

Effects of Artificial Intelligence Chatbot-Integrated Instruction on Science-Positive Experiences and Attitudes toward Artificial Intelligence: Focusing on the Unit of Stellar Types and Evolution

Heungjin Eom¹, Dongkuk Lee^{2*}

¹Gumi Sandong High School, Gyeongsangbuk-do, Republic of Korea, ²Department of Information and Computer Education, Teachers College, Kyungpook National University, Daegu, Republic of Korea

*Corresponding Author: dklee@knu.ac.kr

ABSTRACT

This study examined the effects of artificial intelligence (AI) chatbot-integrated instruction with embedded scaffolding on high school students' science-positive experiences and attitudes toward AI in the Earth science unit on stellar types and evolution. To this end, the researchers developed an instructional program grounded in the Exploratory Scientific Data Analysis Inquiry Model and designed an AI chatbot to support students' inquiry processes and conceptual understanding. The participants were 138 11th-grade students, and a quasi-experimental one-group pre-test-post-test design was employed. The results indicated that the intervention significantly improved students' science-positive experiences across all subdomains – affective experience in science learning, science self-concept, motivation for science learning, science career aspirations, and attitudes toward science. In addition, students' attitudes toward AI significantly improved across cognitive, affective, and behavioral dimensions. Qualitative findings revealed that the AI chatbot's immediate feedback and hints reduced students' perceived cognitive burden in science learning and encouraged more active engagement in self-directed problem solving and collaborative inquiry. Students also came to perceive AI as a useful tool for learning, career exploration, and everyday problem-solving.

KEY WORDS: Artificial intelligence chatbot, astronomy education, attitudes toward artificial intelligence, scaffolding, science-positive experiences

INTRODUCTION

Artificial intelligence (AI) chatbots can actively intervene in learning by interpreting learners' questions in real time and providing appropriate explanations, examples, and feedback, while also offering tailored support that aligns with learners' levels of understanding and contexts (Kuhail et al., 2023). In domains such as science learning, where understanding relationships among concepts, constructing explanations, and generating questions are essential, AI chatbots can function as cognitive tools that facilitate inquiry (Chang et al., 2023). Through dialogue with a chatbot, learners can externalize their thinking in language and progressively refine concepts by repeatedly generating additional questions and explanations (Graesser, 2016). This process promotes self-explanation, elaboration, and metacognitive monitoring for deeper conceptual understanding. Because chatbots respond immediately and provide varying levels of feedback, they can extend the individualized cognitive support that has traditionally been limited in conventional whole-class instruction (Labadze et al., 2023).

However, concerns have been raised that providing AI chatbots to learners without deliberate instructional design may hinder learning rather than support it (Birenbaum, 2023). Learners may uncritically accept information or engage only

in superficial question-and-answer exchanges (Zhai et al., 2024). In addition, inaccurate information, excessive cognitive offloading, and misalignment with learning goals may lower the quality of learning. These concerns suggest that chatbots' educational effects depend not on the technology alone but on how they are designed to support thinking. Recent systematic reviews have repeatedly highlighted limitations, such as insufficient grounding in instructional theory and a lack of evidence on long-term and psychological effects (Debets et al., 2025).

Recent studies have begun to examine the potential of AI chatbots equipped with scaffolding that adjusts support according to learners' levels of understanding and responses (Kuhail et al., 2023). Scaffolding provides cognitive support gradually through hints, guiding questions, partial explanations, and elaborated explanations, encouraging learners to develop their own thinking while still receiving appropriate assistance when needed (Liu et al., 2024). This scaffolding promotes self-explanation and conceptual elaboration, thereby preventing excessive dependence and supporting inquiry-based learning (Li et al., 2025).

These cognitive and instructional characteristics also carry implications for the affective dimension of science learning, which is closely tied not only to conceptual understanding but

also to how learners experience and perceive the discipline. Affective variables, such as attitudes toward science, interest, and motivation, have long been recognized as important factors influencing students' engagement in science learning and their perceptions of science-related careers (Osborne et al., 2003). In this context, science-positive experiences have recently been used in science education research as indicators of multiple affective characteristics (Shin et al., 2017). Instruction that promotes active participation and interaction has been shown to enhance these experiences (Freeman et al., 2014), and chatbot-based instruction may likewise strengthen participation and feedback experiences (Hew et al., 2023). At the same time, learning experiences involving AI chatbots may also shape attitudes toward AI (Ait Baha et al., 2024), as learners develop perceptions of AI's usefulness, trustworthiness, and applicability during the process, which may in turn affect their future acceptance and use of AI technologies.

The high school Earth science unit on stellar types and evolution includes astronomical concepts difficult to experience directly, making it challenging to foster students' understanding and interest; therefore, interactive explanations and inquiry-based support are especially important (Lelliott and Rollnick, 2010). In this context, AI chatbots can effectively expand learning experiences for such abstract concepts by prompting learners to generate questions, providing conceptual explanations, and offering feedback at varying levels (Lee et al., 2023).

However, previous studies have examined the educational effects of generative AI primarily in relation to cognitive achievement or within specific learning contexts, and have tended to attribute learning effects to the mere presence of technology rather than to explicit AI orchestration. Research on educational chatbots has repeatedly highlighted limitations, including insufficient theory-based design, narrow evaluation criteria, and a lack of long-term effect verification (Debets et al., 2025). In secondary science education, few studies have comprehensively analyzed the effects of chatbot-based instruction grounded in instructional design, including scaffolding, with a focus on affective variables such as science-positive experiences and attitudes toward AI. Such an approach is also aligned with the perspective of human–AI collaboration and orchestration, in which the roles of humans and AI are designed and coordinated in complementary ways (Holstein and Olsen, 2023).

Accordingly, this study examines the effects of AI chatbot-integrated science instruction with embedded scaffolding strategies on high school students' science-positive experiences and attitudes toward AI. To this end, instruction was designed and implemented for the unit on stellar types and evolution, and pre- and post-intervention changes across six lessons were analyzed to examine affective outcomes. The study further aims to explore the educational effects of chatbot-integrated instruction from an AI orchestration perspective and to provide implications for designing science instruction using generative AI. The research questions are as follows.

- RQ1: What effects does science instruction using an AI chatbot with embedded scaffolding have on high school students' science-positive experiences?
- RQ2: What effects does science instruction using an AI chatbot with embedded scaffolding have on high school students' attitudes toward AI?

LITERATURE REVIEW

Educational Potential of AI Chatbots in Science Education

AI chatbots are AI systems that interact with learners by understanding and generating natural language using large language models (LLMs). In school settings, they can provide contextually appropriate explanations, examples, and feedback in response to learners' questions (Jeon and Lee, 2023). These unique characteristics distinguish AI chatbots from static digital learning materials that deliver pre-determined content. They are closely aligned with the nature of science learning, as learning experiences can be dynamically constructed in response to learners' responses. The educational potential of AI chatbots in science education manifests in at least three ways.

