Tool or Toy? Student Views on ChatGPT in Culturally Responsive Computing Education: A Preliminary Study

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***Abstract*—Despite ongoing efforts to diversify engineering, underrepresented minority (URM) students face persistent systemic barriers to equitable participation. Beyond just access, culturally relevant pedagogy (CRP) and near-peer mentorship have shown to improve student engagement and retention. However, the currently sparse pool of URM STEM graduates limits students' access to formally educated mentors of similar cultural and ethnic backgrounds, challenging the scalability of representative CRP-based engineering programs. Free AI tools like large language models (LLMs) can offer novice programmers natural language support for debugging code and exploring new concepts, but it remains unclear whether they can provide enough technical support to help scale URM-led engineering education programs. We investigate the potential for LLMs, specifically ChatGPT 3.5, to meaningfully support CRP in an embedded systems summer course taught at a community center within the AVELA - A Vision for Engineering Literacy & Access framework. We ask how URM students will naturally adopt ChatGPT within the educational program when presented without scaffolding: as a learning tool to enhance their knowledge of class-related content, or as a toy that distracts from it? Analysis of classroom observations, student surveys, final presentations, and individual ChatGPT logs revealed a disconnect between students' personal interest and the course objectives. While students were able to use ChatGPT for course-related learning, they rarely did so. Instead, they primarily used it to enhance their knowledge of topics related to personal interest, suggesting a lack of motivation or perceived relevance of ChatGPT as a tool, rather than a lack of ability to use it. These preliminary findings suggest that without intentional integration and guidance, CRP frameworks cannot expect students to effectively leverage ChatGPT to enhance engineering related content.**

***Index Terms*—Engineering Education, Large Language Models, Software tools, Culturally Relevant Pedagogy**

Fig. 1. Students presenting their smart hydroponic farm prototype at William Grose Center for Cultural Innovation to community members and peers.

I. Introduction

The "digital divide", or gap between those with access to technology and digital literacy and those who do not [1], is not always the main barrier of entry to engineering fields. For Black/Latine underrepresented minority students (URM) a lack of culturally supportive learning environments is also a key barrier [2]. Near-peer mentorship and classrooms that uplift URM identities culturally responsive and relevant pedagogy [3]–[5] and liberatory computing [6] increase student engagement, retention, and success in STEM fields [2], [7]. Unfortunately these frameworks are difficult to scale. Black and Hispanic/Latine demographics comprise only 14% of the U.S. engineering workforce and 19% of STEM bachelor's degree holders, despite making up more than 33% of the total U.S. population [8]–[10]. This limits the availability of technically proficient and culturally representative mentors for URM students. This gap renders many URMs unprepared or unable to participate in STEM [9], [11], [12], resulting in many URM communities without the capacity to advocate for change or benefit from economic opportunities in growing technological fields. However, while URM students may be limited in their access to both culturally representative *and* technically trained mentors, can they leverage other technical tools to support their learning?

Artificial Intelligence (AI) tools like ChatGPT that are built upon LLMs are transforming how students access and engage with technical content. In computing education, they have shown notable benefits for novice learners, including real-time code generation, natural language explanations of complex topics, and support for self-paced learning [13], [14]. Prior works indicate that LLMs have the potential to accelerate productivity in embedded systems, especially among students with limited prior experience [14], [15]. These advantages make LLMs promising instructional support tools, especially when access to experienced mentors is limited.

The growing use of LLMs in education is not without concern. LLMs frequently exhibit "hallucinations", instances where the LLM confidently outputs false or fabricated information [16], and are trained on internet-scale data that can encode and reproduce harmful biases [17]. These issues are particularly salient in multicultural learning contexts, where cultural assumptions or inaccurate guidance can disproportionately affect URM learners [3]. Despite their increasing popularity, little is known about how URM students engage with LLMs in practice. We explore the following **Research Question: Do students, without explicit instruction on how to use AI, adopt ChatGT as a tool to further their learning in a culturally responsive course, or as a novel toy, pulling their focus away from class content?**

We conduct this study within the AVELA - A Vision for Engineering Literacy & Access (AVELA) framework [2], [7] to inform strategies for effectively integrating AI-driven support into culturally responsive pedagogy (see Fig. 1). This study makes the following specific contributions to the emerging body of research on AI-assisted learning in culturally responsive computing education:

- **Characterization of Natural Engagement.** We investigate how students interact with ChatGPT without explicit scaffolding, assessing if they adopt it as a tool for academic support, comparable to traditional tools, or treat it as a novelty with limited instructional value.
- **Evaluation of ChatGPT Use Cases in CRP.** We analyze students' ChatGPT prompts to understand how it can be used in a culturally affirming classroom environment to uplift students' interests and identities. This includes identifying patterns of engagement, topic focus, and prompt construction quality.
- **Implications for Future Research and Instruction.** Our preliminary findings point to the need for further research into how LLMs can be integrated into equity-centered learning environments. Our study lays the groundwork for future investigations on how to scaffold student and instructor use of AI tools to support culturally responsive technical education, particularly in contexts with limited access to technically-expert near-peer mentors.

