IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, June 2026
Impact Factor: 8.2

The Use of Artificial Intelligence Tools and its Impact on the Learning Outcomes of Computer Science Students

Xyrus L. Bautista[1], Ryan N. Santos[2], Jayson V. Sereno[3], Jessica Rose E. Fernandez[4]
Bachelor of Science in Computer Science, College of Computing and Information Sciences[1,2]
Faculty, College of Computing and Information Sciences[3]
Surigao Del Norte State University, Surigao City, Philippines
xyruslitang0@gmail.com ryannapoles09@gmail.com
jaysonsereno368@gmail.com jfernandez@ssct.edu.ph

Abstract: *This study focuses on the use of Artificial Intelligence (AI) tools and their impact on the learning outcomes of Computer Science students. AI tools are commonly used by students for coding, research, problem-solving, and completing academic tasks. The study aims to determine how AI tools affect students' academic performance, learning efficiency, and programming skills. A quantitative research design using survey questionnaires is used to collect data from Computer Science students. The findings are expected to show that AI tools help improve productivity and support learning, but excessive use may affect students' critical thinking and independent problem-solving skills. The study may help provide guidance on the proper and responsible use of AI tools in education*

Keywords: Artificial Intelligence, AI Tools, Learning Outcomes, Computer Science Students, Academic Performance, Educational Technology.

I. INTRODUCTION

In recent years, the use of Artificial Intelligence (AI) tools has gained significant attention in the field of education, particularly within computer science programs. AI-powered tools such as code generators, intelligent tutoring systems, and automated debugging assistants are increasingly utilized to support students in mastering complex programming concepts (Córdova-Esparza et al., 2024). Research indicates that these tools offer distinct advantages, including instant feedback, increased coding efficiency, and enhanced accessibility, which have fundamentally transformed the pedagogical landscape for students. Because programming courses are traditionally characterized by high cognitive demand, AI tools are frequently viewed as essential resources for improving student understanding and academic performance. However, alongside these benefits, critical concerns have emerged regarding how frequent reliance on AI may influence long-term learning outcomes. Specifically, there is a growing need to investigate whether overdependence on these tools might erode a student's ability to think critically and solve problems independently (Elnaffar et al., 2024).

Several studies have examined the impact of artificial intelligence tools on learning outcomes in computer science education. Alanazi et al. (2023) conducted a systematic review and meta-analysis on the influence of AI tools on learning outcomes in computer programming and found that AI-based systems significantly improve students' programming performance and conceptual understanding. Similarly, Yilmaz and Yilmaz (2024) reported that the use of generative AI tools positively affects students' computational thinking skills, programming self-efficacy, and learning motivation. In a regional context, Aghiomesi et al. (2024) evaluated the impact of generative AI tools in tertiary institutions and found improvements in problem-solving skills, coding accuracy, and academic achievement. While Oribhabor (2023) identified perceived usefulness and institutional support as key determinants of AI adoption, Qureshi

(2023) highlighted potential challenges such as overreliance and ethical concerns. Despite these findings, existing studies have largely focused on general skill development, motivation, and adoption factors. There remains a lack of focused research examining how the structured and frequent use of AI tools directly influences specific learning outcomes, particularly within the high-stakes environment of programming courses. This study seeks to bridge this gap by investigating the direct relationship between AI tool usage and the mastery of core programming competencies.

Despite the growing adoption of Artificial Intelligence tools in computer programming courses, there is still uncertainty regarding their overall impact on the learning outcomes of Computer Science students. While previous studies suggest that AI tools can improve motivation, engagement, and academic performance, concerns persist about students' overdependence on these tools. As noted by **(Elnaffar et al. 2024)**, excessive reliance on generative AI may limit the development of essential programming skills such as logical reasoning, problem-solving, and independent coding. If this problem remains unresolved, students may graduate with a superficial understanding of programming logic, ultimately affecting their readiness for the industry. This study seeks to address the problem of determining how the structured use of Artificial Intelligence tools influences the learning outcomes of Computer Science students in programming courses. Specifically, it aims to examine whether AI tool usage supports meaningful learning or creates cognitive challenges that affect students' long-term skill acquisition

To address these identified gaps, this study proposes a **quantitative research approach** to examine the relationship between the use of Artificial Intelligence tools and the learning outcomes of Computer Science students. By employing a **descriptive-correlational design**, the study will collect numerical data through structured surveys and academic performance records to measure key variables. The independent variable, **AI Tool Usage**, will be evaluated based on the frequency and nature of use of generative AI platforms such as ChatGPT, Claude, and Gemini.

