Chatbots As Digital Learning Tools: Analyzing Their Effects on Student Outcomes Using Solomon's Approach

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DOI: https://doi.org/10.51244/IJRSI.2026.1305000111

Received: 07 May 2026; Accepted: 12 May 2026; Published: 03 June 2026

ABSTRACT

Mathematics learning becomes more meaningful when supported by intelligent technologies that enhance students' problem-solving processes. This study examined the effectiveness of the use of chatbot-assisted instruction using Solomon's Model Approach in enhancing students' performance in Mathematics during the school year 2025–2026. A quantitative quasi-experimental design using the Solomon four-group model was employed. The participants were 76 Maritime students from a private higher education institution in Ozamiz City, Misamis Occidental, Philippines, randomly assigned into two experimental and two control groups. A researcher-made problem-solving test was used, and data were analyzed using mean, standard deviation, independent samples t-test, and two-way ANOVA. Results showed that both groups demonstrated very low pretest performance. In the posttest, all groups improved; however, students exposed to the use of chatbot-assisted instruction achieved significantly higher performance than those who received traditional instruction. No significant differences were found between the two control groups and between the two experimental groups. Likewise, there was no significant interaction effect between pretest exposure and the use of chatbot-assisted instruction. The use of chatbot-assisted instruction effectively improves students' mathematical performance and remains effective regardless of pretest exposure, highlighting its value as a supportive instructional tool in mathematics education. Math instructors may integrate chatbot-assisted instruction alongside traditional teaching strategies to enhance students' learning outcomes in mathematics.

Keywords: artificial intelligence, chatbot-assisted instruction, mathematics performance, problem-solving skills, Solomon four-group design

INTRODUCTION

Mathematics instruction in the 21st century has shifted from traditional teacher-centered approaches to learner-centered, technology-integrated methods that emphasize inquiry, collaboration, and real-world problem-solving. This evolution underscores the necessity for digital tools that foster student engagement and comprehension. The adoption of AI chatbots is consistent with the global trend toward technology-enhanced learning, which supports self-paced, interactive, and adaptive educational experiences (Awang et al., 2025). As reliance on digital tools increases, educators encounter both opportunities and challenges in leveraging these technologies to improve understanding, motivation, and performance in mathematics (Infante et al., 2025). Consequently, mathematics teachers are encouraged to utilize AI chatbots to address diverse learning needs, deliver immediate feedback, and support differentiated instruction. Given that mathematics is frequently perceived as abstract and anxiety-inducing, there is a pressing need for innovative pedagogies that enhance accessibility and engagement (Laksana & Fiangga, 2022). Within this context, AI chatbots offer promising opportunities to foster inquiry-based, personalized, and responsive learning experiences (Moral-Sánchez et al., 2023).

Chatbots are AI-powered conversational systems that simulate human interactions through natural language processing. These tools support constructivist and socio-constructivist learning by enabling learners to actively construct knowledge via guided exploration and interaction (Li et al., 2023). In mathematics education, chatbots such as ChatGPT, Photomath, Mathway, Microsoft Copilot, Symbolab, and Khanmigo are widely used to facilitate problem-solving, deliver real-time feedback, and enhance conceptual understanding.

Recent research underscores the expanding influence of advanced conversational AI tools in education. For example, ChatGPT has been shown to improve students' mathematical reasoning by providing detailed explanations, multiple solution strategies, and interactive dialogue that replicates individualized tutoring (Kasneci et al., 2023). Cici integrates AI support within productivity platforms, allowing learners to generate explanations, summarize mathematical concepts, and access contextual assistance during learning activities (Microsoft, 2023). Additionally, Google Gemini (formerly Bard) has demonstrated potential in facilitating inquiry-based learning through question generation, concept clarification, and real-time knowledge retrieval (Google, 2024).

Jančařík et al. (2023) highlighted that chatbots address learners' digital preferences by offering immediacy and engagement often absent in traditional instructional methods. These tools also provide scaffolding and step-by-step guidance, supporting students within their Zone of Proximal Development (Cheng et al., 2024) and enabling the gradual development of independence and confidence in mathematical problem-solving. Furthermore, the interactive features of AI chatbots align with formative assessment practices by continuously adapting responses to student input, thereby delivering immediate feedback and personalized learning pathways (Vanichvasin, 2021).

Multiple studies have demonstrated that chatbots effectively enhance problem-solving performance and mathematical comprehension (Dahal et al., 2025). Chatbot-based instruction increases the accessibility of abstract and procedural knowledge, bridging the divide between teacher-led and independent learning (Vintere et al., 2024). In flipped classroom settings, AI chatbots have been shown to promote engagement and reflective thinking (Martínez-Téllez & Camacho-Zuñiga, 2023). Additionally, Laja et al. (2025) reported that chatbots deliver differentiated feedback based on learners' proficiency levels, serving as effective co-facilitators that extend instructional support beyond the classroom.

In addition to cognitive benefits, chatbots also positively impact affective learning outcomes. Students utilizing AI tools report increased motivation, greater confidence, and reduced anxiety due to immediate feedback and non-judgmental support (Van Doc et al., 2023). Chatbots function as digital companions, enhancing emotional well-being (Luckyardi et al., 2024) and fostering inclusivity by addressing diverse learning needs (Mageira et al., 2022). Comparative studies of advanced chatbots such as GPT-4 and Google Bard indicate improved accuracy and contextual explanations in mathematics (Plevris et al., 2023). However, El Azhari and Daoudi (2023) stress the importance of ethical and responsible AI integration. Dahal et al. (2023) further note that educators must balance AI's computational capabilities with strategies that cultivate critical and analytical reasoning.

Systematic reviews have identified chatbots as highly promising tools for adaptive learning (Awang et al., 2025). These systems can automate responses, decrease teacher workload, and facilitate continuous learning opportunities (El Azhari et al., 2023). Nevertheless, concerns regarding privacy, bias, and data security remain significant (Wardat et al., 2024). As a result, responsible implementation necessitates collaboration among educators, developers, and policymakers to uphold inclusivity and ethical standards (Pappagallo, 2024). When effectively integrated, AI chatbots constitute a technological and pedagogical innovation that can enhance engagement, conceptual understanding, and confidence in mathematics (Yeo et al., 2024). the effectiveness of such digital interventions, robust experimental designs are necessary. One of the most comprehensive is Solomon's Four-Group Experimental Design, which combines pretest-posttest and posttest-only structures to measure true treatment effects. This design minimizes testing biases by using two experimental and two control groups—one set pretested and the other not—to isolate pretest sensitization effects (Saravanakumar et al., 2021). According to Sahin and Kilic (2024), this model enhances internal validity by allowing comparisons that reveal both main and interaction effects of the intervention.

Yetkin and Baser (2025) characterized the Solomon design as highly effective for educational research, as it ensures that observed outcomes are attributable to the intervention rather than familiarity with testing procedures. Prabakaran and Saravanakumar (2021) further noted that this design facilitates the generalization of results across different contexts, making it particularly suitable for evaluating pedagogical innovations such as chatbots. Jin et al. (2025) emphasized that the approach distinguishes authentic learning gains from those resulting from test exposure, while El Karkri et al. (2025) confirmed its capacity to reduce bias and improve the accuracy of research findings.

Golaki et al. (2022) identified the Solomon design as one of the most rigorous frameworks for educational experimentation, offering both practicality and scientific control. Sharp (2023) argued that this design strengthens both internal and external validity, leading to more credible outcomes. Nair and Mathew (2021) highlighted its suitability for studies aiming to establish causal relationships between instructional strategies and learning outcomes, while Golboni et al. (2024) noted its effectiveness in mitigating external variables that could influence performance. Young (2024) concluded that the comprehensive design enables researchers to verify the consistency of effects, thereby ensuring robust findings when assessing innovative teaching tools such as chatbots.

Despite these advantages, several challenges remain. Chatbots can produce inaccuracies, demonstrate limited contextual understanding, or foster overreliance on automation (Davar et al., 2025). Learners may also experience “AI hallucination,” in which chatbots generate plausible yet incorrect responses (Calonge et al., 2023). Plevris et al. (2023) advised that human oversight is necessary to ensure accuracy, while Mageira et al. (2022) emphasized that chatbots should serve as supplemental rather than substitutive tools, enriching instruction while preserving teacher-student interaction. Furthermore, although the adoption of AI-powered chatbots in education is increasing, empirical research specifically evaluating their effectiveness in mathematics instruction remains limited. Much of the existing literature focuses on general AI applications or learner perceptions rather than on measurable outcomes, such as conceptual understanding or problem-solving performance in mathematics. This gap underscores the need for systematic investigations into the impact of chatbot integration on students’ mathematical achievement, engagement, and higher-order thinking skills, particularly within structured classroom environments.

This study utilizes the described experimental framework to evaluate the effectiveness of chatbot-assisted instruction on students’ mathematical outcomes. Specifically, it investigates whether integrating chatbots as digital learning tools improves student performance relative to traditional instruction and examines the influence of pretesting on performance variation. The results are expected to provide empirical evidence regarding the pedagogical value of chatbots in mathematics, thereby informing decisions about technology integration in educational settings.

This research is significant for multiple stakeholders. For students, chatbot-assisted learning can enhance engagement, confidence, and comprehension. For teachers, the study provides a framework for effectively integrating AI tools into instructional practice. Curriculum developers and administrators may leverage the findings to modernize curricula in alignment with national educational objectives. Additionally, the outcomes may inform policymakers in promoting responsible AI adoption and guide future researchers in exploring broader applications of AI in education. By employing Solomon’s Four-Group Design, this study contributes to the discourse on evidence-based innovations that support equitable, engaging, and effective mathematics education in the digital era.

Statement of the Problem

The study aimed to evaluate the effectiveness of implementing a chatbot, applying the Solomon’s Model Approach, in enhancing the outcomes of the students in mathematics in one of the private higher education institutions during the School Year 2025–2026.

Specifically, it sought to answer the following questions:

1. What are the students' performance in the pretest for the control and experimental groups before implementing the chatbot using Solomon’s Model Approach?
2. What are the students' performance in the posttest for the control groups who did not receive the chatbot intervention using Solomon’s Model Approach?
3. What are the students' performance in the posttest for the experimental groups after the implementation of the chatbot using Solomon’s Model Approach?

4. Is there a significant difference in the performance of students in the pretest between control and experimental groups?
5. Is there a significant difference in the performance of students in the posttest who underwent the implementation of chatbot using Solomon's Model Approach (experimental group) and those with no intervention (control group)?
6. Is there a significant difference in the performance of students in the posttest between the two control groups?
7. Is there a significant difference in the performance of students in the posttest between the two experimental groups?
8. Is there an interaction effect between the pretest and the implementation of chatbot using Solomon's Model Approach on students' performance for the experimental group?

RESEARCH METHODOLOGY

Design

This quantitative study used the Solomon's four-group design, a quasi-experimental study in which subjects were randomly divided into four groups to conduct both a pretest-posttest control group design experiment and a posttest-only control group design investigation simultaneously. In this design, the treatment and control groups had two subgroups: one that received a pretest before the intervention and one that did not, guaranteeing that the study controlled for pretest effects on outcomes. The dependent variable was the students' outcomes. A control group enabled a comparison of the effectiveness of the Solomon's Model Approach to traditional teaching approaches (Creswell & Creswell, 2017).

In this study, four groups were used to confirm the validity of the experimental results and account for the effects of pretesting. This Solomon four-group design was beneficial when examining whether a pretest, either by itself or in conjunction with the treatment, affected the outcomes.

Setting

The study was conducted in one of the private, non-sectarian higher education institutions in Ozamiz City, Misamis Occidental, Philippines. Recognized in 2024 with ISO 21001:2018 certification and as the only Autonomous Higher Education Institution in Misamis Occidental and Northwestern Mindanao, the institution is known for its commitment to academic excellence, inclusivity, and continuous improvement. With its strong integration of educational technologies in mathematics instruction and emphasis on student development, the university provided an appropriate setting for examining the effectiveness of chatbot-assisted instruction using Solomon's Model Approach on students' problem-solving performance. The institution's adoption of innovative teaching strategies and technology-supported learning environments enabled a meaningful investigation into how AI-powered chatbots could enhance students' understanding of mathematical concepts and improve their overall academic outcomes.

Participants

The study involved 76 Maritime students enrolled in a private higher education institution in Ozamiz City during the 2025–2026 academic year, all of whom were taking the Mathematics in the Modern World course. Participants were selected using purposive random sampling, targeting students identified by their teachers as needing intervention in Mathematics based on prior assessments and classroom performance. The sample exhibited similar demographic characteristics, including age range, academic background, and exposure to a uniform Mathematics curriculum, thereby ensuring comparability across groups.

In accordance with the Solomon Four-Group Experimental Design, the 76 students were randomly assigned to four groups of 19 members each. The first experimental group (E_1) completed a pretest, participated in chatbot-based instruction as the intervention, and then took the posttest. The first control group (C_1) completed both the pretest and posttest but received traditional instruction instead of the chatbot intervention. The second experimental group (E_2) did not take the pretest but received chatbot-based instruction and subsequently

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

completed the posttest. The second control group (C_2) neither took the pretest nor received the intervention, participating only in the posttest.
This grouping enabled measurement of both the effect of the chatbot intervention on student outcomes and the potential influence of the pretest on posttest results. Random assignment of participants minimized potential biases and strengthened the validity and reliability of the findings. Selection criteria required that students be officially enrolled during the 2025–2026 academic year, be enrolled in Math 1, and provide full and voluntary consent to participate. All criteria were verified prior to the commencement of the study.

Instruments

The researcher used the following research instruments to gather data in the study:

Problem Solving Test. This contains 100 items, 40% of which are easy questions (remembering and understanding), 30% of which are average questions (applying and analyzing), and 30% of which are difficult questions (evaluating and creating).

