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Learning, Motivation, and Ethical Awareness in Computer Science Students: AI as a Learning Support

Luis Humberto Gonzalez-Guerra[1]; María Yolanda Burgos-López[2]; Arturo E. Cerón-López[3]
[1,2,3] Tecnologico de Monterrey, México, *lhgonzalez@tec.mx, yolanda.burgos@tec.mx, arturo.ceron@tec.mx*

Abstract*– Contemporary Computer Science students increasingly exhibit high levels of digital fluency and familiarity with artificial intelligence (AI) technologies. This paper describes an instructional approach implemented in an undergraduate course on Analysis and Design of Algorithms that integrates AI-supported learning to enhance student understanding, motivation, and ethical awareness. Students engaged with AI tools outside the classroom to explore explanations of specific algorithms, while in-class sessions focused on critically examining, discussing, and adapting these explanations through problem-oriented tasks. This design positioned AI as a supportive learning resource rather than a substitute for student reasoning, promoting active engagement with algorithmic concepts. Analysis of student learning experiences indicates that combining AI-supported exploration with challenging in-class activities was associated with increased interest and effort. Students demonstrated heightened motivation when working with contemporary technologies, particularly when required to analyze, adapt, and apply algorithmic solutions, while also developing awareness of the risks of overreliance on AI-generated content and the importance of personal responsibility and academic integrity. Overall, this work illustrates the educational potential of AI-supported learning when embedded within a pedagogically guided framework. Learning outcomes were assessed through pre-test and post-test instruments to measure learning gains, and student motivation and ethical awareness were evaluated using a structured questionnaire, providing evidence of the approach's influence on motivation, learning development, and ethical awareness in computer science education.

Keywords*-- AI-supported learning, Computer Science education, educational innovation, higher education, active learning, student motivation, ethical awareness.

I. INTRODUCTION

The increasing presence of artificial intelligence in higher education has prompted renewed discussion about how learning activities should be designed in Computer Science programs [1]. While AI-based tools can support learning through explanations, feedback, and adaptive guidance, their educational impact largely depends on pedagogical integration rather than technological capability alone [2, 3]. Recent work emphasizes the need to balance AI use with instructional approaches that promote active learning, critical thinking, and student responsibility, particularly in contexts where AI-outputs can be consumed uncritically [4, 5]. Within this context, Computer Science students represent a particularly relevant population, as they are frequent users of emerging technologies and future professionals who will evaluate and develop AI-enabled systems. Understanding how these students engage with AI-supported learning environments is therefore important for designing educational practices that preserve intellectual rigor while supporting motivation and ethical awareness [5, 6, 7]. Despite this growing interest, empirical guidance on how AI-supported learning can be pedagogically integrated into advanced Computer Science courses remains limited [8].

Within educational settings, artificial intelligence has increasingly been conceptualized as a supportive learning resource rather than a substitute for student effort or instructor expertise. Research on AI-supported learning suggests that AI tools can facilitate conceptual understanding and exploratory learning when embedded within a pedagogically guided framework [3, 9, 10]. Importantly, the educational impact of AI depends on its instructional positioning. Studies emphasize that AI is most effective when it functions as cognitive scaffolding, supporting sense-making processes while leaving analytical judgment and problem-solving responsibilities with the learner [7, 11]. From this perspective, the use of AI reinforces rather than replaces established learning principles, underscoring the continued importance of instructional design and instructor mediation [2, 12].

Active learning is widely recognized as a foundational principle of effective Computer Science education, particularly in domains that require abstraction, algorithmic reasoning, and problem-solving. Prior research consistently demonstrates that students develop a deeper understanding when they actively analyze, adapt, and apply knowledge rather than passively receive explanations [13, 14]. In this context, AI-supported learning can serve as an entry point to active engagement by providing preliminary explanations that students subsequently examine, discuss, and refine. When AI-supported exploration is combined with problem-oriented classroom activities, instructional time can be redirected toward higher-order cognitive processes, positioning the classroom as a space for validation, adaptation, and conceptual deepening [3, 15].

