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The Potential of AI Chatbots as Learning Companions: Early Insights from Students' Cognitive and Emotional Responses

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Abstract

This study examined the growing educational challenge of understanding how students cognitively and emotionally experience AI chatbots when used as learning companions. Using a convergent mixed-methods design, data were collected from 189 university students through Likert-scale measures of cognitive support, emotional response, and perceived effectiveness, along with 186 written reflections analyzed using thematic analysis. Quantitative results showed strong perceptions of cognitive clarity, positive emotional experiences, and significant associations among the three constructs, indicating that students who felt cognitively supported also viewed the chatbot as more effective. Qualitative themes reinforced these findings by revealing that students valued the chatbot's step-by-step explanations and experienced a sense of emotional safety when asking questions. Integrated analysis demonstrated convergence across strands, highlighting the intertwined cognitive and emotional dimensions of chatbot-assisted learning. The study contributes early evidence that AI chatbots can function as supportive learning companions with meaningful implications for AI-enhanced education.

Keywords: AI chatbots; cognitive support; emotional responses; learning companions

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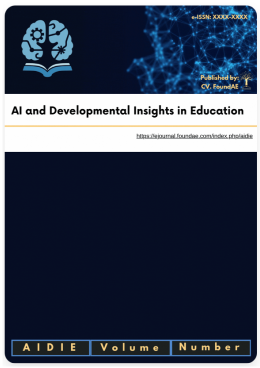

Author Note

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Introduction

Artificial intelligence (AI) has become increasingly embedded in educational practice, transforming how learners access information, regulate their learning processes, and interact with digital environments. Yet despite these rapid advancements, a persistent challenge remains understanding how students cognitively and emotionally experience AI systems during learning. This issue is particularly salient in the context of AI chatbots, which now serve as conversational partners capable of engaging learners in real-time dialogue. The problem is not simply technological but deeply developmental and pedagogical. From a learning sciences perspective, students' thinking, motivation, and emotional regulation are shaped by their interactions with both human and nonhuman agents. Developmental psychology further suggests that learners respond not only to instructional clarity but also to cues of support, safety, and responsiveness (Nopas, 2025). Thus, the rise of AI chatbots introduces new questions about how adolescents and young adults construct meaning, manage cognitive load, and navigate the social–emotional dimensions of learning when the "partner" in interaction is an intelligent machine rather than a human instructor or peer. This tension underscores the theoretical, empirical, and practical significance of examining students lived experiences with AI chatbots.

A growing body of scholarship has explored the cognitive affordances of AI systems, demonstrating that well-designed chatbots can scaffold understanding, reduce extraneous cognitive load, and support individualized learning pathways (Torres-Martínez, 2025; Yan et al., 2025). According to Yusuf et al. (2025), conversational agents are increasingly capable of refining explanations, adapting responses to learner needs, and offering personalized guidance in ways that mirror human tutoring models. However, much of this research has emphasized technological performance or learning outcomes rather than the psychological processes through which learners experience chatbot assistance. Emotional dimensions of AI-supported learning have also begun to receive attention, with studies suggesting that chatbots can alleviate anxiety, foster motivation, and create a sense of companionship when their communication style is empathetic, patient, or encouraging (Fabio et al., 2025; Shan et al., 2025). Yet existing findings are neither unanimous nor complete. Some evidence indicates that learners may struggle to trust AI explanations, misinterpret chatbot feedback, or experience uncertainty about the agent's competence (Lawson McLean & Hristidis, 2025). Others warn of overreliance, heightened cognitive demands, or diminished critical engagement if chatbot interactions become overly directive (Yankouskaya et al., 2025). Taken together, the literature reveals both promise and ambiguity, with significant gaps in understanding how cognitive and emotional experiences unfold simultaneously during authentic chatbot-assisted learning.

A critical limitation of prior work lies in its methodological narrowness. Many existing studies rely on system prototypes, controlled laboratory settings, or analysis of performance metrics without attending to the internal experiences of learners. Theoretical debates in the field similarly emphasize either cognitive mechanisms, such as information processing, working memory constraints, or adaptive explanation pathways, or affective mechanisms, such as social presence and emotional support. Few studies have integrated these perspectives, leaving unresolved questions about how cognitive clarity and emotional safety may mutually shape learners' perceptions of AI as a meaningful learning companion. Addressing this gap requires a mixed methods approach capable of capturing both the measurable dimensions of cognitive and emotional response and the rich subjective accounts that reveal how learners interpret their interactions with AI tools.