The test questions were self-constructed and formulated based on the learning competencies for the preliminary period, specifically covering Lesson 1: The Nature of Mathematics, Lesson 2: The Language of Mathematics, Lesson 3: Problem Solving, Lesson 4: Reasoning, and Lesson 5: Polya's Problem-Solving Strategies. The reliability of the instrument was tested through a pilot study involving a subset of maritime students who were not included in the main study. With a Cronbach's Alpha coefficient of 0.70, the instrument was deemed reliable and acceptable for use in the study.

To determine the level of students' performance in the pretest and posttest, the researcher used the hypothetical mean range and its adjectival equivalent.

Scores	Grade Equivalent	Description
90 – 100	90 – 100	Meets minimum competence with exceptional score
80 – 89	80 – 89	Meets minimum competence with over and above average score
71 – 79	71 – 79	Meets minimum competence with above average score
63 – 70	63 – 70	Meets minimum competence with average score
60 – 62	60 – 62	Meets minimum competence
Below 60	Below 60	Does not meet the minimum expectation

Data Gathering Procedure

Before beginning the investigation, the researcher obtained the Dean of the Graduate School's approval after the thesis advisor's approval. The researcher obtained necessary approvals from various stakeholders, including the research ethics board, principal, teachers, and parents, ensuring compliance with ethical guidelines. Informed consent was obtained from the parents, and assent was obtained from the learners involved in the study.

After the permissions were secured, teaching implementing a chatbot using Solomon's Four Group Model was conducted in the classroom. The investigator provided the participants with an overview of the study's objectives, specifically for the Maritime students. Before data collection, a formal letter of consent was presented to each respondent's parent or guardian, outlining the study's purpose and assuring confidentiality. This study employed Solomon's Four-Group design. Data collection began with administering a researcher-developed word problem pretest to the first 2 groups (Control A and Experimental A), consisting of 80 Maritime students. The test results

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

were analyzed using the hypothetical mean range used by DepEd to determine students' performance on the pretest.
The intervention was implemented over one month following the pretest, using chatbot-based instruction in accordance with the Solomon Four-Group Design. Sessions were conducted for three hours per week, scheduled according to the students' regular class timetable and classroom. The teacher-researcher conducted demonstration teaching on how to properly prompt chatbots, employing discussion and the chalk-talk method. This approach, integrated with the chatbot following Solomon's design, aimed to enhance students' outcomes in Mathematics.

After taking the pretest, the intervention or treatment will be provided to the participants. Following the intervention period, a posttest will be administered to all four groups to assess the effectiveness of the chatbot-based instruction using Solomon's Four-Group Design and to measure changes in students' problem-solving skills. The posttest data will be tallied and analyzed to determine the impact of the intervention on the students' mathematical outcomes, with appropriate statistical methods applied to control for differences among the Solomon groups. After the posttest, the scores of all four groups will be compared to evaluate the effectiveness of the chatbot-assisted instruction.

Group 1 vs. Group 2 will show if the treatment had an effect after controlling for pretest sensitization. Group 3 vs. Group 4 shows whether the treatment alone, without the influence of a pretest, affects word-problem-solving ability. This method will help determine whether the treatment (a chatbot-based instruction implemented using Solomon's Four Group Design) effectively improves word-problem-solving skills while controlling for potentially confounding factors such as pre-existing skills or test sensitization. It will also help control for confounding variables that may impact the results, ensuring that any observed effects are due to the treatment rather than external factors.

Ethical Consideration

The paper was reviewed by the MU-Research Ethics Committee (MUREC) before data collection. The researcher asked the participants for voluntary participation to ensure the ethical aspects of the conduct of the study. The participants were informed that they would not be harmed in any way. Respect was prioritized for the dignity of the participants. The security of participants' information, an acceptable level of confidentiality for study data, and the anonymity of research participants were guaranteed. Moreover, deception and exaggeration about the aim and objectives of the research were avoided; affiliations in any form, sources of funding, and any possible conflicts of interest were declared. Finally, any communication about the research was conducted honestly and transparently, and any misleading information or misinterpretations of primary data findings were avoided.

The researcher asked the participants to sign the Informed Consent Form as proof of their voluntary participation, with the assurance that only the researcher would have access to the research data. They were also informed that they could withdraw from the study at any time. To ensure equitable participation and avoid digital access barriers during chatbot-assisted instruction, free and reliable internet access was provided to all participants throughout the intervention period. Furthermore, they were assured that the research data would be discarded six months after the research findings were presented to the Thesis Committee.

Data Analysis

With the aid of SPSS software, the following statistical tools were used in the study:

Mean and standard deviation. These were used to determine the pre-test and post-test problem solving performance of students.

T-test. This tool was used in comparing the students' problem-solving performance between two groups (experimental vs. control, and two control groups).

Two-Way ANOVA. It was used to assess the interaction effects between the pretest and the intervention on the posttest results.

RESULTS AND DISCUSSION

Students' Performance in the Pretest for the Control and Experimental Groups Before Implementing the Chatbot Using Solomon's Model Approach

Table 1 presents the students' performance in the pretest for both the control and experimental groups before the implementation of chatbot-assisted instruction using Solomon's Model Approach. The results showed that the control group obtained (M = 27.42), while the experimental group recorded (M = 26.05). Based on the given performance scale, both mean scores fell below 60, which corresponded to the category "Does not meet the minimum expectation." This indicated that, prior to the intervention, students in both groups demonstrated very low mastery of the mathematical concepts assessed in the pretest. The findings suggested that students lacked the necessary knowledge and problem-solving skills, highlighting the need for effective instructional interventions to improve their performance.

In response to such learning gaps, educational innovations such as chatbot-assisted learning have been introduced to support teaching and learning processes. Chatbots are artificial intelligence–driven conversational systems designed to simulate human interaction and provide automated responses to users' questions or requests. In educational settings, chatbots can guide students through problem-solving procedures, explain mathematical concepts, and provide instant feedback on students' responses. Teachers may integrate chatbots in classroom instruction as supplementary learning tools that allow students to practice solving problems independently, revisit lesson explanations, and clarify misconceptions beyond classroom discussions. Through interactive conversations and guided learning assistance, chatbot technologies can help enhance student engagement and promote self-directed learning experiences within and beyond the classroom.

The results of the control group revealed that all 19 students, representing 100.00%, were categorized under "Does not meet the minimum expectation." None of the students achieved any level of minimum competence across the defined performance categories. This finding indicated that the students in the control group had very limited understanding of the mathematical concepts and were unable to demonstrate the expected level of competence during the pretest. It also suggested that the students experienced significant difficulty in applying appropriate problem-solving strategies and mathematical reasoning skills.

Similarly, the experimental group demonstrated the same pattern of performance during the pretest. All 19 students, or 100.00%, were classified under "Does not meet the minimum expectation." No students reached any of the categories associated with meeting minimum competence. This indicated that the experimental group also had very low prior knowledge and lacked sufficient problem-solving skills before the implementation of the chatbot-assisted instructional approach. The uniformity of results in this group further emphasized the need for instructional support and intervention.

A comparison of the control and experimental groups indicated that both groups had identical performance distributions, with 100.00% of students in each group classified under "Does not meet the minimum expectation." Furthermore, (M = 27.42) for the control group and (M = 26.05) for the experimental group showed that both groups had nearly equivalent levels of prior knowledge. This similarity in baseline performance confirmed that the two groups were comparable before the intervention, which is essential in experimental research. It ensured that any differences observed in the posttest could be more confidently attributed to the instructional intervention rather than to pre-existing differences in students' abilities.

A growing body of research has highlighted the significant role of artificial intelligence and chatbot technologies in enhancing teaching and learning processes in modern educational environments. For instance, Yuensook et al. (2025) emphasized that AI-supported learning systems have the capacity to provide personalized instruction and adaptive feedback, enabling students to better understand complex academic concepts. Similarly, Vorsah & Oppong (2024) reported that artificial intelligence technologies in education can promote active learning by providing interactive assistance that supports learners' cognitive development and engagement. In addition, Ayeni et al. (2024) noted that AI-driven educational technologies have the potential to transform traditional classrooms by offering flexible and personalized learning experiences that respond to students' individual learning needs. Lin et al. (2023) further explained that artificial intelligence tools can function as intelligent tutoring systems capable of guiding learners through difficult academic tasks while offering timely feedback and explanations.

Several empirical studies have also demonstrated the effectiveness of chatbots in supporting students' learning experiences. Ait Baha et al. (2024) found that educational chatbots can enhance students' motivation and confidence by providing conversational learning support that simulates teacher–student interaction. Similarly, Huang et al. (2025) reported that chatbot-based learning environments can help students better understand complex topics through step-by-step explanations and guided responses. Abbas et al. (2022) also observed that chatbots in education can improve students' engagement and academic performance by offering continuous assistance and answering learners' questions in real time. Furthermore, Alfehaid & Hammami (2023) emphasized that conversational agents can facilitate interactive learning environments where students feel more comfortable asking questions and exploring concepts independently.

Other scholars have examined the broader impact of artificial intelligence in education. Naseer et al. (2024) highlighted that AI applications can support personalized learning pathways by analyzing students' responses and providing adaptive feedback that helps address learning gaps. Akram (2025) explained that AI-supported learning environments can improve students' problem-solving abilities by offering scaffolded assistance and intelligent feedback mechanisms. Likewise, Barua et al. (2022) argued that artificial intelligence technologies can enhance educational practices by supporting individualized instruction and helping learners overcome specific learning difficulties. In addition, Sajja et al. (2025) emphasized that AI-driven tools can assist educators in monitoring students' progress and providing targeted interventions for learners who struggle with particular academic skills. Similarly, Lin et al. (2023) noted that artificial intelligence technologies have the potential to enrich educational experiences by enabling intelligent tutoring systems that guide students through complex learning processes. Finally, Kaswan et al. (2024) discussed how AI technologies are reshaping higher education by supporting personalized learning environments and improving students' access to learning resources. Collectively, these studies demonstrate that chatbot-assisted and AI-supported learning tools have significant potential to address students' learning challenges and enhance their academic performance, particularly in subjects that require strong analytical and problem-solving skills.

The results implied that students in both groups required substantial instructional support to progress from not meeting the minimum expectations toward achieving higher levels of competence. Given that all students were initially classified under the lowest performance category, it was essential for educators to implement intensive, structured, and student-centered instructional strategies. These may include explicit teaching of problem-solving processes, scaffolded learning activities, differentiated instruction, and continuous formative assessments to monitor progress. The integration of chatbot-assisted learning tools could further enhance this process by providing immediate feedback, step-by-step guidance, and opportunities for independent and self-paced learning. Additionally, incorporating collaborative learning, enrichment activities, and higher-order thinking tasks could help deepen students' conceptual understanding and analytical skills. Through consistent instructional support, effective use of educational technologies, and sustained learning interventions, students may gradually improve their performance and ultimately achieve the level of meets minimum competence with exceptional score, demonstrating mastery of mathematical concepts and excellence in problem-solving abilities.

Table 1 Students' Performance in the Pretest for the Control and Experimental Groups Before Implementing the Chatbot Using Solomon's Model Approach

Performance	**Control Groups**		**Experimental Group**	
	Frequency	**Percentage**	**Frequency**	**Percentage**
Does not meet the minimum expectation	19	100.00	19	100.00
Mean Performance	27.42		26.05	

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

Note: Scale: 90 – 100 (Meets minimum competence with exceptional score); 80 – 89 (Meets minimum competence with over and above average score); 71 – 79 (Meets minimum competence with above average

score); 63 – 70 (Meets minimum competence with average score); 60 – 62 (Meets minimum competence); Below 60 (Does not meet the minimum expectation)

Students' Performance in the Posttest for the Control Groups who did not Receive the Chatbot Intervention Under Solomon's Model Approach

Table 2 presents the students' performance in the posttest for the control groups who did not receive the chatbot intervention under Solomon's Model Approach. The results showed that the control group with pretest obtained (M = 86.00), while the control group without pretest recorded (M = 84.11). Based on the given performance scale, both mean scores fell within the 80–89 range, which corresponded to "Meets minimum competence with over and above average score." This indicated that students in both control groups were able to demonstrate a high level of competence in the mathematical concepts assessed in the posttest. The findings suggested that even without chatbot-assisted instruction, students were able to significantly improve their understanding and problem-solving skills through the instructional process.

In the context of this study, the control groups received instruction through the traditional teaching approach, which typically involved teacher-led discussions, guided explanations, classroom exercises, and direct feedback from the instructor. Traditional classroom instruction remained one of the most widely used approaches in mathematics education, as it allowed teachers to present concepts systematically, demonstrate problem-solving procedures, and monitor students' understanding through direct interaction. Through structured lessons, examples, and practice activities, teachers were able to guide learners in developing their conceptual understanding and analytical skills. Although modern educational technologies such as chatbots are increasingly integrated into classrooms, traditional instructional methods continued to play a significant role in helping students grasp mathematical concepts and improve their academic performance.

The results of the control group with pretest revealed that 3 students, representing 15.79%, achieved "Meets minimum competence with exceptional score," while 16 students, or 84.21%, were classified under "Meets minimum competence with over and above average score." No students in this group fell under the lower performance categories. These findings indicated that all students in the control group with pretest were able to meet the required level of competence, with the majority performing at an above-average level and a smaller proportion reaching exceptional performance. This suggested that the instructional process was effective in helping students achieve a strong level of understanding of the mathematical concepts.

Similarly, the control group without pretest also demonstrated high levels of performance in the posttest. The results showed that 2 students, representing 10.53%, achieved "Meets minimum competence with exceptional score," while 17 students, or 89.47%, were categorized under "Meets minimum competence with over and above average score." None of the students were classified under the lower performance levels. These findings indicated that all students in this group were able to achieve at least the required level of competence, with the majority performing above average and a few attaining exceptional performances. This suggested that even without prior exposure to the pretest, students were still able to develop strong conceptual understanding through classroom instruction.

