# Leveraging Algorithm Instruction with AI Chatbots: A Detailed Exploration of Their Impact on Students' Computational Thinking

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***Abstract*—This research aims to understand the effect of algorithm instruction with artificial intelligence-based chatbots on students' Computational Thinking (CT) skills. A quasi-experimental approach was employed, involving two groups: an experimental group where some students used conversational Artificial Intelligence (AI) bots as learning assistants and a control group where students used no such technology. The proposed research tools were the pre and post-tests and the questionnaires, which targeted users' rating of the chatbot's usefulness, user interface, and its influence on learning motivation. Analysis of the collected data was done using independent t-tests to compare the results between groups as well as correlation analysis to find the connection between AI chatbot utilization and students' computational thinking skills. This study shows a positive increase in the overall CT skills of the experimental group compared to the control group. Instead, a positive relationship was found between the degree of the use of the chatbots and the students' computational thinking performance. Accordingly, this research points to the inclusion of AI-based chatbots into algorithm instruction as a valuable approach to raising computational thinking disposition, learning motivation, and learning outcome. Therefore, the application of the value of AI technology indicates the possibility of transforming the implementation and teaching of an algorithm in higher education.**

***Keywords*—chatbot, computational thinking, algorithm, Artificial Intelligence (AI)-based instruction**

## I. Introduction

In the context of the modern school, Computational Thinking (CT) skill is, at present, one of the essential skills that learners must develop to pursue a Science, Technology, Engineering, and Mathematics (STEM) career. It may be described as a process of problem-solving that encompasses several characteristics and dispositions, including the ability to pose problems, recognize patterns, and design and implements algorithms; computational thinking equips students in the best way possible to approach and solve a problem of their choice The concept of computational thinking is therefore useful in developing problem-solving skills, and can be defined as a process of problem-solving encompassing several characteristics and dispositions such as posing problems, identifying patterns Given the fact that society will soon be automizing many of its processes, computational thinking becomes fundamental not only for computer science students but for whoever interacts with information [1]. Unfortunately, there is evidence that many students have difficulties in understanding these concepts, let alone being able to apply them, especially in algorithm courses. A key area of programming and computer science is algorithms yet because of their abstract nature they become challenging. It can be quite hard for students to grasp how algorithms are put into practice and thus it is hard for them to see the application that corresponds with their book knowledge. This gap is most clearly seen in school learning environments confined in their paradigms of Standards, mathematical problem-solving algorithms, and rote learning [2].

Historically, methods of teaching computer science are mostly focused on delivering lectures and following the data presented in textbooks [3]. In many a case, the teachers tend to focus more on introducing the concepts and theories as opposed to their practical use learners tend to memorize the procedures leading to the formulation of an algorithm without understanding the fundamental values, the principles behind it, or the effects it is likely to bring about. This poses a problem because, with such learning utilitarianism, the student is capable of cramming lots of information to pass an exam and cannot yet solve such problems [4]. Besides, this sort of engagement deficit results in demotivation and demoralization and sap the capability of applying computational thinking in different situations. The separation between content knowledge and technical training is a major problem for teachers who are trying to prepare children for the future technological society. It is equally important to see that as the market now opens up for highly skilled workers, especially in STEM areas, education institutions apply modern methods of teaching that improve the understanding of students on algorithms and computational thinking [5]. The degree of change that is needed in education has generated interest in new possibilities for using technology in computer science education.

The modern development in Artificial Intelligence (AI) has provided potential opportunities for educational improvement. The most promising tools are AI-based chatbots, with the possibility to act as engaging and interactive learning assistants in the algorithm's teaching process [6]. These chatbots can take students through conversation, give an on-the-spot commentary on the methods used by the students to solve problems, and even pose problems that need to be solved algorithmically. Indeed, since they can tailor the learning process to the individual, chatbots can assist in overcoming some of the current difficulties related to the explanation of complex algorithms and the proper approach during the implementation of computational thinking [7]. Herein below, the learner is furnished with details of how AI chatbots can improve algorithm instruction. Firstly, they can give feedback to students while they are solving the problems and should immediately notice any wrong impression that the students have developed. Such immediate, on-demand assistance can be helpful in 'locking in' learning and keep students on the right track as they grapple with the problems [8]. Secondly, chatbots can provide opportunities for individualized learning that address learner needs. Thanks to the options of analyzing the students' replies and outcomes, chatbots can change the level of the tasks proposed and share materials that are relevant to their level of comprehension, which contributes to their differentiated education. However, there are some promising attributes. The problem of the lack of experimental studies devoted to recognizing the effects of AI chatbots for students' CT using algorithm classes remains significantly to be solved in the current state of the art [9]. Whereas literature reviews to the best of the authors' knowledge have established the usefulness of AI in education, little research has examined the use of chatbots as an instructional aid for enhancing algorithm comprehension and CT abilities. This gap raises a significant challenge in improving instructional approaches because many teachers might not understand how AI technologies can help reformulation algorithm learning [10].

There is research on the impact of chatbots in educational environments, and while some of them suggest that it has a positive effect on learning interactions and the capacity to improve learning retention, others have demonstrated That the capability of improving on enhanced learning processes is quite limited [11]. This incoherent finding reveals research gaps in investigating the effectiveness of chatbots in the instruction of algorithms. Furthermore, they pointed out that some limited theoretical models or approaches have been developed specifically to implement and support chatbots in learning environments. Specifically, this work aims to fill this gap by conducting a systematic study of the impact of AI chatbots on students' computational thinking in algorithm courses. The research will address several key questions: What role do AI chatbots play in students' perceptions of algorithms? What do they imply about students' problem-solving skills? In what manner do they contribute to constructive participation and motivation in learning conditions? This research gap will be filled by this study employing a quasi-experimental design that will compare students who traditionally received their instructions with those who interacted with the AI chatbot [12]. Finally, this research aims to join the research gap in the topic of the exploration of effective teaching approaches in computer science. From this study, the understanding of how and the extent to which students' computational thinking can be influenced by AI chatbots is visualized; therefore, it may help educators and institutions know how AI technologies better help can improve algorithm teaching and prepare students for the advanced future digital environment. The work will not only enhance existing literature on computational thinking and AI in education but also offer guidelines for practitioners as they incorporate such technologies into their classrooms.

