[Traditional Research Paper]: Fostering Teenagers' Understanding of Community-Center Edge AI Systems

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[Traditional Research Paper]: Fostering Teenagers' Understanding of Community-Centered Edge AI Systems

Abstract

Edge AI (on-device machine learning using sensor-rich microcontrollers) offers an underexplored platform for K–12 AI education that foregrounds physical computing, authentic engineering trade-offs, and community relevance. This qualitative multi-artifact case study examined how twelve youth (ages 11–13) engaged with edge AI design during a two-week informal learning camp structured around the Community-Engaged Engineering Design (CEED) framework, which integrates the Engineering Design Process (EDP) with collaborative stakeholder engagement principles drawn from the IAP2 (International Association for Public Participation) spectrum and the Collaborative Design Framework. Across three teams, we analyzed brainstorming reports, prototypes, and showcase posters to address two research questions: (1) how learners identify and frame community-relevant problems for edge AI solutions, and (2) how learners leverage scaffolded activities to integrate sensors, inference logic, and community need. Findings reveal that specificity of community framing served not only as a motivational scaffold but as a cognitive one: teams with more defined user contexts produced more coherent sensor-inference logic. Stakeholder engagement reached the consult level at most, reflecting the time constraints of informal settings. This study advances informal learning design by modeling how edge AI and participatory engineering frameworks can be integrated for youth communities.

Introduction

Artificial Intelligence (AI) is fundamentally reshaping society across healthcare, transportation, employment, and civic participation, yet K–12 education most often introduces learners to AI through narrow engagement with generative tools such as chatbots and text-to-image models. While these cloud-based systems can be engaging, they rarely connect learners to their physical environment, foster understanding of how AI systems sense and respond to real-world data, or engage students in addressing authentic problems within their own communities. This disconnect limits opportunities for youth to see themselves as creators and critical evaluators of AI technologies that will shape their futures [1].

Edge AI offers a more grounded alternative. Unlike cloud-based systems that process data remotely, edge AI allows data to be sensed, processed, and acted upon directly by small, local devices such as microcontrollers with embedded sensors [2]. The constraints of edge computing (limited resources, power considerations, and efficient algorithms) introduce learners to authentic engineering trade-offs that mirror professional practice. When integrated into sensor-rich, open-ended learning experiences, edge AI enables learners to simultaneously develop technical competencies (data collection, signal processing, model training, system integration) while addressing problems that matter to their communities [2].

Despite growing interest in K–12 AI education, most interventions remain focused on cloud-based or unplugged approaches and are rarely situated within community-engaged engineering contexts [3], [4].This matters: engineering education researchers have long documented that authentic community partnerships deepen both technical learning and civic identity [3], [5], but short-format informal programs face a structural tension when attempting to implement them. Authentic co-design requires sustained stakeholder relationships that are difficult to establish within bounded program formats, and this tension is particularly consequential in AI education, where building systems for a community without that community's input carries real ethical stakes. This study addresses that challenge directly. We designed and implemented a two-week curriculum grounding youth in hands-on edge AI learning through the Community-Engaged Engineering Design (CEED) framework, and we examine both how learners navigated community problem-framing and AI system design, and what levels of authentic community participation proved achievable within these constraints.

This study addressed two research questions:

RQ1. How do learners identify and frame community-relevant problems for which edge AI offers a viable solution?

RQ2. In what ways do learners leverage brainstorming reports and prototyping activities to integrate sensors, data processing, and inference into their proposed solutions?

Related Literature

AI Education in Informal and K–12 Settings

Research on K–12 AI education has grown substantially, yet most curricula center on generative or cloud-based tools that abstract away the sensing, processing, and inference pipeline [1]. Work by Touretzky and colleagues [6] has mapped foundational AI literacy competencies for K–12, but physical computing and edge inference remain understated in these frameworks. Informal learning environments, including museum programs, summer camps, and makerspaces, have shown particular promise for broadening participation in computing by reducing prerequisite barriers and foregrounding design agency [3], [4]. Critically, however, few informal AI programs explicitly situate learning within community-engaged engineering contexts, a gap that matters because engineering education researchers have found that authentic community problem contexts deepen both technical learning and students' sense of engineering identity [3], [5].