The dependent variable, **Academic Performance**, will be measured through three specific indicators: **Study Dedication** (quantified by the average number of hours spent studying), **Logical Thinking** (assessed through the ability to trace and understand code structures), and **Problem-Solving Ability** (measured by the capacity to develop independent algorithmic solutions). This methodology is appropriate as it allows for a statistical determination of the significance and strength of the relationship between AI integration and student mastery. The findings are expected to contribute to the existing body of knowledge by providing empirical evidence that addresses the ethical and pedagogical challenges identified by **Córdova-Esparza et al. (2024)**. Furthermore, the results will assist educators, curriculum developers, and academic institutions in making informed decisions regarding the effective and responsible integration of AI tools in programming curricula.

OBJECTIVES OF THE STUDY

The primary goal of this research is to investigate the relationship between the utilization of Artificial Intelligence (AI) tools and the academic performance of Computer Science students. Specifically, this study aims to achieve the following:

- **To determine the frequency and nature of AI tool usage** (e.g., ChatGPT, Claude, Gemini) among Computer Science students in their academic activities.
- **To evaluate the level of Academic Performance** of the respondents in terms of:
- **Study Dedication** (Average hours spent studying);
- **Logical Thinking Ability**; and
- **Problem-Solving Skills**.
- **To analyze the significant relationship** between the frequency of AI tool usage and the identified factors of academic performance.
- **To identify the potential challenges** related to overreliance and cognitive offloading as a result of AI integration in programming tasks.
- **To propose recommendations** for educators and students on the responsible and effective integration of AI tools in the Computer Science curriculum.

II. RELATED LITERATURE

Swaraj and Chavan's study (2024) on the impact of the use of ChatGPT on the cognitive thinking and creativeness of human beings highlighted how AI, although the basis for creating innovation itself, simultaneously threatens to standardize human cognitive thinking and creativeness. This, in a way, implies how the "Independent Variable" of AI use has a direct link to the "Dependent Variable."

This concern was further supported by another study done by **Klingbeil et al. (2024),** which revealed that human users, in most cases, are likely to experience a "delegation bias" in how they evaluate the overall output generated by the AI, failing to properly critique it. The results obtained from the experiments presented by the authors revealed that there is a likely decrease in human performance due to the "trust and reliance," especially in the use of incorrect solutions in logic applications.

In terms of the cognitive load, **Grützner & Schreck (2024)** studied the "student-perceived cognitive load" of LLM-generated programming assignments. The study found that "although AI may help students overcome some of the difficulties with programming syntax, AI-generated code may actually increase 'extraneous cognitive load' for students if the code is too complex for the students' current level." This suggests that unless there is guidance, AI may result in "shallow knowledge" of programming concepts.

In this context, **Khan et al. (2024)** highlighted the importance of improving automated feedback instruction in terms of Cognitive Load Theory and stated: "This approach ensures pedagogical software tools are always appropriate to the student's mental capacity and don't overwhelm it."

Finally, **Gonzaga et al.** (2024) posited that for AI systems to be effective, it was important to integrate them into the curriculum in a bid to encourage independence. Gonzaga et al.'s research indicated that for the AI to ensure the desired effectiveness, it should act as a vehicle for the students to learn by means of "incremental assistance" and not through replacing the logical reasoning of the students, which was critical in their long-term acquisition of essential programming skills.

III. RESEARCH METHODOLOGY

3.1 Research Design

This research applies a quantitative methodology approach that focuses on describing and identifying a correlation between the application of AI tools and Computer Science students' academic results. Descriptive techniques characterize the nature and level of AI tool usage, whereas correlation analysis will establish the statistical association and significance between the dependent and independent variables.

The independent variable is AI Tool Usage. It will be assessed using two metrics: (1) frequency and (2) the contextual application of generative AI tools like ChatGPT, Claude, and Gemini. The dependent variable is Academic Performance. Three factors will describe it: (1) Study Dedication, (2) Logical Thinking, and (3) Problem-solving Ability. These components will be measured based on the hours of study, code tracing and understanding abilities, and the formulation of individual algorithms.

This research design is suitable since it allows quantifying AI tool usage and academic results. Numerical data can be collected using questionnaires. Correlation analysis can identify the relationship's direction and strength. The proposed research design can reveal issues related to excessive AI usage and cognitive offloading in programming education.

