Utilization of Artificial Intelligence and Perceived Programming Skills of Third Year Information Technology Students at Quezon City University

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ABSTRACT

This study examined the perceived influence of Artificial Intelligence (AI) utilization on the programming skills of third-year Bachelor of Science in Information Technology (BSIT) students at Quezon City University. Specifically, the study focused on students' self-reported perceptions regarding coding speed, debugging accuracy, coding productivity, learning effectiveness, and the perceived positive and negative influences of AI-assisted programming tools. A quantitative descriptive-correlational research design was employed, involving 284 purposively selected third-year BSIT students during Academic Year 2025–2026. Data were collected using a researcher-made questionnaire administered through Google Forms. The instrument underwent expert validation and pilot testing prior to the actual conduct of the study, yielding acceptable reliability coefficients using Cronbach's alpha. Descriptive statistics such as frequency, percentage distribution, and weighted mean were utilized, while Spearman's rho and Analysis of Variance (ANOVA) were used to determine significant relationships and differences among variables. The findings revealed that respondents generally agreed that they possess positive programming-related behaviors and experiences in terms of coding speed, debugging accuracy, coding productivity, and learning effectiveness. Respondents also strongly agreed that AI tools help them understand programming concepts, improve debugging accuracy, and support problem-solving strategies. However, they likewise agreed that excessive AI utilization may contribute to overdependence, reduced independent problem-solving, decreased manual coding practice, and inaccurate reliance on AI-generated outputs. Despite these perceptions, Spearman's rho analysis showed no statistically significant relationship between AI utilization and perceived programming skills ($r_s = 0.074$, $p = 0.211$). The findings suggest that while students perceive AI tools as beneficial in supporting programming-related learning experiences, such perceptions do not necessarily indicate measurable improvements in actual programming competence. The study recommends the responsible and balanced integration of AI tools in programming education while encouraging independent coding practice, critical thinking, and problem-solving activities.

Keywords: Artificial Intelligence, Perceived Programming Skills, IT Students, AI-Assisted Learning, Programming Education

INTRODUCTION

Artificial Intelligence (AI) is one of the most significant technological advancements influencing education today. However, while AI tools are increasingly used in programming education, many existing studies rely primarily on students' perceptions and experiences rather than direct assessments of actual programming competence. In this context, the present study focuses specifically on the perceived influence of AI utilization on the programming-related experiences and self-assessed programming skills of third-year BSIT students at Quezon City University. The study does not measure actual programming performance through practical examinations or standardized coding assessments. In recent years, Higher Education Institutions have increasingly adopted AI chatbots and AI-based systems to help students learn complex subjects and accomplish academic tasks more efficiently. These technologies provide automated assistance, personalized feedback, and immediate responses to students' questions, thereby improving the overall learning experience. Studies have shown that AI chatbots can significantly enhance students' learning outcomes and academic performance (Wu

& Yu, 2023). Furthermore, the continuous development of artificial intelligence has become essential in supporting modern educational practices.

Artificial Intelligence has also become increasingly common in higher education institutions, particularly among Information Technology (IT) students. Many students and programmers use generative AI tools to assist in writing code, debugging programs, and improving coding efficiency. Tools such as GPT and GitHub Copilot are widely utilized to simplify complex programming tasks by providing suggestions and automated support during software development. Studies have shown that AI-assisted programming tools can improve coding productivity and support students in learning programming concepts more effectively (Puryear & Sprint, 2022).

The integration of Artificial Intelligence in programming education has been widely adopted in universities and has introduced several positive effects that support students' technical proficiency. AI-assisted tools help students complete tasks more efficiently and improve their understanding of complex coding concepts. Studies have shown that the use of Artificial Intelligence can enhance productivity and improve students' learning performance (Silva et al., 2024). However, despite these advantages, the use of AI also presents certain disadvantages that may affect students' critical thinking, problem-solving, and decision-making skills. Overdependence on AI tools may reduce students' ability to complete programming tasks independently (Abubakar et al., 2025).

