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A Student-Led Workshop for Building AI Literacy through Embodied AI and Robotics

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Abstract

Generative artificial intelligence (genAI) has become an everyday study companion for university students, yet most experience it as a disembodied text interface, i.e., a chatbot. Embodied AI, where physical agents such as robots interact with humans and their environment through large language models (LLMs), offers a concrete way to expand AI literacy and curiosity about human–robot collaboration. This paper reports on a pilot outreach workshop designed and led by two undergraduate computer science students who extended the capabilities of a PiCarX robotics kit by coupling its onboard rule-based Python control with real-time API calls to proprietary LLMs. The 90-minute event invited students from across disciplines to observe live demonstrations and discuss how LLMs can interpret sensor data, issue control decisions, and engage in natural-language reasoning about physical contexts.

A voluntary IRB approved post-workshop survey (N=30) assessed participants' attitudes, engagement, and intentions to explore embodied AI further. The survey consisted of short, custom designed Likert style items probing general AI attitudes, perceptions of the robot, intrinsic motivation, and technology acceptance. Item design was informed by prior instruments commonly used in AI education and human robot interaction research, but standardized scales were not administered verbatim. Open ended reflections captured themes of curiosity, perceived accessibility, and ethical considerations.

Results indicate strong agreement that the workshop helped students move beyond viewing AI as a purely text-based tool, increased interest in embodied AI, and motivated concrete next steps such as projects, courses, or research involvement. Qualitative responses further suggest that students developed a more nuanced understanding of both the possibilities and limitations of LLM-driven robotic systems. Together, these findings demonstrate how student led, low cost demonstrations of embodied AI can support AI literacy and serve as an accessible bridge between abstract AI concepts and tangible engineering practice.

1 Introduction

Artificial intelligence (AI) has become a prominent topic across engineering curricula [1], driven in part by the widespread availability of large language models (LLMs) and generative AI tools [2]. For many undergraduate students and young learners, however, exposure to AI remains largely disembodied, encountered primarily through text-based interfaces such as chatbots or code-generation tools. While these systems offer accessibility and immediate engagement, they often obscure the relationship between AI reasoning and physical action, sensing, and environmental constraints that are central to real world engineering systems [3]. As a result, students may develop a narrow or incomplete understanding of AI as a purely abstract or software-centric technology.

By contrast, embodied AI [4], where perception, decision making, and action are situated within a physical agent, plays a critical role in robotics, autonomous systems, and cyber physical engineering applications. Contemporary robotic systems typically rely on complex pipelines involving perception models, state estimation, planning algorithms, and control frameworks [5]. These pipelines often incorporate advanced machine learning techniques such as convolutional neural networks, reinforcement learning, or large-scale robotics foundation models. While powerful, such approaches are technically demanding and difficult to integrate into early undergraduate learning experiences or informal educational settings([6], [7]).

Recent advances in LLMs have introduced an alternative entry point into embodied AI: using language-based models as high level planners, code generators, or orchestrators of robot behavior. Although LLM-driven approaches introduce tradeoffs, including increased latency and reliability concerns [8], they offer a comparatively legible and approachable abstraction for novice learners [9]. From an educational point of view, LLMs can function as an intermediate "cognitive layer" that allows students to reason about robot behavior using natural language, while still engaging with core concepts such as sensing, planning, and system integration.

This paper explores the educational potential of this approach through a student-led workshop centered on the PiCarX [10] mobile robotics platform. Rather than positioning LLM-based control as a replacement for traditional robotics methods, the workshop intentionally framed LLMs as a pedagogical bridge, specifically a means to make autonomous behavior understandable, inspectable, and discussable for general engineering students. The workshop was designed and delivered by two undergraduate mentors and combined live demonstrations, technical explanations, and interactive activities. Students observed and interacted with a PiCar-X robot executing embodied tasks, including object approach, obstacle avoidance, and maze navigation, using an agentic workflow that integrated classical computer vision techniques, planning algorithms, and LLM-based reasoning.