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CONCEPTUAL FRAMEWORK

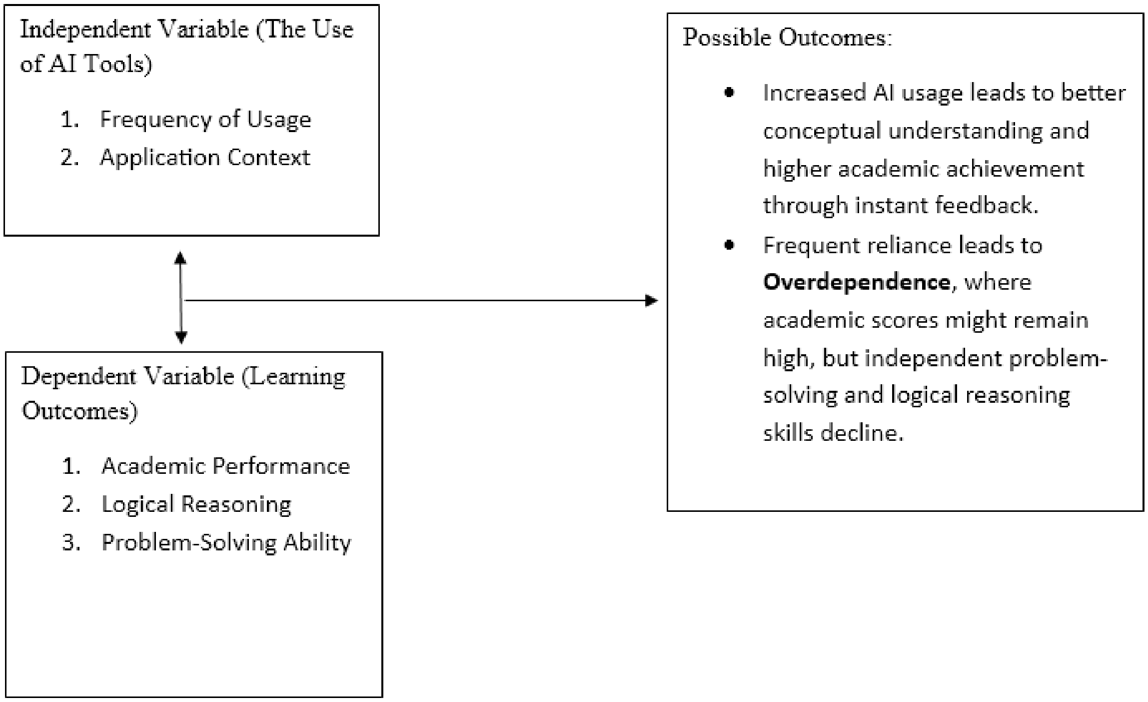

Figure 1. Conceptual Framework of the Study

3.2 Population and Sampling

This will involve the selected Computer Science students who are currently taking programming subjects and using AI tools in their academic studies. The researchers believe that these students would make the best respondents since they have experienced firsthand the use of AI tools in their academic studies.

The researchers will adopt simple random sampling in choosing the respondents. Simple random sampling ensures that all Computer Science students have equal chances of participating in the study. This reduces biasness and unfairness during the selection process.

The respondents will be chosen randomly from the list of Computer Science students taking programming subjects. This technique increases the accuracy and reliability of the collected data.

The following criteria must be met in the selection process of respondents:

- Must be a Computer Science student
- Must be taking programming subjects
- Must have used AI tools in academic work

Simple random sampling is appropriate since it offers an equal chance to all eligible students to participate in the study.

3.3 Data Collection

For data collection, the researchers will utilize a structured survey questionnaire via Google Forms. This mode of data collection is preferred since it is practical, easy to use, and efficient in acquiring responses from Computer Science students who use Artificial Intelligence (AI) in their learning process.

There will be two major sections in the questionnaire. Section one will be concerned with information regarding the extent of AI tools utilization among students. Information will be sought concerning the frequency with which students

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use various platforms such as ChatGPT, Claude, and Gemini, as well as the kind of activities in which the students use the mentioned technologies. Examples of activities include coding, debugging, lesson study, and programming.

The second section will assess the extent to which the respondents benefit from the utilization of AI tools in their learning. This information will be measured with regards to three major variables: Study Dedication (average number of hours spent studying), Logical Thinking Ability (ability to trace and understand code structures), and Problem-Solving Skills (ability to independently devise algorithms).