Student motivation plays a critical role in learning outcomes and persistence in Computer Science programs.

Research indicates that motivation is closely related to perceived relevance, autonomy, and tasks that are appropriately challenging [9, 16, 17]. While contemporary technologies such as AI can increase student interest, motivation is not driven solely by technology. Studies suggest that sustained engagement emerges when students are required to exert cognitive effort and demonstrate understanding through analysis, application, and adaptation [18, 19, 20]. These findings suggest that the motivational value of AI in education primarily depends on pedagogical design rather than technological novelty.

As AI tools become more prevalent in higher education, ethical considerations have emerged as a central concern in Computer Science education. Research has raised concerns regarding overreliance on AI-generated content, potential erosion of critical thinking, and risks to academic integrity [5, 21, 22]. Easy access to generative AI-outputs may obscure cognitive processes unless students are explicitly guided to critically evaluate and contextualize AI-generated information [4, 23]. Ethical awareness is therefore essential to ensure that AI supports learning rather than undermines it. Prior work suggests that ethical reasoning is most effectively developed when considerations of responsibility and integrity are embedded within disciplinary learning activities rather than treated as isolated topics [24, 25, 26, 27].

Taken together, existing literature supports pedagogically guided approaches that integrate AI into Computer Science education while preserving active learning, student motivation, and ethical responsibility. Research suggests that AI can enhance learning when it is positioned as a supportive resource, embedded within challenging activities, and accompanied by explicit guidance on responsible use [2, 3, 11]. This theoretical perspective informs the instructional approach presented in this work, which examines how AI-supported learning activities can engage digitally fluent students, motivate sustained effort through meaningful challenges, and foster ethical awareness by emphasizing AI as a tool for learning rather than a substitute for student intellectual work.

II. Background

Current cohorts of students entering Computer Science programs are increasingly characterized by strong digital literacy and frequent exposure to advanced technologies, including AI–based systems. Many students arrive at university with prior experience using digital tools for accessing information, generating content, and solving problems, often perceiving AI-based systems as convenient and readily available sources of support [7]. However, this early familiarity with technology does not necessarily imply a deep understanding of foundational computing concepts. Research has shown that digitally fluent students may still exhibit gaps in core areas such as algorithmic thinking, abstraction, and systematic problem-solving, creating challenges for instructors seeking to balance engagement with conceptual rigor [5, 6]. As a result, Computer Science education faces the challenge of designing learning experiences that acknowledge students' technological expectations while ensuring that fundamental disciplinary knowledge is developed in a structured and meaningful way. This tension underscores the need for pedagogical approaches that integrate contemporary tools without compromising essential learning outcomes.

A. AI-Based Tools and Foundational Learning in Software Development

In professional software development contexts, the adoption of AI-based tools has increased rapidly over the past few years. Empirical studies and industry-focused research report that development teams commonly use large language models (LLMs) and AI-powered assistants to support tasks such as code generation, debugging, documentation, and test creation [3, 8, 13]. These tools are frequently integrated into development environments and workflows, where they are valued for their potential to reduce repetitive effort and accelerate task completion.

Recent empirical evidence suggests that AI-based development tools can lead to measurable productivity gains, particularly through reduced task completion time and increased efficiency in routine programming tasks [18, 19]. However, prior work emphasizes that their effectiveness depends strongly on users' ability to critically evaluate, adapt, and contextualize AI-generated outputs. As a result, industry adoption highlights the importance of preparing students to engage thoughtfully with AI-supported environments rather than treating AI-outputs as authoritative or final solutions [10].

Although AI tools are becoming commonplace in professional practice, their effective and responsible use presupposes a solid foundation in core Computer Science concepts. Educational research consistently demonstrates that understanding topics such as algorithmic design, complexity analysis, and correctness is essential for assessing the quality and appropriateness of AI-generated solutions [5, 14]. Without this foundation, students risk engaging with AI tools superficially, relying on generated outputs without the capacity to identify errors, limitations, or inappropriate assumptions [1].