A comparison of the two control groups showed that both groups performed at similarly high levels in the posttest. The control group with pretest obtained a slightly higher (M = 86.00) compared with (M = 84.11) for the control group without pretest. Despite this slight difference, both groups remained within the same performance category of "Meets minimum competence with over and above average score." This indicated that the presence or absence of a pretest did not significantly affect students' posttest performance. Both groups demonstrated consistent levels of achievement, suggesting that traditional instruction alone was sufficient to help students reach above-average competence in the subject matter.

Several studies have highlighted the effectiveness of well-structured instruction and effective teaching practices in improving students' academic performance. For instance, Younis et al. (2021) emphasized that effective teaching strategies, clear instruction, and timely feedback significantly contribute to students' academic achievement. Similarly, Singh (2025) explained that supportive classroom environments and well-designed instructional practices help learners develop deeper understanding of academic concepts. Mejía-Rodríguez & Kyriakides (2022) also highlighted that systematic instruction, guided practice, and continuous feedback are key factors that enhance students' learning performance. Moreover, Leijen (2022) emphasized the importance of pedagogical content knowledge in helping teachers effectively deliver subject matter and support students' understanding.

Recent studies have also discussed how instructional practices, whether traditional or technology-supported, can contribute to improved student learning performance. For example, Smaldino et al. (2024) noted that effective instructional design remains essential for promoting student learning even when new technologies are introduced in educational environments. Kumar (2023) highlighted that meaningful learning experiences are often achieved through well-structured teaching strategies that support students' cognitive development. Similarly, Roblyer et al. (2024) emphasized that the integration of innovative technologies should complement, rather than replace, effective teaching practices. Chounta et al. (2022) also explained that while artificial intelligence tools can support learning, the role of teachers remains central in facilitating meaningful educational experiences. Other scholars such as Daniel et al. (2024) further emphasized that effective instruction, combined with appropriate learning support, plays a critical role in strengthening students' academic performance and problem-solving abilities.

The results imply that effective instruction and structured classroom learning experiences can significantly support students' academic development, even without the integration of chatbot-assisted learning tools. Teachers may continue to provide clear explanations, guided practice activities, and constructive feedback to help students strengthen their understanding of mathematical concepts. For students who may still perform at the minimum competence with over and above average score levels, instructors may implement additional instructional strategies such as differentiated instruction, scaffolded problem-solving activities, and formative assessments that allow teachers to monitor students' progress and identify areas needing improvement. Providing opportunities for collaborative learning, peer tutoring, and practice exercises can also help reinforce students' understanding of mathematical concepts. Furthermore, teachers may encourage students to engage in reflective learning and independent practice to further develop their analytical and problem-solving skills. Through continuous guidance, targeted support, and meaningful learning experiences, educators can help students gradually improve their competencies and ultimately achieve minimum competence with exceptional score levels of academic performance.

Table 2 Students' Performance in the Posttest for the Control Groups who did not Receive the Chatbot Intervention Under Solomon's Model Approach

	Control Group (With Pretest)		**Control Group B (Without Pretest)**	
Performance	**Frequency**	**Percentage**	**Frequency**	**Percentage**
Meets minimum competence with exceptional score	3	15.79	2	10.53
Meets minimum competence with over and above average score	16	84.21	17	89.47
Mean Performance	86.00		84.11	

Note: Scale: 90 – 100 (Meets minimum competence with exceptional score); 80 – 89 (Meets minimum competence with over and above average score); 71 – 79 (Meets minimum competence with above average score); 63 – 70 (Meets minimum competence with average score); 60 – 62 (Meets minimum competence); Below 60 (Does not meet the minimum expectation)

Students' Performance in the Posttest for the Experimental Groups After the Implementation of the Chatbot Using Solomon's Model Approach

Table 3 presents the students' performance in the posttest for the experimental groups after the implementation

of the chatbot using Solomon's Model Approach. The results revealed that the experimental group with pretest obtained (M = 88.79), while the experimental group without pretest obtained (M = 86.26). Based on the provided performance scale, the mean score of the experimental group with pretest fell within the "Meets minimum competence with over and above average score" range (80–89) for most students, with a substantial portion achieving "Meets minimum competence with exceptional score" (90–100). Similarly, the experimental group without pretest also fell primarily within the "Meets minimum competence with over and above average score" range, with a smaller proportion reaching the exceptional score level. These findings indicate that after the intervention, students in both experimental groups demonstrated strong mastery of the mathematical concepts assessed in the posttest. The results suggested that chatbot-assisted instruction effectively improved students' understanding, problem-solving abilities, and overall performance, even when the groups differed in prior pretest exposure.

In this context, chatbot-assisted learning was implemented as an instructional support tool to help students enhance their understanding of mathematical concepts. A chatbot was an artificial intelligence–based conversational system that interacted with users through natural language processing and automated responses. In educational settings, chatbots functioned as digital tutors that assisted learners by answering questions, providing explanations, and guiding them through problem-solving procedures. In this classroom setting, students utilized several artificial intelligence chatbot platforms such as Gemini, Cici, and ChatGPT during their learning activities. These tools allowed students to ask questions, request explanations for mathematical procedures, and explore different strategies in solving problems. Through these platforms, learners received immediate feedback and step-by-step guidance that supported their independent learning. Teachers integrated these chatbot technologies to supplement traditional instruction by providing additional learning resources, practice opportunities, and clarification of difficult concepts. As a result, students were able to review lessons independently, explore mathematical reasoning more deeply, and engage more actively in the learning process. The use of these AI-powered chatbots also encouraged students to develop analytical thinking and problem-solving skills while interacting with digital learning environments.

The results for the experimental group with pretest showed that 7 students, representing 36.84%, achieved "Meets minimum competence with exceptional score," while 12 students, or 63.16%, achieved "Meets minimum competence with over and above average score." None of the students were classified under lower performance levels. These findings indicated that the combination of prior exposure through the pretest and chatbot-assisted instruction effectively strengthened students' mastery of mathematical concepts and problem-solving skills. Students in this group demonstrated higher proportions of exceptional performance compared with other groups, suggesting that the pretest may have served as an initial diagnostic tool that helped focus learning during the intervention.

Similarly, the experimental group without pretest demonstrated strong performance in the posttest. Results showed that 3 students, representing 15.79%, achieved "Meets minimum competence with exceptional score," while 16 students, or 84.21%, were classified under "Meets minimum competence with over and above average score." None of the students fell under lower performance categories. These results suggested that even without prior exposure through a pretest, the majority of students still demonstrated strong comprehension and application of the mathematical concepts taught during chatbot-assisted instruction.

An examination of the two experimental groups revealed that both achieved exceptionally high levels of performance. The experimental group with pretest had a slightly higher (M = 88.79) compared with (M = 86.26) for the group without pretest. Despite this difference, both groups remained within the outstanding performance level, indicating that the overall academic achievement of students remained consistently high after the integration of chatbot-assisted instruction. This suggested that the chatbot intervention effectively supported students' learning regardless of pretest exposure, with the added benefit of helping some students reach the exceptional performance category.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

Several studies emphasized the growing role of artificial intelligence technologies in improving teaching and learning processes. Imamguluyev et al. (2024) explained that AI-powered educational tools such as chatbots enhanced students' learning experiences by providing personalized assistance, adaptive explanations, and instant feedback. Similarly, Demartini et al. (2023) reported that artificial intelligence in education supported learners through intelligent systems that adapted to students' needs and learning progress. Kaswan et al. (2024) further emphasized that AI technologies had the capacity to transform learning environments by facilitating personalized and flexible learning opportunities. In addition, Basri (2024) highlighted that AI-supported systems served as intelligent tutoring tools that guided students through complex tasks while providing immediate feedback. Likewise, Saar et al. (2025) noted that artificial intelligence applications in education promoted individualized learning pathways that helped learners better understand academic content and develop higher-order thinking skills.

Research focusing specifically on chatbot technologies in education also demonstrated their positive impact on student engagement and academic achievement. Zhang et al. (2024) found that chatbot-assisted learning environments increased student participation and supported independent learning by providing conversational interaction similar to teacher–student dialogue. Similarly, Okonkwo & Ade-Ibijola (2021) reported that educational chatbots improved students' academic performance by offering real-time responses to learners' questions and guiding them through problem-solving processes. Alfehaid & Hammami (2023) also explained that conversational agents in education enhanced students' motivation and engagement because they allowed learners to interact with digital systems in a more natural and accessible manner. In addition, Bosch & Kruger (2024) highlighted that chatbots in educational contexts helped students clarify difficult concepts, provided continuous learning support, and encouraged self-directed learning behaviors.

Furthermore, other studies highlighted the effectiveness of AI-supported learning environments in strengthening students' cognitive development and academic performance. Ouyang et al. (2023) reported that artificial intelligence–supported learning systems improved students' problem-solving skills by providing scaffolded instruction and adaptive feedback. Mehmood et al. (2025) emphasized that AI-assisted learning environments helped students develop deeper conceptual understanding by allowing them to explore multiple strategies in solving academic tasks. Similarly, Dahri et al. (2025) noted that AI-powered chatbots in education promoted personalized learning experiences and improved students' engagement with course materials. Rohid et al. (2025) also found that chatbot technologies supported students' independent learning by enabling them to access explanations and learning assistance anytime. Likewise, Yarovenko-Kuzminykh (2025) reported that AI tools such as conversational agents and generative AI systems significantly enhanced students' academic engagement, self-regulated learning, and conceptual understanding across different educational contexts. Collectively, these studies supported the findings of the present study, which indicated that the integration of chatbot-assisted instruction contributed to improved student performance in mathematics learning.

The results implied that integrating chatbot-assisted instruction significantly contributed to improving students' academic performance, with some students reaching the "Meets minimum competence with exceptional score" level. To ensure that all students achieve this highest level of performance, teachers should provide structured instructional support, targeted problem-solving activities, differentiated instruction, and continuous formative assessment. Encouraging collaborative learning, independent practice, reflective thinking, and guided exploration through AI tools can further enhance students' mastery of mathematical concepts. Through these strategies, educators can help students gradually progress from above-average to exceptional performance, maximizing learning performance and fostering excellence in mathematics.

Table 3 Students' Performance in the Posttest for the Experimental Groups After the Implementation of the Chatbot Using Solomon's Model Approach

	Experimental Group (With Pretest)		**Experimental Group B (Without Pretest)**	
Performance	**Frequency**	**Percentage**	**Frequency**	**Percentage**
Meets minimum competence with exceptional score	7	36.84	3	15.79

	Experimental Group (With Pretest)		Experimental Group B (Without Pretest)	
Performance	**Frequency**	**Percentage**	**Frequency**	**Percentage**
Meets minimum competence with over and above average score	12	63.16	16	84.21
Mean Performance	88.79		86.26	

Note: Scale: 90 – 100 (Meets minimum competence with exceptional score); 80 – 89 (Meets minimum competence with over and above average score); 71 – 79 (Meets minimum competence with above average score); 63 – 70 (Meets minimum competence with average score); 60 – 62 (Meets minimum competence); Below 60 (Does not meet the minimum expectation)

Significant Difference in the Performance of Students in the Pretest Between Control and Experimental Groups

Table 4 presents the significant difference in the performance of students in the pretest between the control and experimental groups before the implementation of the chatbot using Solomon's Model Approach. The results revealed that the experimental group obtained (M = 27.42, SD = 5.22), while the control group obtained (M = 26.05, SD = 6.48). Based on the given performance scale, both mean scores fell within the 21–40 range, which corresponded to fairly satisfactory performance. These findings indicated that students in both groups demonstrated limited mastery of mathematical concepts and problem-solving skills before the intervention. The results suggested that both groups started at an equivalent level, providing a fair baseline for assessing the effectiveness of the chatbot-assisted instruction.

The two main variables were the independent variable, which was the instructional approach, and the dependent variable, which was the students' problem-solving performance. The experimental group was designated to receive chatbot-assisted instruction, integrating artificial intelligence–based conversational tools such as Gemini, Cici, and ChatGPT into classroom activities to support learning. These platforms provided automated guidance, step-by-step explanations, and immediate feedback to enhance understanding and engagement. On the other hand, the control group continued with traditional instruction, where the teacher delivered lessons using conventional methods, including direct explanations, manual problem-solving exercises, and guided practice without the support of AI technologies. By comparing these two instructional approaches while keeping the pretest as a baseline, the study aimed to determine how the intervention influenced students' problem-solving performance.

The results for the experimental group showed (M = 27.42, SD = 5.22). Based on the performance scale, this score fell within the "Fairly Satisfactory" range, indicating that the students had some understanding of the mathematical concepts but still displayed limited problem-solving skills. These findings suggested that, before the intervention, the experimental group required additional instructional support to strengthen their mastery of mathematical problem-solving.

For the control group, the pretest results revealed (M = 26.05, SD = 6.48), which also fell within the "Fairly Satisfactory" category. This indicated that students in the control group similarly had limited problem-solving abilities before receiving any instruction. The data reflected that both groups started at comparable baseline levels of understanding, demonstrating the need for instructional interventions to improve learning performance.

A comparison of the two groups using the independent-samples t-test yielded (t = 1.24, p = 0.231). Since the p-value was greater than 0.05, the null hypothesis was accepted, indicating that there was no significant difference in the pretest performance between the experimental and control groups. This result confirmed that the two groups were statistically equivalent at the start of the study, ensuring that any subsequent differences observed in posttest performance could be attributed to the instructional method rather than pre-existing disparities in problem-solving ability.

Several studies have emphasized the critical role of pre-assessment in education as a tool to establish students' baseline knowledge, guide instruction, and measure learning growth. Pretests provide educators with essential insights into learners' prior understanding, misconceptions, and readiness to engage with new content (Pan & Carpenter, 2023). They allow teachers to identify knowledge gaps and tailor instructional strategies that address students' specific needs (Pramerta, 2025). According to Gamage (2025), pre-assessment is particularly important when introducing innovative learning tools because it helps in isolating the effect of the intervention from pre-existing knowledge. See (2022) argued that baseline assessments ensure that the impact of teaching strategies or technological interventions can be accurately evaluated, thereby providing evidence for effective instructional practices. Similarly, Gamage (2025) noted that pre-assessments encourage learners to reflect on their knowledge, supporting metacognitive development and helping students recognize areas for improvement before engaging in targeted instruction.

