2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC

Host Sponsor UNC Charlotte

Paper ID #53324

Who Benefits from AI-Assisted Programming? Revealing Hidden Variables Through an Intersectional Analysis of the Student Experience

Dr. Sri Yash Tadimalla, University of North Carolina at Charlotte

Sri Yeswanth (Yash) Tadimalla holds a Ph.D. in Computing and Information Systems with an interdisciplinary focus in Sociology and a Master of Science in Computer Science from UNC Charlotte. A Bachelor of Technology in Computer Science and Engineering from the Hyderabad Institute of Technology and Management. He currently serves as a Computing Innovation (CI) Fellow focused on AI Education at the Computing Research Association (CRA) in Washington, DC. At CRA, he is supporting research and outreach across multiple NSF-funded initiatives and serves as the lead Fellow for the NAIRR Pilot Expansion AI EDU RCN. Dr. Tadimalla actively contributes to various global multilateral organizations, including the United Nations, through thought leadership, coordinating consultations, and producing policy reports, with a specific focus on civil society engagement, education, and innovation within negotiations around AI governance and capacity building. He has presented his work as a keynote speaker and researcher at distinguished international conferences (ASEE, ACM-SIGCSE, IEEE-FIE, AAAI, UN) across diverse global locations in 20+ countries.

Mary Lou Maher, University of Sydney

Mary Lou Maher is a Professor in the School of Computer Science at the University of Sydney. Her research and teaching focus on AI in education and co-creativity.

Who Benefits from AI-Assisted Programming? Revealing Hidden Variables Through an Intersectional Analysis of Student Programming Experience

Sri Yash Tadimalla
Department of Human Centered Computing and Education
University of North Carolina Charlotte
Charlotte, U.S.A
stadimal@charlotte.edu

Mary Lou Maher
School of Computer Science
University of Sydney
Sydney, Australia
mmarylou.maher@sydney.edu.au

***Abstract*—AI chatbots (ChatGPT, Gemini, Co-pilot) are transforming the programming education landscape [1]. Advanced models are increasingly accessible and offer significantly sophisticated support that is influencing how students engage with learning programming concepts and tasks. Building upon prior research, this study investigates how students' intersectional identities influence their interaction with and perceived effectiveness of AI tools in programming education. Specifically, we ask: (1) How does a student's identity affect their access to, perception of, and attitudes toward AI-assisted programming experiences? (2) Does applying an intersectional identity lens reveal different insights from the same dataset compared to analyses that do not account for identity? To explore these questions, we conducted a study with 50 participants from diverse intersectional backgrounds, recruited from an AI literacy course. The study involved a pre-task assessment, a programming task with access to an AI chatbot (OpenAI GPT 3.5) followed by a reflective survey on students' experiences with the AI tool. By triangulating data from performance metrics, pre- and post-assessments, and reflection responses, we uncover preliminary associations between students intersectional identities and AI tool usage, task outcomes, and their AI perceptions and attitudes. Our findings suggest that students' gender and race meaningfully shape both their interactions with and their perceptions of the AI tools. While statistical significance in intersectional analyses remains a challenge due to sample size and variable complexity, the study provides valuable insights into how identity influences AI-assisted learning. These results underscore the importance of adopting nuanced, identity-aware approaches when designing and evaluating AI-based educational technologies.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

As AI software tools become more commonplace, their potential to transform the student experience has greatly increased. Recent work has evaluated the performance of Large Language Models (LLMs) in varying fields and in higher education and found its performance to be passable most of the time [2] [3] [4] [5]. Many universities are responding to the increasing availability of ChatGPT interaction by banning its use in assignments and exams. A major concern is the uncertainty of whether the use of tools based on GPT LLMs will reduce learning by increasing reliance on AI to generate answers to questions. There are numerous concerns about policy and the ethics of AI contributions to students' assignments and exams, including: how to address the use of AI in the syllabus; policy perspectives on cheating; the inclusion of AI use in learning outcomes; ownership of code or material developed; the educational use of AI integrated coding environments; the use of AI in auto graders; and AI literacy for future jobs in which AI is available to support work. Before these tools can be meaningfully introduced into a course, research is needed to study the impact of these AI tools on student learning. Understanding how students from diverse backgrounds engage with AI tools is essential for equitable education [6, 7]. There is a need for rigorous empirical studies to explore the impact of AI tools on student learning in programming courses, centering on a student identity lens [8, 9, 10]. Specifically, this research aims to address the following research questions:

- How does using AI tools during programming impact student programming experience?
- Does student identity impact how students perceive and interact with AI tools like ChatGPT?
- How does an intersectional analysis lens expose hidden insights when studying students' perceptions of AI as a learning tool in programming courses?

By investigating these hypotheses, educators can better understand how to integrate AI tools into programming courses to enhance learning outcomes while promoting diversity and inclusion. Building on previous work that explored the student experience by analyzing students' competency-building and cognitive experiences while using AI tools during a programming exercise [11], we present preliminary results from an intersectional analysis of students' interactions, perceptions, and attitudes toward the use of AI tools. This data is presented through a thematic and intersectional analysis.

II. Background

The integration of Artificial Intelligence (AI) tools, particularly Large Language Models (LLMs) such as ChatGPT, Co-Pilot, and Claude, into programming education has sparked both enthusiasm and concern among educators and researchers [12, 13, 14]. These tools offer real-time, 24/7 assistance, potentially enhancing the learning experience for students. However, their impact on student learning outcomes and equitable access requires careful examination. Recent advances in deep learning and neural network architectures have led to the development of LLMs that surpass previous models in capabilities [15]. LLMs demonstrate remarkable abilities such as general linguistic intelligence and unsupervised multitask learning [16], positioning them as "general-purpose" models that can even enhance their training through usage [17]. In programming, LLM assistance can resemble a highly intelligent compiler or a pair programming partner, offering new opportunities for human-centric programming research. Studies have found that students prefer LLM-powered tools over traditional code completion tools [18]. Some studies show that compared to individual programming, AI-assisted pair programming significantly increased intrinsic motivation and reduced programming anxiety, producing outcomes comparable to human–human pair programming [1].

Tools like GitHub Copilot, Amazon CodeWhisperer, and Replit Ghostwriter utilize LLMs to provide code suggestions within code editors. GitHub Copilot, for instance, has shown a 91.5% success rate in generating valid code, with correct code in 28.7% of cases and partially correct code in 51.2% [19]. The frequent exposure to these suggestions raises questions about their influence on student learning: Will consistent exposure to syntactically correct code enhance learning, or will incorrect suggestions cause frustration and demotivation? Additionally, since Copilot performs better with popular languages like Java and common problems [20], there is concern that students might complete assignments without fully understanding the material [21]. Access to AI tools integrated into coursework offers real-time, personalized support, enabling students to work at their own pace and schedule. This accessibility can foster self-paced learning and potentially broaden the success spectrum in computer science (CS) education by accommodating a diverse student population [22]. AI tools, such as chatbots, may engage students who might otherwise avoid direct interaction with instructors or teaching assistants, thus supporting varied learning preferences. Research has shown that AI can favor access to education by supporting collaborative environments and providing intelligent tutoring systems [23].

Advances in AI algorithms present opportunities to build models that learn from student behavior patterns, potentially offering explainable advice to students at risk [24]. Such tools could address disparities in preparedness among students, contributing to more equitable educational outcomes. The perception of technology and its accessibility significantly influence who pursues careers in CS [25]. Factors contributing to a student's sense of belonging—such as interpersonal relationships, perceived competence, personal interest, and scientific identity—are linked to their likelihood of persisting in the field [10, 26, 27, 28]. AI tools that provide supportive, personalized learning experiences may enhance these factors, especially for underrepresented groups who may face disparities in preparedness and access [29].