Studies on AI-supported learning further suggest that students benefit most when AI use is intentionally sequenced after, or alongside, the development of foundational knowledge [2, 6, 9]. When learners first engage with core concepts through guided instruction and active learning, AI tools can subsequently function as supports for exploration, reinforcement, and application. This pedagogical sequencing helps ensure that AI enhances learning rather than replacing essential cognitive processes, reinforcing student responsibility for understanding.

B. Integrating Learning, Motivation, and Ethical Awareness

For AI-supported learning to be effective in Computer Science education, it must be embedded within a broader pedagogical framework that integrates learning outcomes, student motivation, and ethical awareness. Motivation has been shown to play a central role in student engagement and persistence, particularly when learning activities are perceived as relevant, challenging, and aligned with real-world practices [9, 17]. The use of contemporary technologies, including AI-based tools, can positively contribute to motivation when combined with tasks that require analysis, adaptation, and problem-solving, rather than simply reproducing solutions.

In parallel, ethical considerations are crucial in guiding the responsible use of AI. Research highlights concerns related to overreliance on AI-generated content, diminished critical thinking, and risks to academic integrity if ethical guidance is not explicitly addressed [4, 21, 28]. Integrating ethical reflection into course activities encourages students to view AI as a learning aid rather than a substitute for their own intellectual work [6]. Prior studies suggest that aligning learning objectives, motivational strategies, and ethical guidance within instructional design can lead to deeper engagement and more effective learning outcomes in Computer Science education [24, 27].

III. Course Design and Implementation

This section presents the design and implementation of the instructional approach adopted in the course. The proposed design integrates AI-supported learning within a pedagogically guided framework that emphasizes active learning, conceptual understanding, and ethical awareness. The instructional approach combines out-of-class exploration using AI tools with in-class activities focused on discussion, adaptation, and application of algorithmic concepts.

A. Course Context and Participants

The instructional approach was implemented in an undergraduate course on Analysis and Design of Algorithms within a Computer Science program. Students typically take the course in their fifth semester, focusing on advanced algorithmic concepts, including design strategies, correctness, and complexity analysis. It was offered over a 15-week academic term, with four hours of face-to-face classroom sessions per week, complemented by individual work conducted outside the classroom.

From the overall course syllabus, ten learning activities were selected across three Modules: Module 2 (String Algorithms), Module 3 (Graph Algorithms), and Module 4 (Computational Geometry), within a course that consists of five modules in total. These modules were chosen because they include algorithmic topics particularly suitable for experimentation, adaptation, and deeper conceptual analysis.

The fifth-semester cohort enrolled in the program during the fall 2025 semester consisted of 215 students distributed across seven class groups. From these, four groups were selected for the study, with two assigned to the experimental condition and two to the control condition. The selection was based on logistical considerations and instructor availability, ensuring consistent implementation of the instructional approach. The resulting sample included 63 students in the experimental groups and 60 students in the control groups. Participants had prior exposure to core programming concepts, data structures, and fundamental algorithms. As students were at approximately the midpoint of their undergraduate studies, they had already developed academic maturity and a clearer sense of their professional orientation within the discipline. While students generally demonstrated familiarity with digital tools and emerging technologies, their levels of confidence and conceptual mastery in advanced algorithmic reasoning varied.

This context provided an appropriate setting to explore the integration of AI-supported learning activities that aim to deepen conceptual understanding, promote active student engagement, and foster motivation and ethical awareness. Moreover, the students' academic maturity and prior disciplinary knowledge created favorable conditions for critically examining AI-generated content and reflecting on its appropriate use within a formal educational environment.

B. Pedagogical Strategy and Classroom Implementation

The pedagogical strategy was designed to promote deep conceptual understanding while maintaining high levels of student engagement and responsibility for learning. Given the advanced nature of the algorithmic content, the approach emphasized active learning practices that required students to analyze, adapt, and apply concepts instead of reproducing solutions. AI-supported learning was intentionally incorporated as a complementary resource to support exploration and clarification, not as a substitute for student reasoning or problem-solving.