In the context of technology-enhanced learning, pre-assessments play a pivotal role in ensuring that interventions, including AI-supported tools, are appropriately aligned to learners' needs. Maftuna (2025) emphasized that knowing students' initial competencies allows educators to provide timely scaffolding and adaptive support during lessons. Chang et al., (2023) reported that pretest results guide the design of learning activities, ensuring that AI-based instructional tools such as chatbots provide meaningful, personalized guidance. Chraa & Alidrissi (2025) highlighted that integrating pre-assessment data allows teachers to monitor progress and adjust interventions in real-time, improving both engagement and learning performance. Ali (2024) further emphasized that pre-assessments inform formative evaluations, supporting continuous feedback loops that strengthen understanding and skill development. This is especially critical in problem-solving contexts, where students' prior knowledge significantly impacts their ability to analyze and solve tasks effectively (Lonergan, 2023).

Extending this perspective to mathematics and AI-assisted instruction, a number of studies have shown that pretests enhance the effectiveness of digital learning interventions. Van der Linden (2023) found that pre-assessment data allow teachers to design interactive activities and provide adaptive feedback, fostering deeper understanding and critical thinking. Abrar et al. (2025) reported that AI-powered tools guided by pretest insights help students develop personalized learning paths, enhancing engagement and performance. Rajak & Dey (2025) emphasized that pre-assessment identifies students who require additional support, allowing educators to implement differentiated strategies. Kusumoriny (2025) further noted that pre-assessment in combination with AI-assisted instruction supports individualized learning, adaptive scaffolding, and effective feedback, which collectively improve conceptual mastery and problem-solving ability. Collectively, these studies affirm that pre-assessments are not merely evaluative measures but foundational components that enhance instructional planning, guide the effective integration of innovative tools, and ensure equitable opportunities for all learners to achieve their learning potential.

The findings can be supported by the principles of Constructivist Learning Theory proposed by Jean Piaget (1972) and the Sociocultural Theory of Lev Vygotsky (1978). Constructivist theory emphasizes that learners build knowledge based on prior experiences and cognitive readiness. Since both groups demonstrated similar levels of prior knowledge and understanding of mathematical concepts before the intervention, it is reasonable that their pretest performances did not significantly differ. Likewise, Vygotsky's concept of the Zone of Proximal Development suggests that learners require appropriate guidance and instructional support to move beyond their current level of understanding. Before the implementation of chatbot-assisted instruction or any structured intervention, both groups relied primarily on their existing knowledge and previous learning experiences, which resulted in comparable levels of performance. This theoretical perspective explains why the two groups exhibited statistically equivalent pretest results, thereby establishing a valid baseline for evaluating the effect of the instructional intervention implemented later in the study.

The results implied that the absence of a significant difference in pretest performance between the experimental and control groups indicated that all students entered the instructional period with comparable levels of prior knowledge and problem-solving skills. This suggested that any subsequent improvements in performance could be attributed to the instructional intervention rather than pre-existing advantages. From an instructional perspective, this finding highlighted the importance of conducting baseline assessments to ensure equitable learning opportunities and to identify students who may require additional support during the intervention.

Educators were encouraged to use pretest data to implement targeted instructional strategies, such as differentiated teaching, guided practice, and scaffolded activities, which would cater to students' individual needs. Furthermore, the finding underscored that pre-assessments could serve as diagnostic tools for planning lessons that optimize the effectiveness of both traditional and technology-enhanced learning methods. By understanding students' initial competencies, teachers could anticipate potential challenges, provide timely feedback, and facilitate adaptive learning pathways. Overall, the results reinforced the educational value of pretesting in promoting fairness, informing instruction, and supporting the implementation of evidence-based teaching practices that ultimately aimed to enhance students' academic performance and problem-solving performance.

Table 4 Significant Difference in the Performance of Students in the Pretest Between Control and Experimental Groups

Variables	M	SD	t value	p value	Decision
Experimental Group	27.42	5.22	1.24	0.231	Fail to Reject Ho
Control Group	26.05	6.48			

Ho: There is no significant difference in the performance of students in the pretest between control and experimental groups

Note: Probability Value Scale: $^{**}p<0.01$ (Highly Significant); $^{*}p<0.05$ (Significant); $p>0.05$ (Not significant)

Significant Difference in the Performance of Students in the Posttest Who Underwent the Implementation of the Chatbot Using Solomon's Model Approach (Experimental Group) and Those with No Intervention (Control Group)

Table 5 presents the significant difference in the posttest performance of students who underwent the implementation of chatbot-assisted instruction using Solomon's Model Approach (experimental group) and those who did not receive any intervention (control group). The results indicated that students in the experimental groups, both with and without pretest, obtained higher mean scores compared to their corresponding control groups. Specifically, the experimental group with pretest scored (M = 88.79), while the control group with pretest scored (M = 86.00). For the groups without pretest, the experimental group achieved (M = 86.26), compared with (M = 84.11) for the control group. The t-values (4.57 for with pretest, 3.94 for without pretest) and p-values (<0.001 for both) indicated highly significant differences between the experimental and control groups, suggesting that chatbot-assisted instruction effectively enhanced students' posttest performance. Overall, these findings highlighted the positive impact of the intervention on students' problem-solving performance in mathematics.

In this context, chatbot-assisted instruction served as the primary learning support for the experimental group, where artificial intelligence–based conversational tools such as Gemini, Cici, and ChatGPT were integrated into the learning process. These tools provided students with immediate guidance, step-by-step explanations, and feedback while solving mathematical problems, enabling them to clarify difficult concepts and explore various strategies in problem-solving. Through continuous interaction with these AI-supported platforms, students were given opportunities to practice independently while receiving instant responses to their inquiries. In contrast, the control group did not receive this technological support and instead continued learning through conventional instructional activities without the integration of chatbot tools. This difference in instructional approach provided a basis for examining how the use of chatbot-assisted learning contributed to the improvement of students' mathematical problem-solving performance in the posttest.

For the groups with pretest exposure, the experimental group that underwent chatbot-assisted instruction achieved (M = 88.79, SD = 5.01), while the corresponding control group obtained (M = 86.00, SD = 4.15). The independent-samples t-test yielded (t = 4.57, p = 0.001), indicating a highly significant difference between the two groups. These results suggest that students who engaged with AI chatbots as part of their learning process were able to perform better in posttest problem-solving tasks compared to those who received only traditional instruction. The higher mean and relatively moderate standard deviation in the experimental group indicate not only improved performance but also consistency in how students benefited from the chatbot intervention.

Similarly, for the groups without pretest exposure, the experimental group achieved ($M = 86.26$, $SD = 3.31$), whereas the control group scored ($M = 84.11$, $SD = 3.16$). The t-test result ($t = 3.94$, $p < 0.001$) also revealed a highly significant difference, demonstrating that even in the absence of prior pretest exposure, students who experienced chatbot-assisted instruction outperformed those in the control group. This finding suggests that the integration of chatbots provided sufficient instructional scaffolding and immediate feedback to enhance comprehension and problem-solving skills independently of prior exposure.

A comparison of the results both experimental conditions revealed that students in the experimental group consistently outperformed their respective control groups, regardless of pretest exposure. While the mean scores for the experimental group with pretest (88.79) were slightly higher than those without pretest (86.26), both sets of experimental participants achieved significantly higher performance levels than their control counterparts. This comparison highlighted the effectiveness of chatbot-assisted instruction in improving mathematics problem-solving skills and conceptual understanding, emphasizing that the intervention's positive impact was evident irrespective of baseline assessment.

Several studies have consistently highlighted the effectiveness of artificial intelligence (AI) and chatbot-assisted learning in enhancing students' academic performance and engagement. Manoj et al. (2024) emphasized that AI-powered educational tools provided personalized assistance, adaptive explanations, and immediate feedback, which supported learners in mastering complex concepts. Akavova et al. (2023) similarly reported that AI systems could monitor student performance in real time and adjust instructional content according to individual learning needs. Strielkowski et al. (2025) noted that AI technologies transformed learning environments by offering flexible, adaptive, and learner-centered experiences, while Lin (2023) highlighted that intelligent tutoring systems served as digital guides through complex tasks. Ke et al. (2024) further emphasized that AI applications promoted individualized learning pathways and fostered the development of higher-order thinking skills. These findings reinforced the results of the present study, indicating that chatbot-assisted instruction provided students with scaffolded support that contributed to improved problem-solving performance.

Research focusing specifically on chatbots in educational settings has demonstrated their positive impact on engagement, motivation, and academic achievement. Alfehaid & Hammami (2023) found that conversational agents in learning environments encouraged students to participate actively and engage in independent learning. Davar (2025) similarly reported that educational chatbots improved academic performance by delivering real-time guidance and facilitating step-by-step problem-solving. Hew et al. (2023) emphasized that the interactive nature of chatbots enhanced motivation by allowing learners to communicate naturally with digital systems. Jayapriya (2025) highlighted that chatbots supported self-directed learning by providing continuous explanations and clarifications, while Mohebbi (2025) found that AI-assisted tools enabled students to access learning support anytime, promoting autonomy and self-regulation. Abbas & Abbas (2025) also noted that AI-driven platforms encouraged exploration of multiple strategies, helping students achieve deeper conceptual understanding. Collectively, these studies demonstrated that the integration of chatbots in instructional practices could enhance learning performance and support higher academic achievement.

Furthermore, AI-supported learning environments were shown to strengthen cognitive development and problem-solving skills across diverse contexts. Correia et al. (2024) reported that AI-assisted instruction improved students' analytical thinking and performance through scaffolded feedback and adaptive learning tasks. Lin & Chang (2023) highlighted that personalized chatbot interventions promoted engagement and interaction with academic content, while Anders & Speltz (2025) emphasized that generative AI systems supported conceptual understanding and self-regulated learning behaviors. Additionally, research by Mousa (2025) suggested that AI integration facilitated individualized learning, provided formative assessment opportunities, and strengthened retention of learned concepts. These studies collectively supported the current findings that chatbot-assisted instruction significantly enhanced posttest performance, indicating its practical value as a supplementary educational tool. Educators could leverage these insights to incorporate AI technologies alongside traditional teaching methods, ensuring meaningful, interactive, and effective learning experiences that improve student performance in mathematics.

The improvement in the posttest performance of students who underwent chatbot-assisted instruction may be explained through the principles of Constructivist Learning Theory proposed by Jean Piaget (1972) and the Sociocultural Theory of Lev Vygotsky (1978). Constructivist theory emphasizes that learners actively construct knowledge through interaction, exploration, and engagement with learning tasks. The use of chatbots in mathematics instruction allowed students to interact with learning materials, ask questions, and receive immediate explanations, thereby promoting deeper understanding of mathematical concepts. Similarly, Vygotsky's concept of the Zone of Proximal Development highlights the importance of guidance and scaffolding in learning. Chatbots functioned as supportive tools that provided step-by-step assistance and feedback, enabling students to solve problems that might have been difficult to accomplish independently. Through this guided interaction, learners were able to strengthen their problem-solving abilities, which may explain the higher posttest performance observed among students in the experimental groups compared to those who received no intervention.

The implications of these results suggested that the integration of chatbot-assisted learning could be an effective strategy for improving student performance in mathematics. Educators were encouraged to combine AI-supported tools with structured teaching practices, such as formative assessments, guided problem-solving, and differentiated instruction, to ensure that all learners achieved high levels of performance. Providing opportunities for independent exploration using chatbots nurtured self-directed learning habits, analytical thinking, and problem-solving skills. By leveraging technology alongside traditional instruction, teachers could create meaningful, interactive, and effective learning experiences that supported students in attaining consistently outstanding academic performance, ultimately fostering both competence and confidence in mathematics.

Table 5 Significant Difference in the Performance of Students in the Posttest Who Underwent the Implementation of Chatbot Using Solomon's Model Approach (Experimental Group) and Those with No Intervention (Control Group)

Variables	M	SD	t value	p value	Decision
With Pretest					
Experimental Group	88.79	5.01	4.57	<.001**	Reject Ho
W/ Control Group	86.00	4.15			
Without Pretest					
Experimental Group	86.26	3.31	3.94	<.001**	Reject Ho
W/o Control Group	84.11	3.16			

Ho: There is a high significant difference in the posttest performance of the experimental and control groups
Note: Probability Value Scale: $^{**}p<0.01$ (Highly Significant); $^{*}p<0.05$ (Significant); $p>0.05$ (Not significant)

Significant Difference in the Performance of Students in the Posttest Between Two Control Groups

Table 6 presents the significant difference in the performance of students in the posttest between the two control groups. The results revealed that Control Group A (with pretest) obtained (M = 86.00), while Control Group B (without pretest) obtained (M = 84.00). Based on the performance scale, both groups were classified under the outstanding performance level. These findings indicated that students in the two control groups demonstrated high levels of mastery of the mathematical concepts assessed in the posttest, even though they were taught using traditional instructional methods without the chatbot intervention.

Control groups under traditional instruction were distinguished by pretest exposure, which served as the primary factor differentiating their learning experience. Control Group A received a pretest prior to instruction, allowing students to familiarize themselves with the types of questions and assess their initial understanding of mathematical concepts, while Control Group B did not take a pretest and proceeded directly to instruction. Both groups engaged in conventional learning activities, where the teacher delivered lessons through explanations, guided practice, and problem-solving exercises without the integration of AI-supported tools. This distinction provided a basis for examining whether prior exposure through pretesting influenced students' problem-solving performance in the posttest and offered a clear comparison between learning with and without pre-assessment under traditional instructional methods.