The respondents will receive the link to the Google Form through online communication channels such as Messenger and email. Before responding to the questionnaire, participants will be informed about the nature of the research. Participation will be voluntary and confidentiality assured.

3.3.1 Data Analysis

Statistical analysis of data collected through survey questionnaires and academic performance records will be conducted in order to address the research objectives. The following statistical measures will be employed in data analysis:

• Frequency and Percentage Distribution: It will be used to present the profile of the respondents, the kind of AI tools they use, as well as the number of AI sessions they conduct each day. It will also help characterize the distribution of responses in terms of Likert scale questions.

• Weighted Mean: Weighted mean will be used to compute the average extent of use of AI tools (frequency and applications of AI tools) and academic performance (Academic Performance, Logical Reasoning, and Problem-Solving Ability) using the four-point Likert scale questions.

• Pearson Product-Moment Correlation Coefficient (Pearson r): The Pearson correlation coefficient will be applied to establish whether there is any significant relationship between AI tools' usage and Computer Science students' learning outcomes. Pearson correlation is applicable since data obtained using the Likert scale is quantitative in nature.

• Spearman Rank Correlation: Spearman Rank Correlation will be used as an alternative where data do not meet the requirements for applying parametric tests such as normality test.

Statistical tests and analyses will be done using suitable statistical software. Significance level is set at $\alpha = 0.05$ implying that any value of p-value less than 0.05 will be considered statistically significant. Interpretation of the findings will be done against the established verbal descriptions on the Likert scale and objectives of the study.

IV. RESULTS AND DISCUSSION

The findings of the study based on the survey administered to 54 Computer Science students at Surigao Del Norte State University (SNSU), are discussed in this chapter. Statistical methods employed for analysing the collected data include frequency and percentage distribution, weighted mean, and Pearson Product-Moment Correlation Coefficient. The presentation of the findings will be categorized according to the respondent profile, the level of AI tool use, the level of learning outcomes, and their significant relationship.

4.1 Profile of the Respondents

This section presents the demographic profile of the 54 respondents in terms of age, sex, preferred AI tool, and number of AI sessions per day.

4.1.1 Distribution by Age

Table 1. Age Distribution of Respondents

Age	Frequency	Percentage (%)
19 Years Old	46	85.19

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20 Years Old	6	11.11
21 Years Old	2	3.70
Total	**54**	**100.00**

From Table 1, the largest number of the respondents (n = 46, 85.19%) were 19 years old, then followed by the 20-year-olds (n = 6, 11.11%), and lastly, the 21-year-olds (n = 2, 3.70%). The above statistics imply that the respondents comprise mainly first- and second-year college students, who are currently enrolled in basic computer science programs where the use of AI tools is most applicable. From the statistics, it can be inferred that the respondents are primarily young and thus tech-savvy.

4.1.2 Distribution by Sex

Table 2. Sex Distribution of Respondents

Sex	Frequency	Percentage (%)
Male	30	55.56
Female	24	44.44
Total	**54**	**100.00**

As can be observed from Table 2 below, males made up the larger percentage of respondents (n=30; 55.56%) whereas females were 44.44% (n=24). The more balanced ratio of male and female respondents guarantees that the research findings would not be biased by gender preferences, making the findings applicable to both sexes in the Computer Science discipline. The marginally larger percentage of male respondents is also aligned with the current trends in the Philippines regarding the number of men and women enrolling in science courses.

4.1.3 Preferred AI Tool

Table 3. Distribution by Preferred AI Tool

AI Tool	Frequency	Percentage (%)
ChatGPT	42	77.78
Dola	9	16.67
Claude	5	9.26
Gemini	4	7.41
Total*	**60**	**111.11**

From Table 3, ChatGPT emerged as the most popularly adopted AI software among the respondents, with 42 out of 54 participants (77.78%) using it. Dola accounted for 16.67% (n = 9) of the respondents, while 9.26% (n = 5) and 7.41% (n = 4) adopted Claude and Gemini, respectively. The prevalence of ChatGPT among the participants can be attributed to its accessibility and proven reliability as a programming assistant AI software. The current study agrees with findings from Swaraj & Chavan (2024) on the same subject area, where ChatGPT emerged as the most popularly used generative AI software among tertiary institution students.

