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"It Makes Me More Efficient": Student Perceptions and Experiences with LLMs in Computer Programming Courses

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***Abstract*—The rapid integration of Large Language Models (LLMs) into computer science education necessitates understanding student perceptions in diverse contexts like Mexican higher education. This study investigates the experiences of 311 computer science students from public and private Mexican universities. A hybrid methodology was employed, first validating the survey instrument through Confirmatory Factor Analysis and reliability tests. Statistical methods were then combined with machine learning in a comprehensive analytical framework. Results reveal a clear narrative: students overwhelmingly perceive LLMs as transformative, significantly enhancing programming efficiency. This core perception is deeply embedded within an interconnected network of positive attitudes and behaviors. Strong correlations between perceived efficiency, positive attitudes, future use intentions, and increased usage frequency create a virtuous adoption cycle. The study concludes that LLMs are firmly rooted in Mexico's programming education, urging a pedagogical shift from "if" to "how" they are used, thereby informing ethical curriculum design and AI literacy initiatives.**

***Index Terms*—Large Language Models (LLMs), Programming Education, Student Perceptions, Technology Adoption, Mexican Higher Education**

I. Introduction

The contemporary higher education landscape is undergoing a profound transformation, driven by the rapid integration of Artificial Intelligence (AI) and, more specifically, Large Language Models (LLMs). These advanced Natural Language Processing systems have evolved from simple chatbots into sophisticated partners capable of understanding, generating, and explaining complex information. In academic settings, their influence is particularly pronounced, offering students unprecedented support in tasks ranging from composition and research to schedule management, thereby fostering more efficient and personalized learning pathways [1]

The pedagogical potential of these technologies is substantial. AI-powered learning platforms are increasingly recognized for their ability to deliver customized support, adapting to individual learning styles and paces by analyzing performance data to provide targeted recommendations [2], [3] This is especially evident in the domain of academic writing, where modern AI tools have transcended basic grammar correction to offer sophisticated feedback on sentence flow, lexical choice, and structural coherence, effectively acting as always-available tutors that help students refine their academic voice. Beyond writing, AI-driven chatbots and virtual tutors serve as essential study companions, providing 24/7 access to explanations of complex concepts and personalized study plans, with some studies reporting significant improvements in student retention and comprehension [4]. These tools also have language dependency problems, performing well only on English inputs [5].

However, it is within the specific domain of computer science and programming education that LLMs have sparked both immense excitement and intense debate. Models such as GitHub Copilot, based on OpenAI's Codex, demonstrate remarkable proficiency in generating, explaining, and debugging code, presenting a paradigm shift in how students approach programming tasks [6]. Proponents argue that these tools can democratize programming education, lowering barriers for novices by providing real-time, contextualized assistance and fostering a more iterative and exploratory learning process [7]. Yet, this promise is tempered by significant concerns. Critics warn that overreliance on LLMs can "short-circuit" the essential cognitive struggle inherent to problem-solving, potentially leading to superficial learning and a failure to retain core programming concepts [8]. Furthermore, the ease of code generation raises critical questions regarding academic integrity, with a notable survey revealing that a majority of computer science instructors perceive LLMs as a substantial threat to the validity of traditional coding assessments due to risks of plagiarism and undetected outsourcing of work [9]. While this debate is global, the adoption and impact of technology are not uniform; they are shaped by local educational contexts, resources, and institutional policies. Much of the existing research on LLMs in education emanates from Global North contexts, creating a gap in our understanding of how these technologies are perceived and integrated in other regions. This study addresses this gap by focusing on the Mexican higher education landscape [10]. It investigates the perceptions and experiences of computer science students at both public and private universities in Mexico, focusing on a central research question: How do students perceive the ease of use and efficiency of LLMs, and how are these perceptions interrelated with their attitudes, future use intentions, and actual usage behaviors? By exploring this network of relationships, this paper aims to provide a critical, context-specific contribution to the ongoing discourse on the future of programming education in the age of AI.

