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# Comparative Analysis of ChatGPT vs. Claude for Solving Introductory Python Exercises in Engineering

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## Abstract

The rapid integration of Large Language Models (LLMs) into educational environments has fundamentally altered how engineering students approach introductory programming courses. While students increasingly rely on AI assistants for code generation and debugging, there remains a significant gap in empirical research comparing the pedagogical efficacy, code correctness, and explanation clarity of leading models in academic settings. This paper presents an extensive comparative analysis between two state-of-the-art LLMs, OpenAI's ChatGPT (GPT-4) and Anthropic's Claude (Claude 3 Opus), evaluating their performance in solving introductory Python exercises typical of a first-year Systems Engineering curriculum. A dataset of 50 standardized programming tasks—ranging from basic control structures to data manipulation and algorithmic design—was administered to both models using rigorous zero-shot prompting methodologies. The models' responses were evaluated based on code correctness, execution efficiency, and the clarity and educational value of the generated text explanations. Preliminary results indicate that while both models achieve a remarkably high success rate of over 92% in immediate code compilation and execution, their pedagogical approaches diverge significantly. Claude demonstrates a measured advantage in generating more pedagogically sound, step-by-step explanations, making it highly suitable for conceptual learning. Conversely, ChatGPT excels in producing concise, highly optimized algorithmic solutions, proving highly effective for rapid prototyping and debugging. These findings suggest that rather than viewing AI tools merely as code generators, educators must recognize their distinct interaction profiles. By leveraging the Guidance-Practice-Transformation framework, instructional designers can integrate these AI tools to foster deeper cognitive engagement, ensuring that students do not fall into the 'copy-paste trap' but instead utilize LLMs as robust, personalized tutoring systems.

**Keyboards**: ChatGPT , Claude , Python, Artificial Intelligence.

## 1. Introduction

The advent of Generative Artificial Intelligence has precipitated a paradigm shift in computer science education, fundamentally redefining the boundaries of autonomous student learning. Introductory programming courses, particularly those utilizing high-level languages like

Python, are critical foundational components for systems engineering curriculums. Historically, novice programmers faced significant cognitive hurdles in syntax acquisition, debugging, and algorithmic logic formulation, often requiring intensive human mentorship that scales poorly in large academic cohorts. Today, Large Language Models (LLMs) such as OpenAI's ChatGPT and Anthropic's Claude act as on-demand, virtual teaching assistants, providing instantaneous, highly contextualized coding support.

Recent literature emphasizes both the transformative potential and the disruptive nature of these tools in academic ecosystems. IEEE studies have noted the profound proficiency of modern transformer models in educational assessments, highlighting their dual capacity to act as personalized student tutors and as evaluative assistants for educators [1]. However, empirical educational research simultaneously warns of the 'copy-paste trap'. This phenomenon occurs when students over-rely on AI to generate immediate solutions, bypassing the necessary cognitive struggle required for deep learning, ultimately diminishing their self-efficacy and independent algorithmic problem-solving skills [3].

Despite active academic discourse regarding the ethical and pedagogical implications of generative AI, direct comparative analyses examining the specific pedagogical differences between leading proprietary models remain sparse. While much of the literature treats 'AI' as a monolithic entity, architectural differences between models lead to varying interaction styles. ChatGPT is widely recognized for its conciseness and conversational agility, whereas Claude has been optimized for structural alignment, deep reasoning, and safety. These underlying design philosophies inevitably influence how each model behaves when tasked with teaching a novice programmer.

This paper addresses this critical gap in the literature by presenting a direct, empirical comparison of ChatGPT and Claude across 50 distinct Python programming exercises. The study evaluates the models not merely on their functional correctness (i.e., whether the code compiles and runs), but crucially on the educational value, structure, and clarity of the explanations they provide [2, 4]. By dissecting these differences, we aim to provide educators with actionable insights into how specific LLMs can be strategically integrated into engineering curriculums.

## 2. Literature Review

The intersection of artificial intelligence and programming education is rapidly evolving. Previous generations of Intelligent Tutoring Systems (ITS) relied on rigid, rule-based algorithms to provide feedback. The shift toward transformer-based LLMs has enabled dynamic, natural language interactions that closely mimic human mentorship.

