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Mapping Students' Artificial Intelligence Usage Profiles in Computer Programming Courses: A Quantitative Descriptive Study

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Abstract

The advent of artificial intelligence (AI) has transformed the way students learn programming in recent years; however, a clear picture of how this technology is actually used on a day-to-day basis has rarely been systematically mapped. This study aims to map the artificial intelligence usage profiles of undergraduate students in Educational Technology within the Visual Programming course. A quantitative descriptive method was employed, involving 172 students as respondents. Data were collected via a 23-item Likert-scale questionnaire (1–5), and subsequently categorised using Azwar's formula to determine low, moderate and high levels of usage. The results indicate that ChatGPT is the most widely used AI tool amongst students, accounting for 76.2% of respondents. Students use AI intensively, primarily to deepen their understanding of concepts they have not yet grasped, rather than merely to complete tasks instantly. Overall, students exhibited a high-category AI usage profile, with 77.3% of all research subjects falling into this category. These findings suggest that students do not merely use AI passively, but rather utilise it as an active and reflective learning companion; this can therefore serve as a basis for universities to formulate more targeted AI integration policies within their visual programming.

Keywords: Artificial intelligence; Visual programming; Intensity of use; Quantitative descriptive

1. Introduction

Generative artificial intelligence has transformed the way students learn programming over the past five years. The integration of digital technology is believed to enhance the effectiveness and efficiency of student learning, particularly in fields that demand high-level problem-solving skills such as computer programming. One of the most significant forms of digital technology to have transformed the learning process over the past decade is generative artificial intelligence (generative AI), which enables users to interact naturally with systems to generate, explain or correct programme code.

This has been confirmed by various empirical findings (Yilmaz & Yilmaz, 2023) which quantitatively demonstrate that the use of generative AI tools has a significant impact on the computational thinking skills, self-efficacy, and learning motivation of programming students. These findings are reinforced by (Hartley et al., 2024), who demonstrate that AI is capable of supporting students' independent learning in coding, as well as by (Idrisov & Schlippe, 2024) who confirm the efficiency of AI in generating programme code. However, not all empirical evidence points in the same direction (Kosar et al., 2024) found that the use of ChatGPT did not result in a statistically significant difference in performance among novice computer science students ($p > 0.05$), whilst (Bassner et al., 2025) revealed a dissociation between improvements in task performance and actual conceptual learning. (Baek et al., 2024) also

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reported that students used AI intensively, yet remained sceptical about the reliability of its outputs.

In fact, the need for effective programming learning strategies is not a new issue that has arisen with the advent of generative AI. (Hadihabibi et al., 2023) demonstrated that programming learning in the context of their research, visual programming requires effective pedagogical strategies to foster students' motivation to learn, as evidenced by the implementation of a gamified flipped classroom, which significantly enhanced students' self-regulated learning compared to conventional teaching methods. These findings confirm that the fundamental issue in programming education is always related to how learning strategies can foster students' independence and motivation; thus, the emergence of generative AI can be viewed as a continuation of these efforts, rather than as a standalone phenomenon.

Based on the data and facts above, it can be concluded that the use of generative AI has become an integral part of students' programming learning practices, although its impact varies depending on how and in what context the technology is used on a day-to-day basis. If the use of AI is indeed contextual, as concluded above, then an understanding of its impact and effectiveness should be preceded by a clear understanding of the usage patterns themselves. However, the majority of previous studies have instead directly tested causal relationships or technology acceptance without first mapping out usage patterns descriptively. (Kosar et al., 2024) employed a controlled experimental design, (Alanazi et al., 2025) applied the Technology Acceptance Model TAM (Kamalı-Arslantaş & Yürüm, 2026) conducted a text-based topic analysis. All three assume that patterns of AI usage are relatively homogeneous, and are therefore adequately represented by a few latent constructs such as perceived usefulness or behavioural intention.