However, building trust between underrepresented students and AI tools is crucial. Historical skepticism towards narratives causing AI and the digital divide can lead to hesitancy in adopting AI assistance [30]. Ensuring that AI systems are trustworthy involves integrating dimensions like safety, fairness, explainability, privacy, and accountability, and being transparent about these aspects with students [31].

By addressing these concerns, AI tools can be more effectively utilized to support diversity and inclusion in programming education. While AI tools offer clear benefits, their impact on fundamental programming skills and critical thinking is a concern. AI tools capable of independently solving introductory programming exercises have only recently become widely available [21, 32, 33, 34]. Heavy reliance on such tools during formative assessments might compromise the development of essential skills [34]. Previous studies have primarily focused on tool performance, model test-taking abilities, or interface usability, rather than on how students interact with these tools and the subsequent impact on learning outcomes [11].

III. Methodology

The study protocol for each participant involved following a multi-step task progression defined by [35]. For the study, we selected ChatGPT (OpenAI) as the AI assistant tool; literature and campus usage trends suggested that ChatGPT was the most widely used AI tool among students. Observations from the first phase indicated that student interactions and roles in engaging with AI tools were similar at an abstract level, with differences mainly due to tool (feature) updates over time [11]. The inclusion criteria for study participants were that they currently or had been a part of a Java programming course. We recruited 60 participants who met our eligibility criteria from an AI literacy course for this phase. Participants were students enrolled at a large public university in the USA, typically in their second or third semester, having completed at least one programming course. This allowed us to focus on the impact of ChatGPT usage in a consistent and controlled manner.

We adopted a mixed methods analysis to combine quantitative data from quizzes with qualitative data from interviews and screen recordings. Quantitative analysis involves statistical methods to analyze quiz scores and task performance, evaluating knowledge improvement and performance differences across conditions. Qualitative analysis included thematic analysis of reflection transcripts to identify patterns and themes related to participants' experiences, perceptions, and attitudes toward AI tools. Coding was performed using established thematic analysis methodologies [36], and themes were cross referenced with demographic data to explore the impact of identity on interactions with AI tools. Followed by applying an intersectional lens to the coded data. By integrating both quantitative and qualitative data, we gain a holistic understanding of how AI tools like ChatGPT influence student learning and attitudes in programming courses.

IV. Results from Pre-Task Survey and Programming Task

In this section we present the results of data collection from 51 students that engaged in the pre- and post-task surveys, and the programming task. In our analysis, we perform a statistical analysis of the group of participants as a whole and then analyze across dimensions of gender, first-generation student status, ethnic or racial category, and LGBTQIA+ community membership.When examining the intersection of these factors, several patterns emerge.

- **Gender Distribution:** The participant cohort consists of 18 females, 28 males, 2 non-binary/third-gender individuals, and 2 students who preferred not to disclose their gender.
- **First-Generation Student Status:** 26 students were not first-generation college students and 24 were first-generation students.
- **Ethnic or Racial Category Distribution:** The ethnic breakdown includes 8 Asian, 14 Black/African-American, 6 Hispanic/Latinx, 1 MENA, 1 Native American/Alaska Native/First Nations/American Indian students, 2 students who self-identify their ethnic category, and 19 White students.

With the majority of participants being traditional college-age students (18–24), there is limited variation in age.

In analyzing the data through an intersectional lens [6, 28], we observe the following grouping (see Table I):

- **Gender and Ethnic or Racial Category:** Among the 51 students surveyed, the female cohort (totaling 18) comprises 3 Asian, 5 Black/African-American, 2 Hispanic/Latinx, 1 Middle Eastern/North African (MENA), and 7 White individuals. The male cohort (totaling 28) includes 5 Asian, 9 Black/African-American, 2 Hispanic/Latinx, 1 Native American/Alaska Native/First Nations/American Indian, and 11 White individuals. Non-binary/third gender students total 2, with 1 identifying as Hispanic/Latinx and 1 as White. Additionally, 2 students preferred not to disclose their gender, both of whom self-identified their ethnic category.
- **First-Generation Student Status and Gender:** Of the students who are not first-generation college students (totaling 26), 7 are female, 15 are male, 2 are non-binary/third gender, and 1 preferred not to say. Among first-generation students (totaling 24), 11 are female, 12 are male, and 1 preferred not to disclose their gender.

Intersectional Group	(n)	%	First-Generation: Yes	First-Generation: No
URM Female	11	21.60%	9	2
URM Male	12	23.50%	6	6
Non-URM Female	7	13.70%	2	5
Non-URM Male	16	31.40%	6	9
Non-URM Unspecified	3	5.90%	1	2
URM Unspecified	2	3.90%	0	2
Total	51	100%	24 (with 1 missing)	26

TABLE I
Number of students distributed across intersectional groups

- **First-Generation Student Status and Ethnic or Racial Category:** Among non-first-generation students, there are 4 Asian, 6 Black/African-American, 3 Hispanic/Latinx, 1 Native American/Alaska Native/First Nations/American Indian, 1 who self-identifies, and 11 White individuals. First-generation students consist of 4 Asian, 8 Black/African-American, 3 Hispanic/Latinx, 1 MENA, 1 who self-identifies, and 7 white individuals.

For the purposes of an intersectional analysis, we define the following cohorts, using the category of ”Underrepresented-minority” (URM) as defined in literature [10, 26]:

- URM Female: Female students who identify as Asian, Black/African-American, Hispanic/Latinx,MENA, Native American/Alaska Native/First Nations/American Indian.
- URM Male: Male students who identify as Black/African-American, Hispanic/Latinx,MENA, Native American/Alaska Native/First Nations/American Indian.
- Non-URM Male: Students who identify as White or Asian and male.
- Non-URM Female: Students who identify as White and female.

Participants whose gender was not specified or who identified as non-binary were omitted from the gender-separated analysis.

A. Pre-Task Survey: Student Attitudes, Perceptions, and Self-assessed Understanding of Programming Concepts

The overall self-reported confidence is notably higher among Non-URM students than among URM students (see Figure 1). Specifically, Non-URM Male students report the highest overall confidence (3.9), followed by Non-URM Female students (3.7). In contrast, both URM Female and URM Male students report overall confidence around 3.0–3.1.

For each specific programming area (Java, arrays, and loops), the Non-URM groups consistently report higher average confidence compared to the URM groups. This suggests that students in the Non-URM categories (primarily White and Asian students) feel more assured in their programming abilities.