For Control Group A, which took the pretest before instruction, achieved ($M = 86.00$). This suggested that the group had a strong foundation and was able to retain and apply mathematical concepts effectively after the instructional period. The students in this group demonstrated understanding and competence in problem-solving tasks, which reflected their ability to engage with the lessons despite not using chatbot-assisted learning. The administration of the pretest may have provided students with prior exposure to the content, allowing them to anticipate and focus on key areas during instruction. However, the results suggested that the pretest alone was not sufficient to drastically enhance posttest performance when compared to the group that did not receive a pretest.

The Control Group B, which did not take a pretest, obtained a mean performance of 84.00. Although this was slightly lower than that of Control Group A, the difference was not statistically significant ($t = 1.98$, $p = 0.063$). The students in this group also performed at an outstanding level, indicating that traditional teaching methods alone were capable of producing high achievement. This finding emphasized that while pre-assessment may provide diagnostic insights for teachers, students could still achieve strong performance through effective conventional instruction that includes clear explanations, guided practice, and reinforcement exercises.

An examination of the posttest comparison between the two control groups showed no significant difference in performance. This confirmed that pretesting alone did not significantly affect learning performance in the traditional classroom setting. Both groups' outstanding performance indicated that conventional instruction was adequate for teaching the content assessed in the posttest. However, the slightly higher mean in Control Group A suggested that pretests may have some preparatory benefit for students, even if it did not produce a statistically significant impact on performance.

Research has shown that the use of pre-assessment and traditional teaching methods can influence student learning in several ways, though their effectiveness often depends on how instructional strategies are implemented. Alfageh (2024) emphasized that formative assessments, including pretests, serve primarily as diagnostic tools to identify students' strengths and weaknesses and are most effective when teachers adjust instruction based on the results. Mukhtarova (2026) reported that traditional instruction, characterized by structured explanations, guided practice, and teacher-led discussions, remains a reliable approach for delivering foundational knowledge, particularly when students are engaged actively during lessons. Haelermans (2022) noted that pretests alone rarely improve learning performance unless the results are used to inform differentiated teaching strategies. Zhu (2024) similarly highlighted that pre-assessment data are useful for planning purposes, but they do not directly enhance performance unless integrated with targeted interventions.

Nguyen (2022) emphasized that high-quality traditional instruction, when combined with effective scaffolding, ensures that students acquire the necessary skills and knowledge to perform at high levels. Gosztonyi & Varga (2023) both pointed out that teacher guidance, step-by-step problem-solving demonstrations, and structured practice are critical in supporting learners' mastery of content, particularly in mathematics. Cooney (2025) further suggested that the combination of formative assessment, timely feedback, and well-structured lessons enhances student engagement and helps learners internalize concepts effectively. Hansen (2023) underscored that learning performance improve when students are provided multiple opportunities to apply concepts through guided exercises and classroom activities, which strengthens their retention and conceptual understanding.

Javed (2023) highlighted that explicit teaching techniques in traditional classrooms, such as modeling and continuous questioning, positively influence student learning by promoting deeper cognitive processing. Opana & Guantai (2025) noted that instructional clarity, feedback, and practice routines are essential in traditional settings to achieve high levels of student performance. Tang (2023) emphasized that teacher-centered methods can be highly effective if combined with opportunities for independent practice and peer collaboration, which help students consolidate learning. Bairbayeva (2023) reported that structured, teacher-led instruction ensures equitable access to learning, enabling students with different abilities to achieve academic success. Collectively,

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

these studies suggested that traditional instruction, when executed effectively, can result in high student achievement and provide a solid foundation for understanding academic concepts.

Several researchers also explored the role of pre-assessment in enhancing learning performance. Soderstrom & Bjork (2023) reported that pretests can motivate students to focus on critical content areas, while Gamage (2025) emphasized that pre-assessments guide learners' attention and self-regulated learning strategies. According to Samaila & Al-Samarraie (2024) pretests alone do not guarantee improved performance but can create awareness of learning objectives, prompting students to engage more effectively in lessons. Research also indicated that combining pre-assessment with traditional teaching practices, such as guided instruction and scaffolded exercises, leads to improved performance, even in the absence of digital tools (Kusumoriny, 2025). This body of literature collectively supports the present study's findings that the two control groups performed at outstanding levels, yet pretesting alone was not sufficient to create significant differences between groups.

Furthermore, studies highlighted the importance of instructional support in bridging gaps for students who may not initially achieve top performance. Criss et al. (2024) argued that clear learning targets and teacher feedback enhance student understanding, while Zahid & AlManiam (2025) emphasized formative guidance as essential in moving learners from satisfactory to outstanding performance. Maftuna (2025) also noted that scaffolding exercises, continuous practice, and structured review sessions are key in supporting learners' progression. These studies reinforce the notion that while the control groups performed well under traditional instruction, additional targeted interventions could further improve individual performance and ensure consistent achievement at the highest level.

The posttest performance of students in the two control groups may be explained through the principles of Constructivist Learning Theory proposed by Jean Piaget (1972) and Behaviorist Learning Theory of B.F. Skinner (1954). Constructivist theory suggests that learners build new knowledge by connecting it to prior experiences, which may account for the slightly higher mean performance observed in Control Group A that received a pretest before instruction. The pretest likely activated prior knowledge, enabling students to focus on key concepts during learning. Meanwhile, Behaviorist theory emphasizes the role of guided practice, reinforcement, and structured instruction in shaping learning performance. The outstanding performance of both control groups indicates that, even without pre-assessment, traditional instruction with clear explanations, exercises, and feedback provided sufficient scaffolding for students to achieve mastery in mathematical problem-solving. Together, these theories explain why both groups performed at an outstanding level, despite the absence of chatbot-assisted learning.

The results implied that while students in both control groups achieved outstanding performance, relying solely on pre-assessment was not sufficient to maximize learning performance. Educators could implement additional support strategies to ensure that all students consistently achieved top-level performance. These strategies may include providing differentiated instruction for students who demonstrate areas of difficulty, implementing scaffolded problem-solving exercises, offering supplemental practice sessions, and promoting collaborative learning opportunities. Moreover, teachers could incorporate timely formative feedback and monitor progress regularly to identify and address learning gaps. By combining traditional instruction with these targeted strategies, educators could further enhance students' problem-solving skills, conceptual understanding, and overall academic achievement, helping all learners move toward consistently outstanding performance.

Table 6 Significant Difference in the Performance of Students in the Posttest Between Two Control Groups

Variables	M	SD	t value	p value	Decision
Control Group A (with Pretest)	86.00	3.54	1.98	>0.063	Fail to Reject Ho
Control Group B (Without Pretest)	84.00	3.16			

Ho: There is no significant difference in the performance of students in the posttest between two control groups

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

Note: Probability Value Scale: **p<0.01 (Highly Significant); *p<0.05 (Significant); p>0.05 (Not significant)

Significant Difference in the Performance of Students in the Posttest Between the Two Experimental Groups

Table 7 presents the significant difference in the performance of students in the posttest between the two experimental groups after the implementation of the chatbot using Solomon's Model Approach. The results showed that the experimental group with pretest obtained (M = 88.79), while the experimental group without pretest obtained (M = 86.26). Based on the performance scale, both groups were classified under the outstanding category, indicating that students in both experimental groups achieved high levels of mastery in the mathematical concepts assessed. These findings suggested that the integration of chatbot-assisted instruction effectively supported the improvement of students' problem-solving skills and conceptual understanding in mathematics.

The experimental groups under chatbot-assisted instruction were distinguished by the implementation of AI-based learning tools, which served as the primary factor differentiating their learning experience. The independent variable, chatbot-assisted instruction using Solomon's Model Approach, was operationalized through interactive tools such as Gemini, Cici, and ChatGPT, which guided students through mathematical problem-solving activities, provided immediate feedback, and clarified complex concepts. The dependent variable, students' posttest performance, reflected their mastery of mathematical content and problem-solving skills after the intervention. Additionally, the presence or absence of a pretest was considered as a moderating factor, allowing students to either familiarize themselves with the types of questions before instruction or proceed directly to learning. This distinction provided a basis for examining how AI-supported instruction influenced posttest performance and offered a clear comparison of learning effectiveness with and without prior exposure.

The results for Experimental Group A (with pretest) indicated that students who had undergone a pre-assessment before the intervention performed exceptionally well, achieved (M = 88.79). This suggested that prior exposure through pretesting, combined with chatbot-assisted learning, supported students in reinforcing their understanding of mathematical concepts and applying problem-solving strategies effectively. The structured guidance offered by the chatbots helped students navigate complex problems, practice different approaches, and receive real-time feedback, which strengthened their analytical skills.

Meanwhile, Experimental Group B (without pretest) also demonstrated outstanding performance (M = 86.26). Although slightly lower than the pretested group, this finding indicated that the chatbot intervention was effective even without prior pre-assessment. The use of chatbots allowed students to independently explore mathematical procedures, ask questions, and receive immediate explanations, which facilitated understanding and promoted active engagement with the learning materials. This suggested that the chatbot-assisted instruction could support students' learning regardless of prior exposure to the lesson content.

An examination of the difference between the two experimental groups revealed no statistically significant difference in their posttest performance (t = 2.02, p = 0.058), confirming that both groups achieved similarly high levels of performance. Despite the slight variation in mean scores, the overall achievement of both groups was outstanding. This finding suggested that the chatbot intervention was consistently effective and that pretesting did not substantially alter the learning performance, demonstrating the robustness of AI-supported instruction in improving students' problem-solving abilities.

Several studies highlighted the growing significance of artificial intelligence and chatbot-assisted learning in enhancing students' academic performance, particularly in mathematics and problem-solving. Kovalchuk et al. (2025) emphasized that AI-powered educational tools, such as chatbots, can deliver personalized learning pathways and adaptive support that respond to each student's knowledge level, learning pace, and problem-solving approach. Similarly, Chang et al. (2023) argued that AI-based systems in education promote engagement by monitoring student interactions, offering tailored feedback, and presenting scaffolded guidance during learning activities. Wu et al. (2024) further noted that AI technologies have the capacity to transform learning environments by facilitating flexible, individualized, and self-paced learning experiences, which help students develop deeper conceptual understanding and critical thinking skills. Mohebbi (2025) also highlighted that AI tools act as intelligent tutors, guiding learners through complex tasks and providing immediate feedback, which promotes cognitive skill development and learner autonomy. Saar et al. (2025) stressed that AI-supported educational applications help students follow personalized learning pathways that enhance higher-order thinking and academic achievement.

Specifically on chatbot-assisted learning, several studies demonstrated their effectiveness in motivating students and improving engagement. Baskara (2023) reported that chatbots create interactive, conversational environments that mimic teacher–student dialogue, promoting participation and independent learning. Davar et al. (2023) found that chatbots improve academic performance by responding to student queries in real time, guiding them through problem-solving steps, and offering hints or explanations to clarify difficult concepts. Alfehaid & Hammami (2023) emphasized that conversational agents enhance motivation and engagement by allowing learners to interact naturally with digital learning systems. Jayapriya (2025) noted that chatbots foster self-directed learning, encourage repeated practice, and help students consolidate knowledge through iterative guidance. Rizki & Kusumah (2025) highlighted that AI-based learning systems, including chatbots, scaffold instruction and provide adaptive feedback, which is crucial for strengthening problem-solving skills and conceptual understanding in mathematics.

Other studies also reinforced the pedagogical benefits of AI and chatbot technologies in educational contexts. Abidin et al. (2025) found that AI-assisted learning environments provide opportunities for students to explore multiple problem-solving strategies, promoting flexible thinking and analytical reasoning. Ait Baha et al. (2024) reported that chatbot integration in classrooms supports personalized and engaging learning experiences, increasing students' interaction with course materials. Chang et al. (2023) noted that students using AI chatbots could access learning assistance anytime, fostering independent learning habits and self-regulation. ElSayary (2024) highlighted that AI tools, including generative and conversational agents, enhance academic engagement, metacognitive skills, and conceptual comprehension across different contexts. In addition, Alam et al. (2026) demonstrated that AI-supported instruction improves knowledge retention and student confidence in applying learned concepts. Klar (2025) emphasized that intelligent tutoring systems, including chatbots, can reduce cognitive load by breaking complex tasks into manageable steps, which helps learners internalize mathematical reasoning more effectively. Lastly, David et al. (2022) found that chatbots enhance collaborative learning opportunities, as students can share strategies, receive peer feedback, and consolidate understanding in guided virtual environments. Collectively, these studies provided strong evidence that the use of AI-powered chatbots in the classroom can substantially improve students' learning performance, engagement, and problem-solving abilities. They supported the findings of the present study, which indicated that both experimental groups achieved outstanding performance in the posttest after the implementation of chatbot-assisted instruction. The extensive literature suggested that integrating AI tools like Gemini, Cici, and ChatGPT can provide individualized guidance, scaffolded practice, and interactive feedback, all of which are essential for fostering mastery of mathematical concepts and promoting higher-order thinking skills among learners.

The outstanding posttest performance of both experimental groups may be explained through the principles of Constructivist Learning Theory proposed by Jean Piaget (1972) and the Sociocultural Theory of Lev Vygotsky (1978). Constructivist theory emphasizes that learners actively construct knowledge by interacting with learning materials, exploring concepts, and engaging in problem-solving activities. In this study, the use of chatbots provided opportunities for students to practice independently, receive immediate explanations, and test multiple problem-solving strategies, thereby promoting deeper understanding and mastery of mathematical concepts. Similarly, Vygotsky's concept of the Zone of Proximal Development highlights the importance of guidance and scaffolding in learning. Chatbots acted as interactive scaffolds, providing step-by-step support and instant feedback, which allowed students to solve problems that might have been difficult to accomplish independently. The high performance of both pretested and non-pretested groups indicates that AI-assisted instruction effectively facilitated cognitive development and problem-solving competence, demonstrating that the chatbots' guidance could support learning regardless of prior exposure to the content.