II. Background and Related work

The integration of Large Language Models (LLMs) in computer programming courses has been a transformative development in education. This small review synthesizes findings from recent studies to explore how these technologies are reshaping programming education and affecting student perceptions and experiences. LLMs like ChatGPT and GitHub Copilot have revolutionized programming education by offering new tools for learning and problem-solving. The impact of these models on student learning outcomes has been mixed, with some studies indicating that increased reliance on LLMs for complex tasks such as code generation and debugging can negatively affect final grades. However, these models have been found beneficial as supplementary tools for explanation and learning support, suggesting a nuanced role for LLMs in education [11], [12]. The integration of social learning and interactive elements in programming courses has also been shown to enhance student engagement and perceived learning outcomes, underscoring the importance of incorporating LLMs to foster collaboration and interaction [13], [14]. In Mexican higher education institutions, the adoption of LLMs like ChatGPT is on the rise. There is a growing awareness of their potential benefits, although concerns about reliability, privacy, and ethical implications remain significant. These concerns highlight the need for careful consideration and robust ethical guidelines to govern the use of LLMs in educational settings [15], [16]

The challenges associated with LLM integration in Mexican institutions also include technical support and ethical guidance, emphasizing the need for institutional frameworks that support their effective use [17], [18]. Despite the promising developments, there are notable gaps in the research. Longitudinal studies that explore the long-term impact of LLMs on student learning and career outcomes are scarce [19]. Additionally, there is a need for more research that considers the cultural and institutional contexts in Mexico, as these can significantly influence the adoption and effectiveness of LLMs. Furthermore, studies focusing on diverse learner demographics within Mexican higher institutions are limited, particularly in understanding how LLMs affect underrepresented groups. This literature review serves as a foundation for our current research, which seeks to delve deeper into the perceptions of students actively using Large Language Models (LLMs) for programming tasks within computer education in Mexico, which seems to be less explored area till date. Our study aims to capture the nuanced experiences and perceptions of these students, providing a more detailed understanding of how LLMs are influencing learning processes, engagement, and outcomes in programming courses. By focusing on the voices of students currently engaged with these technologies, we aim to contribute to the ongoing dialogue about the integration of LLMs in educational settings and offer insights that could inform future pedagogical strategies and policymaking in computer education. This research is particularly significant in the context of Mexican higher education, where the adoption of LLMs is expanding, yet there remains a need to address technical, ethical, and cultural considerations to optimize their use.

III. Methodology

This study employed a quantitative research approach to investigate computer science students' perceptions of Large Language Models in Mexican higher education. This study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki and received approval from the relevant institutional review boards at the participating universities. Prior to their involvement, all participants were provided with a detailed information sheet explaining the study's purpose, procedures, potential risks and benefits, and their right to withdraw at any time without penalty. Informed consent was obtained from each participant. All data were anonymized to protect participant confidentiality throughout the research process. The participants' demographic information is presented in Table 1.

TABLE I: Demographic and Background Information of Participants

Variable	Category	N
Gender	Male	195
	Female	109
	Prefer not to say	7
Age	17–20	125
	21–25	162
	26–30	19
	31+	4
Programming Experience	Less than a year	115
	1–2 Years	153
	3–4 Years	40
	5 Years and above	3
Programming Experience with LLMs	Some familiarity	146
	Very Little	87
	Regular User	74
	Expert	4
Participant Universities	Public	150
	Private	161

Data were collected through a structured survey administered to students at both public and private universities, focusing on constructs related to efficiency, attitude, and usage behaviors. The measurement items were developed through a comprehensive literature review and adapted to the specific context of LLM-assisted programming, ensuring content validity through expert review and pilot testing (Table 2). The research followed a rigorous data validation process beginning with Confirmatory Factor Analysis to verify the measurement model's convergent validity, confirming that all items properly loaded onto their intended constructs. Reliability testing was subsequently conducted to establish the internal consistency of the measurement scales. Following this validation phase, the study employed a dual analytical approach combining traditional statistical methods with machine learning techniques to comprehensively examine the relationships between variables and identify key patterns in student perceptions. The whole framework for investigating impact of LLMs on programming is depicted in Figure 1. This integrated methodology allowed for both the validation of measurement instruments and the exploration of complex relationships within the data, providing a robust foundation for understanding how students perceive and interact with LLMs in their programming education.

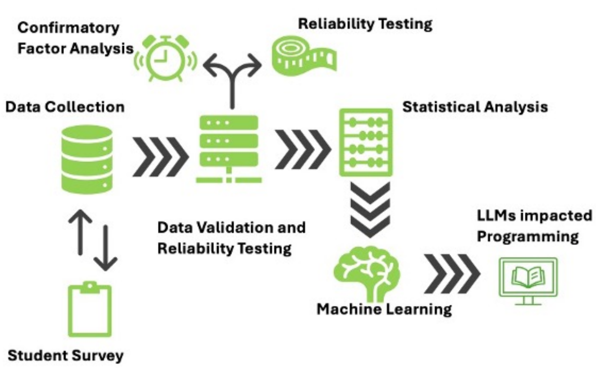

Fig. 1: Framework for Investigating the Impact of LLMs on Programming.