Although previous studies have explored the role of Artificial Intelligence in education and programming, most researchers have focused only on either its advantages or disadvantages. Limited studies have examined both the positive and negative effects of AI, particularly in relation to the technical proficiency of IT students. Additionally, there is a lack of local studies involving Information Technology students in the Philippine setting. Therefore, this study aims to examine the perceived influence of Artificial Intelligence utilization on the self-reported programming skills and programming-related learning experiences of third-year IT students at Quezon City University. Specifically, the study explores students' perceptions regarding coding speed, debugging accuracy, coding productivity, learning effectiveness, and the perceived positive and negative influences associated with AI-assisted programming tools.

A. Statement of the Problem

This study focuses on third-year Bachelor of Science in Information Technology (BSIT) students at Quezon City University during the Academic Year 2025–2026. It examines the respondents' programming skills in terms of coding speed, debugging accuracy, coding productivity, and learning efficiency, as well as the influence of Artificial Intelligence (AI) in programming, particularly in terms of overdependence on AI tools, reduced problem-solving skills, decreased manual coding practice, and inaccurate reliance on AI-generated outputs. The study relies on the self-reported perceptions of the respondents and does not include practical examinations or direct assessments of actual programming performance.

Specifically, this study seeks to answer the following questions:

1. What is the demographic profile of the respondents in terms of

    1.1. age; and

    1.2. gender?

2. What is the programming skills level of the respondents in terms of:

    2.1. faster coding speed;

    2.2. debugging accuracy;

    2.3.coding productivity; and

    2.4. learning efficiency?

3. Is there a significant difference in the programming skills level of the respondents when grouped according to their profile?

4. How do the respondents assess the Artificial Intelligence in programming skills in terms of:

   4.1. Overdependence on AI tools;

   4.2. Reduced problem-solving skills;

   4.3.Decreased manual coding practice; and

   4.4.Inaccurate reliance on AI output?

5. Is there a significant relationship between programming skills level and Artificial Intelligence as assessed by the respondents?

B. Limitation of the Study

Since the study relies on survey-based self-reported responses, the findings should be interpreted as students' perceptions regarding AI utilization and programming-related experiences. The study does not objectively evaluate actual programming competence through practical coding examinations or experimental assessments.

C. Hypotheses

Ho: There is no significant difference in the programming skills level of the respondents when grouped according to their profile.

Ho: There is no significant relationship between programming skills level and Artificial Intelligence as assessed by the respondents

RELATED STUDIES

The reviewed literature highlights the growing integration of Artificial Intelligence (AI) in education, particularly in higher education and programming-related fields. Studies consistently show that AI tools have become widely used by students to support learning, improve accessibility to educational resources, and simplify academic tasks. According to Aniella Mihaela Vieriu and Gabriel Petrea (2025), a large percentage of students use virtual assistants such as ChatGPT and Google Assistant for academic purposes, demonstrating the increasing dependence on AI-powered technologies in learning environments. In the Philippine context, K. Tarray and colleagues (2025) further emphasized that AI-based learning tools help college students improve their academic performance by providing instructional support and easier access to learning materials. These findings suggest that AI contributes significantly to enhancing students' learning experiences and academic efficiency.

Several studies also revealed that AI positively influences students' technical skills, particularly in programming and Information Technology education. Research conducted by H. Güner and E. Er (2025) showed that students who utilized AI tools in programming classes demonstrated better understanding of coding concepts and experienced more positive learning outcomes. Similarly, Y. Jing and colleagues (2024) found that AI helps students solve programming tasks more quickly and effectively. K. Naznin and colleagues (2025) also highlighted that AI supports personalized learning, coding, and writing tasks by offering adaptive assistance and immediate feedback. In the fields of Information Technology and Engineering, AI was recognized as an effective tool for improving technical proficiency by reducing repetitive programming activities and allowing students to focus more on complex problem-solving tasks (M. Micic, 2024). Moreover, Vidya Handur and colleagues (2016) emphasized the importance of hands-on learning in developing technical knowledge, while Ramazan Yilmaz (2023) explained that AI-based learning systems can improve programming and computational thinking skills through instant responses and interactive support. Local studies also support these findings, as students from Davao Oriental State University reported that AI-powered tools such as ChatGPT helped them solve programming problems and generate code efficiently (Montejo et al., 2026). Likewise, an integrative review published in Diversitas Journal (2026) concluded that AI can improve programming skills, critical thinking, self-confidence, and writing abilities among students in Philippine classrooms.