First, they can function as cognitive tools that help learners externalize and expand their thinking about scientific concepts. Science learning requires learners to understand relationships among concepts, explain phenomena, and express their ideas with supporting evidence (National Research Council, 2012). Through dialogue with an AI chatbot, learners can articulate their thoughts and progressively refine their understanding by iteratively generating follow-up questions and explanations (Tang and Putra, 2026). This process promotes self-explanation and elaboration, thereby helping learners move beyond the passive reception of scientific concepts toward their active reconstruction.

Second, AI chatbots can serve as personalized learning tools by providing adaptive support tailored to learners' levels and responses (Chang et al., 2023). In science classrooms, even when the same concept is taught, learners often require different explanations and supports depending on their prior conceptions, misconceptions, and levels of understanding (Hewson and Hewson, 1983). AI chatbots can adjust the depth and form of explanations based on how learners ask questions and respond, while supporting more flexible conceptual understanding through diverse examples and expressions (Chang et al., 2023). This suggests their potential to extend individualized support in science learning, which has traditionally been limited in whole-class instruction.

Third, AI chatbots can foster interaction-based learning environments that sustain learners' engagement in scientific inquiry (Chang et al., 2023). Science learning involves iterative inquiry processes such as question generation, hypothesis testing, evidence evaluation, and explanation revision (National Research Council, 2012). Because chatbots can respond immediately to learners' inputs, they can help sustain these processes. As a result, learners are encouraged to ask questions, respond actively, and monitor their understanding,

rather than passively receiving information, thereby transforming science learning into a more inquiry-oriented and participatory experience.

AI Orchestration and Scaffolding Strategies in Science Education

The educational potential of AI chatbots may vary depending on how these chatbots are designed and used. In particular, when AI orchestration is applied to systematically design the roles of humans and AI, learning activities, and interactions based on learning goals and task characteristics, the educational effects of AI chatbots may be more strongly manifested. AI orchestration is an instructional design strategy that distributes humans and AI roles according to learning goals and task characteristics while coordinating interactions throughout the learning process (Holstein and Olsen, 2023). It is important as it extends AI beyond simple tool use to the design of decision-making structures and intervention patterns across the entire learning process (Holstein et al., 2019).

One important orchestration strategy for AI chatbots in science education is scaffolding, which involves gradually adjusting the type and intensity of cognitive support according to learners' current levels of understanding and responses, beginning with minimal support and moving toward more elaborated support (Van de Pol et al., 2010; Wood et al., 1976). Because science learning emphasizes revising misconceptions and developing relationships among concepts, scaffolding that flexibly adjusts to learners' responses becomes especially important (Basu et al., 2017). Since chatbots can respond in real time, they are well-positioned to deliver appropriate support aligned with learners' understanding and enable individualized inquiry processes.

Prior research has categorized such staged scaffolding in various ways. For example, Hannafin et al. (1999) classified scaffolding in constructivist learning environments into four types – conceptual, procedural, strategic, and metacognitive – based on the functions and purposes of learning support. Conceptual scaffolding helps learners understand key concepts and relationships relevant to problem-solving. Procedural scaffolding guides task execution and tool use. Strategic scaffolding promotes the expansion of learners' thinking by suggesting different problem-solving approaches. Metacognitive scaffolding supports learners in monitoring their own understanding and regulating their learning processes. These four types have recently been applied in digital and AI-based learning environments.

More specifically, scaffolding can be procedurally applied to AI chatbots in four stages (Collins et al., 1989; Quintana et al., 2004). First, the exploration stage provides minimal hints or directional prompts to guide learners' initial thinking. Second, the expansion stage uses guiding questions to deepen thinking and examine concepts from multiple perspectives. Third, the refinement stage offers partial explanations and corrective feedback to enhance conceptual accuracy. Fourth, the integration stage provides elaborated explanations

and structures relationships among concepts to develop a systematic understanding of the concept as a whole. These stages are not necessarily fixed or sequential; rather, they can be flexibly cycled and adjusted according to learners' responses and levels of understanding (Van De Pol et al., 2010).

Affective Effects of AI Chatbot Use in Science Education

In science education, learning outcomes are shaped not only by cognitive understanding but also by affective dimensions, such as learners' experiences and perceptions of science. Beyond concept acquisition, science learning influences a range of affective factors, including interest, confidence, attitudes, and career awareness, which serve as important variables in explaining learners' sustained participation in science learning (Ainley and Ainley, 2011; Osborne et al., 2003). In this context, "science-positive experiences" have increasingly been emphasized in science education research as a key indicator of multiple affective characteristics. This construct reflects learners' positive emotions, perceptions, and relationship with science and is commonly associated with affective experience in science learning, science self-concept, motivation for science learning, science career aspirations, and attitudes toward science (Shin et al., 2017). Instruction that promotes active participation and interaction tends to enhance these experiences, and learning environments that involve question generation, explanatory activity, and repeated feedback may boost learners' confidence, interest, and positive perceptions of science learning (Armbruster et al., 2009; Freeman et al., 2014). From this perspective, AI chatbot-integrated instruction has the potential to enhance science-positive experiences. Chatbots equipped with scaffolding can strengthen successful learning experiences and self-efficacy by supporting learners as they gradually extend their understanding of concepts through appropriate, level-aligned guidance. These experiences may foster more positive emotions and attitudes toward science learning and ultimately contribute to improved science-positive experiences.

Meanwhile, learning experiences involving generative AI may also shape attitudes toward AI, which include learners' perceptions of how useful and trustworthy AI technologies are, as well as their willingness to use them in learning and problem-solving processes (Schepman and Rodway, 2020). In particular, actual interaction with AI in learning contexts may shape these attitudes beyond abstract perception (Song et al., 2025). AI chatbot-integrated instruction may therefore positively influence attitudes toward AI by allowing learners to experience AI not merely as an information-providing tool but as a collaborative learning tool (Lee et al., 2023).

METHODOLOGY

Participants

This study used a convenience sample of 11th-grade students enrolled in S High School, a coeducational school in a small provincial city. Participants had completed Integrated Science as part of the common 1st-year curriculum and learned

foundational concepts related to stellar evolution. At the time of the study, they were taking Earth Science I, a general elective science course under the 2015 Revised National Curriculum.

During instructional program design, consultations were held with a professor of science education, a professor of astronomy education, a doctoral researcher in science education, and a master's student in science education regarding the program design and participant suitability.

A total of 141 students completed the pre-test, 139 participated in the instructional program, and 138 completed the post-test. The final analysis included 138 students who completed the pre-test, participated in the program, and completed the post-test. The final sample consisted of 63 male and 75 female students. Before assessments and surveys, we explained each study phase, intended data use, and privacy measures. The study began after we received written informed consent from students and their parents or guardians.

Development of the Instructional Program and AI Chatbot Instructional program

The instructional program was developed based on the Exploratory Scientific Data Analysis Inquiry Model (ESDA), which emphasizes the selection and use of instructional tools. The ESDA model is designed so that learners first explore and select tools for classroom use, and then identify problems by analyzing data with those tools. The model integrates tool use, conceptual understanding, and inquiry activities (Son and Jeong, 2020).