Students were asked to engage with AI tools outside the classroom to explore explanations of specific algorithms. For example, before a session on Dijkstra's algorithm, the instructor asked students to use a generative AI tool to investigate (1) the type of problem the algorithm solves, (2) its time and memory complexity, (3) a step-by-step procedure for its operation (4) a graphical example illustrating its execution, and (5) a C++ implementation of the solution function, with the explicit expectation that students would interpret and understand the code rather than reproduce it mechanically. During classroom sessions, students were then required to solve problems using the same algorithm under modified conditions, such as scenarios with dynamic edge weights, which demanded adjustments to the standard approach. These variations were intentionally introduced to assess students' understanding of underlying principles and to promote flexible application rather than rote reproduction.

Throughout this process, the instructor played an active role in facilitating learning by guiding discussions, prompting reflection, and encouraging students to justify their decisions. Rather than providing direct solutions, the instructor supported students in comparing alternative approaches and analyzing the implications of different algorithmic choices, thereby helping prevent uncritical reliance on AI-generated explanations. This instructional mediation reinforced conceptual understanding and responsible engagement with AI tools.

C. Data Collection and Ethical Considerations

Data collection was designed to capture students' learning, motivation, and ethical perceptions regarding the use of AI-supported activities.

Learning outcomes were measured using a pretest–posttest instrument consisting of 55 dichotomous (true/false) items. These items were developed by the course instructors to assess students' understanding of key algorithmic concepts addressed in Modules 2 (String Algorithms), 3 (Graph Algorithms), and 4 (Computational Geometry). The items were designed to reflect the learning objectives of each module and were distributed proportionally based on instructional time and the number of topics covered.

The instrument aimed to evaluate students' conceptual understanding, algorithmic reasoning, and ability to identify correct and incorrect applications of algorithmic techniques. Rather than focusing on rote memorization, the items required students to recognize underlying principles, interpret algorithm behavior, and detect common misconceptions in algorithm design and analysis. The items were reviewed by course instructors with experience in teaching algorithms to ensure content validity.

Sample item: "True or False: Dijkstra's algorithm always produces correct shortest paths even when negative edge weights are present."

Although the items span multiple algorithmic topics, they were collectively used to capture an overall measure of students' understanding of algorithmic problem-solving. In this context, Cronbach's alpha was calculated as an exploratory indicator of internal consistency to assess the reliability of the instrument as a whole, acknowledging that the test encompasses a range of related but not identical subdomains.

Learning gain was calculated using the normalized gain metric described in [29]. This measure quantifies performance improvement from an initial state (pretest) to a final state (posttest) within a pretest–posttest framework. Equation (1) presents the calculation for an individual student, where g_i represents the normalized learning gain, Pre_i denotes the student's pretest score, and $Post_i$ denotes the posttest score. The reference value of 55 corresponds to the maximum possible score on the test.

$$g_i = \frac{Post_i - Pre_i}{55 - Pre_i} \times 100 \tag{1}$$

Given this, the normalized learning gain mean for a group is described in equation (2).

$$\langle g \rangle = \frac{1}{N} \sum_{i=1}^{n} (g_i) \tag{2}$$

Student motivation, ethical awareness, and perceptions regarding the use of AI as a learning support were captured through a structured questionnaire administered after the instructional intervention. The questionnaire employed a five-point Likert scale [30] to elicit students' self-reported motivation, attitudes toward AI-supported learning, and views on appropriate and responsible AI use within an academic context. In addition, instructor observations during classroom sessions provided complementary qualitative insights into student engagement and interaction.

Ethical considerations were addressed as an integral part of both the instructional design and the data collection process. Students were informed about the purpose of the study and were asked to provide consent to participate in the instructional experiment. Participation will be voluntary, and all responses will be analyzed anonymously to protect confidentiality. Throughout the course, explicit guidance will be provided regarding responsible AI use, emphasizing that AI tools should support learning and understanding rather than replace individual reasoning or academic work. This ethical framing will be reinforced during classroom discussions and aligned with the broader goal of fostering academic integrity and responsible engagement with AI technologies in Computer Science education.