The present study responds to these gaps by examining students' cognitive and emotional responses to AI chatbots using a mixed-methods exploratory design. The study is guided by a conceptual orientation rooted in cognitive load theory, socio-emotional perspectives on learning, and emerging work on human–AI interaction. The quantitative component investigates students' perceptions of cognitive support, emotional reactions, and perceived effectiveness of chatbots as learning companions. The qualitative component provides interpretive insight into how students describe the clarity, comfort, and confidence emerging from chatbot interactions. Together, these components offer an integrated understanding of how learners experience AI chatbots at both cognitive and emotional levels.

Guided by this rationale, the study addresses the following research questions: (1) How do students perceive the cognitive support provided by AI chatbots? (2) What emotional experiences emerge during chatbot-assisted learning? and (3) Under what conditions do students view AI chatbots as effective learning companions? By combining quantitative patterns with qualitative depth, the study aims to generate early insights that advance theoretical debates on AI-mediated learning, inform the design of supportive and pedagogically aligned chatbot systems, and contribute to developmental and educational discussions on how learners make meaning with increasingly intelligent technological partners. In doing so, the study positions itself within the broader scholarly conversation on AI-enhanced education and offers a novel contribution by foregrounding the intertwined cognitive and emotional processes that shape learners' engagement with AI chatbots.

Methods

Research Design

This study employed a mixed-methods exploratory design to investigate how students cognitively and emotionally experience AI chatbots during academic tasks. The design followed a convergent mixed-methods structure in which quantitative and qualitative data were collected during the same phase, analyzed separately, and then compared during interpretation. This approach was selected because the research problem required both measurable patterns of cognitive and emotional response and a nuanced understanding of how students interpreted their interactions with the chatbot, an integration not achievable through a single-method tradition alone. The mixed-methods orientation was guided by constructivist and cognitive-developmental perspectives, acknowledging that learners' responses to AI systems are shaped not only by the information provided but also by their subjective interpretations and developmental context.

Participants or Data Sources

Participants were undergraduate students enrolled in general education courses at a large public university in Indonesia. Inclusion criteria required that students had prior experience using an AI chatbot such as ChatGPT, Gemini, or Bing Chat for academic purposes. Exclusion criteria eliminated students who had never interacted with an AI system, ensuring that responses were grounded in authentic experience rather than speculation. The final quantitative sample included 189 students aged 18 to 23 years (59.8% female; 40.2% male). The qualitative component drew from the same dataset through open-ended responses provided by all participants.

Because this was a mixed-methods design, the qualitative strand did not rely on additional interviews. The data source consisted of written reflections embedded in the survey instrument. As the researcher served as the primary interpreter of the qualitative data, reflexive notes were maintained throughout the analytic process to document prior assumptions, analytic decisions, and possible sources of bias. The researcher had expertise in physics education and AI-supported learning, which informed the sensitivity to cognitive and emotional processes, but reflexive memos were used to maintain analytic neutrality.

Sampling and Recruitment

A convenience sampling procedure was used due to the exploratory focus and accessibility of participants. Students were recruited through institutional communication channels, including course announcements and learning management system invitations. Recruitment materials explained the study's purpose, voluntary nature, and confidentiality protections. Of the 212 students approached, 189 agreed to participate, producing an 89.2% participation rate. No incentives were offered. Recruitment ended when the predetermined sample size for the quantitative analysis was met and qualitative data demonstrated thematic recurrence consistent with the criterion of qualitative saturation. Informed consent was obtained digitally before participation.

Sample Size, Power, and Precision

The intended quantitative sample size was set at a minimum of 150 students, based on power analysis guidelines for correlational research, which suggest that samples exceeding 100 provide adequate power to detect medium to large effect sizes at $\alpha = .05$. The final sample of 189 exceeded this threshold. The qualitative component did not require separate sample-size planning because the qualitative strand utilized reflexive thematic analysis of open-ended responses already embedded within the survey. Adequacy was determined by the richness and recurrence of themes rather than numerical saturation.