The ESDA model consists of the following stages: Tool exploration, data collection, data transformation and interpretation, problem identification and refinement, problem solving (inductive/deductive inquiry), and conclusion and expression. In the tool exploration stage, students examined the attributes and variables of the data to be used in class and selected appropriate tools and software. During data collection, they were introduced to methods aligned with the program's objectives. In the data transformation and interpretation stage, students explored meanings in the collected data and engaged in activities designed to interpret them using scientific knowledge. The problem identification stage involved exploring questions that emerged from the data interpretation, with students identifying problems through a variety of approaches. In the problem-solving stage, students organized their interpretations, identified relationships, and engaged in causal reasoning by connecting the data to scientific knowledge, while additional data were used to strengthen their interpretations. In the conclusion and expression stage, students used tools to effectively communicate their findings.

Based on this framework, lessons were designed such that the chatbot served functions of question generation, concept explanation, and feedback provision at each stage. The lesson structure and learning objectives are presented in Table 1.

Development of the AI chatbot

The AI chatbot was implemented using MagicSchool, a generative AI-based educational platform built on an LLM

that supports natural language understanding and generation, context-aware responses, and tailored feedback. It also provides prompt templates and activity design features appropriate for teaching and learning contexts (Fassbender, 2025). In particular, it offers an environment well-suited for AI orchestration, as teachers can design the interaction structures and the directions of chatbot responses.

Based on these technological features, the chatbot incorporated the scaffolding types proposed by Hannafin et al. (1999) and Kim et al. (2026), as shown in Table 2. In this study, scaffolding was categorized into conceptual, procedural, strategic, and metacognitive scaffolding, and these four types were integrated to support learners' cognitive and metacognitive activities.

The AI chatbot was designed to adjust scaffolding based on learners' response patterns. For example, when students demonstrated insufficient conceptual understanding or provided no response, the chatbot offered basic hints and examples. When learners struggled during task performance, it strengthened procedural guidance, and when partial understanding was identified, additional questions were posed to extend learners' thinking. Metacognitive scaffolding was applied across all stages to encourage continuous self-monitoring.

This multidimensional scaffolding design allowed diverse forms of support to operate organically based on learners' levels of understanding and response patterns, rather than providing support at a single level. In particular, by simultaneously supporting conceptual understanding, inquiry performance, problem solving, and self-regulated learning, the AI chatbot was intended to function not merely as an information-providing tool but as an instructional tool that supports learners throughout the inquiry process. The interaction between students and the AI chatbot is illustrated in Figure 1.

Validation of the instructional program and the AI chatbot

To assess validity, an expert review was conducted. A total of 11 reviewers, including experts in science education and educational technology (e.g., professors and doctoral researchers) and in-service teachers, participated in the review. They reviewed the structure and content of the generative AI-based instructional program for learning the concepts in stellar types and evolution, the appropriateness of the lesson objectives, the chatbot's suitability for supporting inquiry, and the appropriateness of the scaffolding strategies embedded in the prompts.

The review materials included the learning objectives and content structure of the six lessons, the scaffolding types applied to the chatbot design, and key prompt design features. To assess content validity, the content validity index (CVI) was calculated for each item, and the mean CVI across all items exceeded 0.80, indicating acceptable validity (Lynn, 1986). Based on the experts' feedback, item wording was revised, and the flow of lesson activities, as well as the chatbot's presentation of feedback and scaffolding, was refined.

Table 1: Content and learning objectives of the instructional program

Lesson	Stage	Learning activity
1	Tool exploration	• Infer the stellar properties that characterize stars. • Identify how to use various tools, such as spreadsheets and AI tools (LLMs).
2	Data collection	• Understand how data can be acquired through astronomical observation. • Collect observational data on stars and select the physical properties needed for analysis. • Model an H–R diagram using stellar properties and distinguish stellar types.
3	Data transformation and interpretation	• Understand how data can be acquired through astronomical observation. • Collect observational data on stars and select the physical properties needed for analysis. • Model an H–R diagram using stellar properties and distinguish stellar types.
4	Problem discovery and formulation	• Collect astronomical big data and select the physical properties needed for analysis. • Use a generative AI (LLM) tool to model a big-data H–R diagram. • Analyze H–R diagrams of star clusters of different ages, identify differences, and infer the causes of those differences.
5	Problem solving (Inductive/Deductive Inquiry)	• Collect astronomical big data and select the physical properties needed for analysis. • Use a generative AI (LLM) tool to model a big-data H–R diagram. • Analyze H–R diagrams of star clusters of different ages, identify differences, and infer the causes of those differences.
6	Conclusion and expression	• Create a visualized H–R diagram representing stellar types and evolution. • Present findings in a storytelling format using data visualizations.

LLM: Large language models

Table 2: Scaffolding strategies embedded in the AI Chatbot

Category	Conceptual scaffolding	Procedural scaffolding	Strategic scaffolding	Metacognitive scaffolding
Core function	Supports learners in identifying key concepts and perspectives by guiding what they should consider	Supports inquiry performance by guiding task procedures and methods for using tools	Suggests pathways and thinking strategies for problem solving	Supports learners in monitoring, planning, regulating, and evaluating their own understanding
Example prompts	“What are the key concepts related to this phenomenon?” “Think about the physical quantity related to the color of a star.”	“First, identify the physical quantities corresponding to the x-axis and y-axis.” “In what order should you proceed to construct an H–R diagram?”	“What differences do you find when you compare this result with another star?” “What strategy would be appropriate for explaining this phenomenon?”	“Why do you think so?” “If you review your answer so far, what would you revise?”

Instruments

To assess changes in participants’ science-positive experiences and attitudes toward AI before and after the program, quantitative instruments consisting of parallel-form items on a five-point Likert scale were administered.

The instrument for measuring science-positive experiences was adapted from the scale developed by Shin et al. (2017) to align with the study objectives. The instrument comprised five domains: affective experience in science learning, science self-concept, motivation for science learning, science career aspirations, and attitudes toward science. It included 35 items—20 positively worded and 15 negatively worded. For attitudes toward AI, the student attitude toward AI scale, developed and validated by Suh and Ahn (2022), was used. It consisted of 26 items across three dimensions – 4 cognitive, 10 affective, and 12 behavioral items – 17 of which were positively worded and 9 negatively worded.

The instruments demonstrated good reliability. Cronbach’s alpha for the science-positive experiences scale was 0.83 for the pre-test and 0.89 for the post-test, whereas for the attitudes toward AI scale, it was 0.82 for the pre-test and 0.85 for the post-test (Nunnally and Bernstein, 1994). Qualitative data

were collected through in-depth semi-structured interviews, reflective journals, chat logs between students and the chatbot, and observation logs.