Participatory and Community-Centered Engineering Design

Community-centered approaches to engineering education draw on traditions of participatory design, human-centered design, and co-design, all of which foreground stakeholder involvement and local knowledge [3], [5]. Bielefeldt and colleagues [5] have documented how community-engaged design projects in undergraduate engineering promote both technical competency and professional responsibility; Coyle and colleagues [3] have examined how service-learning structures in engineering curricula affect students' community partnership skills and civic identity. The IAP2 Public Participation Spectrum operationalizes degrees of community engagement, ranging from informing stakeholders to empowering them as co-decision-makers [7], offering a concrete analytic vocabulary for assessing participation quality in these settings. Yet despite this body of work in formal higher education contexts, community-engaged engineering design remains largely unexplored in informal K–12 AI learning environments, and its integration with AI-specific learning goals is nearly absent from the literature.

Conceptual Framework

Engineering Design Process

In the context of engineering education, the Engineering Design Process (EDP) serves as a foundational framework for developing learners' problem-solving, analytical, and creative thinking skills. As outlined by the National Research Council [8], the EDP consists of a sequence of iterative stages: frame and investigate, brainstorm, plan, create, test, evaluate, and communicate. This structured progression guides learners from problem identification to solution refinement, emphasizing rigor and the use of scientific engineering principles.

However, the EDP has limitations in educational settings that involve community-based challenges. Its traditional structure often lacks mechanisms for incorporating diverse perspectives or local knowledge. To address this, educators are increasingly using approaches like human-centered design and participatory methods that prioritize stakeholder involvement and responsiveness to community needs [9], [10].

Collaborative Design Framework

The Collaborative Design Framework (CDF) by Meroni and colleagues [11] addresses community challenges by systematically embedding stakeholder collaboration throughout the process, promoting cultural awareness and locally meaningful solutions.

The framework is structured around two intersecting dimensions. The first contrasts the focus of activity: *topic-driven* efforts center on understanding the current challenge, while *concept-driven* efforts focus on shaping and refining solutions [11]. Though topics and concepts are cognitively linked—concepts cluster around topics, and topics consist of related concepts [12]—we use this distinction analytically to trace how learner reasoning moves from problem understanding to solution development.

The second reflects styles of guidance. *facilitation* emphasizes active listening and mutual learning to foster inclusive dialogue, while *steering* draws on the facilitator's expertise to challenge assumptions and provoke new ways of thinking [11].

Together, these dimensions define four collaborative orientations: *discovering and exploring options, imagining possibilities beyond the current, creating and developing solutions, and expanding and consolidating ideas* [11]. Each reflects a distinct mode of stakeholder engagement and guides participatory activities throughout the design process.

Community-Centered Engineering Design: An Integrated Framework

This study introduces the Community-Engaged Engineering Design Framework (CEED), which combines the structured logic of engineering design with the inclusive strategies of collaborative stakeholder engagement. By integrating these two perspectives, the framework effectively supports community-focused engineering challenges.

The visual representation of CEED (Figure 1) combines the iterative phases of the EDP with the quadrant-based CDF, organized along two axes: *topic-driven* versus *concept-driven* and *facilitating* versus *steering*. Each design phase is supported by stakeholder engagement informed by the IAP2 spectrum: *inform, consult, involve, collaborate, and empower* [7]. These levels reflect a progression from minimal to maximal stakeholder influence, with *empower* as the highest. While all five may appear throughout the process, each stage typically emphasizes particular modes of participation:

- **The initial stage (frame and investigate)** prioritizes *collaborate* and *empower* to allow stakeholders to shape how problems are identified and framed.
- **The intermediate stage (brainstorm, plan, and create)**, centers on *involve* and c*ollaborate* as community members co-develop and refine potential solutions.
- **The final stage (test, evaluate and communicate** emphasizes *consult* and *involve* as stakeholders provide feedback, validate relevance, and help adapt solutions to local contexts.