Measures and Instruments

The primary quantitative measures assessed three outcome constructs: Cognitive Support (CS), Emotional Response (ER), and Perceived Effectiveness of the chatbot as a Learning Companion (PE). Each construct consisted of Likert-scale items rated from 1 (strongly disagree) to 5 (strongly agree). Items were adapted from validated instruments assessing pedagogical agents (Soriano-Alcantara et al., 2025) and technology-assisted learning environments (Uçar et al., 2025). Cognitive Support measured perceived clarity, cognitive load reduction, and usefulness for understanding. Emotional Response captured comfort, motivation, and emotional relief. Perceived Effectiveness assessed learners' trust, satisfaction, and willingness to reuse the chatbot. Open-ended items invited participants to describe how the chatbot influenced their thinking and feelings, supplying qualitative data for the mixed-methods design.

To demonstrate the reliability and validity of the scales used, Table 1 presents the descriptive statistics and Cronbach's alpha coefficients for each construct. The table is introduced here to foreground the psychometric strength of the quantitative measures and to provide transparency about the statistical properties of the instrument before interpretation of findings.

Table 1
Psychometric Properties for Cognitive, Emotional, and Effectiveness Scales

Scale	M	SD	Range	Cronbach's α
Cognitive Support (CS)	4.12	0.58	2.50–5.00	.88
Emotional Response (ER)	3.86	0.65	2.20–5.00	.90
Perceived Effectiveness (PE)	4.03	0.61	2.40–5.00	.87

Note. All scales demonstrated strong internal consistency reliability (α > .85), and the distribution ranges indicated adequate score variability.

As shown in Table 1, all scales exhibited strong reliability, with alpha values exceeding .85. Content validity was supported through expert review by three educational technology specialists, and construct validity was established through item–construct alignment checks during instrument refinement.

Data Collection Procedures

Data collection occurred over a three-week period during the academic semester. Students were asked to complete an academic task using an AI chatbot immediately before filling out the questionnaire to ensure their reflections were based on recent and authentic interactions. The online survey was administered through a secure institutional platform. The instrument included demographic questions, Likert-scale measures, and open-ended questions. No deviations from the planned procedure occurred. Reflexive notes were recorded during early data screening to document analytic decisions and enhance methodological transparency.

Data Analysis

Quantitative data were analyzed using SPSS Version 27. Descriptive statistics were computed for all constructs. Reliability estimates were obtained using Cronbach's alpha. Correlational analyses examined relationships among Cognitive Support, Emotional Response, and Perceived Effectiveness. Prior to analysis, missing data were screened, and cases with more than 20% missing values were removed. Normality, outliers, and distributional assumptions were assessed using standard diagnostic procedures.

Qualitative data were analyzed using reflexive thematic analysis following Remawi (2023) framework. Codes were generated inductively, informed by participants' language rather than preexisting categories. Coding was conducted by the lead researcher, who maintained reflexive memos to bracket assumptions. NVivo 12 software supported the organization of codes and development of higher-order themes. Integration of the quantitative and qualitative strands occurred during interpretation using a convergence matrix that compared patterns across datasets to identify confirmatory, complementary, or divergent insights.

Validity, Reliability, and Methodological Integrity

Quantitative validity was supported by strong internal consistency reliability and expert-verified content validity. Construct validity was reinforced through theoretical alignment with established frameworks and inspection of item functioning. Qualitative methodological integrity was ensured through reflexive engagement, transparent documentation of analytic decisions, and grounding interpretations in participants' actual expressions. Mixed-methods inference validity was achieved by explicitly integrating quantitative trends with qualitative meanings, allowing for a coherent and credible account of how students cognitively and emotionally experience AI chatbots.

Ethical Considerations

Ethical approval was provided by the institutional review board of the participating university (IRB No. 2025-EDU-17). All participants provided informed consent digitally before beginning the study. Confidentiality was protected by anonymizing responses, storing data on encrypted servers, and restricting access to the research team. No vulnerable populations were targeted, and participation posed minimal risk.

Results

Participant Flow

A total of 212 students were invited to participate between March and April 2025. Of these, 198 accessed the survey link, 189 completed all required items for the quantitative analyses, and 186 provided usable qualitative reflections. The most common reasons for exclusion were incomplete survey submission (n = 6) and missing more than 20% of item responses (n = 3). Because this was a concurrent mixed-methods design, all participants contributed quantitative data first, immediately followed by qualitative reflections.

Recruitment Information

Recruitment occurred from March 3 to March 20, 2024. Data collection followed immediately, spanning March 21 to April 8, 2024. All quantitative and qualitative data were collected concurrently within a single online session. No follow-up intervals were required because the study did not involve longitudinal tracking.