This assumption is logically questionable. If patterns of AI usage do indeed vary as indicated by the differing findings in paragraph 1 then models that test causal relationships alone will not be able to adequately capture this diversity. This conjecture is reinforced by the systematic review by (Yalwa et al., 2026) which concluded that the majority of research on generative AI in programming education remains focused on effectiveness and attitudes, whilst descriptive-quantitative mapping of students' actual usage profiles remains very limited. Even the profiling efforts previously undertaken by (Rico-Juan et al., 2023) only covered task-completion patterns on online judging systems, rather than the comprehensive use of generative AI assistants. Consequently, there is a clear research gap: the absence of a systematic and quantitative mapping of students' AI usage profiles within the context of computer programming learning. Based on the general premise that digital technology influences the learning process, empirical evidence that the impact of AI is variable, and the gap in the descriptive mapping of AI usage patterns, this study was designed to address these needs in a logical and systematic manner.

This study aims to map the profile of students' use of artificial intelligence in visual programming courses through a descriptive quantitative approach. This approach was chosen as it aligns with the nature of the research question, namely to describe the 'as-is' conditions in the field, rather than to test causal relationships between variables. By providing descriptive data on the types of tools, frequency, purposes and contexts of AI use, this study is expected to complement previous explanatory findings and serve as an empirical basis for formulating policies on the integration of AI into the programming curriculum.

2. Method

This study employs a quantitative approach with a descriptive research design. This type of research was chosen because its primary objective is to map and describe the 'as-is' conditions regarding the profile of artificial intelligence (AI) usage by undergraduate students in Educational Technology at Malang State University, within the visual programming course, without applying any treatment, manipulating variables, or testing causal relationships between variables (Creswell & Creswell, 2017; D. Sugiyono, 2013).

The primary data collection technique in this study was a questionnaire. According to (D. Sugiyono, 2013) a questionnaire is a data collection technique carried out by providing respondents with a set of written questions or statements to answer. Questionnaires are used because they are capable of reaching a relatively large number of respondents efficiently, uniformly, ly and systematically, so that the data obtained can be processed quantitatively. The questionnaire was designed based on the indicators of the research variables and utilised closed-ended statements on a 1–5 Likert scale, so that respondents' answers could be scored and analysed descriptively. In addition, observation and documentation were used as supporting techniques to obtain additional data relevant to the research focus. Prior to use, the instrument was tested for validity and reliability to ensure that the data produced were accurate and consistent (P. P. Sugiyono, 2016).

For data collection, only one questionnaire was used, which had been specifically adapted. In determining the descriptive statistical analysis—which was carried out using SPSS 27—the TPACK proficiency level could be calculated manually using the category-level formula presented as follows (Azwar, 2022).

Table 1. Measures of Central Tendency

Measures of Central Tendency	Formula
Maximum Score (Xmax)	Number of Items (n) × Maximum Score
Minimum Score (XMin)	Number of Items (n) × Minimum Score
Theoretical Mean (μ)	$\frac{Maximum\ Score + Minimum\ Score}{2}$
Standard Deviation (σ)	$\frac{Maximum\ Score - Minimum\ Score}{6}$

The next stage involves determining categories based on the scores obtained by primary school teachers. (Azwar, 1993) states that the aim of this categorisation is to divide individuals into distinct groups in stages according to the continuum of measured characteristics. In this study, three levels of categories were used, namely (Azwar, 1993).

Table 2. Category Level Formula

Interval	Category
X < (μ-1σ)	Low
(μ-1σ) ≤X> (μ+1σ)	Medium
(μ+1σ)≤X	High

3. Results and Discussion

3.1 Result

3.1.1. Data description and respondent characteristics

This study involved 172 students taking a visual programming course, spread across five course offerings A-E. Data were collected via an online questionnaire using a 1–5 Likert scale comprising 23 statements. The following shows the distribution of data from the study subjects

Results can be presented in graph, table, or descriptive form. Loading tables and figures should contain only essential information from research results. Analysis and interpretation of these results is necessary before they are discussed.