Question	Very Low	Low	Average	High	Very High
1. Confidence in Applying Java Programming Skills	2	13	26	7	3
2. Confidence in Knowledge and Comprehension of ”Arrays in Java”	2	9	27	9	4
3. Confidence in Knowledge and Comprehension of ”Loops in Java”	2	9	26	10	4
4. Experience with AI Tools for Programming	6 (No Exp)	6	18	17	4

TABLE II
SELF-REPORTED PRE-SURVEY RESPONSES ON STUDENT SELF-EFFICACY QUESTIONS

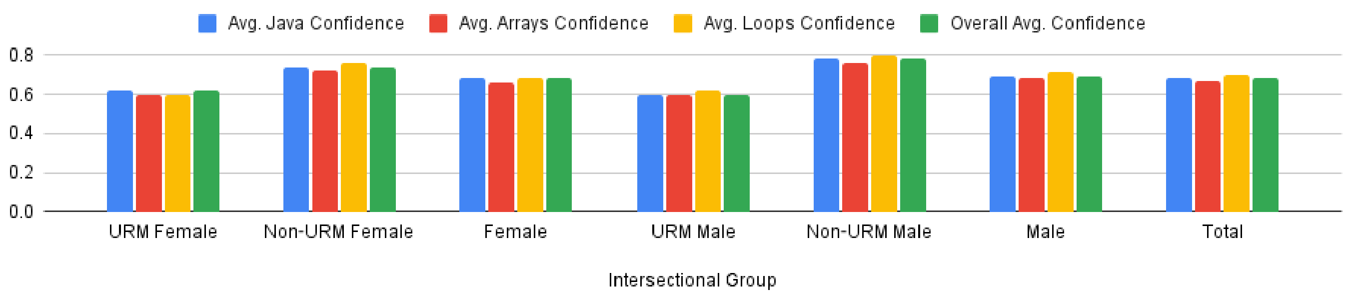

Fig. 1. Intersectional Analysis of pre-task survey student self-efficacy

The differences in self-reported confidence may reflect varying levels of prior exposure, access to support resources, or the impact of cultural and social factors on self-efficacy in programming. These findings suggest that targeted instructional interventions—such as mentorship programs, confidence-building workshops, or additional support sessions—might help boost the confidence of URM students.

B. Programming Task: Student Performance in Programming

The analysis of participant performance reveals several trends across the programming tasks, quizzes, total awarded points, and total calculated scores across three concepts.

Measure	Average	Median	Std. Deviation
Programming Task 1	4.58	5	1.35
Programming Task 2	4.25	5	1.81
Programming Task 3	3.23	5	2.4
Pre-task Quiz	2.57	3	1.54
Post-task Quiz	3.31	4	1.44
Total Awarded Points	17.83	18	4.00
Delta Pre-Post	0.14	0	0.47
Actual Task Understanding	3.62	3.8	0.90

TABLE III
PARTICIPANT PERFORMANCE IN PROGRAMMING TASK, *SOME PARTICIPANTS HAVE MISSING QUIZ SCORES, AFFECTING THE TOTAL NUMBER CONSIDERED FOR AVERAGES.

As shown in Table IV, non-URM Male students report the highest levels of understanding, followed by URM Males, then URM Females, with Non-URM Females reporting the lowest. This pattern suggests that factors linked to both race and gender may influence how confident students feel about their grasp of programming concepts. Non-URM Male students (predominantly White or Asian males) may benefit from prior experiences or cultural factors that boost self-confidence. The learning gains, as indicated in the (Δ Pre–Post Quiz) show the following pattern:

URM Groups: Both URM Females and URM Males exhibit modest improvements on the quizzes. Non-URM Groups: Both Non-URM Female and Non-URM Male groups show almost no average improvement, suggesting a possible ceiling effect—perhaps they started with higher baseline knowledge, leaving less room for measurable gains.

Although Non-URM students report higher initial understanding, their minimal quiz gains might indicate that the assessment captured little improvement, potentially due to a ceiling effect. In contrast, URM students, starting from a slightly lower baseline, still manage to show modest gains, suggesting that the inclusion of AI tools provided some benefit.

V. SELECT RESULTS FROM INTERSECTIONAL ANALYSIS OF STUDENT REFLECTIONS

In this section, we present the intersectional analysis of the qualitative data collected from participants through the open-ended reflection exercise. Our goal is to explore their experiences with using AI for programming tasks involving loops and arrays, their perceptions of using AI tools in programming, and their attitudes towards the use of ChatGPT for coding. In this paper, we analyze select questions to identify common themes and demonstrate intersectional insights. Table V presents all of the questions from the post-task reflection activity.

A. Question 5) ”Did having AI in the process of programming help you?

As shown in Figure 2, both Non-URM and URM Male groups show a relatively high frequency of codes indicating that AI helped with learning and that it functioned as a “Good Tutor.”

Intersectional Group	Actual Task Understanding			Δ Pre–Post Quiz		
	Mean	Median	SD	Mean	Median	SD
URM Female	3.56	3.5	0.96 (min 2.2, max 5)	0.26	0.23	0.37 (range –0.25 to 1)
URM Male	3.76	3.8	0.76 (min 2.6, max 4.8)	0.21	0.37	0.56 (range –0.5 to 1)
Non-URM Female	2.8	3.4	1.23 (min 1.2, max 4.2)	0.04	0	0.52 (range –1 to 0.6)
Non-URM Male	3.9	4.2	0.99 (min 1.8, max 5)	0.048	0	0.44 (range –1 to 0.67)