Despite these advantages, the reviewed studies also emphasized the challenges and negative effects associated with excessive reliance on AI technologies. Richard Arum and colleagues (2025) pointed out that students with stronger academic support systems tend to benefit more from AI tools, suggesting that unequal access to guidance and resources may widen the gap in students' technical competencies. Furthermore, studies by B. Qureshi (2023) revealed that although AI-assisted tools can improve performance in programming tasks, they may also lead to inaccurate code generation, misconceptions, and overdependence on automated systems. Similarly, A. Scholl and N. Kiesler (2024) found that beginner programmers often struggle to determine the accuracy and reliability of AI-generated responses, which may negatively affect the development of independent problem-solving and long-term technical mastery. In addition, R. Mellado and C. Cubillos (2025) stressed that the effectiveness of AI-mediated learning still depends on active student engagement and critical thinking. Although AI can enhance motivation and knowledge acquisition, students must remain actively involved in the learning process to fully develop their technical and analytical skills.

Overall, the reviewed literature demonstrates that Artificial Intelligence has both positive and negative effects on students' technical proficiency, particularly in programming and Information Technology-related education. AI improves learning efficiency, accessibility, coding productivity, confidence, and technical support. However, excessive dependence on AI tools and lack of critical evaluation may weaken students' independent problem-solving, critical thinking, and deeper technical understanding. Therefore, the effectiveness of AI in education largely depends on how students utilize these technologies and how educators guide them toward responsible and balanced AI usage.

DESIGN AND METHODOLOGY

A. Research Design

This study adopts a quantitative descriptive-correlational research design to determine the role of artificial intelligence (AI) in influencing the technical skills of third-year Bachelor of Science in Information Technology (BSIT) students at Quezon City University. Descriptive correlational research is a type of research design that tries to explain the relationship between two or more variables without making any claims about cause and effect. It includes collecting and analyzing data on at least two variables to see if there is a link between them (Bhat, n.d.).

The correlational component is utilized to determine whether a statistically significant relationship exists between AI-related technical skills and non-AI technical skills. Correlational research is a type of non-experimental research in which researchers measure two or more variables and assess the relationship or correlation between them without any manipulation (Ganesh, 2025). This methodological approach is appropriate for studies that seek to quantify variables and identify statistical relationships among them.

B. Respondents of the Study

The respondents of the study are third-year Bachelor of Science in Information Technology (BSIT) students enrolled during Academic Year 2025–2026 at Quezon City University. A total of 284 students participated in the study, representing sections SBIT-3A to SBIT-3R. The study focuses exclusively on third-year Information Technology students because they have already completed several programming and technical courses and have substantial experience in using artificial intelligence tools in academic and programming-related tasks. These students are considered the most appropriate respondents because they possess the technical background and direct experience necessary to evaluate how AI affects programming skills and technical competence.

C. Sampling Technique

The study uses purposive sampling as the sampling technique. Purposive sampling is a non-probability sampling method in which respondents are deliberately selected based on their characteristics that are directly relevant to the objectives of the study (Nikolopoulou, 2022). In this research, the respondents were intentionally chosen because they are third-year BSIT students at Quezon City University who have substantial academic exposure to programming, software development, and the use of artificial intelligence tools in coding-related tasks. These characteristics make them particularly suitable for examining the influence of artificial intelligence on technical skills.