II. Background and Related Works

Despite growing excitement about how AI and LLMs, like ChatGPT-3.5, can be used in education, there is a lack of research addressing how these tools affect URM students' learning experiences in engineering. While prior work has deeply explored culturally responsive pedagogy and equity-centered frameworks in CS education [2], [5]–[7], [18], [19], little is known about how LLMs can aid the enactment of these approaches to teaching and learning. For instance, social design experiments and intergenerational co-design have shown promise in promoting equity by embedding cultural context into the learning process [20]–[22]. Unfortunately, there are too few technical experts to serve the needs of the many young people who wish to learn. This is where AI-assisted learning tools, like the ChatGPT-3.5 LLM, hold potential to support instruction, but not without concern. As LLMs have previously supported novice programmers in debugging, ideation, and developing frameworks of functions [13]–[15], they may help fill instructional gaps in under-resourced classrooms [23] by providing technical expertise. However, without culturally responsive scaffolding and critical engagement students risk using hallucinated or generalized answers that either strip away at learning objectives or stifle student creativity and ability to incorporate their lived experiences in their learning [3], [14], [24], perpetuating the very inequities we aim to alleviate.

A. Culturally Responsive Pedagogy (CRP)

CRP is an educational framework that leverages students' cultural backgrounds, experiences, knowledge, and consciousness as foundational to effective teaching and learning [5]. Culturally Responsive Computing (CRC) is an extension of CRP in engineering, computing, and related concepts [25]. CRC emphasizes the need for teaching strategies that are relevant and responsive to the students' cultural backgrounds and lived experiences with the learning content [26]. Among these strategies emerges the newer framework of "Liberatory Computing" centering racial justice, identity development, and critical consciousness within computing education [6]. Rooted in Black radical traditions and critical pedagogy, this approach positions computing not only as a technical skill but as a tool for social transformation. The framework aims to have students develop activism skills through a sound racial identity that enable them to confront and transform the multilayered systems of oppression in which racism persists through computing and digital technologies [6], [27].

CRP addresses the barriers of entry in computing and engineering that span beyond the digital divide. Even with URM students who have physical access to technology, they still experience marginalization in computing classrooms [7]. Liberatory Computing ensures that Black students cultivate a strong racial identity, critical consciousness, collective obligation, and a liberation-centered academic and achievement identity.

Previous studies with the AVELA framework found that students from Black and Latinx urban communities were hesitant to use school-provided computing tools due to the absence of engaging, culturally affirming learning environments [2]. This hesitancy is compounded by the lack of visible URM mentors and educators in computing [28], contributing to students' alienation and weakening their STEM aspirations. These findings underscore the need to go beyond technology access and address deep-rooted cultural and representational inequities. Without frameworks that affirm students' racial identities while linking their lived experiences to class content through representative mentors and relevant projects, students may see computing as irrelevant, or even as reinforcing systems of exclusion. Yet, scaling culturally responsive practices remains difficult, as its teaching is rooted in social relationships, and Black and Latinx professionals make up just 14% of the engineering workforce and 19% of STEM degree holders in the U.S. [8], [10]. This shortage of technically trained, culturally representative mentors presents a major barrier to scaling effective programs, one that innovative technologies like AI may help bridge [29].

B. Promises and Perils of ChatGPT in Education

ChatGPT can produce convincing but flawed code. For embedded systems, these flaws can manifest as code that is inconsistent with correct models of hardware, potentially misleading students with less technical fluency [15], [30]. These limitations also appear in explanations of physical tasks. ChatGPT-3.5 can generate inaccurate instructions for circuit wiring or system setup. It may even produce distorted, inaccurate instructions, or misleading schematic diagrams, adding confusion rather than clarity [16], [30]. Additionally, bias in ChatGPT outputs can subtly reinforce stereotypes and harmful assumptions about marginalized groups [3], often under the guise of neutrality [27].

