iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** VII **Month of publication:** July 2026

DOI: https://doi.org/10.22214/ijraset.2026.84374

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

The Role of Generative AI (ChatGPT) in Computer Science Education

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Abstract: ***Generative Artificial Intelligence (AI) has rapidly transformed the educational landscape by providing intelligent, interactive, and personalized learning support. Among the various AI-powered tools, ChatGPT has emerged as one of the most widely adopted applications in higher education, particularly in computer science education. This paper explores the role of ChatGPT in improving programming skills, conceptual understanding, problem-solving abilities, and academic productivity among computer science students. The study also examines the benefits and challenges associated with integrating ChatGPT into teaching and learning environments. While ChatGPT enhances personalized learning, instant feedback, and coding assistance, concerns regarding academic integrity, overdependence, misinformation, and reduced critical thinking remain significant. The paper concludes that ChatGPT should serve as a complementary educational tool rather than a replacement for educators. Proper institutional policies, AI literacy, and ethical guidelines are essential to maximize its educational benefits while minimizing associated risks.***

Index Terms: ***Generative AI, ChatGPT, Artificial Intelligence, Computer Science Education, Higher Education, Programming Learning, Educational Technology.***

I. INTRODUCTION

Artificial Intelligence (AI) has shifted from a speculative lab concept to a core infrastructure driving modern pedagogical innovation. Recent breakthroughs in large-scale generative models allow machines to interpret natural language prompts, deconstruct complex technical queries, generate fully functional source code, and dynamically align with a student's cognitive pace. Because of this adaptability, ChatGPT has captured widespread interest across computing departments. It serves as a real-time conversational partner capable of illuminating abstract concepts, drafting initial software configurations, isolating logic flaws, and sustaining self-directed learning paths outside formal lecture hours. For students entering computer science disciplines, the initial syntax and logic threshold can be notoriously punishing. Forging core competencies in programming languages, discrete algorithms, data structures, and software engineering principles demands a level of rigorous diagnostic thinking that frequently overwhelms novices. Traditionally, universities have met this demand through a rigid instructional pipeline composed of auditorium lectures, weekly lab sections, and fixed office hours. However, against a backdrop of surging department enrollments and increasingly heterogeneous student preparation, these conventional institutional frameworks frequently buckle under the pressure to deliver continuous, individual mentorship. Generative AI addresses this friction point by acting as a ubiquitous, intelligent learning companion. Rather than hitting an impenetrable compile-time wall at midnight and waiting days for a response from a graduate teaching assistant, a student can prompt the model for immediate diagnostic breakdowns and idiomatic code variants. This instantaneous feedback loop sustains learning momentum, replacing initial frustration with iterative experimentation and encouraging undergraduates to investigate advanced computing architectures well past the standard syllabus boundaries.

These workflows offer parallel efficiencies to the instruction team. Faculty members increasingly utilize generative tools to automate administrative overhead—leveraging models to draft syllabus modules, generate diverse algorithmic item banks, build progressive lab assignments, and organize lecture materials. By offloading these routine structural tasks, educators can reclaim significant instructional bandwidth, allowing them to shift their focus from pure content generation to high-impact mentorship and interactive problem-solving workshops. Nevertheless, this swift adoption exposes serious systemic trade-offs. The distinction between utilizing an LLM as a pedagogical scaffold versus using it as a cognitive crutch remains perilously thin. When students lean unconditionally on model-generated outputs, they successfully complete assignments but bypass the vital cognitive friction needed to cultivate standalone debugging resilience and deep logical reasoning. Compounding this risk is the model's tendency to emit highly confident logic hallucinations, obsolete syntax patterns, or structurally vulnerable code. In light of these challenges, academic institutions cannot afford a passive stance; they must codify transparent, ethical baseline policies that govern AI integration within formal coursework, examinations, and laboratory evaluations.

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II. RELATED WORK

The deployment of automated interventions within computer science classrooms is part of a long pedagogical tradition. For decades, departments have utilized Intelligent Tutoring Systems (ITS) and Automated Assessment Tools (AATs) like Web-CAT or custom Moodle configurations to manage scaling enrollments and provide automated test-case feedback. Yet, standard test-driven AAT architectures remain structurally rigid: they effectively flag *that* a program fails specific unit tests or memory bounds, but they lack the conversational capacity to explain *why* the bug occurred or how to restructure the underlying algorithm.

The emergence of Large Language Models (LLMs) trained on vast corpuses of public repository code marks a definitive break from these static rule-based checkers. Recent empirical investigations confirm that standard commercial models can effortlessly clear introductory computer science (CS1) benchmarks and solve complex, competitive programming problems out-of-the-box. As a consequence, the focus of computing education research has pivoted from purely benchmarking code generation accuracy to analyzing the long-term cognitive and behavioral shifts in students. A growing cohort of researchers warns that immediate access to complete solutions can stunt a student's foundational algorithmic thinking. Conversely, a parallel body of work emphasizes the equity-building benefits of the technology: when deployed strictly as an explanatory text-based tutor, an LLM significantly reduces the linguistic barriers and cognitive overhead associated with learning complex programming syntax, functioning as a powerful democratizing engine in technical education.