DOI: 10.48175/IJARSCT-36506

ISSN 2581-9429 IJARSCT

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4.1.4 Number of AI Sessions Per Day

Table 4. Distribution by Number of Daily AI Sessions

Sessions Per Day	Frequency	Percentage (%)
0 sessions	0	0.00
1–2 sessions	38	70.37
3–5 sessions	13	24.07
6–10 sessions	3	5.56
Total	**54**	**100.00**

As evident from Table 4, each of the 54 respondents utilized AI-based tools at least once daily. The frequency of their engagement was mainly within 1–2 times per day (n = 38; 70.37%), which reflects moderate and regular usage. Additionally, some individuals utilized AI-based tools up to 3–5 times daily (n = 13; 24.07%), whereas others used them 6–10 times per day (n = 3; 5.56%). In the absence of any respondents who utilized AI-based tools 0 times daily, it can be said that AI tools are an integral part of each respondent's daily study routine. This information is particularly relevant since the frequency of AI usage seems consistent and moderate, indicating that AI assistance is a routine practice rather than an emergency measure.

4.2 Level of AI Tool Usage

This section presents the weighted mean scores of the respondents' AI tool usage, evaluated along two dimensions: Frequency of Usage and Application Context. Responses were rated on a four-point Likert scale interpreted as follows: 3.50–4.00 = Strongly Agree (Very High); 2.50–3.49 = Agree (High); 1.50–2.49 = Disagree (Low); 1.00–1.49 = Strongly Disagree (Very Low).

4.2.1 Frequency of Usage

Table 5. Weighted Mean of Frequency of AI Tool Usage

Indicator	Weighted Mean	Verbal Interpretation
Academic Performance		
1. Achieve higher scores in lab exams by producing functional code more effectively.	3.09	Agree / High
2. Improve my quiz results on programming logic by using the tool's instant feedback to clarify concepts.	3.17	Agree / High
3. Deliver practical exercises with higher accuracy and fewer logic errors.	3.20	Agree / High
Subscale Mean	**3.15**	**Agree / High**
Logical Reasoning		
4. Analyze how a program processes inputs and	3.26	Agree / High

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outputs.		
5. Justify the steps used in a coding solution.	3.35	Agree / High
6. Examine whether code logic is valid.	3.33	Agree / High
Subscale Mean	**3.31**	**Agree / High**
Problem-Solving Ability		
7. Determine approaches to new programming problems.	3.17	Agree / High
8. Troubleshoot issues in my code.	3.19	Agree / High
9. Apply learned solutions to similar coding tasks.	3.20	Agree / High
Subscale Mean	**3.19**	**Agree / High**
Overall Weighted Mean	**3.22**	**Agree / High**

Weighted means for the variable Frequency of AI Tool Usage according to the learning outcome dimension are shown in Table 5. Overall, a high mean of 3.22 suggests that learners agree that AI tool usage supports their learning positively in all respects. The highest mean was reported on the subscale Logical Reasoning (3.31), meaning that students find AI tools particularly useful for assessing the correctness of program logic. Problem-Solving Ability scored the next highest mean of 3.19, and the lowest subscale mean of 3.15 was achieved for the dimension of Academic Performance. All three variables fall under the category of High.

As can be seen from the results, the idea raised by Gonzaga et al. (2024) that AI tools can function as proper scaffolds during learning, particularly when promoting logical reasoning, is supported. In addition, Khan et al. (2024) pointed out that AI-generated feedback consistent with Cognitive Load Theory may help learners better understand programming logic without exceeding the capacity of working memory.

4.2.2 Application Context

Table 6. Weighted Mean of Application Context of AI Tool Usage

Indicator	Weighted Mean	Verbal Interpretation
Academic Performance		
10. Quizzes so I can understand tricky code before I turn it in.	2.85	Agree / High
11. Performance tasks to make sure my code actually works.	3.06	Agree / High
12. Practical exams to help me practice and solve problems faster.	3.19	Agree / High

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Subscale Mean	**3.03**	**Agree / High**
Logical Reasoning		
13. Code analysis to see exactly how different parts of a program work.	3.35	Agree / High
14. Step-by-step logic so I can follow an algorithm that feels too complex.	3.35	Agree / High
15. Mental checks to see if my own plan for the code makes sense.	3.22	Agree / High
Subscale Mean	**3.31**	**Agree / High**
Problem-Solving Ability		
16. Debugging tasks so I don't get stuck on small errors for too long.	3.13	Agree / High
17. Alternative solutions to find a better way to solve a tough challenge.	3.26	Agree / High
18. Project planning by breaking down big instructions into simple steps.	3.28	Agree / High
Subscale Mean	**3.22**	**Agree / High**
Overall Weighted Mean	**3.19**	**Agree / High**

Table 6 contains the mean scores for the subscales related to Application Contexts of AI tool Usage. The overall weighted mean score (Agree/High level) of 3.19 shows that students effectively apply AI tools for completing academic tasks such as quizzes, performance tasks, analysing codes, and debugging. In terms of means for the subscales, Logical Reasoning got the highest mean score of 3.31, while Problem-Solving Ability and Academic Performance obtained 3.22 and 3.03, respectively. It should be noted that Item 10 "Using AI tools for completing quizzes" was rated the lowest (2.85), showing possibly more constraints on academic integrity when using AI tools in assessments.