While existing studies highlight the benefits and drawbacks of ChatGPT, they largely center on traditional programming in well-resourced, majority-student contexts. Our study extends this work by examining how URM students engage with ChatGPT in a culturally responsive setting. Rather than focusing solely on correctness, we consider how students relate to the tool in terms of identity, interest, and learning goals.

III. Methods

A. Positionality

Our team is primarily composed of URM researchers. Four identify as black, one identifies as Hispanic, one identifies as Asian, and one identifies as white. At the time of writing, all authors are active members, contributors, or partners of the AVELA nonprofit through which the class was taught. As people affiliated with predominantly white institutions, we are attuned to the systemic inequities facing URM students in computing. Many of us are also experienced educators and active users of LLMs, which informs our dual perspective as both practitioners and researchers. We acknowledge that our connection to AVELA and interactions with LLMs may shape how we interpret data and frame conclusions; however, we believe our positionalities offer culturally informed insights and strengthen the study's relevance. By naming these positional dynamics, we aim to support transparency and allow readers to better understand our interpretive lens.

B. Embodiment of Study

The study examines how URM students in culturally responsive embedded systems courses engage with and perceive ChatGPT when it is freely available for classroom use, without scaffolding. The course was taught over 8 weeks in the summer at the William Grose Center for Cultural Innovation using 40 hours of embedded systems content from AVELA's culturally responsive computing framework [2], [7]. Students were provided laptops with the Arduino software, Arduino toolkits with the Arduino microcontroller, a breadboard for prototyping, and a variety of sensors and user interface devices like soil moisture sensors and display screens for them to use in their final projects. AVELA also provided each student a new ChatGPT-3.5 account to track their logs. The course objective was to design a "Smart Farm" - a system to automatically water William Grose Center for Cultural Innovation's microgreens farm whenever the soil was detected as being dry. The AVELA framework provided culturally relevant instruction, mainly in framing the content around the context of URM farming and allowing students to explore notable URM figures in farming and how their own identities can tailor how they approach their final projects. Fig. 2 outlines our study conjecture, linking the class outlines and provided materials to the data we expected to collect and observe, to our anticipated class outcomes.

The course engaged 18 URM secondary students and 2 Black, male, near-peer instructors, both with mentorship experience, but only one with technical embedded systems knowledge [29]. Table I overviews the demographics of the 8 students who completed the course, although they may not have completed the course objective and final project. Most students were recruited through the William Grose Center for Cultural Innovation community via email blasts, or word-of-mouth. This study was approved by the University of Washington's IRB. Written consent and assent were obtained from all participating students and parents prior to data collection. We also note that while the AVELA model focuses on engaging URM students, this course welcomed students of all backgrounds.

Both peer-to-peer and near-pear mentor-to-peer conversation was encouraged to engage with students on personal levels to help them feel more connected with the class content [18], [31], [32]. Near-peer mentorship was vital for affirming the students' identities in the space as assets and in motivating them to see themselves as capable to complete class objectives. Notably, instructors simply gave students permission to use ChatGPT-3.5 as a resource to help them when they got stuck alongside other traditional tools like Google and StackOverflow. Although students were not provided with thorough training on how to use ChatGPT-3.5 for their