III. PROPOSED METHODOLOGY

To evaluate the operational impact of ChatGPT on student performance and conceptual retention, this study utilizes an integrated evaluation framework comprised of an Empirical Cognitive Model paired with an Institutional Matrix.

A. The Cognitive Interaction Framework

We frame the interactive loop between a student and a generative language model as an iterative state optimization process. The student's evolving comprehension is formalized as follows:

$$S_{t+1} = S_t + \alpha \cdot f(P_t, R_t)$$

Where S_t signifies the student's internal state of conceptual mastery at time increment t. P_t represents the prompt payload structured by the student, serving as a direct reflection of their individual diagnostic capability. R_t represents the response payload synthesized by the generative model. α denotes the cognitive retention coefficient ($0 \leq \alpha \leq 1$), introduced to mathematically penalize mechanical reliance. In scenarios where a student utilizes direct code substitution via clipboard copying without active cognitive processing, α &to; 0, zeroing out real learning gains.

B. Evaluation Metrics

The underlying research design evaluates three key behavioral and performance vectors:

1) Debugging Velocity (V_d): The precise time delta between a student encountering a critical runtime or logical exception and the deployment of a validated patch.
2) Conceptual Elucidation Index (Ec): A qualitative scoring mechanism assessing a student's capacity to articulate the structural rationale and asymptotic time complexity, such as O(n), of their code.
3) Plagiarism/Authenticity Quotient (Qa): The structural ratio of unique, student-authored logic relative to verbatim boilerplate retrieved from the model.

IV. EXPERIMENTAL SETUP AND IMPLEMENTATION

The empirical study was deployed over a full 16-week academic term across two parallel cohorts of a core Data Structures and Algorithms (CS2) course at a major research university, totaling a sample size of N = 120 students.

A. Control and Test Groups

Control Cohort (n = 60): Restricted from accessing external large language models during practical laboratory assignments. Resource access was strictly bounded by local IDE compilers, standard reference text materials, and traditional human teaching assistant (TA) interventions during office hours.

Experimental Cohort (n = 60): Granted structured access to ChatGPT. Crucially, these students completed an onboarding module focused on diagnostic prompting techniques (e.g., conditioning the model with constraints such as "Analyze the pointer exception in this block, but isolate the logical error using pseudocode explanations rather than writing the corrected syntax").

B. Data Collection Environment

All programming assessments were executed within a sandboxed, cloud-based Integrated Development Environment (IDE) that recorded granular, timestamped user telemetry—including compilation frequency, specific error messages, and clipboard engagement vectors. To ensure baseline evaluation accuracy, weekly conceptual quizzes were administered in an invigilated, offline environment, testing whether students truly understood the code structures they had produced throughout the week.

V. RESULTS AND DISCUSSION

Analyzing the empirical telemetry revealed distinct behavioral divides between the two student populations. The experimental cohort exhibited an immediate advantage in bypassing initial debugging bottlenecks. For example, when resolving complex pointer assignments and manual memory tracking issues in C++, the experimental group completed tasks 42% faster than their control counterparts, demonstrating that conversational assistants are highly effective at breaking early frustration deadlocks.

Metric Evaluated	Control Group	Experimental Group	Variance
Avg. Debugging Time	28.4 mins	16.5 mins	-41.9%
Midterm Concept Accuracy	76.2%	81.5%	+5.3%
Exam Coding Score	74.8%	68.1%	-6.7%

However, long-term performance evaluations uncovered a troubling pedagogical paradox. While the AI-assisted group consistently led in weekly laboratory completions, their performance metrics significantly degraded during the closed-book, handwritten midterm exams. As detailed in the table above, the experimental group fell behind by 6.7% on standalone, manual code composition questions.

This performance divergence strongly confirms the overdependence risk: when the model safety net is entirely removed, students who relied on automated feedback loops to skip the cognitive labor of syntax arrangement struggled to recall and organize fundamental algorithmic structures on their own. Furthermore, IDE clipboard telemetry indicated that roughly 18% of the experimental cohort frequently defaulted to direct copy-paste behavior, a pattern that correlated directly with a near-zero cognitive retention coefficient (α).