TABLE IV
INTERSECTIONAL ANALYSIS OF STUDENT PROGRAMMING TASK PERFORMANCE

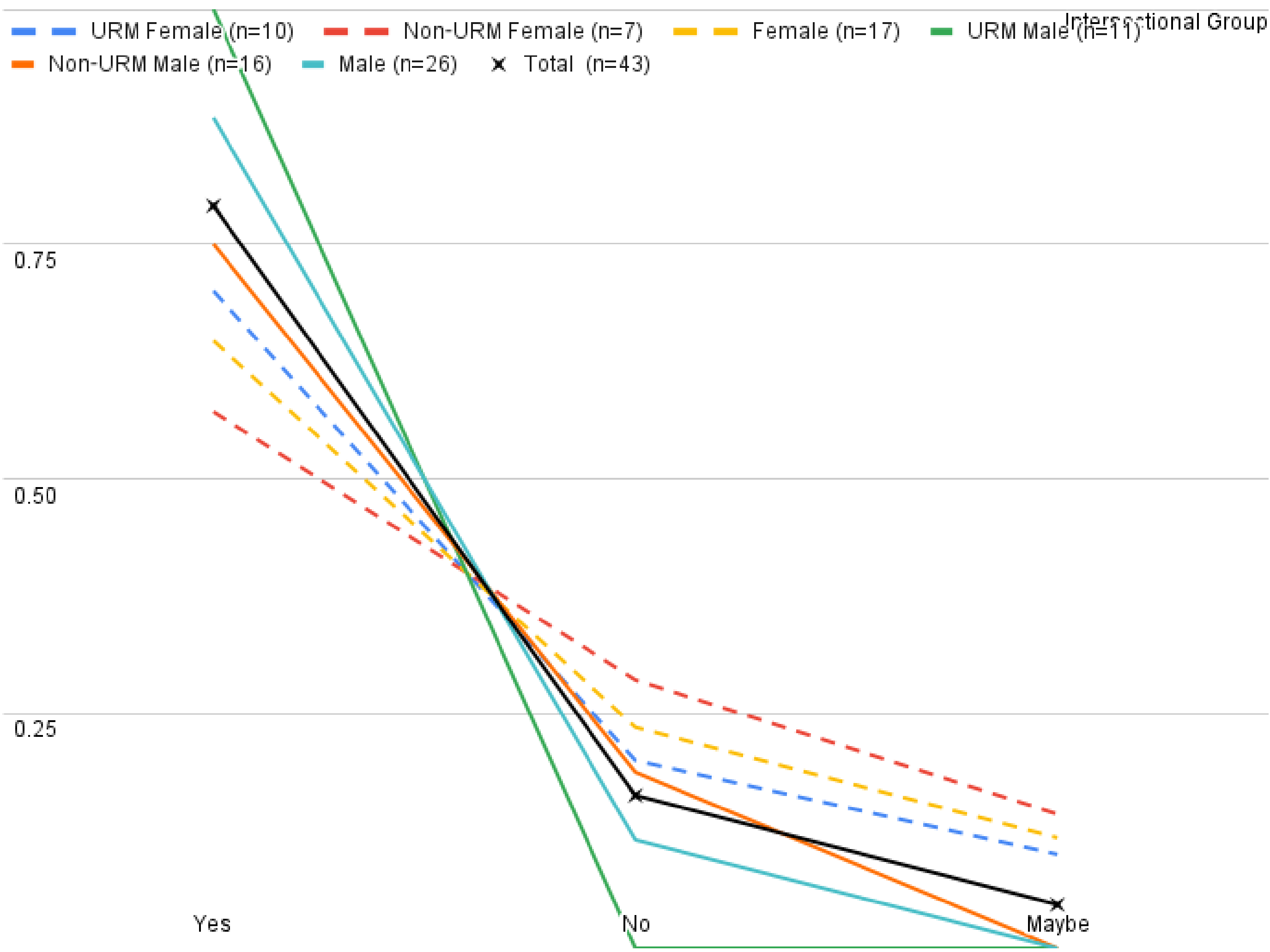

Fig. 2. Q5 Did having AI in the process of programming help you?

However, Non-URM Females reported slightly more ambivalence (e.g., instances of "AI did not help with learning") and a few remarks on AI hallucinations, which suggests nuanced experiences. Non-URM Females were the highest number of "AI helped with learning" codes overall, but they also reported a highest count for "AI did not help with learning", indicating mixed experiences even within a generally positive stance. Codes for "Good Tutor" are consistently high among URM respondents and Non-URM Males, whereas Non-URM Females and the non-gender–specified Non-URM group show slightly lower counts. "Bad Tutor" mentions, although less frequent overall, appear in several groups—suggesting that while many find the AI useful, a subset in each demographic is critical of its instructional role. "Felt Supported" is a dominant theme across most groups. However, the Non-URM Female group has a lower frequency relative to its N, which may indicate that this group experiences less consistent support from the AI tool. The codes "AI did not help with learning" and "AI Hallucination/Did not Hallucinate" provide insight into concerns over reliability. For example, while URM Males reported no instances of "AI did not help with learning" (except one in the case of a conflicting code) and no mentions of "did not hallucinate" except where noted, Non-URM Males and Non-URM Females expressed more concerns. Such differ-

Q.No	Question Statement
Q2	"Can you explain how each of your solutions works? How did you feel while trying to do the programming? (Researcher rates on a scale of 1-5 Task 1: Task 2: Task 3:)"
Q3	"Do you think your knowledge and comprehension of Loops and Arrays improved by performing the task? (100-150 words) Yes/No, Explain"
Q4	"On a scale of 1-5 where would you rate your understanding of loops and arrays (1 being lowest and 5 being highest) No correct answer"
Q5	"Did having AI in the process of programming help you? = Yes/No/Maybe/Don't know Answer each of the prompts as an explanation..."
Q6	"Do you think the way you used the AI tool should be considered cheating? Why or why not? Would it currently be seen as cheating?"
Q7	"Does your experience with using this AI tool motivate you to continue learning more about programming? (scale of 1-5) Please explain."
Q8	"How confident are you with programming in JAVA after your experience with using this AI tool? (scale of 1-5). Please explain."
Q9	"Are you more confident about being successful in this degree? (scale of 1-5) With access to AI tools, Please explain."
Q10	"Do you have any concerns about the use of AI tools in the classroom and professionally?"

TABLE V
OVERVIEW OF REFLECTION QUESTIONS

ences might reflect variations in trust, with some groups more willing to overlook errors than others. "Used AI to Code/learn Code" appears across groups but is most prominent among URM Males and the non-gender–specified Non-URM group. This suggests that these groups are not only assessing AI's role as a tutor but also actively integrating it into their coding practices. Across the responses an intersectional Lens provides clear differences between gender based groups experiences.

B. Question 6) "Do you think the way you used the AI tool should be considered cheating? Why or why not? Would it currently be seen as cheating?"

As shown in Figure 3, an intersectional analysis of the thematic responses reveals notable differences across demographic groups, especiall between Female students. URM female students had the highest amount of concerns in contrast to the Non-URM female students who had the least concerns. URM female and Male participants frequently stressed the importance of context—emphasizing that the acceptability of AI use depends on the specific assignment and learning objectives—and underscored ethical use, insisting that AI should only supplement genuine engagement. In contrast, Non-URM male and female respondents were more inclined to view AI as a valuable, supplementary learning aid, often arguing that when used responsibly, it does not constitute cheating. Non-URM male participants tended to be more critical of AI practices that bypass personal effort—highlighting concerns about copy-paste shortcuts and the resultant lack of genuine learning—while Non-URM female participants expressed ambivalence, often weighing both the benefits (such as increased efficiency and support) and potential ethical pitfalls, sometimes drawing on analogies (like comparing AI to calculators) to support their nuanced stance.

C. Question 7) "Does your experience with using this AI tool motivate you to continue learning more about programming? (scale of 1-5) Please explain."

As shown in Figure 4, URM status was a key indicator for motivation levels with URM females having the lowest negative responses and Non URM Males having the highest Negative responses. Among URM Female respondents (n = 11), the mean motivation rating is 3.8 with nearly two-thirds (63.6%) answering "Yes" that the AI tool motivates them to continue learning programming. URM Male respondents (n = 7) show a slightly higher proportion of "Yes" responses (71.4%) with a mean rating of 3.71. For Non-URM Female respondents (n = 7), the mean rating is a bit lower at 3.29, with 57.1% "Yes." Non-URM Male respondents (n = 17) have the lowest mean rating (3.19) and the lowest "Yes" percentage (47.1%), with 41.2% saying "No." Overall, female respondents (n = 18) average 3.59 on the scale and tend to lean toward "Yes" (61.1%), whereas male respondents (n = 25) average around 3.35 with a more mixed distribution (54.2% Yes, 37.5% No).

D. Question 8) "How confident are you with programming in JAVA after your experience with using this AI tool? (scale of 1-5). Please explain."

As shown in Figure 5, we see a similar phenomenon as Q7 where URM Females had the lowest (less confident) responses with Non-URM Males having the highest Less confident) responses. Both URM Females and URM Males generally report moderate confidence. However, URM Males tend to have a slightly higher average than URM Females. Non-URM females show a similar moderate confidence. Non-URM males indicate the lowest confidence levels, suggesting that this group may feel less assured in their Java skills after the AI tool experience.

E. Question 10) "Do you have any concerns about the use of AI tools in the classroom and professionally?"

As shown in Figure 6, Male respondents, particularly those in the Non-URM Male category, are much more likely to express concerns about the use of AI tools compared to female respondents. URM Female respondents show a lower level of expressed concern. The disparity between groups may indicate differences in how AI is perceived based on both gender and URM status. For example, it could be that non-URM males feel more informed, have more access, and are more critical of AI's implications in the classroom or professional environments. On the other hand, URM Females may be less informed about potential negative impacts, or they might see AI tools as more beneficial to their learning or professional development. Small sample sizes in some groups (e.g., URM/ Non-URM Female) suggest caution when generalizing these findings, but the overall pattern does highlight a gender difference.

