) show that students perceive greater competence and autonomy when the chatbot provides immediate feedback and employs an empathetic communication style. These findings reinforce the postulates of Self-Determination Theory (Deng et al., 2024; Renfeng et al., 2025), which depend on satisfying the psychological need for autonomy, competence, and relatedness. Chatbots that successfully balance these three elements generate sustainable motivation, resulting in greater willingness to learn and more consistent behavioral engagement.

Another significant trend relates to chatbots' ability to reduce anxiety and academic stress. In line with value-control theory principles (Chernenko, 2024), environments that promote a sense of control and provide supportive feedback can reduce the negative emotional states associated with failure. The analyzed studies demonstrate that chatbots that adopt a supportive role rather than an evaluative one allow students to practice, make mistakes, and correct them without fear of judgment. The emotionally safe learning space that chatbots provide is especially relevant in online learning environments, where distance from a tutor can intensify academic anxiety.

Similarly, student satisfaction has been identified as a global indicator of emotional well-being and perceived success when interacting with the chatbot. Students report higher levels of satisfaction and sustained engagement with the learning environment when the tool successfully integrates functional clarity, empathetic support, and academic relevance. These results align with expectancy-confirmation models, which posit that satisfaction depends on the extent to which experiences either exceed or confirm initial expectations. In university settings, student satisfaction is also associated with retention and loyalty to digital learning modalities.

On the other hand, the review reveals significant limitations and gaps. Although the socio-affective approach is gaining ground in the literature, there is still conceptual and methodological fragmentation in the measurement of variables. Most studies rely on self-reported instruments without triangulating with behavioral or interaction data, which makes it difficult to establish robust causal relationships. Furthermore, quasi-experimental and exploratory designs predominate, with limited representation of longitudinal or multimodal analyses. These gaps in methodology open the possibility of moving toward more robust research models that combine mixed-methods approaches and consider cultural or contextual variations in the socioaffective perception of AI-mediated learning.

From a theoretical perspective, the findings prompt us to reconsider the role of chatbots as socio-affective agents. Rather than being a neutral instrument, this type of technology embodies communicative values that can reinforce or transform pedagogical practices. Incorporating the emotional dimension into their design does not mean humanizing the machine artificially; rather, it means recognizing that the educational relationship, even when mediated by AI, is based on empathy, trust, and mutual recognition. Therefore, the future of chatbots in higher education depends on their ability to balance cognitive intelligence and affective sensitivity while respecting the authenticity of the human experience.

Finally, the discussion suggests that applying the socio-affective approach to higher education improves performance and satisfaction while contributing to the humanization of educational technology and strengthening its ethical dimension. This perspective opens an emerging field of research aimed at developing more inclusive interaction models. In these models, artificial intelligence does not replace the educator; rather, it amplifies the educator's capacity to support, understand, and motivate students in an increasingly complex and sensitive learning ecosystem.

6. CONCLUSIONS

This scoping review synthesizes global research to offer three central contributions to the understanding of chatbots in higher education. First, it establishes that socio-affective factors—notably motivation, anxiety reduction, and satisfaction—are not peripheral but central to student engagement and perceived success with conversational agents. Second, it identifies a persistent methodological gap: the field heavily relies on self-report data, with a notable scarcity of studies triangulating these findings with behavioral metrics, limiting causal claims. Third, it underscores that chatbots designed with empathetic, adaptive, and supportive dialogue can act as potent socio-affective mediators, potentially humanizing digital learning environments and supporting student well-being.

The evidence indicates that the effectiveness of these tools is contingent on their ability to connect with students on an emotional and relational level. Chatbots that incorporate empathetic communication, adapt to user states, and provide non-judgmental support positively influence key mediators of learning such as self-efficacy, intrinsic motivation, and sense of belonging.

Furthermore, the findings suggest that a socio-affective approach fosters student integration into the virtual learning community. Most universities currently maintain a blended learning model, making this approach particularly relevant. In contexts where digital or hybrid education predominates, this type of emotional connection is valuable because it mitigates isolation and strengthens student retention. However, studies measure socio-affective variables inconsistently, which limits the ability to establish consistent impact patterns. The absence of standardized instruments and the lack of triangulation between self-reported and behavioral data constitute methodological challenges that future research should address.

Conceptually, while influential frameworks such as Self-Determination Theory and the Technology Acceptance Model offer valuable insights into adoption and motivation, they ultimately provide short-term evidence. In the case of adoption, this short-term evidence can be problematic because it does not account for socio-affective variables, which can be affected by time when conducted over a full academic period. However, the present review was designed to map the empirical evidence from studies that applied chatbots as an educational tool. As a result of this application, the studies reported the results shown. Consequently, future research should actively employ these and other theories to structure hypotheses and interpret findings, moving from descriptive mapping to explanatory and predictive models of socio-affective interaction with chatbots. Models that emphasize the central role of emotions in accepting conversational agents highlight the need for hybrid pedagogical approaches to maintain academic quality standards. These approaches integrate the emotional, ethical, and communicational dimensions and recognize the chatbot as a symbolic actor in the contemporary educational landscape.

Finally, the gathered evidence calls into question the effectiveness of incorporating a socio-affective approach into the design of educational chatbots in humanizing digital learning environments by balancing technological efficiency with emotional sensitivity. Systems that can interpret students' emotional signals and respond empathetically have the potential to promote well-being, self-regulation, and academic retention. However, this prospect also demands ethical reflection on the limits of artificial intelligence use. Higher education institutions must accept the responsibility that comes with this issue, and there is a call to develop institutional policies that ensure the responsible, inclusive, and transparent use of these technologies.

Consequently, the future of chatbot-mediated learning depends on universities' and researchers' ability to integrate the socio-affective dimension into pedagogical design and promote a balanced relationship between knowledge and emotion. Only then will it be possible to establish a person-centered educational paradigm instead of viewing artificial intelligence as a mere substitute for human interaction.

6.1. LIMITATIONS OF THIS STUDY

This study focused on research about learning in any subject area where chatbots are used in higher education. Studies based on technology acceptance models were excluded from further publication. One significant limitation of this study is its inability to compare socio-affective variables between predictive models (i.e., technology acceptance models) and models that implement chatbots (i.e., those included in this study). Another limitation is the lack of variation in search terms, which could have broadened the scope of the research. Other limitations include the time required to obtain the results and the article's submission deadline. More studies could have been included if the search had been updated before submission.

6.2. DIRECTIONS FOR FUTURE RESEARCH

Future research should compare the socio-affective elements of predictive technology adoption models and conversational agent implementation models to assess their implications for the academic performance of higher education students. Additionally, future research is encouraged to explore variations in search methodology and include databases not covered in this study.

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