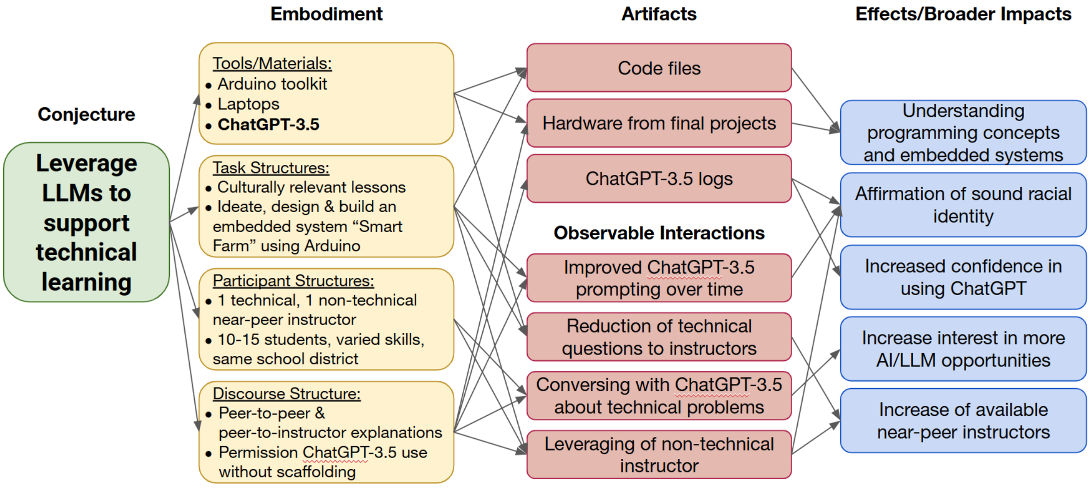

Fig. 2. Conjecture map illustrating the theoretical framework guiding this study. Linking tools like Arduino & ChatGPT, student and task structures, and discourse patterns to observable student behaviors and learning artifacts, showing hypothesized pathways to expected outcomes.

projects, instructors provided a brief overview on what ChatGPT-3.5 was and how it can be prompted with questions to give all students a similar baseline understanding. Students were not explicitly encouraged to use any one tool or the other to allow us to explore how and if they naturally engage with ChatGPT-3.5 as a learning tool.

C. Surveys

We conducted pre- and mid-way surveys to assess students' interest in the course content and perceptions of ChatGPT. The surveys included Likert-scale questions (1 = Strongly Disagree to 5 = Strongly Agree) measuring students' self-efficacy to use ChatGPT to successfully get the answers they were looking for, their interest in ChatGPT, their interest in Arduino, their confidence in finishing the project, ability to communicate their problems to both ChatGPT and human instructors, and their learning styles. This data was used to assess students' growth and opinion changes throughout class.

D. ChatGPT-3.5 Log Analysis

To better understand how students engaged with ChatGPT during the course, we analyzed 32 unique prompts submitted directly by students. These prompts were written independently by the students without instructor assistance. Although all students were familiar with ChatGPT, only 8 of the 18 Students used it at least once over the 12-week course. We analysized the ChatGPT-3.5 logs through consensus-based inductive thematic analysis [33]–[35]. The first researcher reviewed all student prompts and generated initial codes through consistent themes that came up within the data itself. A second researcher, blind to the first coder's assignments, independently applied the same coding framework to the dataset. Inter-rater reliability was calculated using Cohen's Kappa [36] to assess agreement across themes. To condense into 8 unique themes, discrepancies were discussed and reconciled to ensure the validity of the final categories. Each prompt was assigned to up to 4 themes, and a manual spreadsheet was used to log and organize the data.

TABLE I
OVERVIEW OF INTERVIEWED STUDENTS' DEMOGRAPHICS, CHATGPT EXPOSURE, AND PROJECT COMPLETION.

Student ID	Project Completed	Gender	Race/Ethnicity	Grade	ChatGPT Exposure
1Red	Yes	Male	Asian/Pacific Islander	9th	-
4Yellow	Yes	Male	Black/African American	9th	-
9Saphire	No	Male	Black/African American	8th	Weekly
10Emerald	Yes	Female	Black/African American	11th	Monthly
11FireRed	No	Female	Black/African American	8th	-
13Diamond	No	Female	Black/African American	11th	-
18White	Yes	Male	Black/African American	12th	Never
19Black	Yes	Female	Black/African American & Asian/Pacific Islander	12th	Weekly

IV. RESULTS

The results of our study offer valuable insights into how URM students engage with ChatGPT without traditional scaffolding. Out of the total 18 students who participated in the course, we received consent from and analyzed the ChatGPT logs and survey responses of 8 of those students. While initial interest in ChatGPT was high, our analysis reveals a complex interplay of student preferences and usage patterns, often diverging from the intended academic application.

A. Final themes and definitions:

The ChatGPT logs were categorized into eight distinct themes to better understand how students interacted with the AI tool. These themes are listed below, with Fig. 3 which illustrates the Cohens Kappa agreement value for each theme and shows the prominence of each theme in students' prompts:

1) **ChatGPT Sensibility:** Prompts intending to understand ChatGPT, such as questions about its sensibility, morality, and general functionalities.

2) **Coding/Software Questions:** Prompts related to coding errors and coding-related inquiries from the students both for class-related and non-class-related topics.
3) **Idea Expansion:** Prompts where students used GPT to elaborate on personal or class-related concepts.
4) **Lack Of Prompt Technique:** Prompts that lacked depth or framing to effectively achieve a desired response.
5) **Gaming Questions:** Prompts that focused on non-course related, gaming interests that students pursued during their leisure time.
6) **Personal Questions:** Prompts related to the students' personal lives or experiences.
7) **Hardware Questions:** Prompts revolving around hardware and circuitry both for class-related and non-class-related topics.
8) **Proper Prompting Technique:** Prompts demonstrating effective prompting strategies while to achieve desirable responses without the need for reframing.