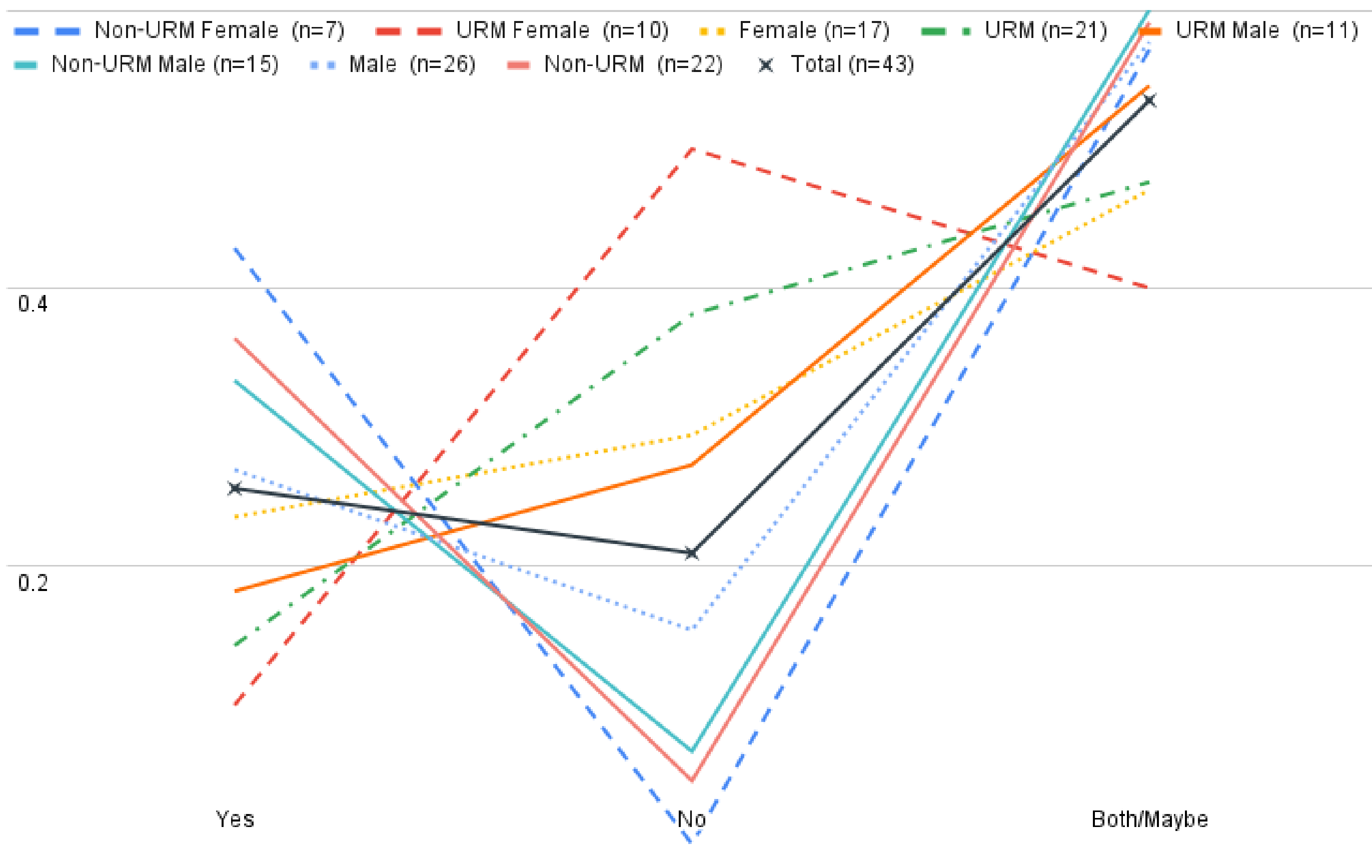

Fig. 3. Q6 Do you think the way you used the AI tool should be considered cheating?

VI. Discussion

The rapid integration of AI tools into the software engineering industry has created a swiftly shifting professional landscape, prompting both excitement and apprehension among computer science students. As the baseline expectations for technical competency evolve, students are increasingly re-evaluating their confidence in successfully completing their degrees and securing future employment. While some view AI access as a democratizing force that bolsters their academic and professional prospects, others experience heightened job anxiety, questioning the long-term value of traditional programming skills in an AI-dominated market. Understanding these contrasting reactions—specifically, how confidence in degree attainment and overarching professional concerns intersect with a student's identity—is essential for contextualizing their overall experience regarding the integration of AI tools in both the classroom and the workplace. The perceptions of AI and its association with systemic inequalities in AI literacy levels lead to complex interplays between the student's attitudes towards AI and their behavior when allowed to use AI.

The accessibility and availability of AI tools, such as ChatGPT, are not uniformly distributed among different communities and demographic groups. This discrepancy results in unequal AI preparedness, with certain groups having greater exposure and resources to develop proficiency in AI-assisted programming. These disparities align with broader systemic inequities present in society, perpetuating existing power imbalances.

Responses to the study design reveal diverse perspectives on AI tools, influenced by their identities. We see particular differences between the intersectional experiences of URM female students and Non-URM male students with other positionalities reflecting similar juxtapositions. This kind of intersectional breakdown can help identify which groups might benefit from targeted discussions or interventions regarding the implementation of AI tools in academic and professional settings. The study highlights the need for further research to better understand these dynamics and to examine AI interactions from the perspective of intersectional identities.

Furthermore, intersectional privileges and barriers shape individuals' experiences when engaging with AI tools for coding and programming. Variables such as gender, race, socioeconomic status, and disability can significantly influence an individual's access to education, opportunities, and resources related to AI. Consequently, this impacts their ability to effectively leverage AI tools and hampers their potential for growth and success in programming domains.

Without considering student identity, it is hard to advocate for the use of AI tools in the classroom and assessments if their impact on various student identity groups is not taken