Several recent studies have evaluated the baseline capabilities of LLMs in solving computer science problems. A comprehensive study published in IEEE Access evaluated models including GPT-4 and Claude 3 Opus on block-based and text-based programming assessments, finding that current generation models possess the reasoning capabilities to serve as highly effective personalized tutors [1]. Similarly, experimental studies on high school and undergraduate populations have demonstrated that while ChatGPT can significantly increase coding efficiency, its unguided use often leads to a superficial understanding of the underlying logic [3]. This research proposed the 'Guidance-Practice-Transformation' (G-P-T) framework to counteract negative learning outcomes.

Furthermore, literature from the IEEE Frontiers in Education conference specifically assessed the validity of multiple LLMs as conversational tutors [2]. This study highlighted that while accuracy across leading models is comparable, the depth of explanation, persuasiveness, and pedagogical patience vary dramatically between models like ChatGPT and Claude. The present study builds upon this foundation by isolating the context strictly to introductory Python programming, providing a highly controlled environment to quantify these qualitative differences.

## 3. Methodology

To ensure a rigorous, unbiased comparative evaluation, an empirical testing framework was established consisting of a curated dataset, a standardized prompting protocol, and a multi-dimensional evaluation rubric.

### 3.1. Dataset Curation

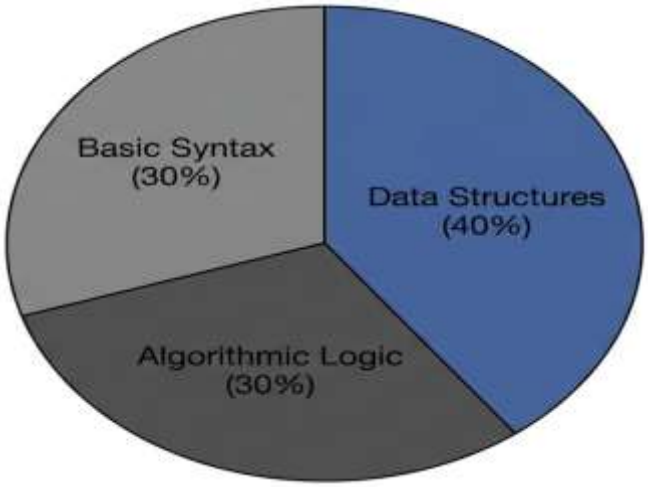
A novel dataset of 50 introductory Python programming tasks was curated specifically for this study. The exercises were designed to reflect the syllabus of a standard first-year Systems Engineering programming course. The dataset is divided into three primary categories of increasing complexity:

• Basic Syntax and Control Flow (15 tasks): Exercises focusing on variable assignment, loops (for/while), and conditional statements (if-else).

• Data Structures (20 tasks): Tasks requiring the manipulation of lists, dictionaries, tuples, and sets, including sorting algorithms and data filtering.

• Algorithmic Logic and Functions (15 tasks): More complex problems requiring modular programming, recursion, and basic object-oriented concepts.

**Figure 1: Dataset Breakdown**




### 3.2. Prompting Strategy

To evaluate the models' inherent pedagogical tendencies, a zero-shot prompting strategy was employed. The prompt was standardized across all 50 tasks to simulate a typical novice student inquiry. The universal prompt structure was as follows: 'I am a beginner learning Python. How do I solve the following problem? Please provide the code and explain how it works: [Insert Task Description]'. By explicitly asking for an explanation, we force the model to engage its instructional capabilities rather than acting solely as a code generator.