B. Students Gravitate Towards Human Instructors

We were motivated to understand students' self-reported favored modality for seeking help in class and if access to ChatGPT had any affect. Our pre-survey indicated a strong initial interest in using ChatGPT for problem-solving (89% agreed/strongly agreed), yet confidence was lower at 50%. Simultaneously, 56% of students preferred one-on-one instructor time, and a significant majority (83%) were confident in communicating with instructors. Midway through the course, while confidence in instructor communication increased to 92%, self-perceived interest and ability to use ChatGPT for answers to course content decreased to 67%. Confidence in communicating with instructors seems inversely related to their confidence in using ChatGPT, suggesting that students pulled away from ChatGPT-3.5 and towards the near-peer instructors as class progressed.

Our classroom observations showed that the students who completed their final projects and presented at the William Grose Center for Cultural Innovation relied heavily on instructor support instead of ChatGPT, despite having used it prior to class. As Student 18 was 1 of 5 consenting students who completed the final project, their only prompt was:

> *how to do a function in arduino*
> **– Student 18**

Yet they were still able to successfully complete their project, indicating that their ChatGPT usage was not a significant enabler in their success in the class. Fig. 4 categorizes the students based on three criteria: (1) over 50% of prompts aligned with course content, (2) over 50% used proper prompting techniques (per methods), and (3) completion of the final project. Although Fig. 4 illustrates that four students who finished the class objectives demonstrated both proper prompting technique and prompted with class related questions, there was also three students who prompted properly and stayed on topic without being able to complete the class. This further emphasizes that access to ChatGPT and the ability to prompt on-topic questions are still insufficient in enabling some students to complete Arduino projects.

In contrast, while Student 4 used ChatGPT throughout the course for off-topic questions, their class related prompts fell under **Idea Expansion** about the "Smart Farming" aspect of the course rather than coding or hardware support.

> *why does rain happen*
> **– Student 4**

Student 4 is an example of one of the few students who both found interest in using ChatGPT and completed the class objectives as stated in Fig. I. As students 18 and 4 had similar class outcomes while having significantly different engagement with ChatGPT, our evidence agrees with prior works that until LLMs are relevantly scaffolded into education, they are more nice-to-have than they are a barrier of success in engineering courses.

C. Misalignment Between Prompt Topics & Course Objectives

There was a clear misalignment between student prompt topics and the class objectives. While 63% of all prompts dealt with some kind of coding, both for class related and non-class related topics, or hardware inquiry, 50% of all prompts were off topic. Students used ChatGPT to engage in a myriad of topics with 12.5% being about **Gaming** and 18.8% about **GPT-Sensibility**. As Student 4 was one of the students who used ChatGPT more heavily in class it is significant to note that 5 out of their 6 prompts were non-class related.

> *what are you ask me a question*
> **– Student 4**

During the student's beginning usage of ChatGPT, not only did many of their prompts lack depth, but they also seem more interested in understanding ChatGPT's sensibility rather than simply diving in to use it. The student later starts using it for their own enjoyment.

> *what does qwerty mean*
> *best character in honkai star rail?*
> **– Student 4**

While Student 4 did attempt to expand on the environmental aspect of the course context by prompting about rain, the student did not take this opportunity to further explore topics of rain or farming with ChatGPT, nor the instructors.

Other examples of student interest in ChatGPT sensibility arise when students ask ChatGPT about itself, before asking follow-up questions to have ChatGPT fact check itself.

> *what time knowledge are you capped at*
> **– Student 13**

When ChatGPT shared its knowledge was capped at September 2021, the student followed up their prompt with a question about a popular game known as "Brawl Stars:"

> *what is the most recent brawl stars update*
> **– Student 13**

ChatGPT then responded with:

> *The most recent Brawl Stars update, known as the Bizarre Circus Update, includes several new features, balance changes, and game modes.*