IV. Results and Discussion

Prior to training the machine learning models, the integrity and reliability of the survey data were rigorously assessed to ensure the quality of the input features. The constructs designed to measure perceptions (e.g., Ease of Use, Attitude etc.) were validated using Confirmatory Factor Analysis (CFA) to establish convergent validity. All factor loadings exceeded the recommended threshold of 0.7, confirming that the individual items strongly represented their intended theoretical constructs and could be reliably used as model features. Furthermore, the internal consistency of each multi-item construct was evaluated using Cronbach's Alpha, with all values ranging from 0.776 to 0.873, comfortably exceeding the accepted standard of 0.70 (Table 2). This two-step validation process ensured that the input data for the subsequent predictive algorithms were both reliable and valid, forming a robust foundation for the machine learning analysis. The collected data present a compelling, overwhelmingly positive picture of students' perceptions of using LLMs for computer programming. The central finding is that students strongly believe using LLMs increases their programming efficiency (EOU1) (Figure 2). This perception

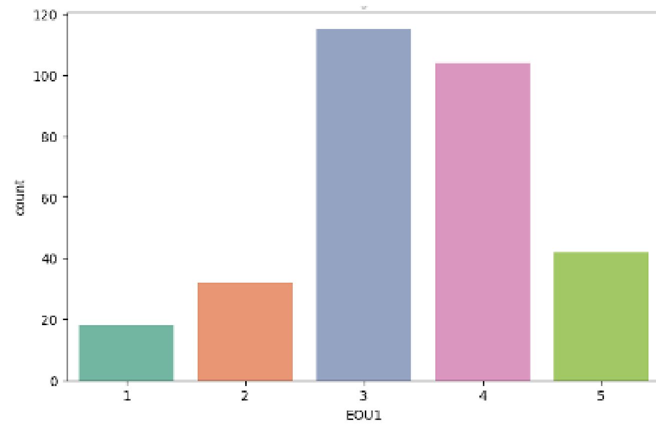

Fig. 2: Class distribution of Target Variable (LLMs in Programming).

is not an isolated opinion but is deeply embedded within a network of positive attitudes, behaviors, and experiences. The distribution of the target variable, EOU1, reveals a significant skew towards the positive end of the scale, with the vast majority of responses clustered at ratings of 4 and 5. This indicates a strong consensus among respondents from both universities that LLMs enhance their productivity and effectiveness in programming tasks. The remarkably low number of negative responses further solidifies this as a predominant trend within the sample.

This perception of increased efficiency is strongly correlated with the students' overall experience of using the technology (Figure 3). The correlation heatmap reveals that EOU1 has

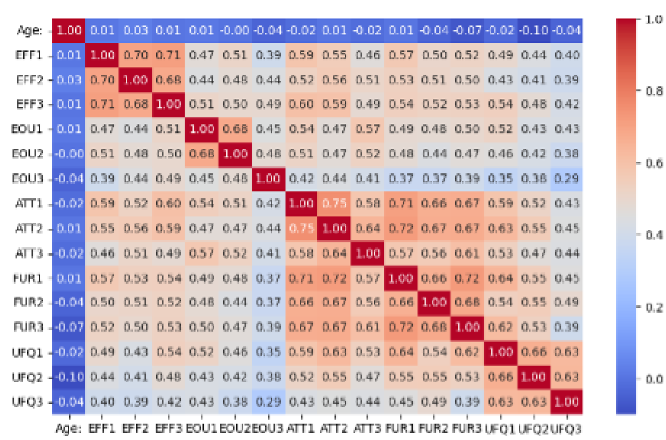

Fig. 3: Correlation Metrics of all the attributes.

notable positive relationships with almost all other measured constructs. Particularly strong correlations exist with other facets of ease of use, such as the belief that LLMs help