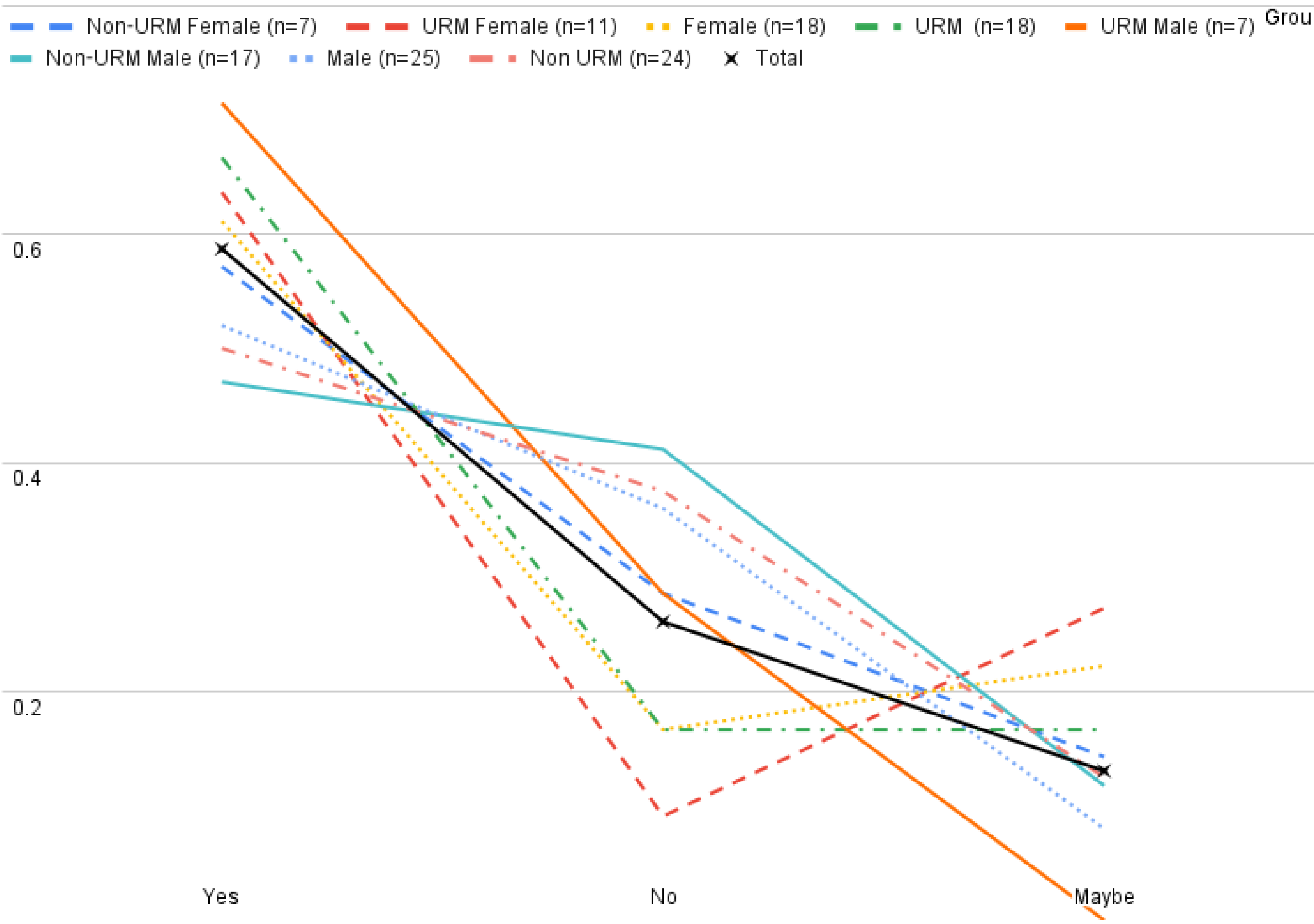

Fig. 4. Q7 Does your experience with using this AI tool motivate you to continue learning more about programming

into account. While AI education researchers study the various impacts of integrating AI in assessment:

- How the use of AI tools impacts the accuracy of assessments and feedback
- The degree to which the use of AI tools should be allowed during assessments,
- How assessments should change to incorporate these AI tools,

Understanding and addressing intersectional dynamics is essential to establishing an inclusive and equitable AI education ecosystem. Initiatives should be undertaken to bridge the AI literacy gap and provide underrepresented communities with support and resources, enabling them to leverage AI tools such as ChatGPT, Claude, and Gemini etc.

VII. Limitations

There are several limitations to this study design that should be considered. First, while the study focuses on introductory programming students, the findings may not be applicable to students at different experience levels or in other programming languages. Second, the statistical strength and broader generalizability of these findings are currently restricted due to the small sample size and the inherent complexities of intersectional analysis. The evidence presented is also largely perception-based, relying heavily on self-reported confidence and qualitative reflections. While this provides a vital foundation for exploring intersectional experiences, future studies must expand the sample size and incorporate deeper quantitative and qualitative analyses of learning outcomes and behaviors to complement these perceptions. Furthermore, the qualitative data collection instrument utilized for the post-task reflections was developed specifically for this exploratory study and has not yet been psychometrically validated. The formal validation of this survey instrument is a necessary step and remains a priority for our future work. Finally, while our analysis considered the intersectional dimensions of gender, race, and first-generation status—we did not explicitly study how students' intersectionaly positionality between the identies of socio-economic status (SES), disability status, linguistic background, neurodivergence, and non-traditional student age influence AI perceptions and engagement. As advanced AI tools increasingly transition to paid subscription models, students without the financial means to purchase these

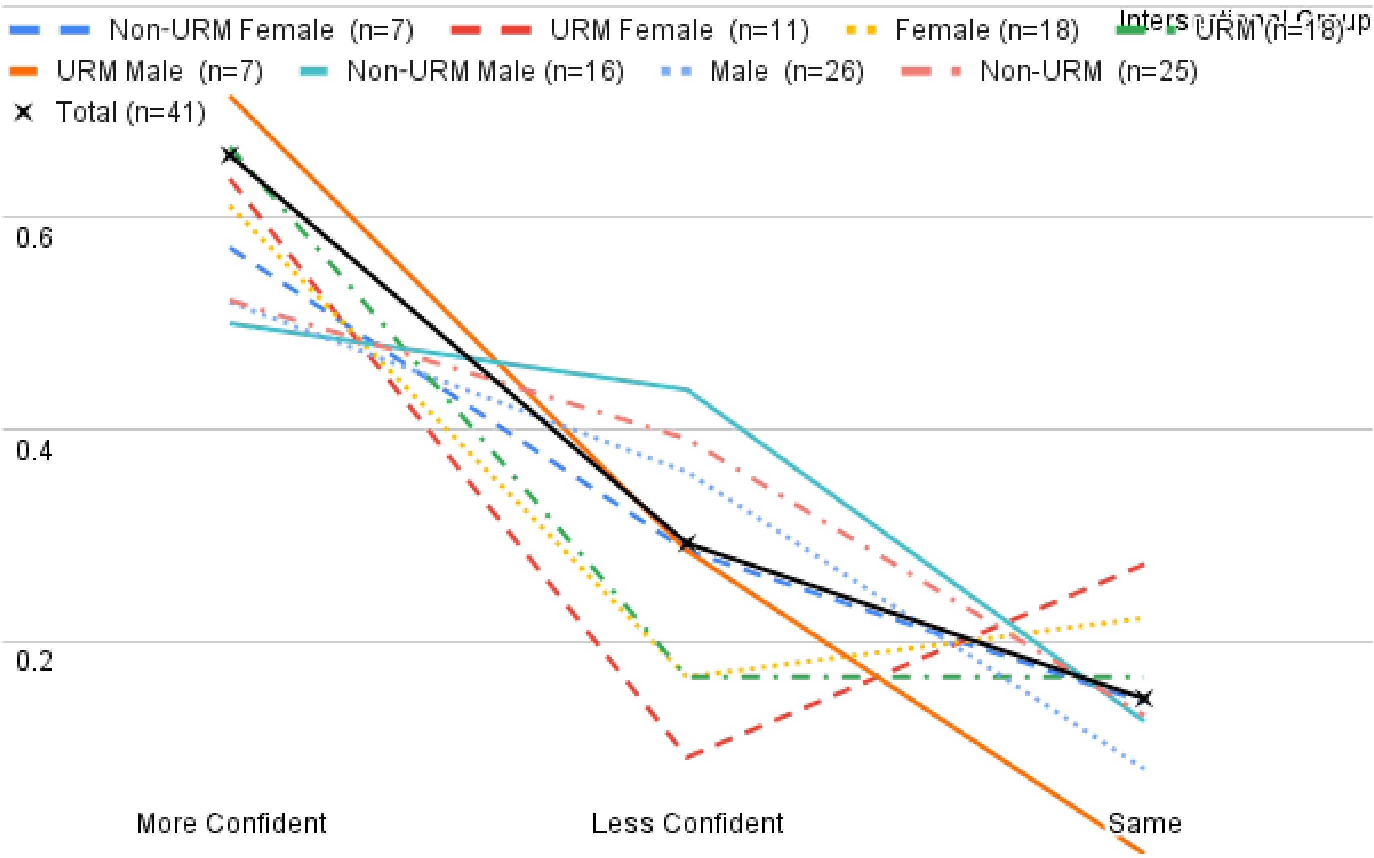

Fig. 5. Q8 How confident are you with programming in JAVA after your experience with using this AI tool?

subscriptions may face a widening gap in access to critical educational technology. Future intersectional research must incorporate SES to fully understand how financial barriers impact AI preparedness and equitable outcomes in programming education.