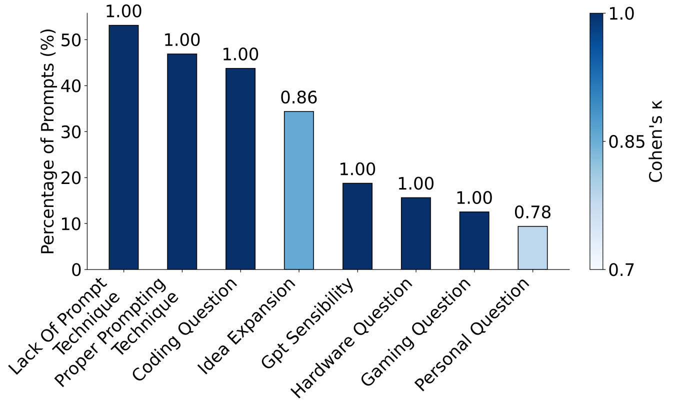

Fig. 3. Frequency of coded themes across student-generated ChatGPT prompts, with color indicating the level of researcher agreement.

The "Bizarre Circus" update released in 2023, meaning ChatGPT's answer on it's knowledge cap was either incorrect or misleading. While unrelated to class content, our conjecture map outlined a hope to see students' improved prompting over time. Fact-checking and critical engagement is beneficial for the students to transform their consumption of outputs from passive to active to develop higher-order thinking. In the case of Student 13, after their off-topic engagement with ChatGPT, by their 3rd day of prompting their prompts were completely on-topic, suggesting an increase in comfortability and trust in the tool. If students are able to gain trust in the tool over time, it is even more critical that they are taught to implement fact-checking and critical thinking before over-reliance becomes a deterrant to learning.

Student 10 uniquely prompted ChatGPT about their own name to see what information ChatGPT would be able to pull from the internet about themselves or about who ChatGPT thinks they are. Although ChatGPT did not return specific information about this student, it mentioned someone of African descent with a similar name who's role focuses on women, peace, and security in Africa. ChatGPT's ability to provide information on someone of the same racial, ethnic, and gender background as the student aides in affirming the student's sound racial identity within the context of the class, which we expected to see from the ChatGPT-3.5 logs (fig. 2). Although the information ChatGPT produced was correct, there was a slight difference in the actual name of the person it was trying to produce that would not have been caught without fact-checking with secondary sources. The student asked no follow up questions to that prompt.

D. Predominantly Exploratory and Recreational Use

Despite the majority of the class having prior familiarity with ChatGPT, most usage leaned towards exploratory learning rather than low-level, class-related topics.

We coded 34% of all prompts as **Idea Expansion**. This theme focused on students who used ChatGPT for high-level elaborations on personal or class-related concepts. As previously mentioned, while Student 4 expanded upon the idea of rain, the lack of follow up or integration of this knowledge into their final project demonstrates an expectant high-level understanding. Other student prompts which fell under this theme *and* were related to class topics also demonstrated high-level understanding with either a lack of knowledge of the concept they were trying to prompt about, improper prompting technique, or lack of follow up.

> *how do u start c coding app*
> **– Student 11**

> *1 second in milliseconds*
> **– Student 19**

Students who were able to expand on ideas in a low-level, did so for personal interests outside of the class topics.

> *What are some important things to learn in roblox coding. What are all of the terms? explain what they are and briefly explain what they do*
> **– Student 9**

> *What are some of the most important things to learn in roblox studio coding for scripting*
> **– Student 9**

> *how do you code movement in unity, how to code unity movement WASD on 3d model*
> **– Student 19**

These findings demonstrate students predominantly engaging with ChatGPT in an exploratory and recreational manner, often diverting from course objectives to pursue personal interests or test ChatGPT's capabilities in non-academic contexts.

E. Disconnect Between Observed Interest and GPT Prompts

Although students showed enthusiasm for hardware in class, their prompt logs showed they did not use ChatGPT to develop those understandings. 2 Of 3 students who asked hardware themed prompts asked:

> *what is a parallel circuit?*
> **– Student 9, 10**

The fourth prompt was a copy and pasted Arduino code error:

> *Compilation error: Missing FQBN (Fully Qualified Board Name) I am trying to run my code in arduino but i am running into an error with a missing board name. What next steps do i need to take in order to solve this problem*
> **– Student 13**

This pattern, where students' observed enthusiasm for practical activities did not translate into substantial use of ChatGPT for learning, is highlighted with hardware-related questions.

F. Insufficient Prompting Skills

In total, 47% of prompts exhibited **Proper Prompting Technique**, compared to 53% showing a **Lack Of Prompt Technique**. Proper prompting technique refers to students who demonstrated effective prompting to achieve their desired results from GPT through highly detailed, unambiguous prompts [15], while a lack of prompting technique indicates instances where students did not effectively communicate their needs. A significant portion of poorly constructed prompts hindered the quality and usefulness of the generated responses.