Altogether, the application of the notion of the Integration of AI chatbots in algorithm instruction outlines the prospect of improving ST's computational thinking disposition. The difficulties arising from the weakness of conventional approaches and the capability of chatbots to provide unique, engaging training appeals to the possibility of altering the way students interact with algorithms. This work seeks to examine these and other related possibilities in a bid to advance the clarification of how AI can be harnessed in enhancing learning in computer science.

## II. Literature Review

In terms of algorithm instruction and students' CT, this section introduces several concepts related to AI chatbots. The framework comprises three main components: These are (1) an Overview of computational thinking and its necessity in the curriculum, (2) the teaching of algorithms, and the problems students encounter, and (3) the position of AI chatbots in learning.

### *A. Computational Thinking*

CT is the implementation of algorithmic thinking alongside other aspects, such as problem-solving strategies in compound tasks. this notion is relevant not only to computer science but also to people in the dynamically developing information society [13]. CT comprises several essential components: the cultural skill in analyzing problems through problem clarification and identification of information and criteria that define successful solutions; where problems are fragmented into workable portions; creation of representations to convert problems into visuals such as flow charts, diagrams or models which help in devising the solutions; developing algorithms to compose logical steps for solving problems through identifying patterns and defining generalized solutions and evaluating their viability; implementation and assessment of problems through effective solutions known as testing of solutions; and Through development of these CT skills, educational systems prepare students to approach future challenges systematically and creatively in technology, engineering, and new Science, Math and other disciplines [14].

### *B. CT Is More Than a Technique Used in Software Development But Is a Key Element, Which Should Be Integrated into Any Scholarly Curriculum*

Computational thinking is beginning to be defined as an explicit learning outcome in the current curriculum. It is especially important to embody CT skills since with the development of technologies students who possess such skills will be ready to solve problems, think critically, and offer more effective solutions. Within the STEM educational paradigm aimed at the development of problem-solving and analytical skills, CT is a way to transition toward comprehension of computational foundations, programming, as well as algorithmizing [15]. However, CT is not confined to computer science; it is for all subject areas. For instance, in the biology field, people have been using computational models in system biology for creating models of ecosystems while in the social sciences field data analysis heavily depends on computed techniques. Incorporation of CT into the curriculum will enable the instructors to promote area Subject interconnections and learning for multiple career opportunities [16].

### *C. Instructions Given by Algorithm and Difficulties Encountered by the Students*

However, despite such significance of algorithms in computer science education, their instruction raises several main challenges among the students. Perhaps the major challenge is that algorithms are abstract concepts and it may not be easy for many learners to understand that concept [17]. The algorithms are generally depicted as a fixed series of operations, and the students experience considerable difficulties in relating these concepts to actual practice. Such misinterpretation not only affects their comprehension of the content but can also cause them to lose every sense of motivation and interest. If students do not understand how algorithms are applied in real-life situations, they may also lose their interest and self-reported learning progress, and observe the information as unnecessary or too complicated [18].

Yet another challenge has to do with algorithmic tasks, which are characterized by problem-solving. Students may get frustrated when solving complex problems that demand higher-order thinking skills in algorithms. Such pressure is quite demanding for the individuals, requiring relevant strategies to help them solve these problems. In such situations, students use tricks to cram algorithms instead of even comprehending the logic behind them [19]. Such a system of studying relies heavily on memorization, so the information that is absorbed hardly penetrates deeper into the brain, which makes the learner have a hard time using knowledge gained in a different or altered scenario. Besides, there is no interaction in the normal approach used in teaching and learning processes to overcome such barriers. Most teachers focus on PowerPoint presentations and come up with an approach that presents the content of the books, which in most cases does not afford students thorough engagement. The following disappointing attributes are due to this approach, Students are likely to be passive receivers of information without being active participants in the learning process. Hence, depending on the learning styles, they may have problems remembering important ideas and facts and may not get the intended message of the content they are reading; which in turn may lead to frustration and disengagement [20]. Many students also suffer from confidence crises in tackling algorithm problems. Whenever they get assignments related to their past failures, the generalized anxiety augments the distress that arises from the inability to understand the content and lowers their self-esteem. This reduces their confidence in their ability to handle problems or learn, and just makes their difficulties in mastering algorithms worsen since they avoid such tasks. Furthermore, there is little chance to practice on your own with algorithms in teaching. Students usually need to solve similar types of problems several times to be comfortable with their applicability. The result is that they may be unable to develop insights fully if they have been trained in courses that do not incorporate adequate practical exercises or project work. The lack of participation in interactive and educational activities can affect their conceptual development in algorithms in problem-solving [21].

At the same time, there is normally little time for practical application in the teaching of algorithms. Students claim that they need to repeat the problem-solving situations to gain more confidence and be more effective. Lacking the practice of actual application of the acquired knowledge in certain practical exercises or project tasks, they may struggle with effective knowledge acquisition. There is no significant interaction and education through practice thus they fail to develop on the aspect of algorithmic thinking and problem-solving. These complex issues all point to the increasing necessity for effective instructional approaches that would lead to enhanced conceptual comprehension of the algorithms. The presented strategies ensure the active participation of students, the relation of material with real-life situations, as well as opportunities for practical training, which define the improvement of teaching outcomes and the development of crucial components of computational thinking.