The results are consistent with Grützner and Schreck (2024) in that applying AI tools in programming might have either positive or negative effects depending on how students use AI tools. Students in this study seem to use AI tools in a structured way by focusing on their ability to learn about the logic and adopt proper problem-solving strategies.

4.3 Relationship Between AI Tool Usage and Learning Outcomes

This section addresses the primary research question: Is there a significant relationship between the use of AI tools and the learning outcomes of Computer Science students? Pearson Product-Moment Correlation Coefficient (Pearson r) was computed at a significance level of $\alpha = 0.05$.

Table 7. Pearson Correlation Between AI Tool Usage and Learning Outcomes

Variables	r-value	p-value	Strength	Decision
Frequency of Usage vs. Application	0.7159	0.0000*	Strong	Reject H_0

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Context (Overall)				
→ Academic Performance	-0.2075	0.1323	Negligible	Fail to Reject H_0
→ Logical Reasoning	0.5997	0.0000*	Moderate	Reject H_0
→ Problem-Solving Ability	0.8970	0.0000*	Very Strong	Reject H_0
**Significant at α = 0.05 (two-tailed)*				

Table 7 below highlights the results from Pearson correlation analyses. Overall, the correlation between Frequency of Usage and Application Contexts had $r = 0.7159$ ($p < 0.001$), meaning that frequency of use had a highly positive connection with the academic contexts in which students used AI tools. This suggests that those who frequently use AI also integrate them more effectively in various academic activities.

Regarding sub-scales, there was a very high positive correlation between Frequency of Usage and Problem-Solving Abilities ($r = 0.8970$, $p < 0.001$), which means that the more students use the AI technology, the greater benefit they receive in relation to their troubleshooting abilities, programming strategies, and the application of the previously acquired knowledge in new circumstances. There was a moderate positive correlation with Logical Reasoning ($r = 0.5997$, $p < 0.001$), thus demonstrating how AI-aided code analysis and stepwise confirmation of its logical accuracy positively affect reasoning abilities of users.

Finally, it is important to mention the fact that no correlation was identified between Frequency of Usage and Academic Performance ($r = -0.2075$, $p = 0.1323$). This result deserves particular attention – although the students report higher problem-solving and reasoning skills in cases of frequent AI usage, they do not have better quiz, test and task completion scores. It is also in line with the findings of Chaudhary et al. (2024) in terms of identifying a specific threshold of dependency above which the effect of AI usage on academic performance decreases. Furthermore, Kosmyna et al.'s (2025) findings regarding neuroscientific evidence about reduced engagement because of increased assistance with cognitive processes can be considered relevant here.

Overall, the results show that there is a highly significant and positive correlation between frequency of using the AI technology and problem solving and logical reasoning outcomes. However, this type of relationship cannot be established in case of academic performance.

4.4 Summary of Findings

The following key findings emerged from the analysis:

1. The respondents were predominantly 19-year-old males (55.56%) with an average of 1–2 AI tool sessions per day. ChatGPT was the most widely used AI tool (77.78%).
2. The level of AI tool usage in terms of Frequency was High (overall mean = 3.22), with Logical Reasoning scoring highest (3.31) among all subscales.
3. The level of AI tool usage in terms of Application Context was also High (overall mean = 3.19), with Logical Reasoning again receiving the highest subscale score (3.31).
4. A strong positive and significant relationship was found between the overall AI tool Frequency of Usage and Application Context ($r = 0.7159$, $p < 0.001$).
5. Problem-Solving Ability was very strongly and significantly correlated with Frequency of Usage ($r = 0.8970$, $p < 0.001$), while Logical Reasoning showed a moderate significant correlation ($r = 0.5997$, $p < 0.001$).
6. No significant correlation was found between AI tool usage frequency and Academic Performance ($r = -0.2075$, $p = 0.1323$), suggesting that frequent AI use does not directly improve formal academic scores.