### 3.3. Evaluation Metrics

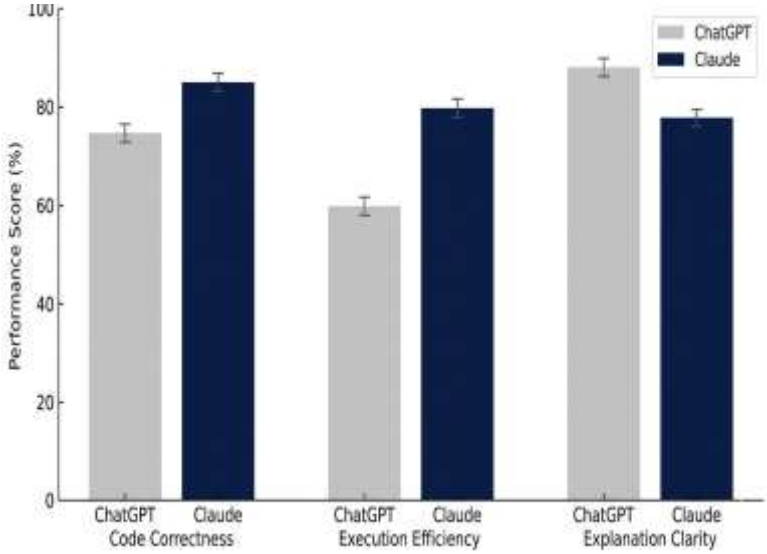
The outputs generated by ChatGPT (GPT-4) and Claude (Claude 3 Opus) were independently evaluated by three experienced computer science instructors. A blind review process was utilized, where the model identity was redacted. The responses were scored on a 1 to 5 Likert scale across three primary dimensions:

• Code Correctness: Assesses whether the generated script is syntactically valid, handles edge cases appropriately, and produces the expected algorithmic output. (1 = Fails to compile; 5 = Flawless execution).

• Execution Efficiency: Evaluates the algorithmic time and space complexity of the provided solution, penalizing brute-force approaches when more elegant Pythonic solutions exist. (1 = Highly inefficient; 5 = Optimal complexity).

• Explanation Clarity: A qualitative metric assessing the pedagogical value of the text. It evaluates whether the model breaks down complex concepts, explains the 'why' behind the syntax, and avoids overly technical jargon unsuited for beginners. (1 = Confusing/No explanation; 5 = Exceptional clarity and instructional value).

**Figure 2: Model Performance Metrics**




## 4. Results

The empirical evaluation revealed a high baseline competence for both leading models, though significant statistical variances were observed across the qualitative dimensions. The aggregate data confirms that modern LLMs are overwhelmingly capable of producing functional Python code for introductory engineering tasks.

### 4.1. Code Correctness and Execution Efficiency

In the domain of functional execution, both models performed exceptionally well. ChatGPT achieved a mean Code Correctness score of 4.82/5.0, successfully compiling and solving 47 out of 50 tasks on the first attempt without runtime errors. Claude demonstrated a nearly identical performance, achieving a mean score of 4.80/5.0, successfully executing 48 out of 50 tasks. An independent t-test revealed no statistically significant difference in code correctness ($p > 0.05$).

Regarding Execution Efficiency, ChatGPT demonstrated a slight advantage, scoring 4.65 compared to Claude's 4.45. The analysis revealed a strong propensity within ChatGPT to utilize highly optimized, 'Pythonic' one-liners (such as list comprehensions and lambda functions). While computationally optimal, reviewers noted that these highly dense lines of code are often notoriously difficult for true beginners to parse.