Student 9 exemplified progressed understanding of prompting. In one of their early prompts they ask:

> *What are some of the most important things to learn in roblox studio coding for scripting*
> **– Student 9**

When they realized that ChatGPT wasn't providing their desired solution, they became less ambiguous and prompted:

> *What are some of the most important things to learn in Roblox studio coding for scripting? Explain things like functions, if statements, and veriables*
> **– Student 9**

This progress demonstrates a need for students to be highly detailed and unambiguous to achieve a desired results. However, most prompts that demonstrated a lack of prompting technique were copied error codes without any additional question, follow up, or clarity included in the prompt to detail what exactly the student wanted to gain from ChatGPT.

Student 9 provided ChatGPT with a role, context, and constraints; however for the embedded systems class, the same student simply copied and pasted an error as the prompt:

> *Error Verifying new_sketch_1721336436255*
> **– Student 9**

This example demonstrates students' over-reliance on ChatGPT to understand the errors and lack of ability to articulate what they are trying to solve.

Student examples of proper prompting technique include instances where students clearly stated what they were trying to gain, how they wanted ChatGPT to go about its explanation, or left minimal room for ambiguity.

> *What are the main tools used in coding and briefly explain what they are and what they do.*
> **– Student 9**

> *how to code unity movement WASD on 3D model*
> **– Student 13**

> *1 second in milliseconds*
> **– Student 19**

Without providing context, the lack of prompting technique limits the usefulness of ChatGPT's response.

G. Need for Scaffolding and Structured Support

The mid-course survey data revealed that even towards the end of class, students varied in knowledge levels of both Arduino and ChatGPT. 67% of students either agreed or somewhat agreed with the statement "I am knowledgeable about Arduino or other similar computing topics" while 33% disagreed with that statement, indicating a potential gap that may require more introductory scaffolding. Additionally, 100% of students had agreeance with the statement: "I am able to use ChatGPT to get the answers I am looking for", but only 25% indicated interest in using ChatGPT to help them solve problems. Even with 100% of students indicating they felt able to use ChatGPT to get the answers they needed, 83% of students agreed with the statement: "I find it difficult to debug my programming projects". This demonstrates a disconnect between students' perceived ability to utilize ChatGPT versus their struggle in situations where ChatGPT could have been a tool.

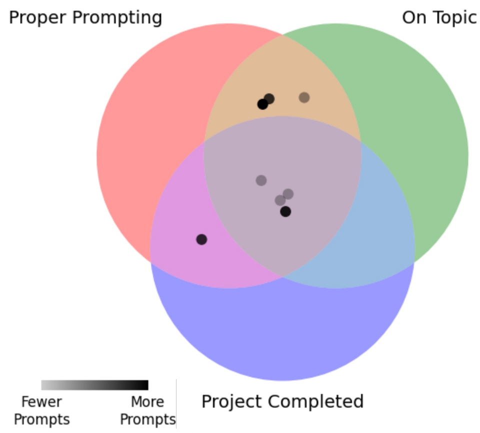

Fig. 4. Venn diagram categorizing students based on whether more than 50% of their prompts were on-topic with course content, more than 50% demonstrated proper prompting technique as defined in the methods, and whether they completed the final class project.

Student summaries from the mid-course survey, further reinforce the need for scaffolding. For example, Student 18 went from "somewhat disagree" to "somewhat agree" for the statement of "I usually need extra support in class". Contrary to our expected effect in Fig. 2, Student 9 lessened in agreeance with the statement "I am knowledgeable about Arduino or other similar computing topics" These student experiences collectively demonstrate a clear need for more structured guidance to effectively engage with both the course material and AI tools, ultimately supporting the meaningful integration of AI into their learning process. Most student feedback in the midway survey indicated an understanding of both the promises and limitations of ChatGPT use for learning.

> *it limits the ability to think of ideas creatively*
> **– Student 10**

> *Its useful but it shouldn't be relied on too much to the point where it becomes a crutch*
> **– Student 18**

> *Depends how it's used, it can be both good and bad*
> **– Student 20**

V. Discussion

This preliminary investigation reveals a significant gap between students' access to LLMs like ChatGPT, and their ability to effectively use them in a culturally responsive environment to achieve classroom objectives. While all students were familiar with ChatGPT, few used it for class content. Instead, most interactions were exploratory or recreational, suggesting in order to be used as "tools" rather than "toys" in the classroom, AI tools need intentional integration, scaffolding, and active engagement.