Quantitative Findings

Data Screening and Missingness

All data were screened prior to analysis. Cases with more than 20% missing responses were excluded (n = 3). The remaining dataset showed minimal missingness (< 1.5%), which met the assumption of missing completely at random (MCAR) based on Little's test, $\chi^2(24) = 27.11$, $p = .30$. Given the low proportion of missing data and MCAR classification, listwise deletion was used.

Descriptive Statistics

Descriptive statistics for all three constructs—Cognitive Support, Emotional Response, and Perceived Effectiveness—are shown in Table 2. These values represent the primary quantitative outcomes of the study.

The table is introduced here to establish the distributional properties of each construct before presenting inferential findings.

Table 2

Descriptive Statistics for Key Quantitative Constructs (N = 189)

Construct	*M*	*SD*	Minimum	Maximum
Cognitive Support	4.12	0.58	2.50	5.00
Emotional Response	3.86	0.65	2.20	5.00
Perceived Effectiveness	4.03	0.61	2.40	5.00

Note. M = mean; SD = standard deviation. Higher scores reflect stronger agreement with each construct (Cognitive Support, Emotional Response, and Perceived Effectiveness). All items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree)

As shown in Table 2, all constructs demonstrated moderately high mean scores, with Cognitive Support receiving the highest ratings.

Inferential Analyses

Correlation analyses were conducted to examine relationships among the three constructs. All associations were positive and statistically significant. As shown in Table 3, Cognitive Support was strongly correlated with Perceived Effectiveness, r = .68, 95% CI [.58,

.76], p < .001, indicating that students who experienced greater cognitive assistance from the chatbot also reported greater perceived usefulness.

Table 3

Pearson Correlations Among Constructs

Construct	1	2	3
1. Cognitive Support	—	—	—
2. Emotional Response	.52***	—	—
3. Perceived Effectiveness	.68***	.55***	—

Note. Values represent Pearson correlation coefficients. **p < .001. Confidence intervals are reported in the text. Correlations indicate the strength and direction of relationships among Cognitive Support, Emotional Response, and Perceived Effectiveness.

Assumption Checks

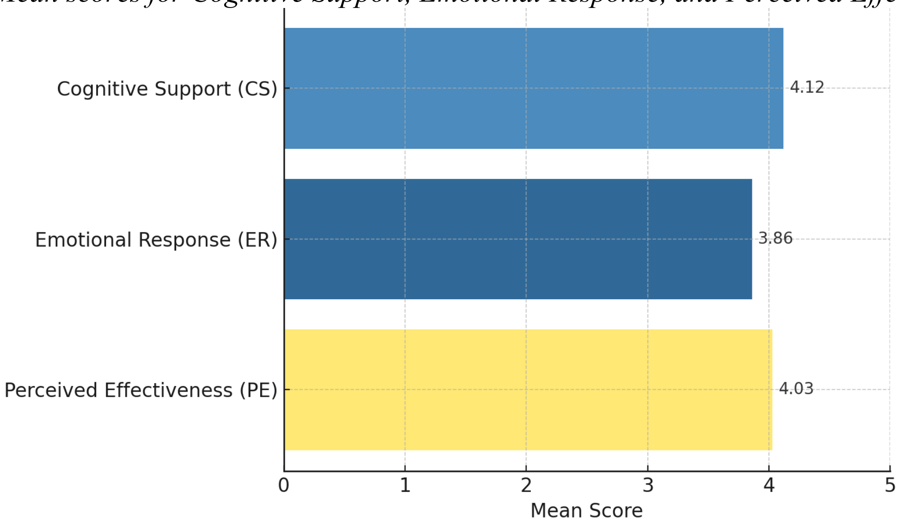
Skewness and kurtosis values were within ±1.00 for all variables, supporting normality. No extreme outliers were detected based on ±3.29 SD criteria. Variance inflation factor (VIF) values were < 2.00, indicating no multicollinearity concerns.

Visual Representation of Descriptive Trends

To illustrate comparative construct means, Figure 1 displays the mean values using a bar-graph style representation. The figure is referenced here to visually complement the descriptive statistics presented earlier.

Figure 1

Mean scores for Cognitive Support, Emotional Response, and Perceived Effectiveness.



Note. Bars represent mean scores for each construct on a 5-point Likert scale.