D. Data Gathering Procedure

The study followed a series of procedures to ensure the systematic and reliable collection of data. First, a survey questionnaire was developed specifically for this study, focusing on the utilization of Artificial Intelligence and its impact on the programming skills of the respondents. The questionnaire underwent review and approval by the adviser, with necessary revisions made based on feedback. Validation of the questionnaire was conducted by statistician, leading to further corrections and improvements. Prior to data collection, participants were provided with informed consent, ensuring their understanding of the study's purpose, confidentiality, and voluntary participation. The questionnaires were then distributed online through Google Forms to Third Year Bachelor of Science in Information Technology (BSIT) students at Quezon City University, who received instructions on accurate and comprehensive completion. After data collection, the gathered data were tabulated, organized, sorted, and tallied for analysis. Statistical tools and techniques were applied to analyze the data and examine the utilization of Artificial Intelligence and its impact on the programming skills of the respondents These procedures ensured the reliability and validity of the collected data for the study

E. Instrument Used

The primary instrument used for data collection in this study is a researcher-made structured questionnaire administered digitally through Google Forms. The use of a standardized questionnaire ensures that all respondents answer the same set of questions using a uniform format, thereby enhancing the consistency, reliability, and accuracy of the collected data.

The questionnaire is divided into four major sections:

The first section gathers the demographic profile of the respondents, including their age, sex, section, and frequency of AI tool usage.

The second section measures the respondents' programming skills associated with the use of Artificial Intelligence in terms of:

2.1. Coding speed

2.2. Debugging accuracy

2.3. Coding productivity

2.4. Learning efficiency

The third section assesses the perceived negative effects of Artificial Intelligence on students' programming skills in terms of:

3.1. Overdependence on AI tools

3.2. Reduced problem-solving skills

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3.3. Decreased manual coding practice

3.4. Inaccurate reliance on AI-generated outputs

The fourth section evaluates the perceived relationship between Artificial Intelligence and programming skills, particularly in relation to improvements in problem-solving strategies, understanding of programming concepts, coding logic, confidence, technical proficiency, and debugging accuracy.

F. Statistical Treatment

1. **Frequency and Percentage Formula:**

The frequency and percentage formulas will be used to represent the variables related to the demographic profile of the respondents in terms of age, gender, and section.

$$\% = \frac{\boldsymbol{f}}{\boldsymbol{N}} \times \mathbf{100}$$

Where:

P = Percentage

f = Frequency

N = Total number of respondents

2. **Weighted Mean Formula:**

This will be used to calculate the weighted average of the questionnaire responses provided by the participants during the data collection phase.

$$WM = \frac{\Sigma(f \times w)}{N}$$

Where:

WM= weighted mean

X= value of each option

W= weight or frequency of each option

N= number of cases

Σ = summation (total of)

3. **Likert Scale Approach**

Likert Scale was used to process the data. It provides a range of response options that measure the respondents' level of agreement or disagreement regarding a specific statement, behavior, or experience. Researchers can capture the variety in respondents' experiences or behaviors and gain a more detailed view of their attitudes or behaviors by using a Likert scale with response possibilities like"strongly agree" to "strongly disagree".

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Table 1. 4-Point Likert Scale

Scale	Ranges	Descriptive Interpretation
4	3.26 – 4.00	Strongly Agree
3	2.51 – 3.25	Agree
2	1.76 – 2.50	Disagree
1	1.00 – 1.75	Strongly Disagree

4. **Spearman's Rho**

This will be used to compare the two variables in our research paper: the use of AI tools and programming skills of the respondents.