Table 3. distribution of research subjects

Category	Data Distribution	Percentage
Male	61	35,5%
Women	111	64,5%

3.1.2. Profile of the types of artificial intelligence tools used by students

The results of the descriptive analysis carried out show that ChatGPT is the most widely used AI tool, with 131 out of 172 students using it, followed by Gemini with 103 students, Claude with 7 students, DeepSeek with 6 students and other AI tools with 4 students. The total number of responses reached 251, as the multiple-response format allowed research participants to list several AI tools they frequently used.

Table 4. types of artificial intelligence tools used by students

Type of AI Tools	Number of Responses Regarding AI Use	Percentage of Total Responses
ChatGPT	131	52,2%
Gemini	103	41%
Claude AI	7	2,8%
DeepSeek	6	2,4%
Others	4	1,6%

3.1.3. The most dominant purpose of AI use

Analysis of the average scores across the five indicators of AI usage purposes shows that “deepening understanding of concepts not yet grasped” ranked highest Mean = 4.22; SD = 0.71, followed by “understanding difficult material/concepts” Mean = 4.20 and “supporting learning in general” Mean = 4.05. Meanwhile, the purpose of “completing programming tasks” ranked lowest Mean = 3.81, although it still fell within the high category. These findings indicate that students’ orientation in using AI leans more towards deepening their understanding of concepts rather than merely completing tasks instantly.

Table 5. Distribution of AI use

Rangking	Objective	Mean	Std.Dev
1	To deepen understanding of concepts not yet grasped	4.22	0.71
2	Understanding difficult material/concepts	4.20	0.88
3	Supporting learning in general	4.05	0.93

4	Searching for literature/references	4.02	0.94
5	Completing programming tasks	3.81	0.98

3.1.4. Frequency of AI Use

The results of the analysis show that the composite total score had a mean of 91.41 with a standard deviation of 10.83, out of a theoretical maximum score of 115. These scores were then categorised into three levels using Azwar's categorisation formula.

Table 6. Frequency of AI Use

Category	Score Range	N	Percentage%
Low	<53.67	1	0.6%
Medium	53.67-84.32	38	22.1%
High	≥84.33	133	77.3%

Based on this categorisation, of the 172 students who participated in the study, the majority namely 133 students (77.3%) fell into the 'High' composite category, whilst 38 students (22.1%) fell into the 'Moderate' category, and only 1 student (0.6%) fell into the 'Low' category. These findings indicate that, overall, the profile of artificial intelligence usage amongst students on the Visual Programming course is classified as high, whether viewed in terms of intensity of use, purpose of utilisation, critical evaluation, independent learning, or the accompanying social support, as outlined in the respective sub-sections above.

3.2 Discussion

This study essentially seeks to answer a simple yet rarely addressed question in previous research: not merely whether AI has a positive impact on programming learning, but how its usage patterns actually manifest in practice. The following section discusses each key finding in sequence, relating them to similar studies outlined in the Introduction.

In terms of the profile of AI tools, the finding that ChatGPT dominates usage (76.2% of respondents, or 52.2% of total choices) is actually not surprising when compared with patterns in other studies. (Baek et al., 2024), in their study of university students, also noted ChatGPT as the most widely used and trusted tool, albeit accompanied by ambivalent attitudes towards its reliability. A similar pattern was also found in the systematic review by (Yalwa et al., 2026), which noted that the majority of research on generative AI in programming education does indeed focus on ChatGPT rather than other models such as Claude or DeepSeek; thus, ChatGPT's dominance in this study actually reflects a global trend, rather than merely a local phenomenon within the University of Malang.