TABLE II: Measurement Items, Sources, and Reliability Statistics

Construct	Measurement Item	Source	CA	CR
EFF	EFF1 – Assisted programming is easy for me EFF2 – Interaction with LLM for programming tasks is easy EFF3 – Use of LLM for programming requires little effort	[20], [21]	0.776	0.871
EOU	EOU1 – Efficiency in programming is increased using LLM EOU2 – Academic programming assignments are more accurate EOU3 – LLM aids in completing tasks on time	[22]–[24]	0.853	0.911
ATT	ATT1 – I am positive about using AI-CAs for programming ATT2 – I believe using AI-CAs is beneficial for my programming tasks ATT3 – I feel confident in using AI-CAs effectively	[25]–[27]	0.873	0.922
FUR	FUR1 – Plan to continue using LLM FUR2 – Would recommend LLM to others FUR3 – Interest in exploring more LLM assistants	[28]	0.869	0.920
UFQ	UFQ1 – Frequent use for programming tasks UFQ2 – Increased usage over time UFQ3 – Heavy reliance for major assignments	[29]	0.842	0.905

complete tasks on time (EOU3) and produce more accurate academic assignments (EOU2). This suggests that students view efficiency not just as speed, but as a holistic improvement in the quality and timeliness of their work. Furthermore, the perception that using LLMs "requires little effort" (EFF3) is one of the strongest correlates with EOU1, indicating that the low cognitive load is a key component of what students define as efficiency. The scatterplots for these variables, such as those for EOU2 and EFF3, visually confirm this relationship, showing a clear upward trend where higher ratings on one variable correspond to higher ratings on the other.

The interconnected nature of these constructs, revealed by the correlation analysis, was further tested using a machine learning model to predict the EOU1 rating (Figure 4). The

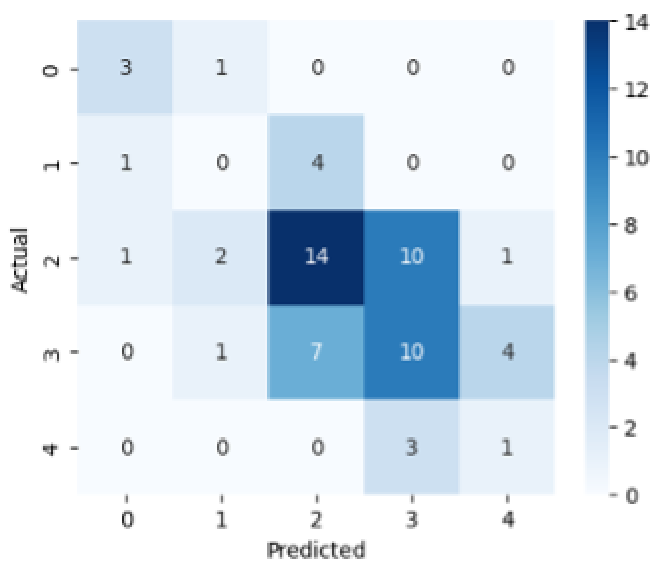

Fig. 4: Confusion Matrix.

resulting confusion matrix provides a nuanced validation of our findings. The model demonstrated a high rate of misclassification, but crucially, these errors were almost exclusively between adjacent categories (e.g., predicting a '3' for an actual '4'). This pattern is not a simple failure of the model but a meaningful reflection of the data's structure. It provides computational evidence that the underlying psychological constructs, Ease of Use, Attitude, Future Use, and Usage Frequency, are fluid and highly interconnected. A student whose responses place them on the border between "agree" and "strongly agree" presents a genuine classification challenge because their perceptions are influenced by this tightly correlated network of factors. The model's ability to predict the general range of a student's perception (e.g., rarely confusing a rating of '1' with a '5') confirms that our survey constructs possess significant collective predictive power, and the "errors" are substantively small and logically consistent with the continuous nature of the latent variables being measured.

Crucially, the data reveal that this practical experience translates into a positive psychological disposition. The Attitude (ATT) constructs, feeling positive about, confident in, and seeing the benefit of AI assistants, show some of the strongest and most linear positive relationships with EOU1 in their respective scatterplots (Figure 5). This indicates that the perceived efficiency gain is intrinsically linked to a favorable mindset. Students do not just find the tool useful in a utilitarian sense; they have developed a genuine confidence and positive attitude towards it. This link between practical utility and psychological acceptance is a critical success factor for technology adoption.