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)}$$

Where:

ρ (rho) = Spearman rank correlation coefficient

d = Difference between the ranks of each paired observation

Σd^2 = Sum of squared rank differences

n = Number of paired observations (respondents)

5. **ANOVA**

It will be used to determine the significant differences in the respondents' profile when grouped according to age and gender.

$$F = \frac{MS_d}{MS_E}$$

Where:

F = ANOVA test statistic

MSd = Mean Square Between Groups

MSe = Mean Square Within Groups

RESULT AND DISCUSSION

A. Demographic Profile of the Respondents

1. **Profile of the respondents as to their Age**

Table 2. Frequency Distribution of the Respondents According to Age

Age	Frequency	Percentage
20 - 22	221	77.8%

23 - 24	47	16.5%
25 & above	16	5.6%
Total	284	100%

Table 2 presents the findings of the survey regarding the age of the 284 respondents. The majority of the respondents were between 20–22 years old, comprising 77.8% of the total participants. In contrast, the age group with the fewest respondents was 25 years old and above, accounting for 5.6% of the total respondents. Meanwhile, respondents aged 23–24 years old represented 16.5% of the total participants.

2. **Profile of the respondents as to their Gender**

Table 3. Frequency Distribution of the Respondents According to Gender

Gender	**Frequency**	**Percentage**
Male	167	58.80%
Female	104	36.60%
Preferred not to say	13	4.60%
Total	284	100%

Table 3 presents the results of the survey regarding the gender of the respondents. The majority of the respondents identified as male, comprising 58.8% of the total participants. Meanwhile, female respondents accounted for 36.6% of the total. On the other hand, the fewest respondents were those who preferred not to disclose their gender.

B. The Programming Skills Level of the Respondents

Table 4. Weighted Mean Distribution of the Coding Speed of the Respondents

Indicator	**Weighted Mean**	**Descriptive Interpretation**
Q1. I can finish my coding assignments in a short period of time.	2.92	Agree
Q2. I am able to write code more quickly when working on programming tasks or activities.	2.92	Agree
Q3. I am able to quickly begin coding after understanding the given problem or task.	3.07	Agree
Q4. I can efficiently move from one coding task to another without significant delays.	2.82	Agree
Q5. I am able to adjust quickly when changes are needed in my code during development.	2.93	Agree
Average Weighted Mean	**2,93**	**Agree**

Table 4 shows the respondents' assessment of coding speed, where all indicators were interpreted as "Agree." The highest mean score was in Q3 3.07%, indicating that the respondents are able to quickly begin coding after understanding the given problem or task, while Q4 obtained the lowest mean score 2.82%, suggesting some difficulty in efficiently moving from one coding task to another without significant delays, although still within the "Agree" range.

Table 5. Weighted Mean Distribution of the Debugging Accuracy of the Respondents

Indicator	Weighted Mean	Descriptive Interpretation
Q1. I am able to correctly identify errors in my code during the development process.	3.04	Agree
Q2. I can analyze and interpret error messages to determine the cause of coding problems.	3.01	Agree
Q3. I am able to fix errors in my code without creating additional issues.	2.82	Agree
Q4. I am able to debug code that involves multiple components or functions.	2.90	Agree
Q5. I am able to apply appropriate solutions to prevent the same errors from occurring again.	3.07	Agree
Average Weighted Mean	**2.97**	**Agree**

Table 5 illustrates the respondents' assessment of debugging accuracy, where all indicators were interpreted as "Agree." The highest mean score was in Q5 3.07%, indicating that the respondents are able to apply appropriate solutions to prevent the same errors from occurring again, while Q3 obtained the lowest mean score 2.82%, suggesting some difficulty in fixing errors in code without creating additional issues, although still within the "Agree" range.

Table 6. Weighted Mean Distribution of the Coding Productivity of the Respondents

Indicator	Weighted Mean	Descriptive Interpretation
Q1. I complete coding assignments and requirements on time.	3.26	Agree
Q2. I spend less time figuring out how to start a programming task.	2.94	Agree
Q3. I accomplish more programming tasks within a single study session.	2.89	Agree
Q4. I can handle multiple programming tasks simultaneously without difficulty.	2.74	Agree
Q5. I finish laboratory and programming activities faster than before.	3.02	Agree
Average Weighted Mean	**2.97**	**Agree**

Table 6 showcase the respondents' assessment of coding productivity, where all indicators were interpreted as "Agree." The highest mean score was obtained in Q1 3.26%, indicating that respondents are able to complete coding assignments and requirements on time, while the lowest mean score was in Q4 2.74%, suggesting some difficulty in handling multiple programming tasks simultaneously without difficulty. Overall, the results imply that respondents show a generally positive level of coding productivity, though multitasking in programming remains a weaker area.