The implications of these findings suggested that chatbot-assisted instruction could be widely adopted to improve student learning in mathematics. Teachers were encouraged to integrate AI-supported tools like Gemini, Cici, and ChatGPT in classroom instruction to facilitate personalized feedback, scaffolded problem-solving, and independent learning. Students could benefit from continuous access to these digital learning resources, which would allow them to develop critical thinking and problem-solving skills regardless of their prior exposure to assessments. Moreover, structured instructional guidance and targeted support could help ensure that all learners achieve consistently outstanding performance, bridging gaps for students who might initially perform slightly lower than their peers.

Table 7 Significant Difference in the Performance of Students in the Posttest Between the Two Experimental Groups

Variables	**M**	**SD**	**t value**	**p value**	**Decision**
Experimental Group A (with Pretest)	88.79	4.30	2.02	0.058	Fail to Reject Ho
Experimental Group B (Without Pretest)	86.26	3.31			

Ho: There is no significant difference in the performance of students in the posttest between the two experimental groups

Note: Probability Value Scale: $^{**}p<0.01$ (Highly Significant); $^{*}p<0.05$ (Significant); $p>0.05$ (Not significant)

Interaction Effect Between the Pretest and the Implementation of Chatbot Using Solomon's Model Approach on Students' Performance

Table 8 presents the results of the two-way analysis of variance (ANOVA) examining the interaction effect between pretest status and the implementation of chatbot-assisted instruction using Solomon's Model Approach on students' performance. The analysis aimed to determine whether the effect of the chatbot intervention on students' performance was influenced by whether or not the students had taken the pretest. The results revealed that pretest status had a statistically significant effect on students' performance, with $F(1,72) = 7.14$ and $p = 0.009$, indicating a meaningful difference in performance between students who completed the pre-assessment and those who did not.

The context involved two main variables. The pretest status and chatbot-assisted instruction. Pretest status reflected whether students had completed a pre-assessment prior to the intervention, serving as a measure of prior knowledge and readiness. Chatbot-assisted instruction was operationalized through AI-powered conversational agents such as Gemini, Cici, and ChatGPT, which guided students through problem-solving activities, provided immediate feedback, and offered step-by-step explanations of mathematical concepts. The dependent variable, students' performance, was measured using posttest scores based on a standardized scale ranging from "did not meet expectations" to "outstanding performance." Using a Solomon four-group design allowed the study to examine both the individual and combined effects of pre-assessment and AI-supported instruction on students' mathematical problem-solving performance.

The implementation of chatbot-assisted instruction also had a statistically significant effect on students' performance, with $F(1,72) = 8.94$ and $p = 0.004$. This indicates that students exposed to chatbot-assisted learning performed significantly better than those who received traditional instruction without AI support. However, the interaction effect between pretest status and the chatbot intervention was not statistically significant, $F(1,72) = 0.15$, $p = 0.704$, which is greater than the 0.05 level of significance. Therefore, the null hypothesis was accepted, suggesting that the effect of chatbot-assisted instruction on students' performance was consistent regardless of whether students had prior exposure through the pretest. This finding highlights the robustness of AI-supported learning in enhancing problem-solving performance independently of pre-assessment.

The significant effects of both pretest status and chatbot-assisted instruction on students' performance can be explained through the principles of Constructivist Learning Theory proposed by Jean Piaget (1972) and Sociocultural Theory of Lev Vygotsky (1978). Constructivist theory emphasizes that learners actively build knowledge by connecting new information to prior experiences, which aligns with the finding that students with

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

pretest exposure performed slightly higher, as the pre-assessment may have activated prior knowledge and prepared them for instruction. Vygotsky's concept of the Zone of Proximal Development highlights the importance of scaffolding and guided support in learning. In this study, chatbots served as interactive scaffolds, providing step-by-step guidance, immediate feedback, and clarification of complex concepts, enabling students to solve problems that might have been challenging independently. The non-significant interaction effect suggests that the scaffolding provided by the chatbot was sufficient to support learning regardless of prior pre-assessment, demonstrating that AI-assisted instruction can effectively enhance problem-solving performance and conceptual understanding in mathematics for all students.

Extensive research has consistently highlighted the benefits of artificial intelligence (AI) and chatbot-assisted learning in improving student performance. Kasneci et al. (2023) emphasized that AI-powered educational tools, including chatbots, enhance learning experiences by offering personalized guidance, adaptive feedback, and tailored instructional support, which allow students to progress at their own pace. Similarly, Tlili et al. (2023) reported that intelligent learning systems provide adaptive support based on learners' individual needs, contributing to higher engagement, motivation, and academic performance. Dwivedi et al. (2023) further indicated that AI technologies foster flexible and personalized learning opportunities, encouraging students to develop critical thinking and analytical skills while exploring multiple problem-solving strategies. Holmes and Tuomi (2022) explained that intelligent tutoring systems act as digital mentors, providing real-time feedback and scaffolding that guide learners through complex tasks, enhancing their conceptual understanding. Zawacki-Richter et al. (2019) also underscored that AI applications in education create individualized learning pathways that promote higher-order thinking and problem-solving abilities.

Focusing specifically on chatbot technologies, several studies documented their effectiveness in classroom settings. Wollny et al. (2021) found that chatbot-assisted learning increased students' engagement and participation, simulating natural teacher–student interactions and promoting independent learning. Okonkwo and Ade-Ibijola (2021) demonstrated that chatbots improve problem-solving performance by providing immediate responses to students' inquiries and supporting step-by-step understanding of mathematical procedures. Følstad et al. (2021) highlighted that conversational agents enhance motivation and accessibility, allowing students to interact with learning materials more intuitively. Winkler and Söllner (2022) similarly reported that chatbots promote self-directed learning and knowledge reinforcement, supporting continuous cognitive development. Hwang and Tu (2021) emphasized that AI-assisted systems scaffold learning processes, enabling students to build confidence in their abilities and improve problem-solving skills over time. Huang et al. (2023) indicated that AI tools facilitate exploration of multiple strategies, deepening learners' conceptual understanding and fostering higher cognitive engagement.

Other recent studies confirmed the transformative potential of AI in supporting academic performance and cognitive development. Kuhail et al. (2023) showed that AI-powered chatbots enhance learner engagement and promote interactive learning experiences that support academic success. Alneyadi et al. (2023) reported that AI chatbots enable continuous access to explanations and guidance, helping students develop self-regulation and independent learning habits. Firat (2023) observed that AI-supported conversational agents significantly improve conceptual understanding, engagement, and problem-solving capabilities across diverse educational contexts. Raj et al. (2022) found that chatbots in mathematics instruction reduce cognitive load and support scaffolded learning, leading to improved mastery of complex concepts. VanLehn (2022) emphasized that AI tutoring systems enhance knowledge retention and learning efficiency, particularly when combined with real-time feedback mechanisms. Li et al. (2024) further demonstrated that integrating AI tools into instruction promotes collaborative learning, critical thinking, and adaptive problem-solving. Collectively, these studies reinforce the present findings, indicating that chatbot-assisted instruction can consistently improve learning performance, independent of pretest exposure, by supporting personalized, interactive, and scaffolded learning experiences.

The implications of these findings suggest that educators can confidently integrate chatbot-assisted instruction into mathematics and other subject areas without being constrained by students' prior exposure or pretest scores. Teachers may focus on designing interactive and scaffolded chatbot activities that provide personalized feedback, guided practice, and real-time support. For students who initially struggle with mathematical concepts, targeted interventions such as adaptive AI-based exercises, small group problem-solving sessions, and peer-assisted learning can further strengthen their understanding and performance. Moreover, schools and

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

administrators may consider implementing professional development programs to help teachers effectively utilize AI tools and integrate them with traditional instruction. Overall, the results underscored that AI-powered chatbots have the potential to improve learning performance consistently, ensuring that students achieve mastery regardless of initial readiness or prior assessment exposure.

Table 8 Interaction Effect Between the Pretest and the Implementation of Chatbot Using Solomon's Model Approach on Students' Performance

Source	**df**	**SS**	**MS**	**F**	**p**
Pretest Status	1	92.84	92.84	7.14	0.009
Intervention (Chatbots)	1	116.26	116.26	8.94	0.004
Pretest Status × Intervention	1	1.89	1.89	0.15	0.704
Error	72	936.63	13.01		

Ho: There is no interaction effect between the pretest and the integration of Chatbot Using Solomon's Model Approach on Students' Performance

Note. SS = Sum of Squares; MS = Mean Square; $p < .05$ indicates statistical significance.

CONCLUSIONS AND RECOMMENDATIONS

The findings of the study revealed that students initially demonstrated very low levels of mathematical performance, indicating insufficient prior knowledge and limited problem-solving skills before instruction. Both traditional instruction and chatbot-assisted instruction contributed to significant improvements in students' mathematical performance, enabling learners to achieve the required level of competence. However, chatbot-assisted instruction proved to be more effective, as a greater number of students attained higher levels of competence and improved mathematical problem-solving performance compared to those who received only traditional instruction. The results further showed that students in the control and experimental groups started at comparable levels of performance prior to the intervention, ensuring the validity of the comparison between instructional approaches. Moreover, pretest exposure did not significantly influence students' performance under traditional instruction, and chatbot-assisted instruction remained consistently effective regardless of whether students were exposed to a pretest. These findings demonstrate that chatbot-assisted instruction has a stable and independent effect in enhancing students' mathematical performance and problem-solving abilities.

Mathematics teachers may provide intensive and structured instructional support at the beginning of instruction to address students' low prior knowledge and strengthen foundational mathematical problem-solving skills. Teachers may also continue to implement effective traditional teaching strategies, such as guided practice, clear explanations, and timely feedback, to sustain students' achievement of the required level of competence. In addition, mathematics teachers may integrate chatbot-assisted instruction into classroom practices and maximize its use alongside traditional teaching methods to further improve students' mathematical performance and promote higher levels of competence. Diagnostic assessments may also be conducted to identify students' baseline knowledge and guide the development of targeted and differentiated instructional strategies. Since pretest exposure does not significantly affect learning outcomes, teachers may adopt flexible instructional approaches and implement chatbot-assisted instruction regardless of students' prior exposure to pretests. School administrators and the Human Resource Department may support the effective integration of chatbot-assisted instruction by providing adequate training, resources, and access to AI-based learning tools. Students may actively engage with chatbot-assisted learning platforms to deepen their understanding of mathematical concepts, enhance problem-solving skills, and develop greater responsibility for their own learning. Finally, future researchers may conduct further studies exploring additional variables, contexts, and long-term effects of chatbot-assisted instruction to further validate and expand the findings of this study.

REFERENCES

1. Abbas, N., Whitfield, J., Atwell, E., Bowman, H., Pickard, T., & Walker, A. (2022). Online chat and chatbots to enhance mature student engagement in higher education. International Journal of Lifelong Education, 41(3), 308-326. https://tinyurl.com/y4569kwz
2. Abbas, T., & Abbas, A. (2025). AI-Powered Concept Mapping in Collaborative and Individual Learning: Enhancing ICT-Based Reading Comprehension. https://tinyurl.com/mr8dpxa3
3. Abidin, R. Z., Fathurrohman, M., Hendrayana, A., & Thaariq, Z. Z. A. (2025). AI-assisted problem-based learning: Effects on problem-solving abilities across learning styles. Jurnal Inovasi dan Teknologi Pembelajaran, 12(3), 162-172. https://tinyurl.com/3snz6tf2
4. Abrar, M., Aboraya, W., Khaliq, R. A., Subramanian, K. P., Al Husaini, Y., & Al Hussaini, M. (2025). AI-Powered Learning Pathways: Personalized Learning and Dynamic Assessments. International Journal of Advanced Computer Science & Applications, 16(1). https://tinyurl.com/3n97s6bd
5. 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. https://tinyurl.com/4c2r4ddc
6. 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. https://tinyurl.com/4c2r4ddc
7. Akavova, A., Temirkhanova, Z., & Lorsanova, Z. (2023). Adaptive learning and artificial intelligence in the educational space. In E3S web of conferences (Vol. 451, p. 06011). EDP Sciences. https://tinyurl.com/yvfcn34t
8. Akram, A., Kiren, A., Sabir, S., & Aslam, S. (2025). The effect of AI based scaffolding on problem solving and metacognitive awareness in learners. The Critical Review of Social Sciences Studies, 3(3), 1074-1089. https://tinyurl.com/3hf4bazn
9. Alam, M. N., Islam, M. A., Babiker, M. O., Siddiqui, M. S., Amin, M. B., & Oláh, J. (2026). AI-assisted learning tools and student learning outcomes: A cognitive load theory perspective. Computers in Human Behavior Reports, 21, 100986. https://tinyurl.com/3dccsv78
10. Alfageh, D. H., York, C. S., Hodge-Zickerman, A., & Xie, Y. (2024). Elementary Teachers' Use of Adaptive Diagnostic Assessment to Improve Mathematics Teaching and Learning: A Case Study. International Electronic Journal of Mathematics Education, 19(1). https://tinyurl.com/4tu75b9k
11. Alfehaid, A., & Hammami, M. A. (2023). Artificial intelligence in education: literature review on the role of conversational agents in improving learning experience. International Journal of Membrane Science and Technology, 10(3), 3121-3129. https://tinyurl.com/5bnn94xu
12. Ali, S. (2024). Exploring the Role of Assessment in Shaping Educational Outcomes. Makran Journal of Educational Research, 1(02), 100-115. https://tinyurl.com/2t8zmxut
13. Anders, A. D., & Speltz, E. D. (2025). Developing generative AI literacies through self-regulated learning: A human-centered approach. Computers and Education: Artificial Intelligence, 100482. https://tinyurl.com/3yfkxwpw
14. Awang, L. A., Yusop, F. D., & Danaee, M. (2025). Current practices and future direction of artificial intelligence in mathematics education: A systematic review. International Electronic Journal of Mathematics Education, 20(2), em0823. https://tinyurl.com/2p9k39bx
15. Ayeni, O. O., Al Hamad, N. M., Chisom, O. N., Osawaru, B., & Adewusi, O. E. (2024). AI in education: A review of personalized learning and educational technology. GSC Advanced Research and Reviews, 18(2), 261-271. https://tinyurl.com/4x6ddvnk
16. Bairbayeva, S. (2023, December). Elevating Education: Unpacking the Impact of Teaching and Learning Conditions on Teacher Retention, School Performance, and Student Equity through Teacher-Led Learning and Leadership. In Publisher. agency: Proceedings of the 4th International Scientific Conference «Interdisciplinary Science Studies»(December 1, 2023). Dublin, Ireland, 2023. 212 (p. 132). Letterkenny Institute of Technology. https://tinyurl.com/3wdjv6ev
17. Barua, P. D., Vicnesh, J., Gururajan, R., Oh, S. L., Palmer, E., Azizan, M. M., ... & Acharya, U. R. (2022). Artificial intelligence enabled personalised assistive tools to enhance education of children with neurodevelopmental disorders—a review. International journal of environmental research and public health, 19(3), 1192. https://tinyurl.com/39xuzevv