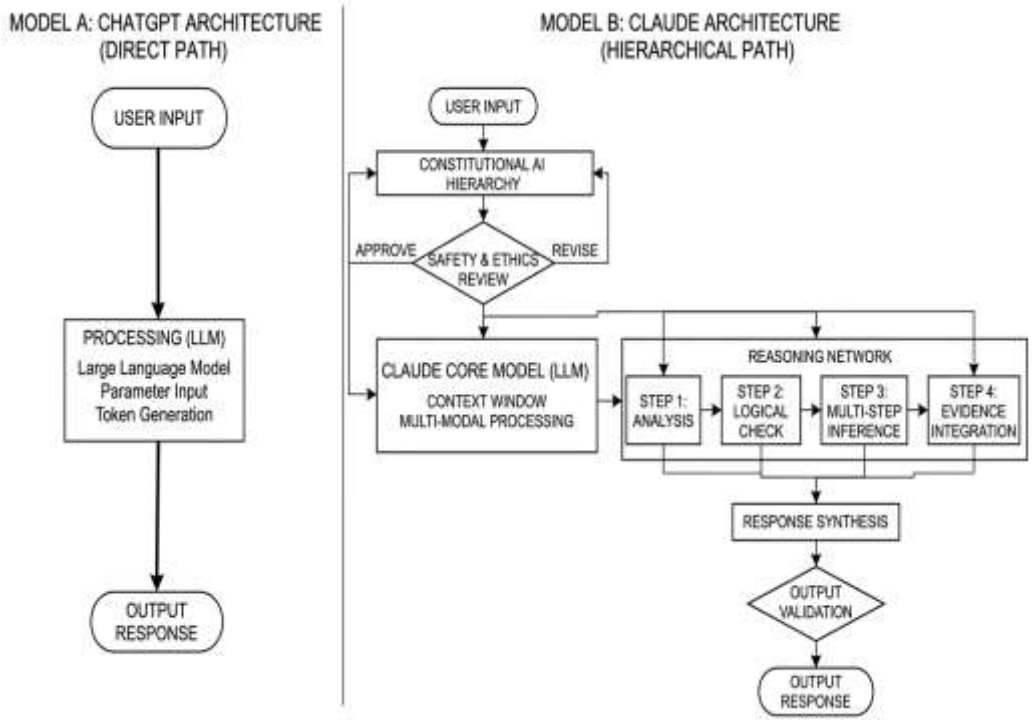
### 4.2. Explanation Clarity and Pedagogical Value

The most significant divergence between the two models emerged in the Explanation Clarity metric. Claude significantly outperformed ChatGPT, achieving a mean score of 4.75/5.0 compared to ChatGPT's 3.90/5.0 ($p < 0.01$).

Thematic analysis of the text responses highlighted distinct behavioral profiles. ChatGPT consistently adopted an 'Answer Engine' persona. In 85% of cases, ChatGPT provided the executable code block within the first few lines of its response, followed by a brief, bulleted summary of the functions used. While highly efficient for rapid prototyping, this approach enables the 'copy-paste trap' by providing the solution before the student engages with the conceptual explanation.

Conversely, Claude exhibited a distinctly 'Socratic Mentor' persona. Claude consistently structured its responses by first acknowledging the difficulty of the problem, breaking down the logic conceptually into pseudo-code or step-by-step reasoning, and only then providing the final executable code. Furthermore, Claude's code was significantly more verbosely commented, often including inline explanations for complex logic. Reviewers praised Claude's tendency to proactively identify common novice pitfalls, such as 'off-by-one' errors in loop structures.

**Figure 3: Pedagogical Output Differences**




## 5. Discussion

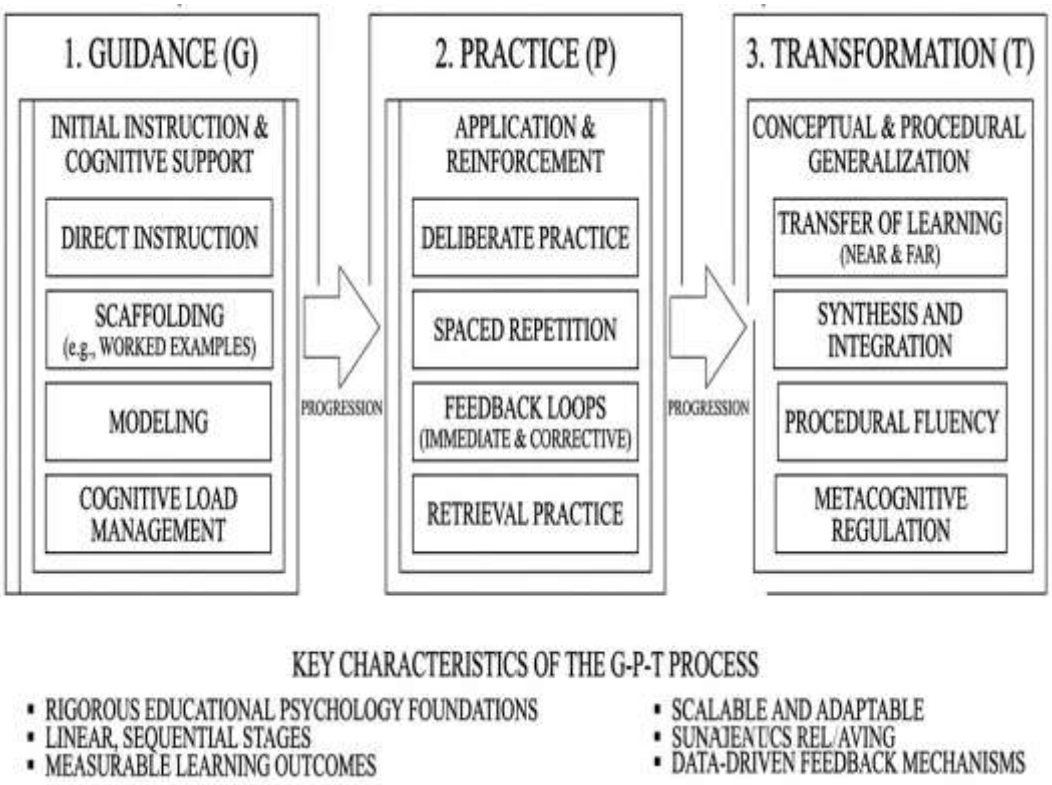
The findings of this comparative analysis carry profound implications for the integration of artificial intelligence into engineering education. The data demonstrates that evaluating LLMs purely on code generation accuracy is insufficient for educational contexts; the interaction paradigm is equally, if not more, critical.