Table 7. Weighted Mean Distribution of the Learning Effectiveness of the Respondents

Indicator	Weighted Mean	Descriptive Interpretation
Q1. I can apply programming concepts to solve different types of problems independently.	3.02	Agree

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Q2. I can manage complex coding tasks with confidence.	2.89	Agree
Q3. I can write code with proper logic and structure without relying too much on others.	2.91	Agree
Q4. I can continue learning advanced programming concepts independently.	3.05	Agree
Q5. I can use logical thinking to break down difficult programming problems.	3.05	Agree
Average Weighted Mean	**2.98**	**Agree**

Table 7 presents the respondents' assessment of their ability to learn programming effectively, where all indicators were interpreted as "Agree." The highest mean scores were in Q4 and Q5 3.05%, indicating that the respondents are confident in learning advanced programming concepts and using logical thinking to solve problems, while Q2 obtained the lowest mean score 2.89%, suggesting some difficulty in handling complex coding tasks, although still within the "Agree" range.

C. The Artificial Intelligence in Programming Skills

Table 8 below shows the respondents' assessment of overdependence on AI tools, where all indicators were interpreted as "Agree." The highest mean score was in Q3 3.07%, indicating that the respondents feel the need to use AI tools even when they have prior knowledge of the solution, while Q5 obtained the lowest mean score 2.68%, suggesting that the respondents rely less on AI tools to confirm whether their code is correct instead of evaluating it themselves, although still within the "Agree" range.

Table 8. Weighted Mean Distribution of the Overdependence on AI tools of the Respondents

Indicator	Weighted Mean	Descriptive Interpretation
Q1. I find it difficult to write code without the assistance of AI tools.	3.06	Agree
Q2. I tend to rely on AI tools when completing most of my programming tasks.	3.03	Agree
Q3. I feel the need to use AI tools even when I have prior knowledge of the solution.	3.07	Agree
Q4. I struggle to complete coding tasks independently when AI tools are not used.	2.97	Agree
Q5. I rely on AI tools to confirm whether my code is correct instead of evaluating it myself.	2.68	Agree
Average Weighted Mean	**2.96**	**Agree**

Table 9. Weighted Mean Distribution of the Reduced Problem Solving Skills of the Respondents

Indicator	Weighted Mean	Descriptive Interpretation
Q1. I have difficulty understanding complex programming logic without AI explanations.	2.98	Agree
Q2. I have difficulty debugging logical errors without AI assistance.	2.99	Agree

Q3. I struggle to plan out program logic or pseudocode without asking an AI first.	2.89	Agree
Q4. I rely on AI to interpret and explain programming problems instead of analyzing them independently.	2.89	Agree
Q5. I feel that my own independent problem-solving skills have weakened due to AI use.	3.01	Agree
Average Weighted Mean	**2.95**	**Agree**

Table 9 demonstrates the respondents' assessment of reduced problem-solving skills, where all indicators were interpreted as "Agree." The highest mean score was in Q5 3.01%, indicating that the respondents feel that their own independent problem-solving skills have weakened due to AI use, while Q3 and Q4 obtained the lowest mean score 2.89%, suggesting that the respondents experience less difficulty in planning program logic or independently analyzing programming problems, although still within the "Agree" range.