This observation is consistent with recent research on AI in education, which highlights that successful adoption is driven not only by performance-related outcomes such as efficiency or task completion, but also by users' psychological and emotional responses to the technology. For example, [30] argues that while AI tools such as large language models enhance

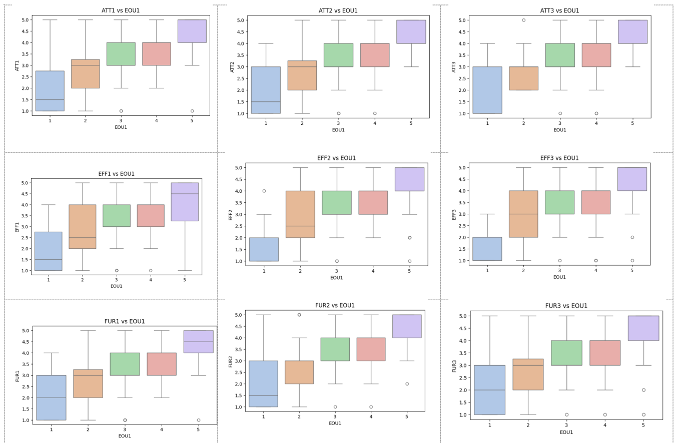

Fig. 5: Visual evidence of positive correlations between Perceived Efficiency (EOU1) and representative measures of (a) Effectiveness, (b) Attitude, and (c) Future Use Recommendation.

learning support, their effectiveness is closely tied to how students perceive and trust these systems during interactions. Furthermore, emerging literature on human–AI interaction suggests that positive attitudes toward AI are often shaped through repeated successful experiences, which reinforce both trust and perceived reliability [31]. In this regard, the present findings contribute to the state-of-the-art by demonstrating that the relationship between practical utility and psychological acceptance is not incidental but rather a critical success factor for sustained technology adoption. As shown in Table III it was observed that the growth delta of $\Delta \approx 3.2$ across the EOU1 ordinal scale. A notable stability plateau occurs within the interval $EOU1 \in [3, 4]$, where the median response remains consistent at ≈ 3.6. However, the transition to the maximum ease-of-use rating ($EOU1 = 5$) triggers a sharp convergence toward the scale ceiling ($y \approx 4.8$). This indicates that while "moderate" usability yields stable performance, the most significant gains in user attitude and efficiency are contingent upon reaching a critical threshold of perceived simplicity.

TABLE III: Quantitative summary of system performance and user perception metrics.

Metric	Notation	Quantitative Value
Global Accuracy	A	44.4%
Growth Factor (EOU1)	$\Delta y/\Delta x$	300% (Increase from 1.6 $\rightarrow$ 4.8)
Stability Plateau	$f(x)$	Med ≈ 3.6 for $x \in \{3, 4\}$
Convergence at Peak	y_{max}	96% of Scale Maximum at $EOU1 = 5$

The analysis also demonstrates that this perceived efficiency has tangible behavioral consequences. The intention for Future Use Recommendation (FUR), including plans to continue using LLMs, recommend them to peers, and explore more such tools, is positively correlated with EOU1 (Figure 5). Students who feel more efficient are more likely to commit to the technology long-term and become advocates for it. This aligns with recent findings by [32], who reports that users who perceive immediate productivity gains from generative AI are more likely to integrate it into long-term workflows and recommend it within their networks. Similarly, the reported Usage Frequency (UFQ), using LLMs often, increasingly over time, and for major assignments, also trends upwards with higher EOU1 scores, which supports recent evidence that students rely more frequently on AI tools when they perceive them as enhancing task performance, particularly for complex academic work [33]. Overall, these findings reinforce that perceived efficiency not only improves immediate outcomes but also drives long-term usage behavior and technology diffusion through student advocacy. This creates a virtuous cycle: perceived efficiency encourages more frequent use, and more frequent use likely further solidifies the perception of efficiency and integration into the student's workflow.

Finally, the integrity of these findings is reinforced by the outlier analysis (Figure 6). The boxplots show that for nearly

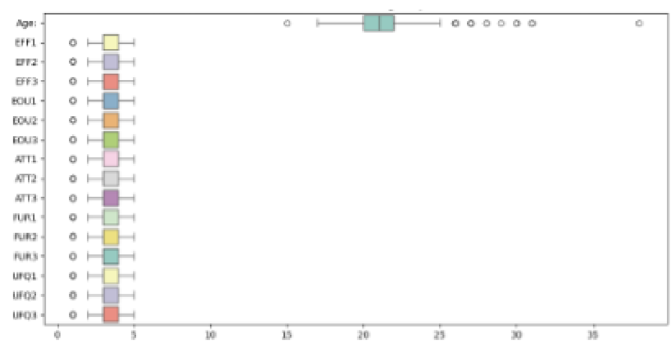

Fig. 6: Boxplots demonstrating the consistency of student responses with minimal outliers.

all variables, including EOU1, there are very few extreme outliers. The data are tightly clustered, with the interquartile ranges consistently located at the higher end of the scale. This lack of significant outliers indicates that the positive responses are not driven by a small subset of extreme enthusiasts but rather reflect a consistent, widespread sentiment across the participant pool. It strengthens the conclusion that the observed strong, positive correlations reliably reflect the sampled student population, painting a coherent picture of LLMs being successfully adopted as an efficient, easy-to-use, and well-regarded tool in computer programming education.