Data Analysis

For the quantitative data, descriptive statistics (means and standard deviations) were calculated for each subfactor of the science-positive experiences scale and attitudes toward AI scales administered before and after the instructional program. Before testing pre–post differences, the normality assumption was assessed using the Shapiro–Wilk test. The significance values (*p*) for all subfactors exceeded 0.05, indicating that the normality assumption was satisfied. In addition, skewness and kurtosis were examined to further check whether the data distributions were distorted. Skewness values were within ± 3 , and kurtosis values within ± 7 , confirming that the data distributions were appropriate for parametric statistical analysis. Accordingly, paired-samples *t*-tests were conducted to examine pre–post changes, and effect sizes (Cohen’s *d*) were calculated to assess the practical magnitude of the effects (Cohen, 1988).

To explore changes in students’ learning experiences and perceptions following the AI chatbot-integrated instruction,

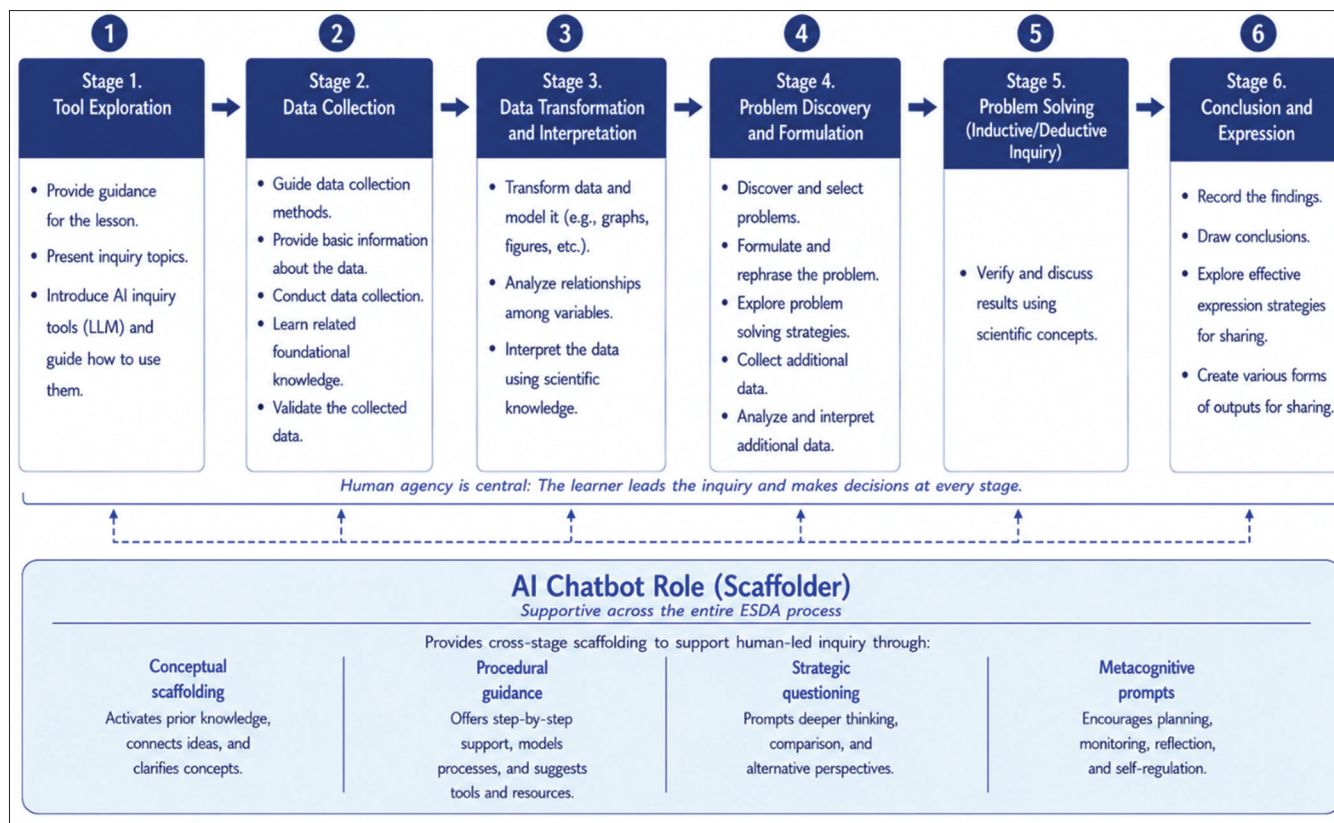


Figure 1: Exploratory scientific data analysis inquiry model-based instructional procedure and student-artificial intelligence chatbot interaction model. This figure was generated using ChatGPT (OpenAI) and refined by the authors

this study used the constant comparative method (Glaser and Strauss, 2017) to complement the quantitative findings. Data were reviewed repeatedly to identify meaning units related to interactions with the AI chatbot, conceptual understanding, problem-solving processes, collaborative inquiry, and changes in perceptions of AI. Next, the similarities and differences among these units were compared and coded, and the relationships among the codes were examined to derive higher-order categories. The resulting categories were interpreted in light of the quantitative findings on changes in science-positive experiences and attitudes toward AI.

To enhance credibility and validity, triangulation was conducted by cross-checking students' reflective journals, chatbot dialogue logs, observation logs, and interview data. In addition, the appropriateness of the codes and categories was reviewed through discussions among researchers.

FINDINGS

Effects of AI Chatbot-Integrated Science Instruction on Science-Positive Experiences

Paired-samples t-tests examined pre-post changes following AI chatbot-integrated instruction. The results are presented in Table 3.

The analysis showed that post-test scores were significantly higher than pre-test scores across all subfactors. Specifically,

affective experience in science learning significantly increased from the pre-test ($M = 3.122$, $SD = 0.618$) to the post-test ($M = 4.312$, $SD = 0.521$), $t = 18.40$, $p < 0.001$, $d = 1.56$, indicating a substantial effect size. Science self-concept also showed a significant increase from the pre-test ($M = 2.710$, $SD = 0.751$) to the post-test ($M = 3.594$, $SD = 0.793$), $t = 10.82$, $p < 0.001$, $d = 0.92$, indicating a large effect size.

Motivation for science learning likewise increased significantly from the pre-test ($M = 3.252$, $SD = 0.699$) to the post-test ($M = 3.949$, $SD = 0.508$), $t = 10.16$, $p < 0.001$, $d = 0.86$, whereas science career aspirations improved significantly from the pre-test ($M = 3.488$, $SD = 0.714$) to the post-test ($M = 4.207$, $SD = 0.609$), $t = 9.78$, $p < 0.001$, $d = 0.83$. Attitudes toward science also increased significantly from the pre-test ($M = 3.623$, $SD = 0.620$) to the post-test ($M = 4.256$, $SD = 0.559$), $t = 9.96$, $p < 0.001$, $d = 0.85$, indicating a large effect size.