Table 10. Weighted Mean Distribution of the Decreased Manual Coding Practice of the Respondents

Indicator	**Weighted Mean**	**Descriptive Interpretation**
Q1. I practice writing code manually less often because of AI	3.05	Agree
Q2. I submit AI-generated code without attempting to write my own solution first.	2.75	Agree
Q3. I turn to AI tools immediately when I encounter a coding problem.	3.03	Agree
Q4. I rely on AI tools instead of trying to write code on my own first.	2.86	Agree
Q5. I rarely write code from scratch since I started using AI tools.	3.00	Agree
Average Weighted Mean	**2.94**	**Agree**

Table 10 presents the respondents' assessment of decreased manual coding practice, where all indicators were interpreted as "Agree." The highest mean score was obtained in Q1 3.05%, indicating that respondents practice writing code manually less often because of AI, while the lowest mean score was in Q2 2.75%, suggesting a lower but still present tendency to submit AI-generated code without attempting to write their own solution first. Overall, the results imply that respondents rely on AI tools in coding activities, which may reduce their frequency of writing code from scratch.

Table 11. Weighted Mean Distribution of the Inaccurate Reliance on AI Tools of the Respondents

Indicator	**Weighted Mean**	**Descriptive Interpretation**
Q1. I sometimes fail to recognize biases or inaccuracies in AI-generated programming solutions.	2.92	Agree
Q2. I use AI suggestions without comparing them to other reliable programming resources.	2.78	Agree
Q3. I sometimes overlook mistakes in AI suggestions because I assume they are accurate.	2.90	Agree

Q4. I use AI outputs even when they do not perfectly match my programming needs.	2.72	Agree
Q5. I may accept incorrect AI explanations of programming concepts without further research.	2.65	Agree
Average Weighted Mean	**2.79**	**Agree**

Table 11 shows the respondents' assessment of inaccurate reliance on AI tools in programming, where all indicators were interpreted as "Agree." The highest mean score was obtained in Q1 2.92%, indicating that respondents sometimes fail to recognize biases or inaccuracies in AI-generated solutions, while the lowest mean score was in Q5 2.65%, suggesting that they are less likely, but still somewhat prone, to accept incorrect AI explanations without further research. Overall, the results show a moderate tendency to rely on AI outputs despite possible inaccuracies.

D. The Relationship Between Programming Skills Level and Artificial Intelligence

Table 12. Weighted Mean Distribution of the Relationship Between Programming Skills Level and Artificial Intelligence Usage

Indicator	**Weighted Mean**	**Descriptive Interpretation**
Q1. Help me to develop better problem-solving strategies in programming.	3.40	Strongly Agree
Q2. Help me understand programming concepts and lessons more efficiently.	3.40	Strongly Agree
Q3. Help me improve the overall logic and structure of my programs.	3.38	Strongly Agree
Q4. Improves my confidence in handling programming tasks.	3.36	Strongly Agree
Q5. Improves my overall technical proficiency in coding tasks.	3.37	Strongly Agree
Q6. Improve my accuracy in identifying and fixing errors in my code.	3.40	Strongly Agree
Average Weighted Mean	**3.39**	**Strongly Agree**

Table 12 presents the weighted mean distribution of the relationship between programming skills level and Artificial Intelligence usage among the respondents, with an overall average weighted mean of 3.39 interpreted as "Strongly Agree." This indicates that the respondents generally perceive AI as having a positive contribution to the improvement of their programming skills and technical proficiency. The indicators "Help me develop better problem-solving strategies in programming," "Help me understand programming concepts and lessons more efficiently," and "Improve my accuracy in identifying and fixing errors in my code" obtained the highest weighted means of 3.40, suggesting that AI tools effectively support problem-solving, concept understanding, and debugging activities. Meanwhile, improving program logic and structure (3.38), technical proficiency (3.37), and confidence in handling programming tasks (3.36) were also strongly agreed upon by the respondents. Overall, the findings indicate that AI-assisted tools significantly help students improve coding efficiency, learning performance, and programming-related skills. These results support the studies of H. Güner and E. Er (2025), Y. Jing et al. (2024), and Ramazan Yilmaz (2023), which emphasized that AI technologies enhance students' programming experiences, coding productivity, and computational thinking skills through immediate feedback and **interactive learning support.**