Beyond technical demonstration, the workshop emphasized peer-to-peer learning and exploratory engagement. Participants were encouraged to ask the two undergraduate presenters questions about system limitations, latency, sensor constraints, and architectural tradeoffs. The workshop concluded with a hands-on activity in which students issued natural language commands to the robot, allowing them to directly experience both the affordances and challenges of LLM-mediated control. This student-centered format aligns with prior work in engineering education that highlights the value of peer instruction, experiential learning, and low-barrier entry points into complex technical domains([11], [12], [13]).

To examine the educational impact of this intervention, we collected post-workshop survey data assessing participants' attitudes toward AI, perceptions of embodied intelligence, interest and perceived competence, and intention to further explore robotics and AI. Quantitative Likert-scale responses were complemented by open-ended reflections, enabling a mixed-methods analysis of how students interpreted and responded to the experience.

This paper is organized as follows. Section 2 reviews relevant background and prior work at the intersection of embodied AI, robotics, and engineering education. Section 3 describes the design and implementation of the student led PiCarX workshop, including the embodied tasks and agentic workflow. Section 4 outlines the study methodology and data collection instruments. Section 5 presents quantitative and qualitative results from the post-workshop survey. Section 6 discusses implications for engineering education, limitations of the study, and directions for future work. Section 7 concludes the paper.

2 Background and Related Work

Research on engineering education consistently highlights the value of hands-on, project-based learning as a mechanism for engaging students with complex technical concepts, with robotics particularly serving as a versatile educational tool, facilitating experiential learning, motivation, and deeper understanding of systems that integrate sensing, control, and autonomous behavior([14], [15]). Systematic reviews of educational robotics research emphasizes how workshops and robotics activities can support problem-solving, collaborative design, and active learning in engineering contexts, often bridging the gap between abstract theory and applied skills through hands-on practice [16].

Parallel to this, there has been considerable work recognizing the importance of outreach programs and workshops in broadening participation and shaping students' early perceptions of engineering disciplines [17], for example, work on robotics outreach programs within college engineering that demonstrated how structured interaction with robotics activities can impact student interest and persistence in STEM fields [18]. Peer led and student organized instructional models also have an established presence in engineering education scholarship. For instance, recent work done on engaging engineering students through experiential robotics outreach illustrates how student involvement in delivery and facilitation can enhance both the learning experience and community engagement, offering a model for bottom up instructional design and knowledge sharing [19]. This aligns with research on service learning and student centered robotics instruction, which highlights the pedagogical benefits of empowering students to lead technical workshops and mentor their peers via student led inquiry (SLI) ([20], [21]).

In parallel with robotics education, the emergence of AI as a key competency for engineering practice has led to increasing interest in AI literacy frameworks and instructional strategies. [22] defines AI literacy as a set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI tools across academic, professional, and personal contexts. While not specific to engineering or robotics, this foundational work has informed subsequent efforts to articulate measurable outcomes and pedagogical approaches for AI education. Recent work on generative AI literacy extends this competency perspective by identifying core skills and knowledge areas necessary for students to engage with AI meaningfully, including ethical reasoning and data literacy [23]. There is now emerging work that combines AI education with tangible computing and robotics to support AI literacy. A workshop focused position in [24] argues that firsthand interaction with AI technologies, including social robots, can more effectively support AI literacy than purely theoretical approaches, particularly when learners engage directly with systems that embody AI behavior. ***By emphasizing interaction and tangible experience, this line of work reinforces the notion that AI literacy is not only conceptual but also experiential***.

Despite these advances, most prior research has treated robotics education, AI literacy, and student led instruction as separate strands rather than interconnected components of a unified educational intervention [25]. ***The current study situates itself at the intersection of these threads by investigating how a student-led workshop that integrates embodied AI through an accessible robotics platform can support AI literacy outcomes among engineering students.*** In doing so, it contributes case level evidence to an emerging body of education research that advocates for experiential, interdisciplinary, and peer driven learning pathways in preparing students for complex socio technical domains.