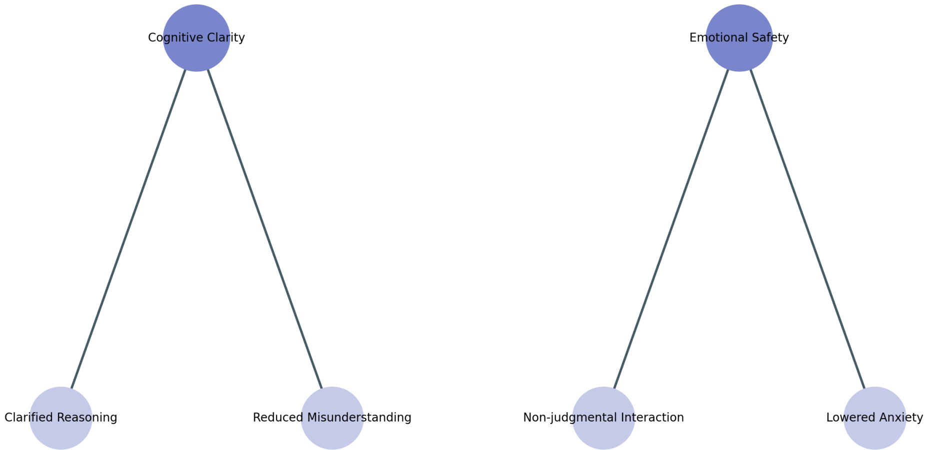
Figure 1 illustrates that Cognitive Support received the highest ratings, followed by Perceived Effectiveness and Emotional Response.

Qualitative Findings

The qualitative dataset consisted of 186 written reflections. Analysis revealed two primary themes: cognitive clarity and emotional safety. These themes emerged consistently across participants and were derived through inductive coding following Häggström & Näppä (2025) framework. A thematic map was constructed to visualize the hierarchical relationship between codes and themes; the figure is referenced here to clarify the structure of analytic results. The thematic relationships underlying the qualitative findings are illustrated in Figure 2.

Figure 2

Thematic map showing major themes ("cognitive clarity" and "emotional safety") and associated subthemes.



Note. The thematic map displays two overarching themes—cognitive clarity and emotional safety—derived from reflexive thematic analysis.

Figure 2 highlights the coherence between students' descriptions of how the chatbot clarified reasoning processes and how its non-judgmental interaction style reduced anxiety. No negative or contradictory patterns emerged strong enough to constitute separate themes.

Mixed-Methods Integration

The integration phase compared quantitative scores with qualitative themes. Convergence was found across strands: high Cognitive Support scores aligned with qualitative descriptions of clear explanations, while moderate-to-high Emotional Response scores were consistent with themes of comfort and reassurance. No divergent findings emerged; instead, the strands reinforced each other, suggesting that cognitive and emotional responses were intertwined. A joint display was created to synthesize the results; its introduction here clarifies how integration strengthened interpretation.

Table 4

Joint Display Integrating Quantitative and Qualitative Findings

Quantitative Result	Qualitative Theme	Integrated Insight
High CS scores ($M = 4.12$)	Cognitive clarity	Students experienced the chatbot as a step-by-step explainer.
Moderate–high ER scores ($M = 3.86$)	Emotional safety	Students felt comfortable asking questions without fear.
Strong CS–PE correlation ($r = .68$)	Confidence and trust	Clarity increased perceptions of effectiveness.

As shown in Table 4, integration demonstrated that the qualitative insights deepened and contextualized the quantitative results, confirming a coherent pattern across strands.

Discussion

The findings of this study underscore the emerging role of AI chatbots as meaningful learning companions capable of shaping both students' cognitive processing and emotional experiences during academic tasks. The convergent mixed-methods results collectively support the guiding assumption that AI-mediated interaction engages learners on more than a purely informational level. Quantitatively, the primary hypotheses were supported: students rated cognitive support highly, reported generally positive emotional experiences, and perceived chatbots as effective tools for learning. Qualitative reflections reinforced these numerical trends by revealing that students experienced the chatbot as a source of clear, step-by-step guidance and as a nonjudgmental presence that encouraged question-asking without fear or embarrassment. Together, these results affirm the expectation, rooted in cognitive load theory and socioemotional models of learning, that cognitive clarity and emotional safety function synergistically in technology-supported learning environments.