### *D. Theoretical Underpinnings of AI in Education*

The incorporation of AI technologies, especially chatbots into learning environments, therefore, is anchored on several theories that show how the use of these technologies can influence the learning processes positively. The most critically outlined framework is the constructivist learning theory which sees learners as building their experiences from the interaction with their environment. This theory makes it clear that learning is an active process in which the students construct their knowledge through interaction [22]. Chatbots share constructivist qualities by allowing the student to participate in discussions where they can learn through questioning a new concept or idea via the chatbot. It enables the students to develop notions regarding algorithms interactively and thus use the newly gathered information in a way that relates it to past experiences. The other theoretical perspective is the Zone of proximal development suggested by Vygotsky, hence the Zone of Proximal Development (ZPD) argument for social interaction and assistance [22]. According to Vygotsky's Social Development Theory, learners are capable of abstract or higher forms of thinking if only with the help of more capable peers, teachers, or tools. With such a pedagogical role in mind, AI chatbots can assume the role of scaffolds in the truly transformative sense, providing the needed stimulation as the students engage with difficult algorithmic content. In this way, chatbots set the context for learning at the so-called zone of proximal development, which means that hints, examples, and explanations given are still slightly beyond the learner's capability to grasp but just enough for an individual to be able to progress forward and be able to effect meaningful learning of the algorithms. This individual help can help students apply it to complex problems that he or she would otherwise consider to be too difficult, thus promoting a growth attitude and improving the learning outcomes [23].

Also, there is a Social Cognitive Theory that was put forward by Albert Bandura which aspects such concepts as observational learning, imitation, and modeling as the major components of the educational process. By this theory, new behaviors and information are learned from observation and the individual's observation and evaluation of the act. chatbots can well serve as an influence on teaching students how a problem might be solved by illustrating algorithmic planning [23]. Through such interaction with chatbots, students can easily appreciate the right strategies to apply to solve the related algorithm issues. Owing to the cyclic nature of CHATBOT, the student can try different approaches to solving a particular problem hence they can foster more critical thinking skills and working persistence in the process of solving a given problem. Such a field environment enables enhancement of learning since students are allowed to meditate on their errors and success with the least interval of time. Consequently, based on the considered research the application of the AI chatbots is supported by the constructivist learning theory, Vygotsky's Zone of Proximal Development, and social cognitive theory. In terms of contributing to discussion-based, individualized learning; offering support when needed; and demonstrating appropriate problem-solving processes, chatbot systems may play an invaluable role in increasing the appreciation and application of algorithms among students while fostering CT competencies [24].

### *E. Empirical Evidence Supporting AI Chatbots in Education*

Amidst increasing studies, there is evidence that pinpoints the role of the AI chatbots in improving the learning experiences in numerous learning environments. One of the most outstanding discoveries is that better student involvement can be attributed to the use of chatbot. It was found in the study that students who use AI chatbots show a higher level of engagement than students who receive normal teachings. Since chatbots engage their users in an active conversation, students are motivated to embrace an active learning model that can transform them into active participants in the learning process [25]. The following recorded interactions illustrate that such increased engagement not only grabs students' attention but also makes them more responsible for their learning processes; students appear to be more active in their learning processes by challenging a conceptual idea mid-lecture. Further, the study has revealed that the use of AI chatbots lead to improved problem-solving skills of the students. Research findings on the effects of chatbots on students' skills and confidence indicate that more students who engage in practice chatbots in solving problems make significant improvements in algorithmic reasoning skills and problem-solving skills. Offering a setting of problem-solving to learners emphasizes the need for chatbots as it allows the learners to practice real-life cases. This way of working gives students more practice in critical thinking and thinking through different strategies by being able to attempt at a problem and get feedback immediately. In this way, learners seem to develop general proficiency in algorithmic difficulties and ensure their own efficacy. Second, the promotion of knowledge retention is still another great benefit of employing AI chatbots, especially in the learning environment. Another aspect of efficiency is that chatbots can give an immediate response and, thus, contribute to better knowledge retention by students receiving individual approaches. Experimental studies show that students' retention and understanding improve when they are encouraged to participate and when they are corrected or advised periodically [25].

This active involvement in learning makes the content go through deeper cognitive online processing where the students change their understandings, beliefs, knowledge, and attitudes as they install new knowledge. Moreover, being involved in Knowledge Dialogue Iteration as a participant of the chatbot, the students can interact multiple times with a subject, thus consolidating the knowledge and achieving better retention. Hence, it may be concluded that education with the assistance of AI chatbots demonstrably enhances learners' engagement, their problem-solving abilities as well as contributes to knowledge acquisition. This study points out the possibility of chatbots to revolutionize the learning process as a teaching aid in developing interactive, supportive, and adaptive learning environments for students from various fields.

## III. Materials and Methods

### *A. Research Type and Design*

This research employed a mixed method, quantitative, and descriptive research design with the quasi-experimental post-test only design for coding tasks, and the control experimental group design for the evaluation of user experience. Both the pre-test and post-test were designed to show the effectiveness of AI the actual control group was randomly assigned, while the treatment group was assigned a priori [26]. The sample consists of two homogeneous groups: where the experimental group and the control group are shown in Fig. 1. To determine the level of the correlation with computational thinking, a survey method was employed for data collection.

### *B. Research Procedure*

The conversation with an AI chatbot is conceptually planned as a responsive, personalized, and active learning conversation where the learning outcomes call for participating in the process of computer thinking. This interaction comprises of live conversational user interface in which students follow a conversational pattern of asking questions and receiving answers. Implementation of the chatbot allows sometimes for concept definitions, a step-by-step guide, and instant response to a student's query or task. Also, it contains error pattern recognition for providing more relevant suggestions based on the needs for need-based learning. As opposed to traditional approaches of teaching, the use of AI chatbots in imparting learning brings the following added advantage: flexibility and adaptability of learning access. This is opposite to normal class teaching where the virtual contact occurs face to face within a classroom, while the chatbot lets the students learn at any place and at any time. A chatbot can also still data from prior chats, which makes it easier for the system to target content in a learning path based on a student's progress. In addition, the chatbot engages students in exploratory learning by posing practical problem-solving situations and scenarios for students to solve. Another advantage is the inclusion of such elements as interactivity, game, concept, and algorithm constructors where necessary. For instance, the chatbot may offer short interactive learning exercises to help improve algorithmic thinking or present, as students develop their algorithms, immediate visuals of the algorithm. This makes it not only engaging but also enhances the aspect of the usefulness of these ideas derived from computational thinking, which is always a weak link in traditional procedures. With these features put in place, the AI chatbot evolves into a learning solution that is adaptive, interactive, and contextual.