DOI: 10.48175/IJARSCT-36506

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V. CONCLUSIONS AND RECOMMENDATIONS

The findings and conclusions of the study on the application of AI tools and their effects on the academic performance of Computer Science students of SNSU are summarized in this chapter. The conclusions are based on the results obtained from the analysis of the collected data from the responses of 54 participants who took part in the survey. Recommendations are also provided for the benefit of students, teachers, university administrators, and researchers.

5.1 Conclusions

The following conclusions were derived from the key findings presented in Chapter 4:

5.1.1 Profile of the Respondents

The sample was largely made up of 19-year-old students (85.19%), suggesting that the sample size included predominantly either first year or second-year students enrolled in basic programming classes. An almost equal ratio between male (55.56%) and female (44.44%) participants suggests that the results obtained from this study can be considered representative for both genders taking the Computer Science course. ChatGPT proved to be the most popular AI software tool (77.78%), which is expected given the fact that it is widely used and is generally accepted as an indispensable helper in coding. What is more important, all respondents indicated that they use AI software on a daily basis (100%). Furthermore, more than two thirds of respondents stated that they use it 1-2 times a day (70.37%). Consequently, it becomes apparent that the use of AI software became a common and regular academic practice.

5.1.2 Level of AI Tool Usage in Terms of Frequency of Usage

The average weighted mean for the frequency of AI tool usage was 3.22 (Agree/High). In terms of the three learning outcome variables, Logical Reasoning obtained the highest subscale mean of 3.31, while Problem-Solving Ability had 3.19 and Academic Performance had 3.15. All three subscales were considered high, suggesting that students generally agree that frequent AI tool interaction facilitates their learning in all aspects of programming expertise.

Based on the findings, the most notable advantage of AI use is its potential to aid students in following the logic of the program, checking whether the coding process is valid, and justifying the steps in the programming process. The relatively low value for the Academic Performance variable compared to others is an early sign that students recognize a difference between AI-assisted skill acquisition and academic performance.

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Based on the findings, the most notable advantage of AI use is its potential to aid students in following the logic of the program, checking whether the coding process is valid, and justifying the steps in the programming process. The relatively low value for the Academic Performance variable compared to others is an early sign that students recognize a difference between AI-assisted skill acquisition and academic performance.

5.1.3 Level of AI Tool Usage in Terms of Application Context

Application Context of AI Tool Usage was found to have a weighted mean of 3.19 (Agree/High). In terms of the means of each subscale, Logical Reasoning once more obtained the highest score (3.31), followed by Problem-Solving Ability (3.22), and Academic Performance (3.03). Significantly lower mean for the latter subscale, especially Item 10 ("Using AI tool for quiz") with a mean score of 2.85, the lowest among all items, suggests that there is some level of consideration among respondents regarding their use of AI tools in situations involving assessments. Conclusion: It may thus be stated that students make good use of AI tools primarily for the purposes of logical verification, understanding algorithms, debugging, and project deconstruction.

DOI: 10.48175/IJARSCT-36506

5.1.4 Significant Relationship Between AI Tool Usage and Learning Outcomes

From the results of Pearson correlation analysis, it can be seen that the Frequency of AI Tool Usage and Application Context demonstrate a highly positive and significant correlation ($r = 0.7159$, $p < 0.001$), indicating that higher frequency of AI tools use is related to more diverse and purposive application of those instruments. The results of correlation analysis show a very high positive and significant correlation coefficient ($r = 0.8970$, $p < 0.001$) for Problem-Solving Ability, which is the most convincing result of this study. In other words, high frequency of using AI tools indicates a close relationship between the tool and the ability to debug the code, choose appropriate methods of programming, and solve problems.

The moderate positive and significant relationship was also found between Frequency of AI Tool Usage and Logical Reasoning ($r = 0.5997$, $p < 0.001$), which supports an idea about the importance of this tool for developing critical and analytical thinking when programming. At the same time, there was no significant correlation found between the frequency of AI tool usage and academic performance of Computer Science students ($r = -0.2075$, $p = 0.1323$). This is perhaps the most important result of the current research, indicating that even though the use of such tools improves some abilities of students in programming (reasoning and problem-solving), their academic performance remains unaffected and demonstrates no significant changes. The absence of significant correlation and its negative direction can be explained by dependency threshold introduced by Chaudhary et al. (2024) and cognitive offloading discovered by Kosmyna et al. (2025) with electroencephalography technique. In general, one may conclude that usage of AI tools by Computer Science students of SNSU is quite frequent and contributes to logical reasoning and problem-solving ability of students. At the same time, there is no correlation between the use of AI tools and academic performance of students.