VIII. Future work

To ensure the integration of AI in programming education does not inadvertently perpetuate existing systemic power imbalances, the research community must pivot from asking simply if AI tools are effective, to asking for whom they are effective and how they can be designed to support all learners equitably. The results of this study can also inform the development of best practices for integrating AI tools into programming education and contribute to a more inclusive and effective learning experience for a diverse student population. We propose the following trajectory for future research:

- Future research must expand upon this exploratory design by deploying large-scale, multi-institutional studies to assess the long-term effects of AI tool usage on students' learning outcomes and attitudes. Tracking students longitudinally will reveal whether early, unstructured access to AI tools bridges the preparation gap or exacerbates disparities in long-term computer science persistence.
- While our findings suggest that gender and race meaningfully shape both interactions with and perceptions of AI tools, future work must broaden this lens. Researchers must systematically measure how variables such as socioeconomic status, disability, neurodivergence, and linguistic background intersect to shape an individual's access and technological preparedness. A first step is to collect sufficient demographic data about students to enable intersectional analyses.
- Moving beyond observational studies, the field must develop and empirically test targeted instructional interventions—such as mentorship programs or confidence-building workshops. Proactive initiatives must be undertaken to bridge the AI literacy gap, ensuring marginalized communities are equipped to leverage these tools ethically and effectively.
- Currently, the educational landscape relies heavily on commercially developed, generalized tools like ChatGPT. Future human-computer interaction research should focus on the participatory design of identity-aware educational technologies.

By actively involving diverse student populations in the design process, we can build intelligent tutoring systems that foster trust, validate competence, and respond to varied cultural contexts. By embracing this intersectional research agenda,

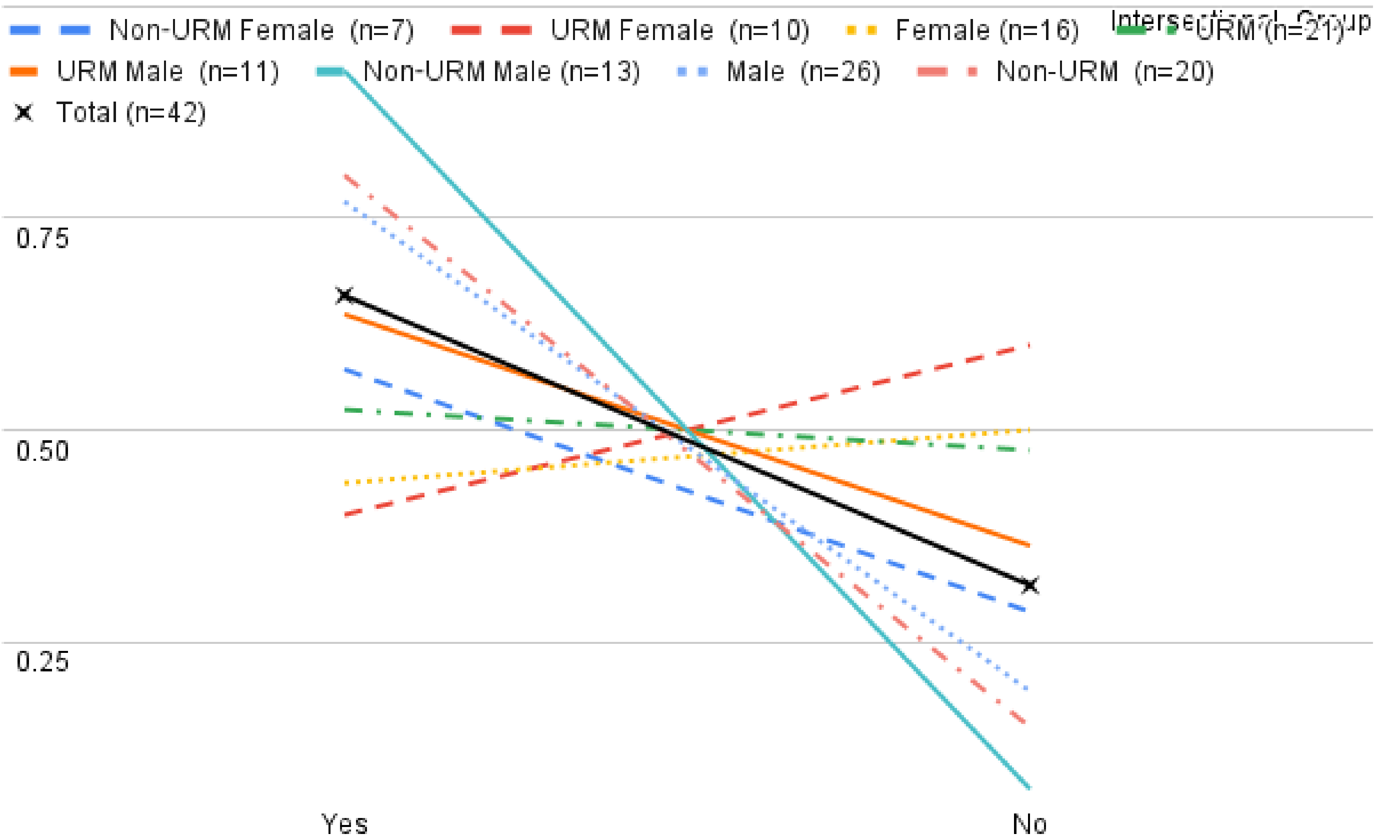

Fig. 6. Q10 Do you have any concerns about the use of AI tools in the classroom and professionally?

the computer science education community can proactively address the complexities of AI integration and establish a truly inclusive and equitable AI ecosystem.

IX. Conclusion

This study design explores the impact of AI tools, such as OpenAI ChatGPT on students' learning and attitudes towards AI in an educational context. By employing a mixed-methods approach, incorporating both qualitative and quantitative data, this study offers a more comprehensive understanding of the participants' experiences, attitudes, and perceptions when using AI-assisted programming tools. The study design contributes to the research community by providing a replicable methodology to assess the effectiveness of AI tools in educational settings. Initial findings suggest that identity plays a significant role in shaping students' experiences with AI tools. The emerging themes offer insight into the potential benefits and limitations of integrating AI tools in programming education. By examining the competency-building and cognitive experiences of students using AI tools during programming tasks with an intersectional lens, we can uncover hidden insights on the impact AI tools in shaping student outcomes and attitudes towards programming and AI technologies.

References

[1] G. Fan, D. Liu, R. Zhang, and L. Pan, "The impact of ai-assisted pair programming on student motivation, programming anxiety, collaborative learning, and programming performance: A comparative study with traditional pair programming and individual approaches," *International Journal of STEM Education*, vol. 12, no. 1, p. 16, 2025.

[2] A. Gilson, C. Safranek, T. Huang, V. Socrates, L. Chi, R. A. Taylor, and D. Chartash, "How does chatgpt perform on the medical licensing exams? the implications of large language models for medical education and knowledge assessment," *MedRxiv*, pp. 2022–12, 2022.

[3] F. Antaki, S. Touma, D. Milad, J. El-Khoury, and R. Duval, "Evaluating the performance of chatgpt in ophthalmology: an analysis of its successes and shortcomings," *Ophthalmology science*, vol. 3, no. 4, p. 100324, 2023.