3 Design and Implementation of the Student-Led Embodied AI Workshop

This workshop emerged from a summer mentorship collaboration between an assistant professor in Computer Science and Engineering and two undergraduate CSE students at UC Santa Cruz who had demonstrated strong curiosity, creativity, and enthusiasm for robotics and AI in prior coursework. The students were introduced to the PiCar-X mobile robotics platform as a hands-on research testbed and were mentored through the process of extending its capabilities using large language models (LLMs) as high level planners. Over the course of the summer, this exploratory research effort evolved into the design of a student led workshop aimed at expanding AI literacy and curiosity about human robot collaboration among undergraduate engineering students.

3.1 PiCar-X as an Educational Testbed

The PiCarX [10] is a low cost, open-source educational robotics kit built around a Raspberry Pi and a set of integrated sensors and actuators, including DC motors, servos, an ultrasonic distance sensor, and a grayscale line tracking module as well as a RPi camera. It supports programming in Python within a Linux environment and is accompanied by a set of open-source example scripts provided by the manufacturer (SunFounder). These characteristics make the PiCarX a suitable platform for undergraduate learning: it is inexpensive, approachable, and flexible enough to support both classical robotics control and more experimental AI enabled workflows. From an educational perspective, PiCarX offers an accessible entry point into embodied systems without requiring students to engage with more complex robotics infrastructures such as full ROS navigation stacks, probabilistic state estimation, reinforcement learning pipelines, or large-scale robot learning frameworks. This simplicity was a deliberate design choice, allowing the workshop to focus on conceptual understanding, system integration, and experimentation rather than extensive technical prerequisites.

3.2 LLM-as-Planner Architecture and Agentic Workflow

The core research idea explored in the workshop was the use of an LLM as a high-level planning and reasoning component for an embodied agent. Rather than training end-to-end learned control policies, the system employed a predefined set of primitive robot actions (e.g., move forward, turn, stop, capture sensor readings), which could be composed dynamically by an LLM through an agentic workflow. Communication between the robot and the LLM occurred through API calls using the OpenAI Agents SDK [26], enabling the model to reason over sensor inputs and select appropriate actions at runtime.

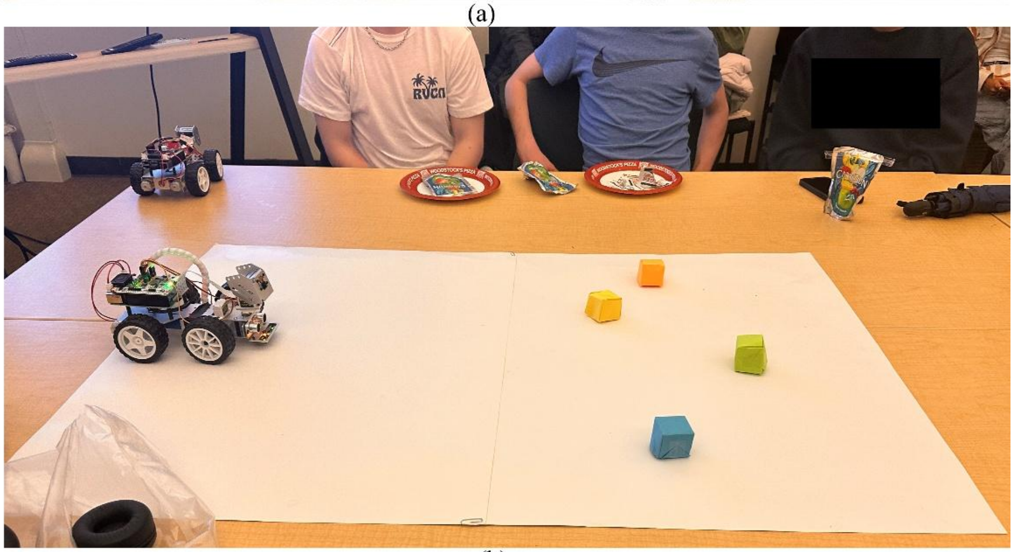
This architecture intentionally trades off performance and latency for legibility and accessibility. A performance tradeoff to API-based LLM calls in guiding robot behavior is that does introduce nontrivial delays, particularly when using reasoning LLM models, and are not suitable for low-level real time control [8]. However, for educational purposes, this approach makes the decision-making process more transparent and approachable for novice learners, who can reason about robot behavior at the level of goals, actions, and constraints rather than mathematical optimization or policy training.