The overall mean also increased significantly from the pre-test ($M = 3.239$, $SD = 0.680$) to the post-test ($M = 4.064$, $SD = 0.598$), $t = 10.03$, $p < 0.001$, $d = 0.85$, indicating a large effect size overall. These findings suggest that AI chatbot-integrated science instruction was associated with statistically significant and practically meaningful improvements across all subfactors of science-positive experiences.

The quantitative improvement in science-positive experiences was also reflected in the qualitative data. Qualitative analysis

Table 3: Paired-samples t-test results for science-positive experiences (n=138)

Category	Pre-test M (SD)	Post-test M (SD)	t	p	Cohen's d
Affective experience in science learning	3.122 (0.618)	4.312 (0.521)	18.40	<0.001	1.56
Science self-concept	2.710 (0.751)	3.594 (0.793)	10.82	<0.001	0.92
Motivation for science learning	3.252 (0.699)	3.949 (0.508)	10.16	<0.001	0.86
Science career aspirations	3.488 (0.714)	4.207 (0.609)	9.78	<0.001	0.83
Attitudes toward science	3.623 (0.620)	4.256 (0.559)	9.96	<0.001	0.85
Overall	3.239 (0.680)	4.064 (0.598)	10.03	<0.001	0.85

indicated that students reported reduced affective burden when learning scientific concepts, increased confidence in problem solving, and a greater willingness to participate in class through AI chatbot-integrated instruction. Four major patterns emerged.

First, students reported experiencing enjoyment and interest during scientific inquiry through their interactions with the chatbot. When students asked about unfamiliar content or entered incorrect responses, the chatbot provided immediate hints and explanations, helping them understand concepts more easily. Student A's statement illustrates that checking and correcting incorrect answers led to a clearer understanding beyond simply identifying the correct answer. Responses from Students A and B suggest that the chatbot encouraged collaborative activity and task engagement and served as a catalyst for participation in problem-solving they would not normally have attempted. This pattern is consistent with the quantitative finding that affective experience in science learning showed the largest effect size.

Student A: "We figured things out together by sharing what we didn't know, and even when we got something wrong, we tried to find the correct answer by looking at why that answer was wrong. As a result, I understood the content better, and it was fun."

Student B: "Using the chatbot to solve difficult problems and doing cooperative activities helped me understand the content more quickly, which I liked. I also liked that it made active participation in class possible."

Second, students reported feeling immersed in learning and engaged in self-directed problem-solving through chatbot interactions. They described how the chatbot's immediate feedback helped them identify errors, check what they did not know, and work through problems on their own. Student D's statement indicates that the chatbot's feedback supported error recognition and self-monitoring. The phrase "I can solve difficult problems on my own now" suggests that the chatbot lowered the perceived threshold of problem-solving and fostered confidence in science learning. This finding is consistent with the observed improvements in science self-concept and motivation for science learning.

Student C: "I lost track of time while solving science problems with the chatbot. It felt really easy when I was solving them."

Student D: "It was fascinating that the chatbot told me which parts I got wrong and what I didn't know. Now I can even solve difficult problems by myself."

Third, chatbot-integrated instruction was associated with increased collaborative inquiry and active participation. Students used chatbot conversations to check their understanding of concepts, compare answers with peers, and construct better explanations. This suggests that the chatbot functioned not merely as an individual learning tool but also as a mediating resource for collaborative inquiry, where students compared answers and adjusted explanations together. In particular, the fact that even students who usually disliked science showed a willingness to participate in task-solving when using the chatbot suggests that chatbot-based instruction may support participation in science learning.

Student A: "I think it was question 7. It was so difficult that no one in our group knew the answer. So I told the chatbot, 'Give us a hint,' and it said, 'Check the physical quantity that determines luminosity.' After that, we looked into luminosity and talked together to find the answer."

Fourth, some students reported positive learning experiences in chatbot-integrated lessons, though they did not necessarily conclude that these experiences had immediately led to a long-term preference for science itself. Comments from Students E and F suggest that chatbot-integrated instruction positively influenced understanding and interest, whereas broader changes in long-term preference for science or general perceptions of studying science may develop more gradually. This means that, although scores for attitudes toward science increased significantly, some students still distinguished between a positive change in their science-class experience and a sustained preference for science as a subject. Accordingly, the observed improvement in attitudes may be interpreted as a positive change arising from short-term classroom experiences; however, repeated, longer-term learning experiences may be needed for this change to develop into a stable, enduring preference for science.

Student E: "When I got stuck, the chatbot gave me hints, so I understood better, and the lesson content came back to me more easily. But whether I actually like science more now. I'm still not really sure."

Effects of AI Chatbot-Integrated Science Instruction on Attitudes toward AI

The subfactors of the attitudes toward AI scale consisted of the cognitive, affective, and behavioral dimensions. Paired-samples t-tests examined pre-post changes following the implementation of the instructional program (Table 4).

Table 4: Paired-samples t-test results for attitudes toward artificial intelligence (n=138)

Category	Pre-test M (SD)	Post-test M (SD)	t	p	Cohen's d
Cognitive dimension	3.351 (0.798)	4.246 (0.671)	11.57	<0.001	0.98
Affective dimension	3.646 (0.543)	4.266 (0.509)	10.43	<0.001	0.88
Behavioral dimension	2.905 (0.635)	3.885 (0.729)	12.69	<0.001	1.08
Overall	3.301 (0.659)	4.132 (0.636)	11.03	<0.001	0.94

The analysis revealed that post-test scores were significantly higher than pre-test scores across all subfactors. Specifically, the cognitive dimension significantly increased from the pre-test ($M = 3.351$, $SD = 0.798$) to the post-test ($M = 4.246$, $SD = 0.671$), $t = 11.57$, $p < 0.001$, $d = 0.98$, indicating a large effect size. The affective dimension also showed a significant increase from the pre-test ($M = 3.646$, $SD = 0.543$) to the post-test ($M = 4.266$, $SD = 0.509$), $t = 10.43$, $p < 0.001$, $d = 0.88$, again indicating a large effect size.

The behavioral dimension likewise increased significantly from the pre-test ($M = 2.905$, $SD = 0.635$) to the post-test ($M = 3.885$, $SD = 0.729$), $t = 12.69$, $p < 0.001$, $d = 1.08$, indicating a very large effect size. The overall mean also increased significantly from the pre-test ($M = 3.301$, $SD = 0.659$) to the post-test ($M = 4.132$, $SD = 0.636$), $t = 11.03$, $p < 0.001$, $d = 0.94$, indicating a large effect size. These findings suggest that AI chatbot-integrated science instruction was associated with statistically significant and practically meaningful improvements across all subfactors of students' attitudes toward AI.

The qualitative findings supported these quantitative results. Through chatbot interaction, students came to perceive AI not merely as a technical artifact but as a tool for learning and problem-solving. At the same time, they expressed both affective familiarity with AI and intentions to use it in the future. Three major patterns emerged.