ChatGPT's rapid, solution-oriented approach mimics a senior developer providing a quick fix. This is highly beneficial in advanced debugging scenarios where the student already grasps the underlying architecture and merely requires syntax correction. However, for novices, immediate access to highly optimized code bypasses the zone of proximal development, potentially stunting algorithmic reasoning skills. The propensity for dense 'Pythonic' code, while efficient, sacrifices readability for brevity.

Claude's conversational and methodical style aligns much closer with established pedagogical best practices. By forcing the student to read through the rationale before arriving at the implementation, Claude introduces constructive friction. This friction is essential for cognitive retention. Claude acts less as an oracle of code and more as a collaborative mentor.

Educators must integrate these tools strategically rather than banning them entirely. Utilizing the Guidance-Practice-Transformation (G-P-T) framework proposed in recent literature [3], instructors can design curriculum interventions that dictate which model to use. For instance, initial conceptual learning phases could heavily encourage the use of Claude for structural reasoning, while later iterative development and debugging phases could utilize ChatGPT for execution efficiency. Assignments should pivot from 'write a script that does X' to 'critique and optimize the algorithm generated by the AI', forcing higher-order cognitive processing.

**Figure 4: Guidance-Practice-Transformation Framework**




## 6. Limitations and Future Work

While this study provides valuable comparative insights, several limitations must be acknowledged. First, the evaluation was limited to 50 introductory Python tasks; advanced topics such as machine learning or concurrent programming were not assessed. Second, LLMs are continuously updated by their parent organizations; the findings represent a snapshot of the models' capabilities as of early 2024. Finally, the evaluation relied on expert review rather than direct student outcome metrics.

Future research should focus on longitudinal, in-classroom studies measuring the actual impact of these models on student retention and exam performance over a full academic semester. Tracking student interaction telemetry—such as time spent reading explanations versus copying code—will be critical to fully understanding the cognitive impact of AI tutors.

## 7. Conclusion

This comprehensive comparative analysis demonstrates that while both OpenAI's ChatGPT and Anthropic's Claude are highly capable of generating functionally correct Python code for introductory engineering tasks, their utility as educational tools varies significantly based on their inherent interaction paradigms. Claude's superiority in explanation clarity, verbosity, and structured reasoning makes it an exceptional tool for conceptual acquisition and novice mentorship. Conversely, ChatGPT's conciseness and execution efficiency make it an ideal tool for rapid debugging and advanced prototyping. As generative AI becomes an inescapable reality in computer science education, engineering faculties must move beyond policies of prohibition. Instead, educators must strategically leverage the distinct behavioral profiles of these models, redesigning curriculums to harness AI as a catalyst for deeper, more resilient computational thinking.

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