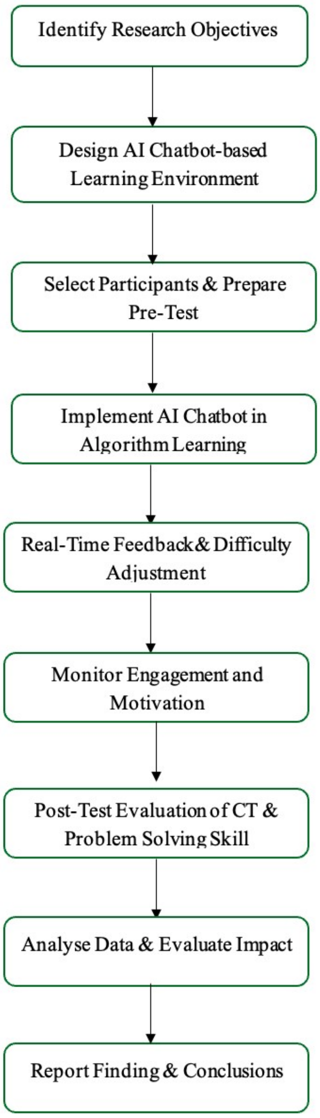


Fig.1. Flowchart of research.

The study began by selecting a sample of students from one or more classes, who were then randomly divided into two groups: in one of them, where students in the class observed different behaviors, and in the other, where students modified behaviors themselves. Before going through the contents of the notes, all students completed a pre-test that tested their prior knowledge of algorithms and programming [27]. In the experimental class, the treatment involved a familiarization session where students came across general information about Artificial Intelligence before they were made to encounter the fundamental features of the appearance of the chatbot. In the second encounter, the students applied AI-supported coding and algorithms for elementary algorithms and discussed the ideas in their groups. During the third session, the students solved a small project dealing with more advanced algorithms that employed artificial intelligence. On the other hand, the control class traditionally studied algorithms and programming without involving interaction with AI. During the first meeting, the usual notes and lectures were made while in the second meeting, basic algorithms were done in groups. During the third session, the control group undertook a small project under the traditional mode of communication whereby most of this was done in the classroom. After the intervention was over, all learners were administered a posttest to measure their performance in achieving objective 2 on algorithms and programming. Further, some of the students and teachers were given interview questionnaires to elicit more of their experiences and attitudes towards the learning process. Observations in the classroom were centered on how the boys and girls engaged and reacted during the learning sessions of both groups. We collected additional qualitative data for analysis. In addition, to assess the students' impressions of the applied learning methods, a perception questionnaire was completed by the students from both groups [28].

The Chatbot-Enhanced Learning Process for Algorithms and Programming was established with several vital architecture components and process flows to help students study. At the core is the Chatbot Interface, which acts as a tutor to the students helping them through their course content and code practice exercises, they may encounter. They presented this work, that has implemented Natural Language Processing (NLP) to allow a good interaction between the students and the chatbot. Course content, assignments, quizzes, etc. are hosted on the Learning Management System (LMS) and, at the same time, the chatbot records students' interactions for analysis of their learning process. The students interact with the chatbot frequently to discuss various complicated algorithmic issues, solve some problems algorithmically, and get feedback. The instructor works with the LMS as a tool to track student performance, facilitate further enrollment of knowledge, and evaluate acquisition. The process of learning is then said to consist of several major stages. In Meeting 1 students are introduced to AI concepts, presented with the chatbot interface, and the goals of the course. It delivers the necessary materials and lessons to guide the students to the next tasks. The Interactive Coding Practice (Meeting 2) contains coding problems that deal with basic algorithms and the chatbot provides the student with suggestions, hints, and descriptions all in real-time. In Project Implementation (Meeting 3), I organize a small project containing advanced algorithms with an AI aspect. The chatbot holds a significant function in the provision of contextual support, namely debugging help and algorithm explanation. However, after the successful completion of the project, a post-test is used to test the level of students' knowledge besides data that is collected by interviews and classroom observations. Besides, a perception questionnaire to measure the ability of the chatbot to improve student learning literacy is employed.

The process flow starts with the students going to the LMS and entering the chatbot section. In the Orientation Phase, the chatbot familiarizes students with basic algorithm concepts and the AI aspects of the application. When students enter Interactive Learning, they perform coding operations in which the chatbot responds promptly. Project Work phase in which the students can use certain retained knowledge practically in a project with constant help from the chatbot. Lastly, the post-test is conducted for students, and besides the test results, the open-ended questions allow for the evaluation of the general impact of the enhanced chatbot-based learning.

*1) Research sample*

The population in this study involves data obtained from the students of the Informatics Engineering Education (PTI) study program undergoing the Algorithms and Programming course in Universitas Negeri Padang in the academic year 2023/2024 academic year. This dataset involves results from two randomly chosen class groups; the experiments class containing 30 students and the control comprising of 30 students in total giving a total of 60 students. The data for the study were collected from the students enrolled in the Algorithms and Programming course in the PTI study program. Universitas Negeri Padang was adopted in the first stage of a two-stage cluster sampling method based on a random allocation technique. The second phase would be the identification of two classes, one which would be taken through experimental manipulation and the other which would be used as the baseline. These types of data may include demographic data (age, gender, education, etc. if applicable) learning outcome data (assignment/quiz/exam results), and the experimental group's intervention data in the form of teaching method/tool use and participation data in the form of attendance and interactions levels, etc. This dataset was selected because this study is aimed at determining the appropriateness of teaching methodologies for students in technology disciplines. In addition, the number of students in Universitas Negeri Padang is large enough for the current study, and proper request was made to access data. The students who were selected in this study are curriculum similar and bias reduced, and the sampling technique allowed for generalization of the results in the PTI study program student population.