Regarding the purposes of use, the results of this study reveal an interesting finding: students used AI more frequently to deepen their understanding of concepts they had not yet grasped Mean = 4.22 than simply to complete tasks instantly Mean = 3.81, the lowest ranking of the five purposes measured). This finding is consistent with(Hartley et al., 2024), who, in their evaluative case study, found that ChatGPT functions more as a companion for self-directed learning than merely as a machine that generates instant answers. Conversely, this finding runs counter to the concerns of (Kosar et al., 2024), whose experiment with novice programming students showed that the use of ChatGPT had no significant impact on academic performance a finding which the researchers interpreted as an indication that students might be using AI passively without truly processing their understanding. The data from this study,

however, point in the opposite direction, showing that students actively direct their use of AI towards conceptual needs, rather than merely transactional ones.

Nevertheless, this optimistic picture needs to be interpreted with greater caution when considered alongside the findings of (Praherdhiono et al., 2026) regarding the ability to formulate prompts among Educational Technology students at Malang State University—a population that is institutionally closely aligned with the respondents in this study. The study found that, of the 125 prompts analysed, only 25.6% of students were genuinely classified as 'Strategic Users' with advanced control over instruction formulation, whilst the remaining 42.4% were still classified as 'Basic Users' whose prompts tended to be ambiguous. This implies that, although in this study students reported a relatively high level of self-perceived ability to compose prompts Mean = 4.14, this does not necessarily reflect an equally high level of technical mastery, given that both studies targeted students from the similar academic discipline of Educational Technology. This gap between self-perception and actual competence was also highlighted by (Awasthi et al., 2024) within the framework of generative AI adoption, which emphasises the importance of critical- -use—that is, the ability to adopt a critical stance, which does not always align with the intensity or level of confidence in using AI.

When the above results are combined with the findings on the dimension of learning autonomy which recorded the highest proportion in the 'high' category across all dimensions 77.3% a picture emerges that is fairly consistent with the research by (Hadihabibi et al., 2023) in the context of visual programming learning, which is identical to that of this study. Their study demonstrated that appropriate pedagogical strategies in this case, a gamified flipped classroom can significantly enhance students' self-regulated learning compared to conventional teaching methods. When read side by side, the two studies by (Soepriyanto et al., 2021) appear to complement one another: one emphasises the importance of independent learning as the foundation for successful visual programming learning, whilst the other reminds us that independence alone is not sufficient without technical literacy in strategically interacting with AI.

Overall, if all the above findings are mapped back to a composite score placing 77.3% of students in the 'high' category, it can be concluded that the profile of AI usage among Visual Programming students in this study tends to indicate a healthy pattern in terms of quantity, yet raises questions regarding its quality particularly regarding prompting literacy, which, as demonstrated by (Praherdhiono et al., 2026) cannot automatically be assumed to be high simply because students belong to the 'digital native' generation. These findings ultimately reinforce the argument put forward by (Yalwa et al., 2026) that research into the use of AI in programming education needs to move beyond merely measuring the intensity or acceptance of the technology alone, towards a more comprehensive mapping of the quality of students' interactions with AI itself

4. Conclusion

This study mapped the profile of artificial intelligence usage among 172 undergraduate students in Educational Technology within the Visual Programming course using a descriptive quantitative approach. The results indicate that ChatGPT was the most widely used AI tool 76.2% of students, with usage oriented more towards deepening understanding of concepts not yet grasped rather than merely instant task completion. Overall, the majority of students 77.3% fell into the high AI usage category, indicating that students have utilised AI as an active learning companion, rather than merely a passive tool for completing tasks. However, the high intensity

of use and students' self-perceived ability to formulate prompts must be interpreted with caution, given that findings from similar studies on comparable populations suggest that students' technical competence in prompting does not necessarily correspond to the high intensity of use. These findings provide an empirical basis for higher education institutions to formulate more targeted AI integration policies, not only focusing on usage intensity, but also on strengthening students' critical literacy and prompting skills. Further research is recommended to explore the relationship between AI usage profiles and the quality of student interactions in greater depth.

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