[4] J. H. Choi, K. E. Hickman, A. B. Monahan, and D. Schwarcz, "Chatgpt goes to law school," *J. Legal Educ.*, vol. 71, p. 387, 2021.

[5] C. Terwiesch, "Would chat gpt3 get a wharton mba," *A prediction based on its performance in the operations management course*, 2023.

[6] L. K. Alford, M. L. Dorf, and V. Bertacco, "Student perceptions of their abilities and learning environment

in large introductory computer programming courses," in *2017 ASEE Annual Conference & Exposition*, 2017.

[7] M. S. Ross, T. L. Fletcher, M. F. Cox, and J. B. Main, "African american women in the academe: a comprehensive literature review through the lens of intersectionality," in *2015 ASEE Annual Conference & Exposition*, 2015, pp. 26–166.

[8] M. Holanda, M. Valadares, S. Cui, and D. Da Silva, "A quantitative study of publications about underrepresented minority undergraduate students in computer science majors in the united states," in *2024 IEEE Frontiers in Education Conference (FIE)*. IEEE, 2024, pp. 1–8.

[9] B. A. Becker, M. Craig, P. Denny, H. Keuning, N. Kiesler, J. Leinonen, A. Luxton-Reilly, J. Prather, and K. Quille, "Generative ai in introductory programming," *Computer Science Curricula*, pp. 438–439, 2023.

[10] A. Lishinski, S. Narvaiz, and J. M. Rosenberg, "Self-efficacy, interest, and belongingness–urm students' momentary experiences in cs1," in *Proceedings of the 2022 ACM Conference on International Computing Education Research-Volume 1*, 2022, pp. 44–60.

[11] S. Y. Tadimalla, M. L. Maher, N. Najjar, and C. Simon, "The impact of ai tools on the student programming experience: Interactions, attitudes perceptions," in *2025 IEEE Frontiers in Education Conference (FIE)*, 2025, pp. 1–10.

[12] J. T. Liang, C. Yang, and B. A. Myers, "A large-scale survey on the usability of ai programming assistants: Successes and challenges," in *Proceedings of the IEEE/ACM 46th International Conference on Software Engineering*, ser. ICSE '24. New York, NY, USA: Association for Computing Machinery, 2024. [Online]. Available: https://doi.org/10.1145/3597503.3608128

[13] J. H. Shen and A. Tamkin, "How ai impacts skill formation," *arXiv preprint arXiv:2601.20245*, 2026.

[14] L. Porter and D. Zingaro, *Learn AI-assisted Python programming: with github copilot and ChatGPT*. Simon and Schuster, 2024.

[15] J. Wei, Y. Tay, R. Bommasani, C. Raffel, B. Zoph, S. Borgeaud, D. Yogatama, M. Bosma, D. Zhou, D. Metzler *et al.*, "Emergent abilities of large language models," *arXiv preprint arXiv:2206.07682*, 2022.

[16] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, and I. Sutskever, "Language models are unsupervised multitask learners," 2019, technical report, OpenAI.

[17] P. Haluptzok, M. Bowers, and A. T. Kalai, "Language models can teach themselves to program better," *arXiv preprint arXiv:2207.14502*, 2022.

[18] P. Vaithilingam, T. Zhang, and E. L. Glassman, "Expectation vs. experience: Evaluating the usability of code generation tools powered by large language models," in *CHI Conference on Human Factors in Computing Systems Extended Abstracts*. ACM, 2022, pp. 1–7.

[19] B. Yetistiren, I. Ozsoy, and E. Tuzun, "Assessing the quality of github copilot's code generation," in *Proceedings of the 18th international conference on predictive models and data analytics in software engineering*, 2022, pp. 62–71.

[20] N. Nguyen and S. Nadi, "An empirical evaluation of github copilot's code suggestions," in *Proceedings of the 19th International Conference on Mining Software Repositories*, 2022, pp. 1–5.

[21] M. Wermelinger, "Using github copilot to solve simple programming problems," in *Proceedings of the 54th ACM Technical Symposium on Computer Science Education V. 1*. ACM, 2023, pp. 172–178.

[22] M. A. Verleger and J. J. Pembridge, "A pilot study integrating an ai driven chatbot in an introductory programming course," in *2018 IEEE Frontiers in Education Conference (FIE)*. IEEE, 2018, pp. 1–4.

[23] F. Pedró, M. Subosa, A. Rivas, and P. Valverde, *Artificial intelligence in education: Challenges and opportunities for sustainable development*. UNESCO, 2019.

[24] Y. Dong, P. Shabrina, S. Marwan, and T. Barnes, "You really need help: Exploring expert reasons for intervention during block-based programming assignments," in *Proceedings of the 17th ACM Conference on International Computing Education Research*, 2021, pp. 334–346.

[25] Y. A. Rankin and J. O. Thomas, "The intersectional experiences of black women in computing," in *Proceedings of the 51st ACM technical symposium on computer science education*, 2020, pp. 199–205.

[26] K. Rainey, M. Dancy, R. Mickelson, E. Stearns, and S. Moller, "Race and gender differences in how sense of belonging influences decisions to major in stem," *International journal of STEM education*, vol. 5, pp. 1–14, 2018.

[27] S. Y. Tadimalla, C. Latulipe, M. L. Maher, M. Mejias, J. Payton, A. Rorrer, J. Fiore, G. Kwatny, and A. Rosen, "Enabling investigation of impacts of inclusive collaborative active learning practices on intersectional groups of students in computing education," in *2023 IEEE Frontiers in Education Conference (FIE)*. IEEE, 2023, pp. 1–10.

[28] S. Y. Tadimalla, M. L. Maher, A. Rorrer, M. Dorodchi, M. Mejias, and N. Najjar, "Connecting the dots: Intersectionality across active learning, classroom climate, and introductory computer science courses," in *Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 1*, 2025, pp. 1099–1105.

[29] M. C. Bottia, R. A. Mickelson, C. Jamil, K. Moniz, and L. Barry, "Factors associated with college stem participation of racially minoritized students: A synthesis of research," *Review of Educational Research*, vol. 91, no. 4, pp. 614–648, 2021.

[30] J. Anderson, L. Rainie, and A. Luchsinger, "Artificial intelligence and the future of humans," *Pew Research Center*, vol. 10, no. 12, 2018.

[31] H. Liu, Y. Wang, W. Fan, X. Liu, Y. Li, S. Jain, Y. Liu, A. Jain, and J. Tang, "Trustworthy ai: A computational perspective," *ACM Transactions on Intelligent Systems and Technology*, vol. 14, no. 1, pp. 1–59, 2022.

[32] M. Wollowski, “Using chatgpt to produce code for a typical college-level assignment,” *AI Magazine*, vol. 44, no. 1, pp. 129–130, 2023.
[33] K. Malinka, M. Perešíni, A. Firc, O. Hujňák, and F. Januš, “On the educational impact of chatgpt: Is artificial intelligence ready to obtain a university degree?” *arXiv preprint arXiv:2303.11146*, 2023.
[34] C. Geng, Y. Zhang, B. Pientka, and X. Si, “Can chatgpt pass an introductory-level functional language programming course?” *arXiv preprint arXiv:2305.02230*, 2023.
[35] M. L. Maher, S. Y. Tadimalla, and D. Dhamani, “An exploratory study on the impact of ai tools on the student experience in programming courses: an intersectional analysis approach,” in *2023 IEEE Frontiers in Education Conference (FIE)*. IEEE, 2023, pp. 1–5.
[36] J. Saldana, *The coding manual for qualitative researchers*, 4th ed. SAGE Publications Limited, 2021.