E. The Relationship Between Programming Skills Level and Artificial Intelligence Using Spearman's rho

Table 13. Spearman's Rho Distribution of the Relationship Between Programming Skills Level and Artificial Intelligence Utilization

Variable	Spearman rho (p)	p-value	Interpretation	Decision
AI Utilization and Programming skills	0.074	0.211	Very Weak Positive Correlation (Not Significant)	Accept Null Hypothesis

Table 13 Spearman's rank-order correlation was used to find out the relationship between artificial intelligence utilization and programming skills amongst Third Year BSIT students. The result showed that there was a very weak positive relationship between these two variables, rs= 0.074, and p= 0.211, which is more than 0.05. This shows that there was no statistically significant relationship between artificial intelligence usage and programming skills. Hence, the null hypothesis was accepted.

F. The Relationship Between the Programming Skills Level of respondents according to their profile

Table 14. Analysis of Variance (ANOVA) on the Difference in Programming Skills Level of Respondents According to Their Profile (Age)

Source of Variation	Sum of Squares (SS)	Degree of Freedom (DF)	Mean of Square (MS)	Computed F-Ratio	p-value	Interpretation
Between Groups	0.083	2	0.041	0.137	0.872	Not Significant
Within Groups	84.596	281	0.301			
Total	84.679	283				

Table 14 shows the Analysis of Variance (ANOVA) . It was done to test if there is a significant difference in the level of programming skills of the respondents based on age. From the results, it can be seen that the computed value of F-ratio is 0.137 with a p-value of 0.872. The p-value being higher than the level of significance of 0.05, it means that the null hypothesis should be accepted. It implies that there is no significant difference in the level of programming skills of the respondents based on age. Therefore, the null hypothesis is accepted.

Table 15. Analysis of Variance (ANOVA) on the Difference in Programming Skills Level of Respondents According to Their Profile (Gender)

Source of Variation	Sum of Squares (SS)	Degree of Freedom (DF)	Mean of Square (MS)	Computed F-Ratio	p-value	Interpretation
Between Groups	4.234	2	2.117	7.395	0.001	Significant
Within Groups	80.445	281	0.286			
Total	84.679	283				

Table 15 presents the Analysis of Variance (ANOVA) on the difference in programming skills level of the respondents when grouped according to gender. The computed F-ratio of 7.395 with a p-value of 0.001 is less than the 0.05 level of significance. This means that there is a significant difference in the programming skills level of the respondents when grouped according to gender. Therefore, the null hypothesis is rejected.

CONCLUSION

Based on the findings of this study, the researchers concluded that most of the respondents are male and between 20 to 22 years old, and they are evenly distributed across different sections, which means the sample is a good representation of the third-year SBIT population. The respondents showed an overall programming skills level of Agree with a weighted mean of 2.96. This means they are good at starting to code quickly after understanding a problem and finishing their assignments on time.

However, they find it hard to switch between different coding tasks, work on multiple tasks at the same time, and fix errors without causing new ones. The respondents also agreed that AI tools affect how they do their programming tasks, with an overall weighted mean of 2.91. They tend to use AI even when they already know the answer, they practice writing code manually less often because of AI, and they feel that their own problem-solving skills have become weaker. On the other hand, the respondents strongly agreed that AI also helps them, with an overall weighted mean of 3.39. AI helps them come up with better ways to solve problems, understand programming lessons more quickly, and find and fix errors more accurately. Therefore, the researchers concluded that AI has both positive and negative effects on students' programming skills.

AI is helpful for learning and debugging, but it also makes students depend too much on AI, practice manual coding less, and feel less confident in their own problem-solving abilities. Because of this, teachers should encourage a balanced way of using AI. AI should be used as a tool to help learn, not as a replacement for basic practice. Teachers should also help students improve their independent debugging, logical planning, and manual coding skills while still allowing guided use of AI.

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