The assessment of the defined CT skills requires techniques aimed at capturing the essence of each part, with the indicators of computational thinking explained in Table 1. Problems-solving tasks such as the proportion, ratio, direct and inverse variation, and system of linear equations are used to assess decomposition through the degree of problem breakdown on a set checklist and rated according to the rubrics from clear to less clear and effective to less effective. In pattern recognition, content knowledge application is based on result-oriented data analysis exercises, construction of day-to-day practical case scenarios and project work, and multiple-choice questions along with explanations of the patterns noticed. Task-wise, abstraction is assessed by activities in the form of constructing models or algorithms that involve the exclusion of unnecessary information and the peer as well as self-assessment of learning. Algorithm design is evaluated by assigning programming problems, flowcharts or pseudocode problems and tests the ability of the student, to logical, clear, and efficient algorithms. While evaluation consists of tasks that allow participants to compare solutions with specific criteria, and critical thinking activities, such as writing essays or group discussions, on aspects of effectiveness and improvement. These methods give formative and summative evaluations of the participants' CT skills in a more rounded approach.

Table 1. Computational thinking skill questionnaire

| Indicator | Description |
|---|---|
| Pattern Abstraction and Generalization | The ability of students to recognize patterns from data or problems and generalize. |
| Systematic Information Processing | The ability of students to use heuristic approaches to process and analyze information systematically. |
| Symbol and Representation System | The ability to simplify abstract concepts into symbolic representations that are easy to understand. |
| Algorithmic Notion of Control Flow | The management of control flow and effective procedures in processing data or solving problems. |
| Structured Problem Decomposition | The ability to break down complex problems into smaller, more easily understood parts. |
| Iterative, Recursive, and Parallel Thinking | The ability to think through cycles of repetition (iteration), recursive thinking, and parallel processing of multiple tasks or data simultaneously. |
| Conditional Logic | Understanding cause-and-effect relationships and conditional logic within a system or algorithm. |
| Efficiency and Performance Constraints | Considering factors that hinder or support efficiency and performance in completing tasks or solving problems. |
| Systematic Debugging and Error Detection | The ability to systematically detect and correct errors in a process or algorithm. |

## C. Research Validity Control

*1) Internal validity control*

To address internal validity in this research the following steps were taken. To reduce selection bias first, students were randomly assigned into control and treatment groups. Second, both groups were on demographic and academic variables; and it also removed variables of age, sex, and pre-existing knowledge of algorithms and programming making both groups quota equivalent. The settings in the learning environment the instructional resources and the time allotted for completion were kept constant whereby the only factor that was manipulated was the teaching methodology. Also, the measuring instruments selected were standardized: questionnaires and tests with validity and reliability confirmed by other researchers. Moreover, there was the use of blinding where the instructors or assessors were unaware of some of the student groups that were given the treatment, this eliminated assessment bias. A post-test was also used instead of a control group to assess changes in student knowledge because of the intervention. Learning session observations were also made to check whether the intervention was delivered according to the plan and to examine the other potential sources of impact.

*2) External validity control*

To enhance external validity, this study recruited subjects from the target population of students with diversity in their academic abilities, their technological experience, as well as their demographic status. It is important to explain all the circumstances that surrounded the present research to help other investigators evaluate the conditions of this study and implement the findings where similar circumstances exist. This study also suggests future replications were to be conducted with different samples in other settings, this analysis would help in determining the extent of generalization of the findings. Also by adopting well-thought-out procedures in computer education, the study increases the chances of comparing the findings with earlier research and apply in different environments. The findings of the study will be disseminated through the use of publications and presentations in conferences, also, the intervention of the study in different educational settings, and the possibility of effect modification by setting.

### *D. Pilot Study*

These pilot surveys were used to estimate the reliability and validity of the chosen research tools and the general technical and logistic difficulties in the main study. Further, it tried to collect preliminary data for the first assessment of the performance of AI in the process of learning algorithms and coding. In the current study, the pilot tests of the research results revealed Cronbach's alpha coefficient reliability score of 0.715 in the computational thinking skills questionnaire to be reliable and suitable for data collection.

### *E. Data Analysis Technique and Hypothesis Development*

The empirical data in this study consists of the quantitative data collected and the subsequent scrutiny to understand the effects of AI use in learning algorithms and programming. Qualitative data was received through tests (pre-test and post-test), which were used to compare the student's computational thinking abilities before and after the application of the solution. Descriptive analysis was used to determine the mean, median, and standard deviation of pre-test and post-test knowledge scores. On the other hand, inferential analysis consisted of t-tests, as well as multiple linear correlation analyses used to compare the mean scores achieved by the control and treatment groups.

The general hypotheses in this study are as follows:

H01: There is no statistically significant difference in the mean scores of students' computational thinking skills between the control group and the experimental group.

H02: There is no statistically significant relationship between AI usage and students' computational thinking skills.

## IV. Result and Discussion

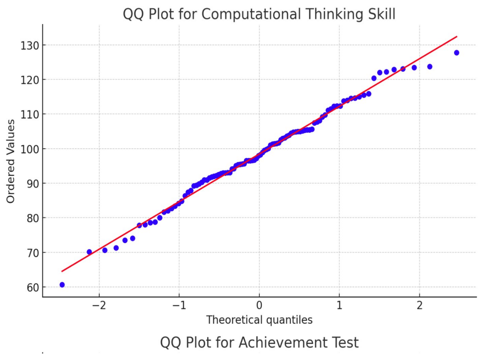
The assessment of coding task effectiveness was conducted through two types of evaluations: an assessment of algorithm design performance using AI tools, and a coding performance evaluation using C++. Based on Table 2, students in the experimental group achieved scores of 75 or above for their algorithm design and coding tasks using AI, indicating that AI is effective in helping students design algorithms.