3.3 Workshop Structure and Demonstrations

The 90-minute workshop began with a guided introduction to the PiCarX hardware, including its motors, servos, Raspberry Pi controller, and onboard sensors. Students were introduced to the Linux-based programming environment and the Python interface used to control the robot. To establish a baseline, the presenters demonstrated several out-of-the-box scripts provided by SunFounder, including keyboard control, line following, cliff detection, and obstacle avoidance. These demonstrations allowed participants to observe how individual sensors and actuators interact in simple, rule-based control scenarios.

The workshop then transitioned to introducing large language models and their potential role in embodied systems. Instead of relying solely on conceptual explanation, the student presenters demonstrated an LLM driven control script in which the robot responded to high level commands generated through GPT API calls. This served as a bridge to the central research question posed to the audience: ***what happens when the human is removed from the control loop, and the robot is allowed to reason and act autonomously?***

(a)



(b)

Figure 1 Student led embodied AI workshop.
(a) Undergraduate presenters leading a peer-based discussion on embodied AI concepts, system design, and architectural tradeoffs.
(b) PiCarX mobile robot executing an object-approach task during a live demonstration

To explore this question, three embodied tasks were presented: (1) moving toward the nearest object, (2) obstacle avoidance with goal reorientation, and (3) maze solving. For each task, the presenters discussed the immediate challenges encountered, such as limited vision, radius accuracy, depth ambiguity, memory requirements and error detection, and described the final implementation used to address these challenges. Classical computer vision techniques (e.g., HSV color masking and ORB feature matching) were combined with planning concepts such as SLAM and A* path planning in the various robot demonstrations, with the LLM acting as a coordinating reasoning layer rather than a low-level controller. Each task was demonstrated live, allowing students to observe both successful behavior and system limitations.

3.4 Interactive Activity and Student Engagement

The workshop concluded with an interactive, student-centered activity designed to encourage experimentation and peer collaboration. Participants were divided into two teams and each team connected to a server running on the PiCar-X. Team members issued natural language prompts (e.g., “move forward at speed 30 for three seconds”), which were translated into executable actions and queued by the system. The teams were tasked with completing a series of challenges involving sensor readings, image capture, and cumulative movement distance.

Initially, students struggled to come up with precise, actionable commands, often issuing vague or underspecified instructions. However, through iteration and discussion, both teams refined their prompts and strategies. By the end of the activity, one team successfully completed all objectives, while the other completed most of them. This progression provided a concrete illustration of both the affordances and limitations of LLM mediated robot control and reinforced the importance of clear specifications, latency awareness, and system constraints.

Throughout the workshop, students actively asked questions related to latency, sensor limitations, model selection, and future extensions, including running models locally and incorporating additional sensors. These discussions reinforced the workshop’s emphasis on critical engagement and provided a natural continuity into broader discussions about embodied AI research directions.

4 Study Methodology and Data Collection Instruments

This study employed a post survey to examine participants’ perceptions of embodied AI, interest and confidence related to robotics and AI, and intentions for future engagement. The study protocol was reviewed and approved by the IRB at the host institution. Participation in the survey was fully voluntary and anonymous, and no incentives were tied to survey completion.

4.1 Recruitment and Participants

The workshop was advertised two weeks prior to the event through departmental communication channels, instructional course platforms, student social media groups, and Discord servers frequented by the undergraduate engineering students. Attendance was open to students across all engineering majors and academic years. Light refreshments (pizza and snacks) were provided for all attendees and were not contingent upon survey participation.

At the conclusion of the workshop, attendees were invited to complete a brief post-event survey. The survey was administered electronically using Qualtrics and accessed via a QR code displayed on the presentation screen. Students were informed that participation was optional, responses would be anonymous, and they could exit the survey at any time without penalty.