Building on Dijkstra's algorithm activity described in Section 3.B, ethical considerations emerged naturally through students' experiences. Several students observed that simply copying and inserting the algorithm obtained from an AI tool did not lead to correct solutions when problem conditions changed. When the algorithm was applied without proper understanding, it often failed to produce valid results, particularly in modified scenarios introduced during classroom activities.

This experience led students to recognize that effective use of AI requires conceptual reasoning rather than mechanical replication. As a result, they became more aware of the importance of critically analyzing AI-generated outputs and assuming responsibility for understanding the underlying algorithmic principles. This reinforced the ethical dimension of AI use, highlighting that responsible engagement involves interpreting, adapting, and validating solutions instead of uncritically adopting them.

IV. Results

This section presents the results obtained from the instructional implementation, focusing on student learning outcomes, motivation, and ethical awareness related to AI-supported activities. Before reporting the substantive findings, the internal consistency of the post-intervention questionnaire was examined using Cronbach's alpha, a widely accepted reliability coefficient for Likert-scale instruments [31]. Cronbach's alpha evaluates the extent to which items within a scale measure the same underlying construct, with values closer to 1.0 indicating higher reliability.

The coefficient was calculated using Equation (3), where k represents the number of items, σ_i^2 denotes the variance of each item, and σ_T^2 corresponds to the variance of the total test score:

$$\alpha = \frac{k}{k-1} \times \left(1 - \frac{\sum_{i=1}^{k} \sigma_{i^2}}{\sigma_{T^2}}\right) \quad (3)$$

Following commonly accepted guidelines, alpha values above 0.70 were interpreted as indicating acceptable internal consistency. This reliability analysis provides a foundation for analyzing the questionnaire-based results reported in the subsequent subsections.

A. Learning Outcomes

Learning outcomes were analyzed using the normalized learning gain described in Section 3.3. For the control group (n = 60), the mean normalized gain was ⟨g⟩ = 0.59 (SD = 0.13), indicating a moderate level of improvement in performance between the pre-test and post-test. Individual gains ranged from 0.28 to 0.91, with the first quartile (Q1 = 0.53), the median (Q2 = 0.59), and the third quartile (Q3 = 0.66), suggesting relatively consistent learning progress across participants.

Sixty-three undergraduate Computer Science students enrolled in an Analysis and Design of Algorithms course participated in the experimental groups. Student learning was assessed with a pre-test before implementing AI-supported learning sessions and a post-test after the intervention. For purposes of comparison, test scores were normalized to a scale of 0–100, and normalized learning gain (g) was calculated to measure conceptual improvement. The mean normalized gain was ⟨g⟩ = 0.61 (SD = 0.17), also reflecting a moderate level of learning improvement. Individual gains ranged from 0.21 to 0.89, with the first quartile (Q1 = 0.54), the median (Q2 = 0.61), and the third quartile (Q3 = 0.73). Compared to the control group, the experimental group exhibited slightly higher average gains as well as greater variability.

Figure 1 presents a comparison of normalized learning gains for the control and the experimental groups, with a marginally higher mean observed in the experimental group. However, the experimental group displays greater dispersion, still consistent as reported in the quartile distribution presented above.

However, the difference between groups is small. After performing an independent t-test (alpha=0.05), we obtained a p-value of 0.47, indicating that there is no evidence that the AI-supported learning sessions are the reason for the marginally higher improvement, suggesting that both the control and experimental instructional conditions supported learning progress in a similar proportion. In other words, integrating AI-supported activities did not negatively impact student learning and may offer limited benefits in terms of learning gains.