An analysis of the efficiency of programming tasks that had been performed in the treatment group by means of AI was carried out. As the study concluded the error analysis, the findings indicated that the students in the treatment group were able to reduce the number of errors as they worked through programming tasks in comparison with the control group that learned in a traditional way. The Longest Common Subsequence (LCS) measurement found an average error rate of 15% in the treatment group, and 35% in the control group. They found that AI-supported students benefit from the visualization and collaborated aspects to understand and implement algorithms. Furthermore, there is evidence that students in the treatment group adopted an improved understanding of algorithm concepts. AI visualization eliminated confusion when they were explaining algorithm sequences thus making their coding less erroneous. The codework by the treatment group was also neater and Automatic Data Analysis (ADA) produced concrete algorithmic structures that enabled the students to plan for algorithms before executing them. The AI platform also provided an area for students to share ideas and to help one another in solving programming assignments which fastened problem-solving and learning processes within seconds due to screen sharing and immediate feedback. The student's motivation and engagement in programming tasks also improved with the help of AI. AI visualization of the algorithms enhanced the level of interest in learning in students while social interaction on the AI platform motivated students to work harder, hence improving their performances. In summary, this research shows that there are beneficial effects of AI usage in learning algorithms and programming; improves competencies in programming and encourages greater computational thinking to be observed among students. Such conclusion presents practical value to the development of information and communication technology education and this work has shown that such an approach is feasible and could improve the learning process.

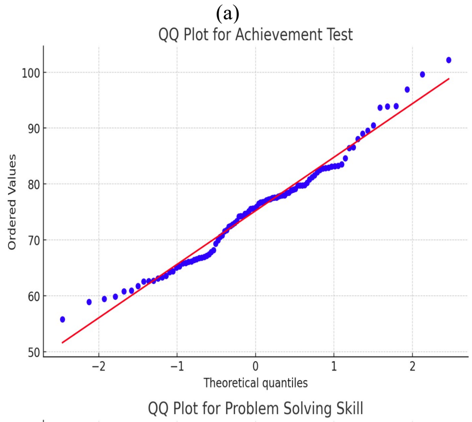
Table 2. Performance assessment data for the algorithm design and coding task in the treated group

| Case | Group | Solution Planning | Preparation | Processing | Results |
|---|---|---|---|---|---|
| Case 1 | Group 1 | 85.00 | 90.0 | 88.75 | 87 |
| | Group 2 | 80.00 | 92.5 | 86.25 | 89 |
| | Group 3 | 88.33 | 85.0 | 91.25 | 92 |
| | Group 4 | 90.00 | 95.0 | 89.5 | 91 |
| | Group 5 | 82.50 | 88.5 | 90.75 | 90 |
| Case 2 | Group 1 | 78.33 | 85.0 | 84.00 | 83 |
| | Group 2 | 88.00 | 80.0 | 87.5 | 86 |
| | Group 3 | 81.67 | 89.0 | 85.25 | 88 |
| | Group 4 | 76.67 | 93.0 | 82.0 | 90 |
| | Group 5 | 84.00 | 83.0 | 88.0 | 85 |
| Case 3 | Group 1 | 87.50 | 82.5 | 86.25 | 88 |
| | Group 2 | 85.00 | 90.0 | 89.0 | 87 |
| | Group 3 | 82.50 | 94.0 | 84.75 | 89 |
| | Group 4 | 88.33 | 79.0 | 87.5 | 90 |
| | Group 5 | 91.67 | 95.0 | 82.5 | 92 |

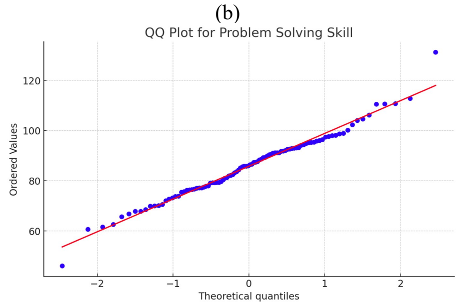
When it comes to problem solving the study also shows that AI technology can enhance the formulation of better skills. This, AI helps students to work on strengths by thinking about many sub-problems or using AI-supported discussion forums when students work on different strategies and problems with peers. This combination assists students to work more methodologically when solving problem-solving tasks which is part of computational thinking. In general, the study yielded positive evidence that the incorporation of AI in algorithms and programming teaching enhances the effectiveness of programming tasks among the treatment group. These findings suggest that computing education should incorporate technology that facilitates visualization and collaboration. Through incorporating AI in the education system, educators can improve student outcomes in every way, through both enhancing and deepening student understanding of programming paradigms and through the development of collaborative and computational thinking which are both deemed vital skills in the increasingly digital-oriented society. This research opens more opportunities and encourages more studies on the use of other forms of innovative technology in their integration toward the enhancement of learners' performance.




(a)




(b)




(c)

Fig. 2. Normality test for the (a) Computational thinking skill, (b) Achievement test, and (c) Problem-solving skill.

### *A. Students' Computational Thinking Skills Between the Control Group and the Experimental Group*

This work also used the t-test as the data analysis tool fit for the research study. Before the parametric test was conducted, some preliminary tests were conducted, these included normality tests and homogeneity tests. If all these prerequisite tests have been met, the data would proceed to this parametric test which is the t-test.

The three Q-Q plots displayed below present the Fig. 2 distribution of the computational thinking skills, the achievement test results, and the problem-solving skills, and all of these seem normally distributed. Most data points in the Q-Q plot for computational thinking lie very close to the reference line with some points slightly off from the line at the upper and lower ends suggesting a normal distribution of most values with minor variations at very high and low scores. In the case of the achievement test however, it can be appreciated from the plot that the departure from perfect normality is very small although there is noticeable curvilinearity and a slight departure from symmetry particularly at low quantiles which tells us some of the low scores may not be perfectly normally distributed. Last is the Q-Q plot of problem-solving, which shows that the data is normally distributed to a reasonable extent with some variation at the tail end. In general, these three datasets are relatively normal, which is critical for parametric analysis despite small deviations at the two ends.

Based on the homogeneity test results in the Table 3, Levene's test and $p$-value for each variable problem-solving, computational thinking, and achievement test were obtained. The $p$-values for all three variables are greater than 0.05 (problem solving: 0.325, computational thinking: 0.453, achievement test: 0.289), indicating that there is no significant difference in variances between the data groups.