4.2 Survey Administration and Anonymity

The survey was designed to be completed in approximately 5 minutes. No personal identification information was collected. To provide limited contextual information about the participant population, respondents were asked to self-report their academic major and current year in the university. These items were included solely for descriptive purposes and were not used to identify individual participants. All survey responses were collected anonymously through Qualtrics. Only aggregated and de-identified data were accessed by the authors for analysis.

4.3 Survey Instrument

The post-workshop survey consisted of 15 items organized into five sections. Likert style items used a five-point scale ranging from Strongly Disagree to Strongly Agree. The instrument was custom designed for this exploratory outreach study to probe participants' attitudes toward AI, perceptions of an embodied AI system, interest and confidence, perceived usefulness, and intentions for future engagement. Item wording was informed by and adapted from prior work in validated instruments for AI attitudes [27], human robot interaction [28], motivation [29], and technology acceptance [30] research. However, standardized or validated instruments were not administered verbatim. The survey also included open-ended reflection prompts.

Section 1. General Attitudes toward AI

Q1: AI can be a helpful tool for learning and creativity.

Q2: I feel comfortable interacting with AI systems such as chatbots or virtual assistants.

Q3: AI technologies sometimes make me uneasy because their decisions are hard to understand. *(reverse-scored)*

Section 2. Perceptions of the Robot

Q4: The PiCarX robot seemed intelligent in how it responded to its environment.

Q5: The robot's behavior appeared understandable or purposeful.

Q6: I found the robot engaging or likable during the demonstration.

Q7: I would enjoy interacting with similar AI-driven robots in the future.

Section 3. Interest and Perceived Competence

Q8: I thought learning about embodied AI through this demonstration was interesting and enjoyable.

Q9: I felt competent that I could understand the ideas presented about how the robot used the language model.

Q10: This experience made me more confident in exploring robotics or AI on my own.

Section 4. Perceived Usefulness and Future Intentions

Q11: Combining large-language-model reasoning with robotics can make human–AI interaction more meaningful.

Q12: The workshop helped me see practical applications of AI beyond text-based chat.

Q13: I intend to learn more about embodied or robotics-based AI after this event.

Section 5. Open Ended Reflection

Q14: What part of today's workshop most changed how you think about AI and robots?

Q15: Describe one concrete step you might take next (e.g., joining a club, taking a course, building a project).

4.4 Data Preparation and Analysis Overview

Quantitative Likert scale responses were analyzed descriptively using medians, interquartile ranges, and response distributions (percentage of Agree and Strongly Agree responses), consistent with best practices for ordinal survey data. Qualitative responses were analyzed using a thematic review to identify recurring patterns related to sense-making, perceived accessibility, and intended next steps. Details of the quantitative and qualitative findings are presented in Section 5.

5 Results

This section reports descriptive results from the post-workshop survey, including participant demographics, quantitative Likert-scale responses, and qualitative themes from open-ended reflections contexts.

5.1 Participant Demographics

Survey respondents (N = 30) represented a range of engineering and computing majors. The most frequently reported majors were Computer Science, Robotics Engineering, Computer Engineering, Electrical Engineering, and Technology and Information Management, with additional representation from Computational Physics and Cognitive Science.

Participants also spanned multiple academic years, with a notable concentration among freshman and sophomore students alongside representation from junior and senior cohorts. The presence of early-stage undergraduates is consistent with the workshop's outreach-oriented design and its emphasis on introducing embodied AI concepts without extensive technical prerequisites.

5.2 Quantitative Survey Results

Across all items, median responses were Agree (4 on a 5-point scale), with interquartile ranges typically between 0 and 1, indicating relatively consistent agreement across participants. For most items, a substantial majority of respondents selected Agree or Strongly Agree.

Attitudes toward AI (Q1–Q3)

Participants expressed broadly positive attitudes toward AI. A large majority agreed that AI can be a helpful tool for learning and creativity and reported comfort interacting with AI systems. Responses to the reverse-scored item on unease about AI decision making showed more variability, suggesting that while attitudes were generally positive, some participants retained reservations about AI interpretability.

Perceptions of the Robot (Q4–Q7)

Responses indicated that participants generally perceived the PiCarX robot as intelligible, purposeful, and engaging. While agreement levels were slightly lower than for general AI attitudes, a clear majority reported that they would enjoy interacting with similar AI-driven robots in the future. This pattern suggests that physical embodiment added credibility and interest without inducing uncritical enthusiasm.