V. Theoretical and Practical Implications

Theoretically, this study contributes to the Learning Sciences by providing a validated model of the factors that influence students' adoption of AI tools in programming education. It positions "perceived efficiency" not just as a utilitarian metric, but as a central, motivating factor in a broader ecosystem of learning technology acceptance. For practice, these findings offer several key insights for educators and institutions in Mexico and similar contexts:

- Curriculum Integration: Instead of resisting LLM use, educators can leverage this student-driven adoption. The focus can shift from whether students use LLMs to how they use them effectively and ethically.

- Pedagogical Design: Assignments can be redesigned to leverage LLMs for iterative development, debugging, and learning new concepts, while emphasizing critical thinking, code validation, and proper attribution.
- Developing AI Literacy: There is a pressing need to integrate formal AI literacy and ethics training into the curriculum to ensure that this powerful tool is used responsibly and does not undermine the development of core programming competencies.
- Assessment Implication: Traditional programming assessments may no longer reflect true student ability, requiring a shift toward process-based evaluation that captures understanding alongside AI-assisted outputs.
- Learning Behavior: Students need to actively balance LLM use with independent problem-solving to avoid over-reliance and ensure genuine skill development in programming education.

VI. Conclusion

This study set out to investigate student perceptions of LLMs within the specific context of Mexican higher education. The findings present a clear and consistent narrative: students in computer science programs overwhelmingly perceive LLMs as a transformative technology that significantly enhances their programming efficiency. This core perception, however, is not an isolated data point. Our analysis reveals that it is deeply embedded in a robust, interconnected network of positive attitudes and behaviors. The strong, positive correlations demonstrate that students who find LLMs efficient are also more likely to hold positive attitudes towards them, feel confident in using them, intend to use them in the future, recommend them to peers, and integrate them more frequently into their academic workflow. This creates a powerful virtuous cycle: the tool's utility fosters a positive psychological disposition, which in turn reinforces its continued use and integration. The near-zero correlation with age further suggests that this phenomenon is widespread across the student demographic we studied.

In conclusion, this study demonstrates that LLMs are widely perceived by computer science students in Mexican higher education as valuable tools that enhance programming efficiency and support academic tasks. This perception is strongly associated with positive attitudes, increased confidence, and a clear intention to continue using and recommending these technologies. The findings highlight the emergence of a reinforcing cycle in which perceived utility drives favorable psychological responses, which in turn promote deeper integration of LLMs into students' learning practices. At the same time, the negligible influence of age suggests that this pattern of adoption is consistent across the student population.

VII. Limitations and Future Research

This study is not without limitations. Its focus on two universities in Mexico means the findings, while insightful, may not be fully generalizable to all educational contexts. Furthermore, the study captures perceptions and self-reported behaviors, which, while valid, would be powerfully complemented by observational studies or analysis of actual coding patterns. Future research should explore the longitudinal impact of LLM usage on learning outcomes and problem-solving skills. It should also investigate the specific pedagogical strategies that most effectively harness the benefits of LLMs while mitigating potential risks like over-reliance. Finally, comparative studies across different countries and educational systems could uncover the socio-cultural factors that shape the adoption of these tools.

In addition, future research should focus on understanding how students calibrate trust in LLMs during programming decision-making, particularly when AI outputs are partially correct or misleading. Longitudinal and experimental studies can examine when students appropriately accept or override AI suggestions, linking these behaviors to actual code quality and learning outcomes. Also, it is recommended to explore adaptive support mechanisms that respond to students' confidence and decision-making patterns, as well as language-specific factors in non-English contexts, such as Spanish in Mexico. Also, there is a need to investigate intervention-based approaches, such as embedding reflective prompts or scaffolding strategies, to promote critical engagement and reduce over-reliance, thereby ensuring that LLMs enhance rather than hinder the development of core programming competencies.

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