First, students perceived AI as a useful tool for practical assistance during learning. They found the chatbot useful because it not only provided correct answers but also explained why answers were incorrect and guided them through the problem-solving process. This pattern links to changes in the cognitive dimension of attitudes toward AI, particularly perceptions of AI's necessity and educational value. In particular, through their interaction with the chatbot, students directly experienced how AI could be used in learning situations, and these experiences likely contributed to their acceptance of AI as a meaningful tool in school education.

Student B: "I thought AI would only check whether the answer was correct, but it actually helped because it explained why it was wrong."

Second, students showed reduced psychological barriers toward AI and described feeling more affectively familiar with it. The chatbot responded without negative judgment to incorrect answers or questions about content students did not understand, and students responded positively to these

interactions. Statements from Students D and G suggest that they perceived AI as both an intellectual tool for problem-solving and a medium that helped clarify understanding. However, expressions such as "smarter than people" or "able to tell us everything we do not know" also suggest a need to foster students' critical evaluation of AI responses alongside their positive perceptions.

Student D: "Even when AI was wrong, it responded nicely, so I didn't feel bad. That made me want to keep going."
Student G: "The chatbot is like glasses that make what I didn't know much clearer. It feels like it could tell us all the things we don't know – everything in everyday life."

Third, students expressed intentions to use AI for future learning, career exploration, and everyday problem-solving, a pattern closely linked to the improvement observed in the behavioral dimension of attitudes toward AI. Student E's statement suggests that the chatbot experience extended beyond science class to an intention to use AI in other subjects as well. Comments from Students A and E also indicate that their experience with AI stimulated their interest in future learning and career-related possibilities. These findings are consistent with the quantitative results, where the behavioral dimension showed the largest effect size.

Student E: "I think I'll probably use AI in other subjects too. When I asked it to summarize key points or solve problems, it did a good job."

Student A: "By using AI and the chatbot this time, I started thinking about AI-related careers and what I might be able to do through artificial intelligence."

DISCUSSION AND CONCLUSION

Discussion

This study examined the effects of AI chatbot-integrated instruction with embedded scaffolding on high school students' science-positive experiences and attitudes toward AI in the Earth science unit on stellar types and evolution.

Following the intervention, students showed significant improvements across all subdomains of science-positive experiences. Post-test scores were significantly higher than pre-test scores for affective experience in science learning, science self-concept, motivation for science learning, science career aspirations, and attitudes toward science with large overall effect sizes. The implications of these findings are as follows. First, the largest effect size was observed for affective experience in science learning, suggesting

that AI chatbot-integrated instruction enabled students to perceive science learning as more interesting and accessible. Qualitative findings also indicated that students enjoyed and were interested in science lessons, reporting that the chatbot helped them correct incorrect answers and clarify concepts by providing immediate hints and explanations. These findings are consistent with prior research showing that AI chatbots may function as supportive tools that help reduce learners' affective burden and facilitate participation in scientific inquiry (Hsu et al., 2023). Second, improvements in science self-concept and motivation for science learning may be attributed to the chatbot's immediate feedback and staged scaffolding. Students reported checking their errors, identifying gaps in their knowledge, and solving problems on their own through interactions with the chatbot. Statements like "Now I can solve difficult problems by myself" suggest that the chatbot lowered the problem-solving threshold and built confidence in science learning. This implies that the chatbot functioned not merely as a tool that provides correct answers, but also as an interactive support tool that helps learners monitor their understanding and engage in self-directed problem-solving (Wu and Yu, 2024). Third, the instruction appeared to promote collaborative inquiry and active participation. Qualitative findings suggest that students used the chatbot to check their understanding of concepts, compare answers with peers, and construct better explanations. Even students who typically showed little preference for science collaborated with peers to complete tasks when supported by the AI chatbot. This is consistent with Xu et al. (2024), who reported that lower-achieving students, like higher-achieving students, actively participated in dialogue with the AI chatbot. More broadly, it suggests that AI chatbots can function not only as individual learning tools but also as mediating tools that facilitate student interaction and collaborative meaning-making (Cress and Kimmerle, 2023; Feng, 2025). Fourth, although attitudes toward science improved significantly in the quantitative analysis, the qualitative data showed that some students distinguished between positive changes in their science classroom experiences and long-term preference for science as a subject. In other words, while students reported improved understanding and interest, they were reserved about whether the intervention had actually made them like science itself. This aligns with Osborne and Dillon's (2008) argument that positive class experiences do not necessarily translate directly into enduring preference for science as a discipline. Thus, the observed improvement in attitudes toward science may be interpreted as a positive change arising from short-term instructional experiences, while also suggesting that repeated, long-term learning experiences throughout the curriculum are needed for these changes to develop into stable, enduring preferences for science.

These findings carry several implications. First, the significant improvement in the cognitive dimension indicates that students came to perceive AI as an important domain worth learning about in school education. The cognitive dimension includes

perceptions of the importance of learning AI in school, the need for AI instruction, and the belief that all students should learn about AI. Thus, chatbot-integrated instruction helped students perceive AI not merely as a technical tool or convenience but as a meaningful domain of knowledge to be learned and understood within school education (Lee et al., 2023). In particular, because the AI chatbot in this study was used directly to learn about stellar types and evolution, students experienced AI not as a separate technological topic but as an educational resource that supports science learning. Second, the improvement in the affective dimension indicates that students came to view AI more positively as a useful and necessary technology for society and everyday life. This dimension includes perceptions that AI is important for social development, makes life more convenient, helps solve real-life problems, will be necessary in the future, and is worth learning about. This is consistent with prior studies indicating that using AI as an educational resource in science education contexts can positively influence learning motivation and attitudes (Fayzullina et al., 2025). Third, the largest effect size was found in the behavioral dimension, which includes intentions to pursue AI-related careers, willingness to participate in AI-related activities, willingness to continue learning about AI, interest in AI-related content, and self-perceptions of AI competence. The particularly large improvement suggests that chatbot use extended beyond understanding or favorable impressions of AI to more practical intentions to continue learning about and using AI. This finding is consistent with prior research showing that repeated chatbot use can significantly enhance behavioral intentions (Bora and Kölemen, 2025). Qualitative data further showed that students expressed intentions to use AI in other subjects, interest in AI-related careers and future learning, and expectations for what they could do with AI. Therefore, repeated use of the AI chatbot in science learning enabled students to experience AI as both a usable learning tool and a resource linked to future competencies.

Implications

The study carries several theoretical and practical implications. First, from a research perspective, the study extends prior work by examining the effects of generative AI-based science instruction on affective variables rather than solely on cognitive achievement. Prior research on educational chatbots has tended to focus on academic achievement, usability, satisfaction, language learning, and higher education contexts, whereas the present study examined both science-positive experiences and attitudes toward AI in a high school science education context. This suggests that research on AI chatbots should move beyond whether learning outcomes improve to explore how learners experience science and perceive AI as a learning tool.