Interest, Confidence, and Usefulness (Q8–Q13)

The strongest agreement was observed for items related to interest, perceived competence, and usefulness. Participants overwhelmingly agreed that the workshop was interesting and enjoyable, helped them understand how AI can extend beyond text-based chat interfaces, and increased their confidence in exploring robotics or AI independently. A large majority also reported an intention to further engage with embodied or robotics-based AI following the workshop.

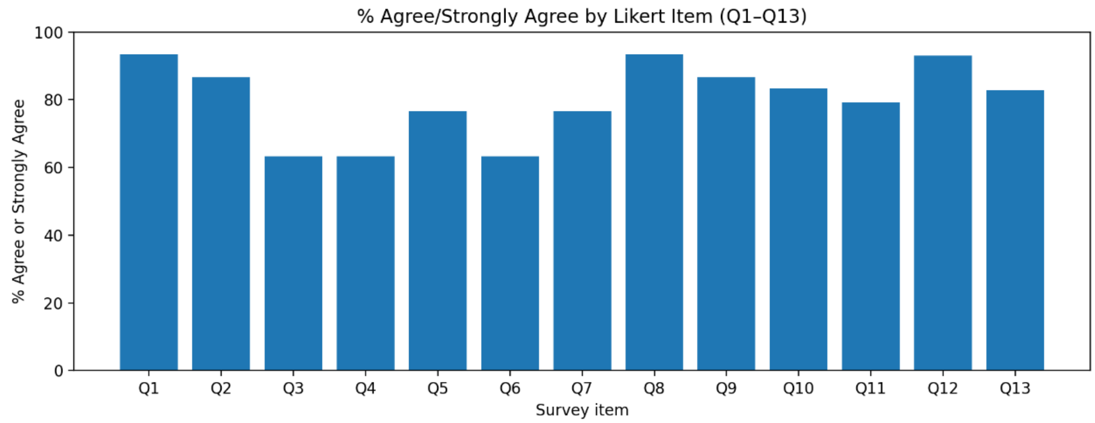


Figure 2 Percentage of Agree and Strongly Agree responses by item.

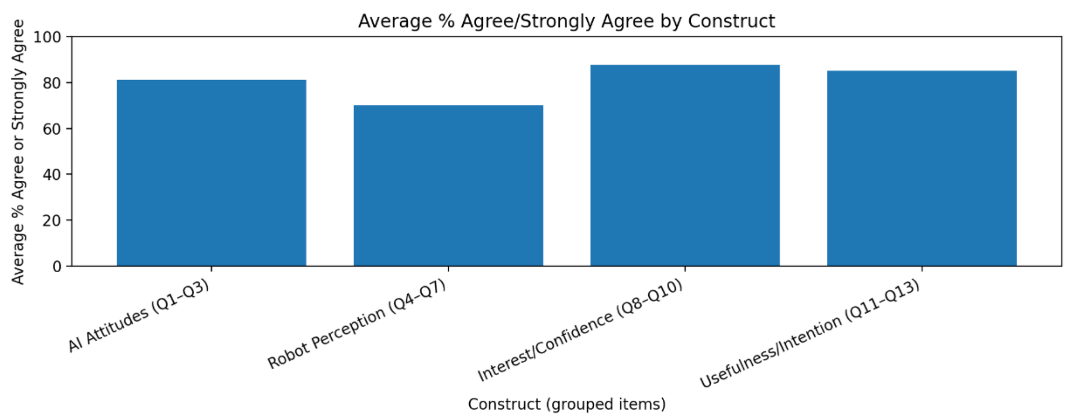


Figure 3 Percentage of Agree and Strongly Agree responses by construct.

5.3 Qualitative Findings from Open-Ended Responses

Open-ended responses to Q14 and Q15 were analyzed using a thematic review to identify recurring patterns in how participants interpreted the workshop and articulated intended next steps. Five prominent themes emerged.