One possible explanation for this result is that both instructional conditions were grounded in active learning principles, requiring students to engage in problem-solving, analysis, and application of algorithmic concepts. As a result, the core learning gains may be primarily driven by the pedagogical design rather than the presence of AI tools alone. Classroom observations further suggest that while students in the experimental groups demonstrated higher levels of engagement and interest when interacting with AI-supported materials, this increased motivation did not necessarily translate into significantly higher performance in the assessed outcomes. Instead, AI appeared to function as a complementary resource that supported exploration and understanding, without substantially altering measurable learning gains within the scope of the intervention.

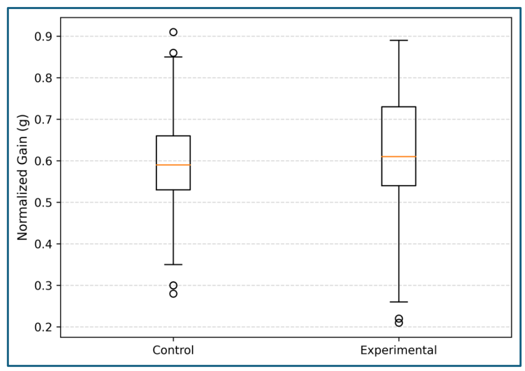

Figure 1: Normalized Learning Gain Comparison.

B. Student Motivation and Ethical Awareness

This section reports students' self-reported perceptions regarding motivation and ethical awareness related to the use of AI-supported learning activities. Data were collected using the post-intervention questionnaire described in Section 3.3, administered to the experimental group (n = 63). The instrument employed Likert-scale items to capture students' attitudes toward learning and responsible AI use. The internal consistency of the questionnaire was acceptable (Cronbach's α = 0.73).

Results indicate consistently positive motivational perceptions. Students found it rewarding to acquire new knowledge (M = 4.79) and reported high interest in course activities (M = 4.84). They also felt motivated when facing challenging tasks (M = 4.44) and expressed strong overall motivation to learn (M = 4.57). Together, these findings suggest that the instructional approach fostered a motivating learning environment that encouraged sustained engagement.

Ethical awareness and responsible AI use also emerged as salient dimensions. Participants agreed that AI supported their learning effectively and responsibly (M = 4.13) and considered its use appropriate when guided by ethical principles and academic integrity (M = 4.10). Students also viewed the use of generative AI as an introduction to course topics as ethically appropriate (M = 4.14).

The highest mean score corresponded to the statement that the instructional strategy improved problem-solving and programming skills while promoting responsible AI use (M = 4.71). Overall, these results indicate that students perceived the approach as both pedagogically valuable and ethically grounded.

V. Conclusions

This study examined the integration of AI-supported learning activities in an undergraduate Computer Science course, with particular attention to student learning outcomes, motivation, and ethical awareness. The results indicate that, although both the control and experimental groups demonstrated comparable learning gains, the observed differences were limited. Consequently, these findings do not provide sufficient evidence to conclude that the use of generative AI leads to superior learning outcomes when compared to traditional instructional approaches.

However, important insights emerged regarding student motivation and ethical engagement. Students in the experimental group reported high levels of motivation and positive perceptions toward the instructional strategy. The use of emerging technologies, such as generative AI, appeared to contribute to sustained interest and engagement, particularly when activities were designed to be challenging and required active participation. These results suggest that while AI may not significantly enhance learning performance, it can play a meaningful role in maintaining student motivation when integrated thoughtfully.

Furthermore, students demonstrated a strong awareness of ethical considerations related to AI use. The findings highlight the importance of framing AI as a learning support rather than a substitute for individual reasoning. When guided by clear ethical principles and academic integrity, students perceived AI as an appropriate and responsible tool for supporting their learning process.

Overall, this work suggests that generative AI should not be viewed as a replacement for traditional pedagogical practices but rather as a complementary resource. Its educational value lies not in outperforming established methods but in its potential to sustain motivation and align with students' expectations for using cutting-edge technologies in their learning experiences. Future research should explore the long-term effects, diverse instructional contexts, and additional pedagogical strategies further to understand the role of AI in Computer Science education.

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