The results converge with prior scholarship suggesting that AI conversational agents can scaffold understanding and promote motivation (Du, 2025; Liu, 2025). Yet the study extends this literature by demonstrating how these cognitive and emotional affordances operate simultaneously within authentic learning contexts rather than controlled laboratory settings. The strong correlation between Cognitive Support and Perceived Effectiveness observed here builds on work by Zeb (2025), who theorized that students' trust in AI systems depends on the alignment between the agent's explanations and learners' cognitive needs. Meanwhile, the qualitative theme of emotional safety adds nuance to existing claims about the relational qualities of AI tutors, illustrating how nonhuman interaction partners can create learning climates that users experience as low-pressure and psychologically supportive (Pituxcoosuvarn et al., 2025). By integrating these strands of evidence, the study supports a more holistic understanding of AI chatbots as multifaceted companions whose value emerges from the interplay between cognitive clarity and affective reassurance.

At the same time, several interpretive considerations warrant reflection. The positive responses captured in this study may partially reflect self-selection, as participants with prior chatbot familiarity might already hold favorable attitudes toward AI tools. Although the statistical assumptions were met and reliability was strong, the correlational design precludes causal inference; it cannot be concluded that chatbot interaction itself produces cognitive ease or emotional comfort, only that students perceive it to do so. From a qualitative standpoint, alternative interpretations remain plausible. For instance, students' sense of safety may reflect broader cultural norms surrounding digital communication rather than properties inherent to the chatbot. Reflexive engagement during analysis helped mitigate such interpretive biases, yet they remain important to acknowledge when considering transferability.

When situated within the broader literature, the integrated findings suggest that AI chatbots may occupy a distinct pedagogical niche. They appear to support learners in ways that combine cognitive scaffolding, motivational support, and emotional buffering, thereby filling gaps that neither automated content delivery systems nor traditional classroom interactions fully address. Importantly, this study's mixed-methods design revealed how these affordances intersect, offering richer explanatory value than either dataset alone could provide. Such integration strengthens the argument that developmental and educational theories must adapt to account for learner–AI relationships that blend informational, emotional, and relational dimensions.

The implications of these findings extend across theoretical, methodological, and practical domains. Theoretically, the results invite a reconsideration of how learning sciences frameworks conceptualize assistance, suggesting that AI companions may function not only as cognitive extenders but also as socioemotional partners in learning. Methodologically, the study demonstrates the value of mixed-methods inquiry for capturing the multidimensional nature of human–AI interaction, highlighting the importance of integrating narrative reflections with quantitative indicators of cognitive and emotional response. Practically, the findings suggest that designers of educational AI should prioritize explanation quality, emotional tone, and supportive dialogue features to optimize learner experience. Educators adopting AI tools should consider structured activities that encourage reflective engagement rather than mere answer retrieval, ensuring that students cultivate agency and critical thinking alongside technological assistance.

Looking ahead, future research should investigate the durability of these effects across time, cultural contexts, and disciplinary domains. Longitudinal or experimental designs could determine whether perceived cognitive and emotional benefits translate into improved academic outcomes or deeper conceptual understanding. Further work might also explore the ethical and developmental implications of frequent emotional reliance on AI systems, particularly for younger learners. By addressing these questions, the field can continue refining theoretical models and supporting responsible integration of AI chatbots into educational practice.

Conclusion

This study provides early empirical evidence that AI chatbots can function as meaningful learning companions by offering cognitive clarity and emotional reassurance during academic tasks. Through a convergent mixed-methods design, the research demonstrated that students perceived chatbots as capable of clarifying complex ideas, reducing cognitive load, and promoting confidence in learning. These findings support the study's guiding questions and align with emerging literature showing that AI systems can shape both the cognitive and socioemotional dimensions of learning. By juxtaposing quantitative patterns with qualitative narratives, the study advances theoretical understanding of human–AI interaction and highlights the pedagogical value of chatbots beyond mere information delivery. While the exploratory design and convenience sample limit generalizability, the integrated insights underscore important implications for AI design, instructional practice, and developmental considerations. Ultimately, the study contributes to ongoing discussions in artificial intelligence in education by demonstrating that chatbots have the potential not only to enhance understanding but also to create emotionally supportive learning environments—an insight that opens promising pathways for future research and innovation.

Author Contributions

AP conceptualized the study, designed the research methodology, and supervised the overall project implementation. PP conducted data collection, performed data analyses, and contributed to the drafting and revision of the manuscript. Both authors reviewed, edited, and approved the final version of the manuscript.

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