Table 3. Homogeneity test

| Variables | Levene's Test | $p$ value |
|---|---|---|
| Problem Solving | 1.234 | 0.325 |
| Computational Thinking | 0.879 | 0.453 |
| Achievement Test | 1.102 | 0.289 |

Since the $p$-values for all variables are greater than 0.05, the assumption of homogeneity of variances is met, meaning the variances of these three variables are considered homogeneous. This is important in statistical analysis, especially when using parametric methods such as ANOVA, which require equal variances across data groups. Thus, the data for problem solving, computational thinking, and achievement test variables can be further analyzed with the assumption of homogeneity ensured.

Table 4. Results of the t-test

| Variables | Groups | N | Mean Differences | t | df | p | Test |
|---|---|---|---|---|---|---|---|
| Problem Solving Skill | Experimental | 30 | 88.24 | 10.456 | 58 | 0.001 | Post-test |
| | Control | 30 | 68.34 | | | | |
| Achievement Test | Experimental | 30 | 82.12 | 7.234 | 58 | 0.002 | Post-test |
| | Control | 30 | 66.78 | | | | |
| Computational Thinking Skill | Experimental | 30 | 78.56 | 14.221 | 58 | 0.000 | Post-test |
| | Control | 30 | 62.35 | | | | |
| Problem Solving Skill | Experimental | 30 | 62.13 | 2.789 | 58 | 1.678 | Baseline Test (Pre-test) |
| | Control | 30 | 61.98 | | | | |
| Achievement Test | Experimental | 30 | 61.56 | 1.789 | 58 | 2.034 | Baseline Test (Pre-test) |
| | Control | 30 | 61.42 | | | | |
| Computational Thinking Skill | Experimental | 30 | 59.78 | 2.901 | 58 | 2.456 | Baseline Test (Pre-test) |
| | Control | 30 | 59.64 | | | | |

The results of the t-test in the Table 4 revealed a significant difference between the experimental and control groups across three primary skills: The participants' problem-solving skills, achievement test, and computational thinking skills before the intervention (Pre-test) as well as after the intervention (Post-test). In the taught skills, the average scores achieved in the experimental group in problem-solving skills were 88.24 compared to the control group that scored 68.34. Analysis of the result indicates that the $t$ statistic equals 10.456 with a $p$-value of 0.001 which means that this difference is statistically significant, therefore, we can conclude that the academic intervention use was beneficial to the problem-solving skills of the experimental group. In the case of the achievement test, the experimental group again showed higher performance, with an overhead of 82.12 as against the head of 66.78 of the control group. The t-calculated value is 7.234 while its associated probability value, $p$ = 0.002 which implies that the difference is statistically significant in other words, the experimental group registered a rise in achievement levels. Further, in the computational thinking skills, the experimental group's average was 78.56 while that of the control group was 62.35. With a $t$ value of 14.221 with $p$ = 0.000, it can be concluded that there is a significant change, proving the effectiveness of the intervention implemented in improving the students' computational thinking skills. In the Baseline Test (Pre-test), the mean differences on all three skills according to the experimental and the control groups were relatively small and insignificant with the help of an Analysis of Variance (ANOVA) that revealed $p > 0.05$ for all variables. This means that at the start of the study, both groups were sufficiently matched in terms of their ability to solve problems, achieve, and apply computational thinking. These results indicate that the experiment group made better progress in problem-solving, achievement, and computational thinking than the control group after the intervention.

### *B. Correlation Analysis of Computational Thinking Skill*

Data was gathered from two groups of students: a treatment group using AI and a control group using traditional learning methods. Students' computational thinking skills were assessed before and after the intervention with validated tests, and the test results were analyzed using Pearson correlation analysis.

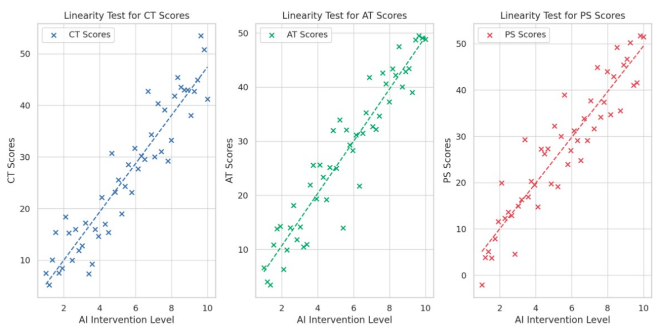



Fig 3. Linearity test results.

Before going further and making the correlation test, the linearity test was made. From Fig. 3, the points are equally spaced across the diagram, which implies that a linear relationship existed for the three variables. As a result, the data can be used for further analysis with the help of the multiple linear correlation test.

Table 5 presents the results of a correlation analysis among four variables: The abbreviations CT (Computational Thinking), AT (Achievement Test), PS (Problem Solving), and AI (Artificial Intelligence). For this analysis, this author employs the Pearson correlation coefficients to establish the connections between these variables. The results also suggest a strong positive correlation between CT and the AT; $r = 0.650$, $p < 0.001$, which means that any changes in CT are positively related to changes in the Achievement Test. Additionally, the correlation between CT and PS is statistically significant and positive at a high level, ($r = 0.780$, $p < 0.001$), which means that the more the students were skilled in CT, the better their problem-solving skills. A very high relationship is also found between CT and AI ($r = 0.900$, $p < 0.001$), which/examples suggest that students who are more advanced in computational thinking are also more likely to understand artificial intelligence. Also, the achievement test has a positive correlation with PS; the coefficient value equals 0.850 and a significance level of 0.000. This means that students, which have higher scores on the Achievement Test can have stronger problem-solving scores as well. Furthermore, the correlation between the achievement test and AI is also significantly positive ($r = 0.850$, $p < 0.001$), thus showing that if the students score high on the achievement test, then there is a high probability that the students understand the principles of AI. In other words, testing the academic performance of students is a measure that is correlated with how students understand and execute AI. On the other hand, there is a close positive relationship between PS, and AI ($r = 0.880$, $p < 0.001$). This implies that problem-solving skills among the students are well connected to the knowledge students have about artificial intelligence. Those students, who are ready to solve some tasks on their own, are also better equipped to accept general ideas connected to AI and apply them in practice.