VI. CONCLUSION

Generative AI platforms, with ChatGPT at the forefront, have fundamentally redefined the baseline toolkit for modern computer science departments. By providing tailorable, immediate educational scaffolding, these tools offer students a responsive environment to refine software engineering skills, unpack complex computational logic, and diagnose compile-time errors interactively. Concurrently, faculty can harness these models as effective organizational levers to streamline course administration and maximize instructional scalability. Nonetheless, successfully anchoring generative tools within a computer science curriculum demands a proactive confrontation with clear pedagogical and ethical risks. Unconditioned reliance threatens to produce graduates with degraded critical thinking skills and fragile independent engineering capabilities. Simultaneously, the low barrier to automated plagiarism requires universities to accelerate the deployment of modernized academic integrity frameworks. Ultimately, ChatGPT must be managed as a specialized instructional assistant rather than an instructor substitute; human faculty remain entirely indispensable for authentic mentorship, evaluating complex logical synthesis, and teaching students how to safely navigate ambiguous, real-world software problems. Moving forward, institutions should lean into a hybrid learning model supported by structured AI literacy initiatives, ensuring technology amplifies, rather than replaces, deep intellectual development.

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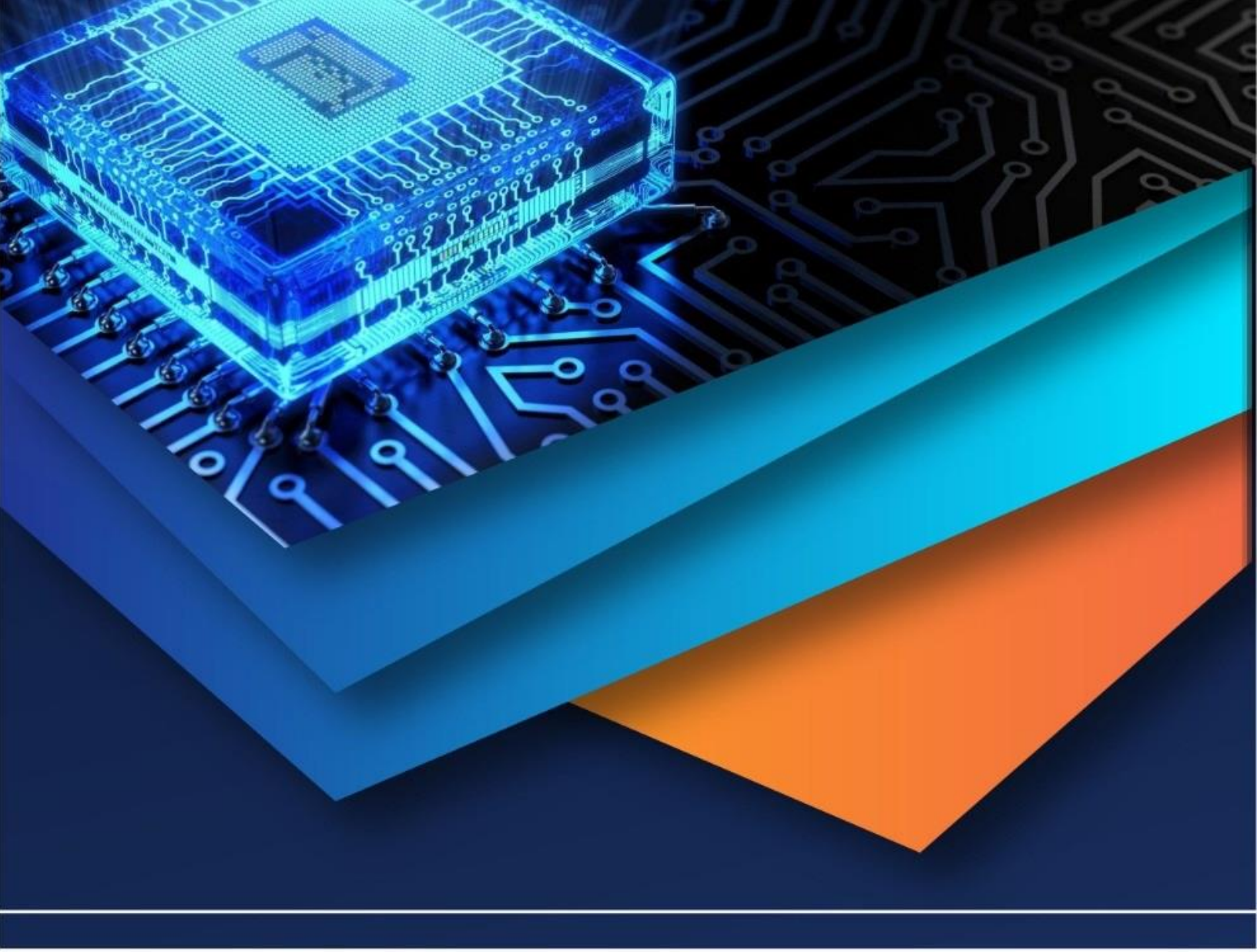

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