Second, from the perspective of AI orchestration, the study presents a practical design framework. AI orchestration views the roles of teachers and AI not as substitutive but as complementary. As Holstein et al. (2019) argued, AI-based classrooms should be designed so that teachers and AI can function in tandem. In the present study, the teacher

designed learning goals, activity flow, prompt structures, and scaffolding types, whereas the AI chatbot provided immediate questions, hints, explanations, and feedback according to learners' responses. This structure demonstrates that, in science education, AI can be used not as a substitute for teachers but as a tool that extends teachers' instructional design.

Third, from a practical perspective, science teachers should not merely introduce AI chatbots into the classroom; they should also deliberately design question structures and feedback flows that guide students' thinking. The large effects observed for affective experience in science learning and the behavioral dimension of attitudes toward AI may be linked to students' experiences of support from the AI chatbot, reduced fear of failure, and opportunities to try again. This aligns with research suggesting that active participation and interaction positively influence learning outcomes (Chi and Wylie, 2014; Freeman et al., 2014). Accordingly, in science education, AI chatbots should be designed not as tools for information retrieval or answer checking, but as inquiry partners that promote question generation, explanation comparison, evidence evaluation, and reflection.

Limitations

This study has several limitations. First, because this study employed a quasi-experimental one-group pre-test–post-test design, it could not fully rule out potential threats to internal validity. In particular, in the absence of a control group, a novelty effect – students' initial enthusiasm or excitement about interacting with an AI chatbot – may have contributed, at least in part, to the substantial pre–post gains in science-positive experiences and attitudes toward AI observed in this study. Accordingly, these gains should be interpreted with caution, as they may reflect a combination of the instructional intervention and the novelty of the technology rather than the instructional intervention alone. Future studies should include control or comparison groups and conduct longer-term or repeated implementations to distinguish sustained instructional effects from short-term novelty effects.

Second, the participants were limited to 11th-grade students from a single high school in a specific region, restricting the generalizability of the findings. Since the effects of chatbot-integrated instruction may vary depending on students' prior experience with AI chatbots, science learning levels, familiarity with digital tools, and school digital infrastructure, future studies should include students from diverse regions, school levels, academic backgrounds, and digital experiences.

Third, the intervention consisted of only six lessons, measuring changes in affective variables over a relatively short period. Although science-positive experiences and attitudes toward AI showed significant improvement, affective variables tend to develop through the accumulation of long-term experiences. Therefore, future research should examine the sustainability of the effects through delayed post-tests or longer-term interventions spanning a semester or a full academic year. Prior research emphasizing the importance

of long-term experiences and learning contexts in shaping science attitudes and interest further supports the need for such follow-up studies. Future research should compare multiple AI chatbot platforms or apply the same scaffolding design across different platforms to examine differences attributable to platform characteristics.

Fourth, although the chatbot was designed to provide scaffolding based on learners' responses, we did not establish a formal procedure to verify whether the intended scaffolding, particularly metacognitive prompts, was delivered consistently across student interactions. This limits our ability to determine whether the scaffolding was implemented as intended and to examine the contribution of specific scaffolding strategies to the observed outcomes. Future studies should standardize the scaffolding protocol by specifying the instructional purpose, the conditions under which each type of support is provided, and the structure of the prompts. Researchers could also systematically analyze chatbot interaction logs using an implementation-fidelity rubric or checklist to examine whether the intended scaffolding was delivered as designed across learners and instructional stages. Such procedures would enhance the reproducibility of chatbot-based interventions and allow a more precise examination of the effects of specific scaffolding strategies.

REFERENCES

- Ainley, M., & Ainley, J. (2011). Student engagement with science in early adolescence: The contribution of enjoyment to students' continuing interest in learning about science. *Contemporary Educational Psychology*, 36(1), 4-12.
- Ait Baha, T., El Hajji, M., Es-Saady, Y., & Fadili, H. (2024). The impact of educational chatbot on student learning experience. *Education and Information Technologies*, 29(8), 10153-10176.
- Armbruster, P., Patel, M., Johnson, E., & Weiss, M. (2009). Active learning and student-centered pedagogy improve student attitudes and performance in introductory biology. *CBE Life Sciences Education*, 8(3), 203-213.
- Basu, S., Biswas, G., & Kinnebrew, J.S. (2017). Learner modeling for adaptive scaffolding in a computational thinking-based science learning environment. *User Modeling and User-Adapted Interaction*, 27(1), 5-53.
- Birenbaum, M. (2023). The chatbots' challenge to education: Disruption or destruction? *Education Sciences*, 13(7), 711.
- Bora, B.Y., & Kölemen, C.Ş. (2025). Integrating AI into instructional design: A case study on digital photography education in higher education. *Contemporary Educational Technology*, 17(3), ep583.
- Chang, D.H., Lin, M.P.C., Hajian, S., & Wang, Q.Q. (2023). Educational design principles of using AI chatbot that supports self-regulated learning in education: Goal setting, feedback, and personalization. *Sustainability*, 15(17), 12921.
- Chang, J., Park, J., & Park, J. (2023). Using an artificial intelligence chatbot in scientific inquiry: Focusing on a guided-inquiry activity using Inquirybot. *Asia-Pacific Science Education*, 9(1), 44-74.
- Chi, M.T.H., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist*, 49(4), 219-243.
- Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. 2nd ed. France: Lawrence Erlbaum Associates.
- Collins, A., Brown, J.S., & Newman, S.E. (1989). Cognitive apprenticeship: Teaching the crafts of reading, writing, and mathematics. In: Resnick, L.B., (Ed.), *Knowing, Learning, and Instruction: Essays in Honor of Robert Glaser*. France: Lawrence Erlbaum Associates, pp. 453-494.