Table 5. Correlation analysis of AI with computational thinking skill

| Skills | CT | AT | PS | AI |
|---|---|---|---|---|
| CT | Pearson Correlation | 1 | 0.650** | 0.780** |
| | Sig. (2-tailed) | | 0.000 | 0.000 |
| | *N* | 67 | 67 | 67 |
| AT | Pearson Correlation | 0.650** | 1 | 0.850** |
| | Sig. (2-tailed) | 0.000 | | 0.000 |
| | *N* | 67 | 67 | 67 |
| PS | Pearson Correlation | 0.780** | 0.850** | 1 |
| | Sig. (2-tailed) | 0.000 | 0.000 | |
| | *N* | 67 | 67 | 67 |
| AI | Pearson Correlation | 0.900** | 0.850** | 0.880** |
| | Sig. (2-tailed) | 0.000 | 0.000 | 0.000 |
| | *N* | 51 | 51 | 51 |

In general, all these scores show a very significant and positive correlation between CT, Achievement Test, PS, and AI. Cumulative development is defined as such improvements in one skill cause improvements in other skills to take place. These findings signify the significance of the computer thinking, problem-solving skills, and academic skills embedded in the learning of artificial intelligence. Such understanding of the relationships makes it easier for educators to develop coordinated curriculum plans that will help supplement each other's teaching to the overall benefit of the students [29].

This work shows that with the aid of relatively new and common modem pedagogy facilitated by AI-based Chatbots, students can improve their grasp of algorithms, as well as their cognitive competence in computational thinking and efficient problem-solving. These results raise confidence in previous studies on the effectiveness of incorporating AI technology in enhancing learners' performance, particularly in algorithms and computer programming courses. Using interactive technologies such as chatbots, students can have direct explanations of algorithm ideas and get immediate feedback as well as appropriate increased difficulty levels to meet the students' learning requirements [30]. This is confirmed by the present study whereby using AI chatbots, proffers immediate feedback for the student to correct his or her mistakes and enable him or her to progress faster in understanding the content. In addition, AI technology promoted students' motivation and the present study proved the conjecture that students' motivation and confidence were significantly increased using the AI chatbots, allowing them to activate the learning algorithm [31]. This research also gives credit to the concept of computational thinking because the participants were able to approach the sets by breaking them into several sub-problems. By using chatbots, students develop a better understanding of how algorithms are used in different real-life situations and improve a computational thinking process [32]. Furthermore, this research also supports constructivism learning theory and Vygotsky's ZPD. In this study, AI chatbots works at the scaffolding zone, that is, while it guides the students which is beyond their Zone of proximal development, it is still enough to enable the students to understand the material at a deeper level.

Keeping biases in mind the following steps were considered in this study: Lastly, the anonymity and confidentiality of participants were maintained to enable them to give their answers naturally as regular consumers without the burden of social pressure. Selection bias was also eliminated by following a random and representative sampling technique. This can be because using validated instruments helps minimize instrument bias because it brings about measure clarity. Data source triangulation was used in a manner that involved using different data sources to improve the results obtained. To reduce the Hawthorne effect in this study, the objective of the study was described in a general way, and no topics were overemphasized. In conclusion, cross-verification and validation in peer reviewing helped to eliminate subsets of biases of the analyst. All these steps enabled the achievement of more accurate and efficient data results and quality.

## V. Conclusion

The results of the present study revealed that the use of AI chatbots integration improves the students' CT skills and problem-solving and consolidates their knowledge of algorithms. Concerning motivation, self-confidence, and especially engagement in the learning process, the interaction with an AI chatbot which is capable of rendering instant feedback and automatically adjusting the level of difficulty to the capacity of the student has actually boosted motivation among college learners. The findings of the present studies also lend evidence to the other learning theories including the constructivist learning, ZPD, and Social cognitive learning theories which pinpoint the key interactions during the process of participation, and the scaffolding and modeling activities for enhancing meaningful learning and development of key competencies. Together with the limitations mentioned above, this research expands the understanding of how AI applications for teaching and learning eliminate some of the challenges faced by traditional teaching approaches in computer science and technology industry. Through the openness and activity of the developed AI chatbot platform, learners can contribute to the distinction of spaces at institutions to become clearer while at the same time improving the quality of learning and readiness of students to embrace the digital economy. In addition to the generated findings, the study offers a contribution to the existing body of knowledge on the application of AI in teaching and learning with an emphasis on improving computational thinking. This shifts the focus on how the use of AI is ideal in helping to teach students, improve teaching of concepts, and nurture skills suitable in today's world of technology.

Nevertheless, there are some limitations related to this study as well. First, the participants' sample was a fairly small number, so the study results can hardly be translated to different, more extensive populations. Also, this study depended on the cross-sectional survey, which may provide subjective information regarding students' learning experiences. An unexpected artifact of the study design is the non-random assignment of participants to both experimental and control groups which might have resulted in problems of sample selection bias. In addition, the study has been carried out with only one technological tool (the AI chatbot) and therefore the generalization of its results to other educational contexts or with students of a different profile is still unknown. Lastly, it was seen that the study does not assess the dependence and therefore durability of computational thinking and improvements in problem-solving with artificial intelligence learning after the intervention. To overcome these shortcomings in future related research, more a larger population sample should be involved, the study should use a longitudinal design to assess the time impact of AI in learning to reduce the effect of different populations at different times, and the study should focus on the use of randomized control trials for to reduce selection bias.

## Conflict of Interest

The authors declare no conflict of interest.

## Author Contributions

MAZ led the study design, data collection, and manuscript preparation; FE handled data analysis and contributed to the results writing; CA conducted the literature review and refined the research questions; OC assisted with experimental design and editing; SAJ supported data collection and methodology; AAZ refined the theoretical aspects, and SI supervised the project and finalized the manuscript; all authors approved the final version.

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