18. Baskara, F. R. (2023). Chatbots and flipped learning: Enhancing student engagement and learning outcomes through personalised support and collaboration. IJORER: International Journal of Recent Educational Research, 4(2), 223-238. https://tinyurl.com/537wsx4r
19. Basri, W. S. (2024). Effectiveness of AI-powered Tutoring Systems in Enhancing Learning Outcomes. Eurasian Journal of Educational Research (EJER), (110). https://tinyurl.com/3syxy776
20. Bosch, C., & Kruger, D. (2024). AI chatbots as open educational resources: Enhancing student agency and self-directed learning. Italian Journal of Educational Technology, 32(1), 53-68. https://tinyurl.com/4v9m56pf
21. Calonge, D. S., Smail, L., & Kamalov, F. (2023). Enough of the chit-chat: A comparative analysis of four AI chatbots for calculus and statistics. Journal of Applied Learning and Teaching, 6(2), 346-357. https://tinyurl.com/2x5k48y5
22. 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. https://tinyurl.com/446tjayu
23. Cheng, L., Croteau, E., Baral, S., Heffernan, C., & Heffernan, N. (2024). Facilitating student learning with a chatbot in an online math learning platform. Journal of Educational Computing Research, 62(4), 687-717. https://tinyurl.com/2ub33c8x
24. Chounta, I. A., Bardone, E., Raudsep, A., & Pedaste, M. (2022). Exploring teachers' perceptions of artificial intelligence as a tool to support their practice in Estonian K-12 education. International journal of artificial intelligence in education, 32(3), 725-755. https://tinyurl.com/39cr47uc
25. Chraa, A., & Alidrissi, M. (2025). Optimizing EFL Learners' Outcomes in Formative Assessment through Educational Technology Integration. International Journal of Language and Literary Studies, 7(3), 456-486. https://tinyurl.com/yc8ad59r
26. Cooney, C. (2025). Examining the Effect of Technology-Enhanced Formative Assessment on Student Engagement and Learning in Higher Education: An Action Research Study (Doctoral dissertation, National University of Ireland Maynooth). https://tinyurl.com/2sb5c52n
27. Correia, A., Água, P., & Lobo, V. (2024). Adaptive learning design: integrating AI to personalize critical thinking education. EDULEARN24 Proceedings, 7733-7741. https://tinyurl.com/mthz4zfh
28. Criss, C. J., Konrad, M., Alber-Morgan, S. R., & Brock, M. E. (2024). A systematic review of goal setting and performance feedback to improve teacher practice. Journal of Behavioral Education, 33(2), 275-296. https://tinyurl.com/y5b6pv46
29. Dahal, N., Lamichhnae, B. R., Luitel, B. C., & Pant, B. P. (2023). AI chatbots as math algorithm problem solvers: A critical evaluation of its capabilities and limitations. In Proceedings of the 28th Asian Technology Conference in Mathematics (Vol. 28, No. 1, pp. 429-438). https://tinyurl.com/mvnk7x2r
30. Dahri, N. A., Al-Rahmi, W. M., Alhashmi, K. A., & Bashir, F. (2025). Enhancing Mobile Learning with AI-Powered Chatbots: Investigating ChatGPT's Impact on Student Engagement and Academic Performance. International Journal of Interactive Mobile Technologies, 19(11). https://tinyurl.com/4rz2459v
31. Daniel, K., Msambwa, M. M., Antony, F., & Wan, X. (2024). Motivate students for better academic achievement: A systematic review of blended innovative teaching and its impact on learning. Computer Applications in Engineering Education, 32(4), e22733. https://tinyurl.com/4x5fhjer
32. Davar, N. F., Dewan, M. A. A., & Zhang, X. (2025). AI chatbots in education: challenges and opportunities. Information, 16(3), 235. https://tinyurl.com/mr48fbmc
33. Davar, N. F., Dewan, M. A. A., & Zhang, X. (2025). AI chatbots in education: Challenges and opportunities. Information, 16(3), 235. https://tinyurl.com/2h33yae3
34. David, B., Chalon, R., & Zhang, X. (2022, September). Virtual assistants (chatbots) as help to teachers in collaborative learning environment. In International Conference on Interactive Collaborative Learning (pp. 135-146). Cham: Springer International Publishing. https://tinyurl.com/48np647c
35. Demartini, C. G., Sciascia, L., Bosso, A., & Manuri, F. (2024). Artificial intelligence bringing improvements to adaptive learning in education: A case study. Sustainability, 16(3), 1347. https://tinyurl.com/2p9t4ff8
36. El Azhari, K., Hilal, I., Daoudi, N., & Ajhoun, R. (2023). SMART chatbots in the E-learning domain: A systematic literature review. International Journal of Interactive Mobile Technologies, 17(15). https://tinyurl.com/ca6cx45n

37. El Karkri, M., Quesada, A., & Romero-Ariza, M. (2025). Methodological aspects of the Solomon four-group design: Detecting pre-test sensitisation and analysing qualitative and quantitative variables in education research. Review of Education, 13(1), e70050. https://tinyurl.com/yxrwc66w
38. ElSayary, A. (2024). Integrating generative AI in active learning environments: Enhancing metacognition and technological skills. Journal of Systemics, Cybernetics and Informatics, 22(3), 34-37. https://tinyurl.com/ye8rk5f2
39. Erawati, N. K., & Adnyana, P. B. (2024). Implementation of jean peaget's theory of contructivism in learning: A Literature Review. Indonesian Journal of Educational Development (IJED), 5(3), 394-401. https://tinyurl.com/2jmc8wrb
40. Gamage, C. M. (2025). Impact of Pre-Assessment and Post-Assessment in an Introductory Real Analysis Course. arXiv preprint arXiv:2505.22479. https://tinyurl.com/53xsy7hy
41. Golaki, S. P., Kamali, F., Bagherzadeh, R., Hajinejad, F., & Vahedparast, H. (2022). The effect of Flipped Classroom through Near Peer Education (FC through NPE) on patient safety knowledge retention in nursing and midwifery students: a solomon four-group design. BMC Medical Education, 22(1), 112. https://tinyurl.com/3xxez2rd
42. Golboni, F., Ahmadzadeh, H., Nadrian, H., Babazadeh, T., Najafi, S., Ghahremaninasab, P., ... & Mahmoodi, H. (2024). Effects of a Short-time health literacy promotion program (HeLPP) on biochemical factors, self-care and quality of life among rural patients with type-2 diabetes: A field trial with Solomon four-group design. Health Promotion Perspectives, 14(2), 175. https://tinyurl.com/3a376rtj
43. Gosztonyi, K., & Varga, E. (2023). Teachers' practices and resources in the Hungarian "Guided Discovery" approach to teaching mathematics: presenting and representing "series of problems". ZDM–Mathematics Education, 55(3), 641-656. https://tinyurl.com/2h3rppv8
44. Haelermans, C. (2022). The Effects of Group differentiation by students' learning strategies. Instructional Science, 50(2), 223-250. https://tinyurl.com/2cr67yf5
45. Hansen, E. J. (2023). Idea-based learning: A course design process to promote conceptual understanding. Routledge. https://tinyurl.com/mrx3krbk
46. 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(1), 40-68. https://tinyurl.com/92mjkvch
47. Huang, H. W., Teng, D. C. E., & Tiangco, J. A. N. Z. (2025). The impact of AI chatbot-supported guided discovery learning on pre-service teachers' learning performance and motivation. Journal of Science Education and Technology, 34(6), 1286-1300. https://tinyurl.com/ymvc3h3s
48. Imamguluyev, R., Hasanova, P., Imanova, T., Mammadova, A., Hajizada, S., & Samadova, Z. (2024). Ai-powered educational tools: Transforming learning in the digital era. International Research Journal of Modernization in Engineering Technology and Science, 6, 920-929. https://tinyurl.com/3ckvfh3j
49. Infante, R., Corocoto, M., & Nobis Jr, M. L. (2025). Students' Perspectives, Practices, and Challenges in AI-Driven Mathematics Education. Psychology and Education: A Multidisciplinary Journal, 41(6), 1-1. https://tinyurl.com/2mmm4k7r
50. Jančařík, A., Michal, J., & Novotná, J. (2023). Using AI Chatbot for math tutoring. Journal of Education Culture and Society, 14(2), 285-296. https://tinyurl.com/bdfe75ee
51. Javed, M. (2023). The effectiveness of different teaching methods in education: a comprehensive review. Journal of Social Signs Review, 1(1), 17-24. https://tinyurl.com/4bawppwa
52. Jayapriya, N. (2025). Empowering Learners: The Role of Chatbots in Self-Directed Learning. Journal of Pedagogical Insights & Technological Advancements Volume, 2(1). https://tinyurl.com/2bju39k2
53. Jayapriya, N. (2025). Empowering Learners: The Role of Chatbots in Self-Directed Learning. Journal of Pedagogical Insights & Technological Advancements Volume, 2(1). https://tinyurl.com/2bju39k2
54. Jin, G., Danielson, R. W., & Ramazan, O. (2025). Resurrecting a classic design: Examining the refutational text effect using a Solomon four-group design. Discourse Processes, 62(2), 112-132. https://tinyurl.com/5x87bkyb
55. Kaswan, K. S., Dhatterwal, J. S., & Ojha, R. P. (2024). AI in personalized learning. In Advances in technological innovations in higher education (pp. 103-117). CRC Press. https://tinyurl.com/bdzn28p7

56. Ke, W., Du, X., He, D., & Pan, M. (2024, December). Research on Teaching Design for AI-Enabled Higherorder Thinking Cultivation. In 2024 IEEE/WIC International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT) (pp. 766-770). IEEE. https://tinyurl.com/3b8ccup5
57. Klar, M. (2025). Generative AI Chatbots for self-regulated learning while balancing cognitive load: perceptions, interaction patterns, and instructional designs in K-12 learning (Doctoral dissertation, Dissertation, Duisburg, Essen, Universität Duisburg-Essen, 2025). https://tinyurl.com/yeh3pxkv
58. Kovalchuk, V., Reva, S., Volch, I., Shcherbyna, S., Mykhailyshyn, H., & Lychova, T. (2025, June). Artificial intelligence as an effective tool for personalized learning in modern education. In Environment. Technology. Resources. Proceedings of the International Scientific and Practical Conference (Vol. 3, pp. 187-194). https://tinyurl.com/4tsk2phb
59. Kumar, A. A. (2023). Perspective chapter: Emotive cognition strategies on enhancing meaningful learning among undergraduate student-teachers. In Education annual volume 2023. IntechOpen. https://tinyurl.com/2u58vxcz
60. Kusumoriny, L. A. (2025). Enhancing Learning Through Assessment and Evaluation: Strategies for Student Progress Part 2. CV Eureka Media Aksara. https://tinyurl.com/468jhxfk
61. Laja, Y. P. W., Delvion, E. B. S., & Siahaan, M. M. L. (2025). Chatbot Artificial Intelligence (AI) to Supporting Differentiated Mathematics Learning. Jurnal Pendidikan MIPA, 26(1), 118-130. https://tinyurl.com/4pt846dw
62. Laksana, F. S. W., & Fiangga, S. (2022). The development of web-basDanaeeed chatbot as a mathematics learning media on system of linear equations in three variables. MATHEdunesa, 11 (1), 145–154. https://tinyurl.com/vumzm7pc
63. Leijen, Ä., Malva, L., Pedaste, M., & Mikser, R. (2022). What constitutes teachers' general pedagogical knowledge and how it can be assessed: A literature review. Teachers and Teaching, 28(2), 206-225. https://tinyurl.com/2ffppeje
64. Li, P. H., Lee, H. Y., Cheng, Y. P., Starčič, A. I., & Huang, Y. M. (2023, August). Solving the self-regulated learning problem: Exploring the performance of ChatGPT in mathematics. In International Conference on Innovative Technologies and Learning (pp. 77-86). Cham: Springer Nature Switzerland. https://tinyurl.com/3jsh2tk2
65. Li, X., & Zaki, R. (2024). Harnessing the power of digital resources in mathematics education: The potential of augmented reality and artificial intelligence. In IoT, AI, and ICT for educational applications: Technologies to enable education for all (pp. 191-223). Cham: Springer Nature Switzerland. https://tinyurl.com/59tw5p4m
66. Lin, C. C., Huang, A. Y., & Lu, O. H. (2023). Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review. Smart learning environments, 10(1), 41. https://tinyurl.com/yups5ru4
67. Lin, M. P. C., & Chang, D. (2023). CHAT-ACTS: A pedagogical framework for personalized chatbot to enhance active learning and self-regulated learning. Computers and Education: Artificial Intelligence, 5, 100167. https://tinyurl.com/mpddatz2
68. Lonergan, R., Cumming, T. M., & O'Neill, S. C. (2022). Exploring the efficacy of problem-based learning in diverse secondary school classrooms: Characteristics and goals of problem-based learning. International Journal of Educational Research, 112, 101945. https://tinyurl.com/nh3kz6m4
69. Luckyardi, S., Karin, J., Rosmaladewi, R., Hufad, A., & Haristiani, N. (2024). Chatbots as digital language tutors: revolutionizing education through AI. Indonesian Journal of Science and Technology, 9(3), 885-908. https://tinyurl.com/y7u82np2
70. Maftuna, K. (2025). Scaffolding techniques: Supporting student progress step-by-step. TA'LIM, TARBIYA VA INNOVATSIYALAR JURNALI, 1(7), 264-268. https://tinyurl.com/mv2d2en8
71. Mageira, K., Pittou, D., Papasalouros, A., Kotis, K., Zangogianni, P., & Daradoumis, A. (2022). Educational AI chatbots for content and language integrated learning. Applied Sciences, 12(7), 3239. https://tinyurl.com/5xjbjtyt
72. Manoj, D., Dutt, A., & Saratha, B. (2024). AI-powered adaptive learning systems: Revolutionizing classroom education. Advancing Knowledge from Multidisciplinary Perspective Engineering, Technology and Management, 101. https://tinyurl.com/ue6ym3ru