5.2 Recommendations

Based on the foregoing conclusions, the following recommendations are offered to the key stakeholders of this study:

5.2.1 For Students

Students are advised to embrace a mindful and purposeful attitude towards the use of AI tools while programming. Because regular use of AI is beneficial to problem-solving skills and logical reasoning abilities but not to academic score achievements, students should consider these technologies as scaffolding means for learning – not as tools to replace critical thinking. Especially:

• Students are encouraged to first solve programming tasks on their own before using AI technologies, thus fostering cognitive engagement and avoiding passivity in the process

• When the AI technology suggests solutions, students are encouraged to break down the logic behind the solutions, annotate the code, and explore other options –turning AI solutions into an educational experience and not the end point of programming.

• Moderate the number of AI sessions, especially during the preparatory period for assessment tasks, allowing for the brain to engage in the effortful cognitive processes that contribute to developing programming expertise.

• Be honest about one's abilities by consistently solving programming tasks without the help of AI tools to assess independent abilities and determine areas for improvement.

5.2.2 For Educators and Instructors

It is advised that programming teachers take advantage of AI technologies as learning resources when building instructional safeguards against AI dependency. The following are some recommendations:

• Create AI-based exercises that allow students to analyse, describe, adapt, and rewrite the program produced by an AI agent in a manner that will prevent AI from being used as a substitute for cognitive processes.

• Create tests that are resistant to AI intervention, such as oral presentations, live coding, whiteboarding, and algorithmic construction, which are done with supervision to make sure that test scores reflect actual competence.

DOI: 10.48175/IJARSCT-36506

• Create policies on the application of AI in tasks to clarify its use during lessons, such as exploration experiments and brainstorming, and in tests, like quizzes and lab work, which are done independently.
• Regularly conduct independent competency tests to verify if the student can reproduce and describe the solution produced with the help of an AI assistant.

5.2.3 For School Administrators and Curriculum Developers

Since AI tool utilization is now widespread among the selected student sample group, the educational organization needs to implement a governance structure before the emergence of AI usage and not as a reaction to its occurrence. In response to this situation, the recommendations below should be implemented:
• Development of an institutional policy regarding AI use for academic purposes, providing both students and lecturers with a set of guidelines and rules for using such technological solutions within various forms of assessments and courses.
• Incorporating AI knowledge into the Computer Science curriculum and discussing issues related to the use of AI tools, cognitive offloading, the moral aspect of AI-written code, and keeping programming abilities while utilizing AI tools.
• Organizing professional development seminars aimed at enhancing knowledge regarding effective AI-integrated pedagogy and conducting assessments that would resist AI.
• Supporting longitudinal studies at the institutional level or collaborating with other schools to accumulate experience with regard to integrating AI into programming education.

5.2.4 For Future Researchers

The current research provides essential empirical groundwork for examining the connection between AI tool use and Computer Science learners' academic achievements in the Philippines. The following areas should be explored in future investigations:
• Implement longitudinal studies that trace how AI tool use and the correlation between it and the learning outcomes change throughout an academic program and whether the insignificant association with Academic Performance alters when the students' progress through their course and take advanced programming and capstone classes.
• Increase the sample size by including Computer Science students at several colleges in the Philippines to examine the generalizability of the results to other educational institutions in the country.
• Assess the distinct impact of individual AI tools (e.g., ChatGPT, Claude, Gemini, and Dola) on the components of learning outcomes since their unique features in terms of design, capabilities, and response styles may produce different cognitive and academic outcomes.
• Include external validation measures, such as students' actual grades, performance on programming assessment exams, and algorithm design evaluations, instead of solely relying on their subjective Likert scale ratings of learning outcomes to gather more reliable data on the association between AI tool use and the learning outcomes.
• Investigate the moderating role of various demographic variables (e.g., learning style, prior programming experience, gender, and academic year level) in the relationship between AI tool use and the learning outcomes to determine their influence on the heterogeneity of the results.
• Consider measuring the cognitive load of programming tasks with cognitive load assessment tools and neuroimaging techniques, which can further explore the neural aspect of AI-assisted learning based on the theoretical framework proposed by Kosmyna et al. (2025).

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IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, June 2026
Impact Factor: 8.2

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