Although 42% of student prompts focused on coding, the majority were not aligned with course objectives. Only 18% of prompts addressed hardware, despite all students showing strong engagement during hands-on hardware activities. This suggests students recognized ChatGPT's technical potential, but lacked the scaffolding, motivation, or skill to apply it effectively for classroom learning. Yet, why were they eager to experiment with it, but reluctant to use it for classwork? This may reflect a form of subtle resistance: students gravitated toward ChatGPT for topics that felt personally meaningful, instead of those in the curriculum. Prior works indicate that students understand a need for fairness when using AI tools [3], [37] and our data shows an increased interest in ChatGPT for personal interest, positioning it well for use within liberatory pedagogies. This supports Liberatory Computing classroom models that center students' identities, interests, and cultural experiences, in the design of AI-integrated learning environments [6]. Students struggling with the material often prioritized interacting with technically experienced mentors over inexperienced mentors with the aid of ChatGPT. This reinforces the idea that effective integration of LLMs into education demands more than availability; it requires thoughtful instructional design that connects AI use to students' immediate learning needs. Effective LLM integration must bridge students' personal curiosities with curricular goals [7], [14].

Prompting technique is also a constraint of using ChatGPT as a learning tool. We coded less than half of prompts as demonstrating effective prompting technique, with a bit over half reflecting limited skill in interacting with ChatGPT, leading to prompts that lacked either clarity or detail.

Our team had hoped that in addition to learning about engineering, further immersing students in engineering through having access to ChatGPT would increase their interest and understanding of both embedded systems and AI/LLM (Fig. 2). Unfortunately, several students also reported anxiety about completing the final project and difficulty debugging programs, both of which suggest the need for clear milestones, targeted support, and confidence-building strategies throughout the course.

These findings align with broader literature emphasizing that AI integration in education must be intentional, culturally responsive, and supported by structured scaffolding. As the internet entered educational settings in the 1990s, meaning learning occurred not through unrestricted access, but through carefully designed scaffold that helped students navigate the internet critically and purposefully [38]. Rather than banning LLMs or assuming students will intuitively use them for learning, educators must guide their use through explicit instruction, critical reflection, and inquiry-based engagement. Effective integration requires environments that connect students' digital curiosity with technical skill-building and personal relevance, especially in classrooms serving URM learners. Future work should address both the potential challenges and promises of LLMs in URM education. We recommend the following:

A. Active Engagement and AI Literacy Instruction

Instructional time should be allocated to teach students how to effectively use tools like ChatGPT, particularly for programming help, debugging, and idea generation. Our results coupled with prior works demonstrate that access to technology and novel tools is simply not enough [2], [7]. Novice embedded systems students require clear guidance to move beyond shallow prompts and toward productive, iterative interactions with LLMs [15], [25].

B. Critical Engagement with AI Outputs

Students must be taught to critically evaluate AI-generated code and explanations. ChatGPT often produces specious responses, which can reinforce misconceptions in novice programmers [16]. Incorporating activities that require students to fact-check or cross-reference outputs against instructor-vetted, reliable sources can promote a deeper understanding of computing concepts [14].

C. Culturally Responsive Framing of AI Tools

For students from underrepresented backgrounds, it is essential to frame LLMs as tools that extend their agency rather than replace their thinking. Culturally responsive teaching practices can help students see themselves as co-creators of knowledge, not passive recipients of AI output [3], [5], [39]–[41]. This framing builds confidence, especially for students who may feel intimidated by computing content or formal technical language. The goal isn't to teach students to be workers, but rather critical creators with AI/LLMs in their toolkit.

VI. Conclusion

Our preliminary study shows that while students are open to using tools like ChatGPT, they rarely apply them to coursework without intentional training or support. This highlights the need for structured AI literacy within culturally responsive computing classrooms. As access to LLMs increases, meaningful use depends on intentional integration, guided instruction, and identity-affirming environments. By observing URM secondary school students' natural engagement with ChatGPT in an embedded systems class within the AVELA framework, we contribute preliminary insight into how LLMs function in culturally competent pedagogy. Moving beyond recreational use requires both technical skill-building and culturally relevant applications. To support equitable engagement, future efforts must align LLM use with course objectives, students' lived experiences, ethical awareness, and connection to community. Then, tools like ChatGPT may help close equity gaps in STEM education.

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