- Cress, U., & Kimmerle, J. (2023). Co-constructing knowledge with generative AI tools: Reflections from a CSCL perspective. *International Journal of Computer-Supported Collaborative Learning*, 18(3), 607-614.
- Debets, T., Banihashem, S.K., Joosten-Ten Brinke, D., Vos, T.E.J., Maillette De Buy Wenniger, G., & Camp, G. (2025). Chatbots in education: A systematic review of objectives, underlying technology and theory, evaluation criteria, and impacts. *Computers and Education*, 234, 1-34.
- Fassbender, W.J. (2025). Of teachers and centaurs: Exploring the interactions and intra-actions of educators on AI education platforms. *Learning, Media and Technology*, 50(3), 352-364.
- Fayzullina, A.R., Filippova, A.A., Garnova, N.Y., Astakhov, D.V., Kalmazova, N., & Zariyova, Z.F. (2025). Artificial intelligence in science education: A systematic review of applications, impacts, and challenges. *Contemporary Educational Technology*, 17(4), ep613.
- Feng, S. (2025). Group interaction patterns in generative AI-supported collaborative problem solving: Network analysis of the interactions among students and a GAI chatbot. *British Journal of Educational Technology*, 56(5), 2125-2145.
- Freeman, S., Eddy, S.L., McDonough, M., Smith, M.K., Okoroafor, N., Jordt, H., & Wenderoth, M.P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences*, 111(23), 8410-8415.
- Glaser, B., & Strauss, A. (2017). *Discovery of Grounded Theory: Strategies for Qualitative Research*. London: Routledge.
- Graesser, A.C. (2016). Conversations with AutoTutor help students learn. *International Journal of Artificial Intelligence in Education*, 26(1), 124-132.
- Hannafin, M., Land, S., & Oliver, K. (1999). Open learning environments: Foundations, methods, and models. In: Reigeluth, C.M., (Ed.), *Instructional-Design Theories and Models: A New Paradigm of Instructional Theory*. Vol. 2. France: Lawrence Erlbaum Associates, pp. 115-140.
- Hew, K.F., Huang, W., Du, J., & Jia, C. (2023). Using chatbots to support student goal setting and social presence in fully online activities: Learner engagement and perceptions. *Journal of Computing in Higher Education*, 35, 40-68.
- Hewson, M.G., & Hewson, P.W. (1983). Effect of instruction using students' prior knowledge and conceptual change strategies on science learning. *Journal of Research in Science Teaching*, 20(8), 731-743.
- Holstein, K., & Olsen, J.K. (2023). Human-AI co-orchestration: The role of artificial intelligence in orchestration. In: *Handbook of Artificial Intelligence in Education*. London: Edward Elgar Publishing, pp. 309-321.
- Holstein, K., McLaren, B.M., & Aleven, V. (2019). Co-designing a real-time classroom orchestration tool to support teacher-AI complementarity. *Journal of Learning Analytics*, 6(2), 27-52.
- Hsu, T.C., Huang, H.L., Hwang, G.J., & Chen, M.S. (2023). Effects of incorporating an expert decision-making mechanism into chatbots on students' achievement, enjoyment, and anxiety. *Educational Technology and Society*, 26(1), 218-231.
- Jeon, J., & Lee, S. (2023). Large language models in education: A focus on the complementary relationship between human teachers and ChatGPT. *Education and Information Technologies*, 28, 15873-15892.
- Kim, H., Hwang, J., Kim, T., Choi, M., Lee, D., & Ko, J. (2026). Impact of generative artificial intelligence on learning: Scaffolding strategies and self-directed learning perspectives. *International Journal of Human-Computer Interaction*, 42(5), 2965-2987.
- Kuhail, M.A., Alturki, N., Alramlawi, S., & Alhejori, K. (2023). Interacting with educational chatbots: A systematic review. *Education and Information Technologies*, 28, 973-1018.
- Labadze, L., Grigolia, M., & Machaidze, L. (2023). Role of AI chatbots in education: Systematic literature review. *International Journal of Educational Technology in Higher Education*, 20(1), 56.
- Lee, J., An, T., Chu, H.E., Hong, H.G., & Martin, S.N. (2023). Improving science conceptual understanding and attitudes in elementary science classes through the development and application of a rule-based AI chatbot. *Asia-Pacific Science Education*, 9(2), 1-48.
- Lelliott, A., & Rollnick, M. (2010). Big ideas: A review of astronomy education research 1974-2008. *International Journal of Science Education*, 32(13), 1771-1799.
- Li, P.H., Lee, H.Y., Lin, C.J., Wang, W.S., & Huang, Y.M. (2025). InquiryGPT: Augmenting ChatGPT for enhancing inquiry-based learning in STEM education. *Journal of Educational Computing Research*, 62(8), 1937-1966.
- Liu, H., Zhang, Y., & Jia, J. (2024). The design of guiding and adaptive prompts for intelligent tutoring systems and its effect on students' mathematics learning. *IEEE Transactions on Learning Technologies*, 17, 1353-1363.
- Lynn, M.R. (1986). Determination and quantification of content validity. *Nursing Research*, 35(6), 382-386.
- National Research Council. (2012). *A Framework for K-12 Science Education: Practices, Crosscutting Concepts, and Core Ideas*. United States: National Academies Press.
- Nunnally, J.C., & Bernstein, I.H. (1994). *Psychometric Theory*. 3rd ed. United States: McGraw-Hill.
- Osborne, J., & Dillon, J. (2008). *Science Education in Europe: Critical Reflections*. Vol. 13. London: The Nuffield Foundation. Available from: https://efepereth.wdfiles.com/local/files/science-education/sci_ed_in_europe_report_final.pdf [Last accessed on 2026 Mar 30].
- Osborne, J., Simon, S., & Collins, S. (2003). Attitudes towards science: A review of the literature and its implications. *International Journal of Science Education*, 25(9), 1049-1079.
- Quintana, C., Reiser, B.J., Davis, E.A., Krajcik, J., Fretz, E., Duncan, R.G., Kyza, E., Edelson, D., & Soloway, E. (2004). A scaffolding design framework for software to support science inquiry. *Journal of the Learning Sciences*, 13(3), 337-386.
- Schepman, A., & Rodway, P. (2020). Initial validation of the general attitudes towards artificial intelligence scale. *Computers in Human Behavior Reports*, 1, 100014.
- Shin, Y., Kwak, Y., Kim, H.K., Lee, S.Y., Lee, S., & Kang, H.S. (2017). Study on the development of test for indicators of positive experiences about science. *Journal of the Korean Association for Science Education*, 37(2), 335-346.
- Son, M., & Jeong, D. (2020). Development of data-driven science inquiry model and strategy for cultivating knowledge-information-processing competency. *Journal of The Korean Association For Science Education*, 40(6), 657-670.
- Song, Y., Huang, L., Zheng, L., Fan, M., & Liu, Z. (2025). Interactions with generative AI chatbots: Unveiling dialogic dynamics, students' perceptions, and practical competencies in creative problem-solving. *International Journal of Educational Technology in Higher Education*, 22, 12.
- Suh, W., & Ahn, S. (2022). Development and validation of a scale measuring student attitudes toward artificial intelligence. *SAGE Open*, 12(2), 21582440221100463.
- Tang, K.S., & Putra, G.B.S. (2026). Generative AI as a dialogic partner: Enhancing multiple perspectives, reasoning, and argumentation in science education with customized chatbots. *Journal of Science Education and Technology*, 35, 128-140.
- Van De Pol, J., Volman, M., & Beishuizen, J. (2010). Scaffolding in teacher-student interaction: A decade of research. *Educational Psychology Review*, 22(3), 271-296.
- Wood, D., Bruner, J.S., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of Child Psychology and Psychiatry*, 17(2), 89-100.
- Wu, R., & Yu, Z. (2024). Do AI chatbots improve students' learning outcomes? Evidence from a meta-analysis. *British Journal of Educational Technology*, 55(1), 10-33.
- Xu, Y., Zhu, J., Wang, M., Qian, F., Yang, Y., & Zhang, J. (2024). The impact of a digital game-based AI chatbot on students' academic performance, higher-order thinking, and behavioral patterns in an information technology curriculum. *Applied Sciences*, 14(15), 6418.
- Zhai, C., Wibowo, S., & Li, L.D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments*, 11, 28.