Theme 1: Embodiment Made AI Tangible

Many participants emphasized that seeing AI operate through a physical robot fundamentally changed how they conceptualized AI. Responses highlighted the importance of physical interaction, navigation, and sensing in grounding AI behavior in real-world constraints.

Theme 2: AI as a System of Integrated Components

Participants frequently referenced the integration of multiple elements from LLMs, computer vision, sensors, planning algorithms, and control logic. Several responses noted appreciation for understanding how these components worked together rather than viewing AI as a single monolithic model.

Theme 3: Recognition of Limitations and Tradeoffs

Rather than expressing uncritical optimism, students articulated an awareness of AI limitations, including latency from API calls, sensing constraints, and cases where human decision making remained faster or more reliable. This suggests that the workshop supported a nuanced understanding of AI capabilities and constraints.

Theme 4: Lowered Barrier to Entry

Multiple responses described the system as "*beginner friendly*" or "*not as hard as expected*," indicating that the LLM-as-planner approach helped reduce perceived complexity. Participants noted that they previously assumed autonomous robotics required far more specialized expertise.

Theme 5: Action-Oriented Motivation

Responses to Q15 demonstrated strong action orientation. Commonly reported next steps included building personal projects, enrolling in related courses, joining robotics clubs or research labs, and independently exploring agent-based tools or simulation environments.

6 Discussion

6.1 Implications for Engineering Education

The findings of this pilot study suggest several implications for engineering education, particularly for AI literacy and early exposure to autonomous systems. First, the results indicate that embodied AI demonstrations can shift students' conceptions of AI from disembodied, text based tools toward system level, physically grounded AI paradigms, thereby aligning definition of AI literacy [22]by supporting critical evaluation of AI capabilities and limitations and promoting meaningful interaction with AI systems.

Second, using LLMs as high-level planners offers a pedagogically accessible entry point into autonomous robotics. Although LLM based control does not reflect any state-of-the-art industrial paradigm, its legibility and flexibility allow novice learners to reason about autonomy, sensing, and decision making without any extensive prerequisites in the specific domain knowledge.

Third, the student-led delivery model contributed meaningfully to engagement. Peer instruction and SLI based interaction lowered affective barriers and encouraged discussion of latency, reliability, and architectural tradeoffs, consistent with prior engineering education work on peer led and experiential learning particularly in the outreach and exploratory contexts.

Finally, the workshop format illustrates a low cost, scalable approach for introducing embodied AI concepts outside formal coursework. Such interventions can be easily implemented and scaled up in various institutions and may be especially effective for early stage undergraduates who are forming initial perceptions of AI and robotics but have limited prior exposure.

6.2 Limitations

The workshop involved a single institution and a relatively small, self-selected sample, which limits generalizability. Data was collected using a post workshop survey only thus changes in attitudes or understanding cannot be causally attributed to the intervention. Also, the study focused on short term perceptions and intentions rather than long term learning outcomes or behavioral follow through.

Additionally, the technical approach demonstrated (LLM-as-planner control) introduces latency and reliability constraints that limit its applicability to real time robotics. While these limitations were explicitly discussed with participants and surfaced in qualitative responses, they nonetheless shape the scope of conclusions that can be drawn.

6.3 Future Work

Future work will explore longitudinal implementations of similar workshops including pre/post assessment designs and follow up measures to examine sustained engagement. Technical extensions may include running small language models(SLMs) locally on edge devices, integrating additional sensors (e.g., lidar), and comparing LLM based control with classical or learning based robotics approaches. Additional research may also investigate how student-led embodied AI workshops can be incorporated into formal curricula or scaled across institutions.

7 Conclusion

This paper presented a student-led workshop that used an accessible robotics platform and an LLM-as-planner architecture to introduce embodied AI concepts to undergraduate engineering students. Survey results indicate that the workshop supported AI literacy by increasing interest, confidence, and perceived usefulness while fostering a nuanced understanding of system limitations and tradeoffs. By combining embodied AI demonstrations, peer-led instruction, and interactive experimentation, this work contributes an initial case study of how emerging AI technologies can be leveraged responsibly and effectively in engineering education.

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