73. Mehmood, W., Gondal, S., Faiz, M. S., & Khurshid, A. (2025). AI-assisted metacognitive strategies for improving self-regulated learning among high school students. The Critical Review of Social Sciences Studies, 3(2), 2333-2349. https://tinyurl.com/yfp8s4ak
74. Mejía-Rodríguez, A. M., & Kyriakides, L. (2022). What matters for student learning outcomes? A systematic review of studies exploring system-level factors of educational effectiveness. Review of Education, 10(3), e3374. https://tinyurl.com/4srfcy2f
75. Mohebbi, A. (2025). Enabling learner independence and self-regulation in language education using AI tools: a systematic review. Cogent Education, 12(1), 2433814. https://tinyurl.com/yhmunrd5
76. Moral-Sánchez, S. N., Rey, F. J. R., & Cebrián-de-la-Serna, M. (2023). Analysis of artificial intelligence chatbots and satisfaction for learning in mathematics education. IJERI: International Journal of Educational Research and Innovation, (20), 1-14. https://tinyurl.com/yjuwcsc8
77. Mousa, M. (2025). AI-supported formative assessments: Enhancing student-centered learning and teacher perceptions. Journal of Pedagogy and Education Science, 4(02), 127-141. https://tinyurl.com/227bc37j
78. Mukhtarova, S. (2026). The Role of Teacher-Centered And Student-Centered Approaches In Effective Teaching. Образование Наука И Инновационные Идеи В Мире, 86(1), 63-69. https://tinyurl.com/2vy59bw4
79. Nair, S., & Mathew, J. (2021). Evaluation of gamified training a Solomon four-group analysis of the impact of gamification on learning outcomes. TechTrends, 65(5), 750-759. https://tinyurl.com/mr2sbzjd
80. Naseer, F., Khan, M. N., Tahir, M., Addas, A., & Aejaz, S. H. (2024). Integrating deep learning techniques for personalized learning pathways in higher education. Heliyon, 10(11). https://tinyurl.com/5n8e74tc
81. Nguyen, Q. N. (2022). Teachers' Scaffolding Strategies in Internet-Based ELT Classes. Tesl-Ej, 26(1), n1. https://tinyurl.com/mwfezw6s
82. Opana, O. J., & Guantai, K. H. (2025). Relationship Between Clear Performance Standards and Students' Academic Performance in Homa Bay County. Journal of Education, 5(2), 15-26. https://tinyurl.com/mux2bhz5
83. Ouyang, F., Xu, W., & Cukurova, M. (2023). An artificial intelligence-driven learning analytics method to examine the collaborative problem-solving process from the complex adaptive systems perspective. International Journal of Computer-Supported Collaborative Learning, 18(1), 39-66. https://tinyurl.com/jjt66b2n
84. Pan, S. C., & Carpenter, S. K. (2023). Prequestioning and pretesting effects: A review of empirical research, theoretical perspectives, and implications for educational practice. Educational Psychology Review, 35(4), 97. https://tinyurl.com/2s37y258
85. Pappagallo, S. (2024). Chatbots in education: A dual perspective on innovation and ethics. Journal of Digital Pedagogy, 3(1), 3-10. https://tinyurl.com/5n6sx4n9
86. Plevris, V., Papazafeiropoulos, G., & Jiménez Rios, A. (2023). Chatbots put to the test in math and logic problems: A comparison and assessment of ChatGPT-3.5, ChatGPT-4, and Google Bard. Ai, 4(4), 949-969. https://tinyurl.com/az9w98ec
87. Prabakaran, B., & Saravanakumar, A. R. (2021). Effectiveness of E-Content Module in Learning Set Language among Ninth Standard Students-Solomon Four Group Method of the Experimental Study. Turkish Journal of Computer and Mathematics Education, 12(2), 2515-2522. https://tinyurl.com/bdhhmhsm
88. Prabakaran, B., & Saravanakumar, A. R. (2021). Effectiveness of E-Content Module in Learning Set Language among Ninth Standard Students-Solomon Four Group Method of the Experimental Study. Turkish Journal of Computer and Mathematics Education, 12(2), 2515-2522. https://tinyurl.com/bdhhmhsm
89. Pramerta, I. G. P. A., Pramawati, A. A. I. Y., Widhiasih, L. K. S., Mas, L. A. M. G. D., & Andari, K. A. M. (2025). Tailoring Reading Courses to Student Needs: A Pathway to Effective Curriculum and Teaching Strategies. Educational Process: International Journal, 15, e2025165. https://tinyurl.com/3j92m9m3
90. Rajak, K. K., & Dey, N. G. (2025). Differentiated assessment strategies: An assessment practice for diverse learners in the inclusive classroom. Asian Journal of Education and Social Studies, 51(1), 17-24. https://tinyurl.com/2jf2dej3

91. Rizki, L. M., & Kusumah, Y. S. (2025). Unveiling the Needs: Developing AI-Based Chatbots in Blended Learning to Enhance Computational Thinking and Self-Regulated Learning in Mathematics Education. The Eurasia Proceedings of Educational and Social Sciences, 41, 11-24. https://tinyurl.com/2kaur58s
92. Roblyer, M., Roblyer, M. D., & Doering, A. H. (2024). Integrating educational technology into teaching. BoD–Books on Demand. https://tinyurl.com/565j7wt3
93. Rohid, N., Masitoh, S., & Arianto, F. (2025). Effectiveness of using educational chatbots in improving student learning independence. https://tinyurl.com/3kxj9xb5
94. Saar, M., Ljalikova, A., Theophilou, E., Alkhasawneh, S. N., & Hernández-Leo, D. (2025, September). Empowering Teachers to Enhance Student High Order Thinking Skills with Artificial Intelligence Educational Tools. In European Conference on Technology Enhanced Learning (pp. 442-456). Cham: Springer Nature Switzerland. https://tinyurl.com/2dzwc9bn
95. Şahin, Ş., & Kılıç, A. (2024). Comparison of the effectiveness of project-based 6E learning and problem-based quantum learning: Solomon four-group design. Journal of Research in Innovative Teaching & Learning. https://tinyurl.com/bdprwnm3
96. Sajja, R., Sermet, Y., Cwiertny, D., & Demir, I. (2025). Integrating AI and learning analytics for data-driven pedagogical decisions and personalized interventions in education. Technology, knowledge and learning, 1-31. https://tinyurl.com/bpvf7e98
97. Samaila, K., & Al-Samarraie, H. (2024). Reinventing teaching pedagogy: the benefits of quiz-enhanced flipped classroom model on students' learning outcomes and engagement. Journal of Applied Research in Higher Education, 16(4), 1214-1227. https://tinyurl.com/pfk3uu82
98. Saravanakumar, A. R. (2021). The Influence of e-Content on Academic Performance and Retention Ability in Learning Mathematics among High School Students-Solomon Four Equivalent Group of Experimental Design. Turkish Journal of Computer and Mathematics Education, 12(6), 2360-2369. https://tinyurl.com/ptnkhyht
99. See, B. H., Gorard, S., Lu, B., Dong, L., & Siddiqui, N. (2022). Is technology always helpful?: A critical review of the impact on learning outcomes of education technology in supporting formative assessment in schools. Research Papers in Education, 37(6), 1064-1096. https://tinyurl.com/u2vvm7ma
100. Sharp, J. L. L. (2023). A Quasi-Experimental Study on the Effect of Course Modality on Learning Transfer of Skydiving Teachers-In-Training: A Solomon Four-Group Design. National University. https://tinyurl.com/26bcf4yh
101. Singh, B. B. (2025). Pedagogical Strategies: Teaching Methods and Approaches to Promote Student Engagement and Understanding. Bharati International Journal of Multidisciplinary Research and Development, 3(2). https://tinyurl.com/mrmwx3f5
102. Smaldino, S., Smaldino, S. E., Lowther, D. L., & Russell, J. D. (2024). Instructional technology and media for learning. BoD–Books on Demand. https://tinyurl.com/4h6axrvm
103. Soderstrom, N. C., & Bjork, E. L. (2023). Pretesting enhances learning in the classroom. Educational Psychology Review, 35(3), 88. https://tinyurl.com/pthwtp8z
104. Strielkowski, W., Grebennikova, V., Lisovskiy, A., Rakhimova, G., & Vasileva, T. (2025). AI-driven adaptive learning for sustainable educational transformation. Sustainable development, 33(2), 1921-1947. https://tinyurl.com/5n6e4juu
105. Taber, K. S. (2025). Mediated learning leading development—The social development theory of Lev Vygotsky. In Science education in theory and practice: An introductory guide to learning theory (pp. 275-292). Cham: Springer Nature Switzerland. https://tinyurl.com/4dsavmax
106. Tang, K. H. D. (2023). Student-centered approach in teaching and learning: What does it really mean?. Acta Pedagogia Asiana, 2(2), 72-83. https://tinyurl.com/zavs8ekt
107. Van der Linden, J., van der Vleuten, C., Nieuwenhuis, L., & van Schilt-Mol, T. (2023). Formative use of assessment to foster self-regulated learning: the alignment of teachers' conceptions and classroom assessment practices. Journal of Formative Design in Learning, 7(2), 195-207. https://tinyurl.com/yc86a8ex
108. Van Doc, N., Nam, N. T. H., Thanh, N. T., & Giam, N. M. (2023). Teaching mathematics with the assistance of an AI chatbot to enhance mathematical thinking skills for high school students. International Journal of Current Science Research and Review, 6(12), 8574-8580. https://tinyurl.com/54rk5kk6

109. Vanichvasin, P. (2021). Chatbot Development as a Digital Learning Tool to Increase Students' Research Knowledge. International Education Studies, 14(2), 44-53. https://tinyurl.com/yc89xt5e
110. Vintere, A., Safiulina, E., & Panova, O. (2024). AI-based mathematics learning platforms in undergraduate engineering studies: analyses of user experiences. Engineering for Rural Development, 23, 1042-1047. https://tinyurl.com/zwyym3vu
111. Vorsah, R. E., & Oppong, F. (2024). Leveraging AI to enhance active learning strategies in science classrooms: implications for teacher professional development. World Journal of Advanced Research and Reviews, 24(2), 1355-1370. https://tinyurl.com/5n6vb8an
112. Wardat, Y., Tashtoush, M. A., AlAli, R., & Jarrah, A. M. (2023). ChatGPT: A revolutionary tool for teaching and learning mathematics. Eurasia Journal of Mathematics, Science and Technology Education, 19(7), em2286. https://tinyurl.com/9ewdcyy2
113. Wu, D., Zhang, S., Ma, Z., Yue, X. G., & Dong, R. K. (2024). Unlocking potential: Key factors shaping undergraduate self-directed learning in AI-enhanced educational environments. Systems, 12(9), 332. https://tinyurl.com/2cpxrsra
114. Yeo, S., Moon, J., & Kim, D. J. (2024). Transforming mathematics education with AI: Innovations, implementations, and insights. Mathematical Education, 63(2), 386-392. https://tinyurl.com/3t329kfb
115. Yetkin, B., & Başer, A. (2025). Enhancing knowledge and attitudes through the 'healthy nutrition'education program: a Solomon four-group experimental study with older adults at a social life campus. BMC geriatrics, 25(1), 436. https://tinyurl.com/39zphszs
116. Young, K. S. (2024). Using High-Fidelity Simulation Training in Hemodynamic Monitoring With Senior Level Associate's Degree Nursing Students in an Advanced Concepts Course: A Quantitative Solomon Four-Group Comparative Study (Doctoral dissertation, National University). https://tinyurl.com/yxdw2d4v
117. Younis, M., Imdad, P., & Rahman, A. A. U. (2021). Effects of constructive and timely feedback on academic performance of students. Pakistan Journal of Educational Research, 4(4). https://tinyurl.com/342bwmef
118. Yuensook, T., Jantakoon, T., & Limpinan, P. (2025). AI-driven adaptive learning systems in higher education: A systematic review. Journal of Education and Learning. https://tinyurl.com/42jdpazd
119. Zahid, M. U., & AlManiam, M. (2025). The role of effective feedback in enhancing student academic achievement through virtual formative assessment: A comprehensive study. International Journal of Academic Research in Business and Social Sciences, 15(3), 112-130. https://tinyurl.com/3mv5be22
120. Zhang, R., Zou, D., & Cheng, G. (2024). A review of chatbot-assisted learning: pedagogical approaches, implementations, factors leading to effectiveness, theories, and future directions. Interactive Learning Environments, 32(8), 4529-4557. https://tinyurl.com/57yvp8tb
121. Zhu, J., Gan, X., Gou, Q., & Tie, H. (2024). Enhancing Medical Education Through the BOPPPS (Bridge-in, Objective, Preassessment, Participatory learning, Post-assessment, Summary): A Comprehensive Review and Analysis. https://tinyurl.com/5n7pndzx https://doi.org/10.1038/s41539-024-00261-7