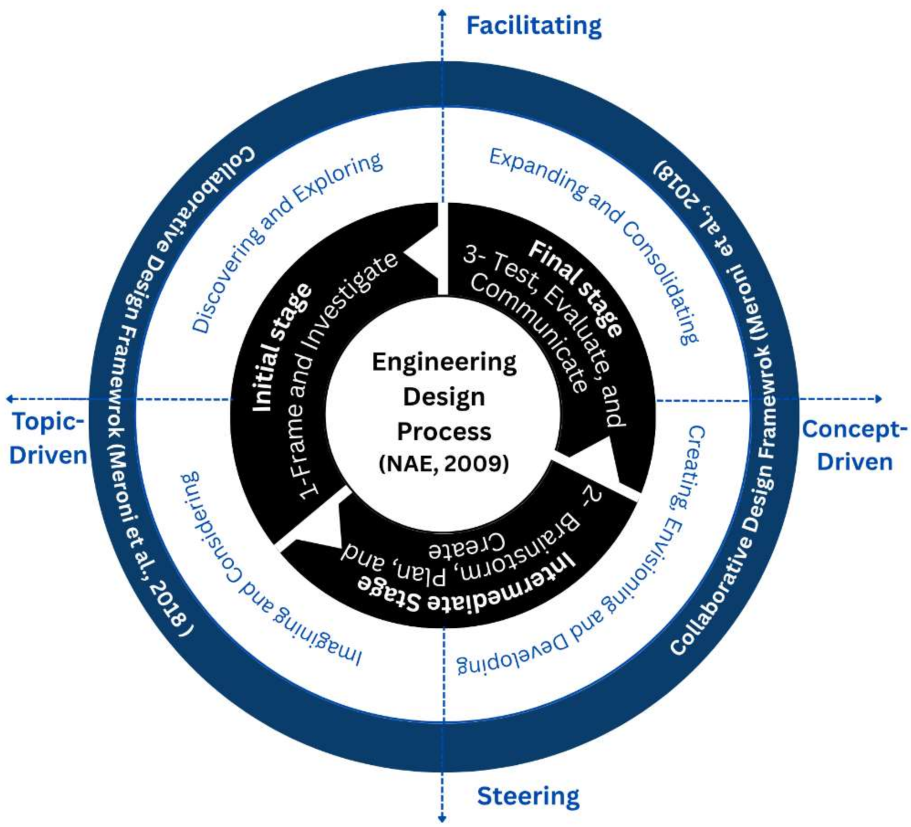


Figure 1. Community-Centered Engineering Design Process

Method

Research Design

This study employed a qualitative multi-artifact case study design [13]. Conducted over the course of a two-week summer camp hosted by a local creativity and innovation museum, the research followed twelve youth, aged 11 to 13, seven of whom identified as girls, as they engaged in approximately 40 hours of structured and exploratory edge AI learning. Participants identified local issues, designed sensor-driven intelligent systems, and presented their prototypes in a culminating public showcase. Teenagers were recruited through purposive sampling [14] from families registered for the museum's summer programming. Recruitment materials emphasized the opportunity to learn about AI and community problem-solving, with no prerequisite technical experience required.

The instructional experience was grounded in the CEED framework, with the EDP at its core providing a systematic engineering foundation for problem framing, solution generation, iterative testing, and communication. Participants engaged with a flexible, in-house educational platform (Figure 2) equipped with sensors and a microcontroller, enabling them to design responsive systems that addressed real-world challenges [15], [16], [17]. To support community-centered reasoning and authentic engagement, the camp integrated thoughtfully designed scaffolds [18], including brainstorming reports, prototype development, and poster creation, along with ongoing facilitation. Facilitators took on stakeholder roles at key moments to simulate dialogue, deepen problem framing, and prompt reflection on user needs.

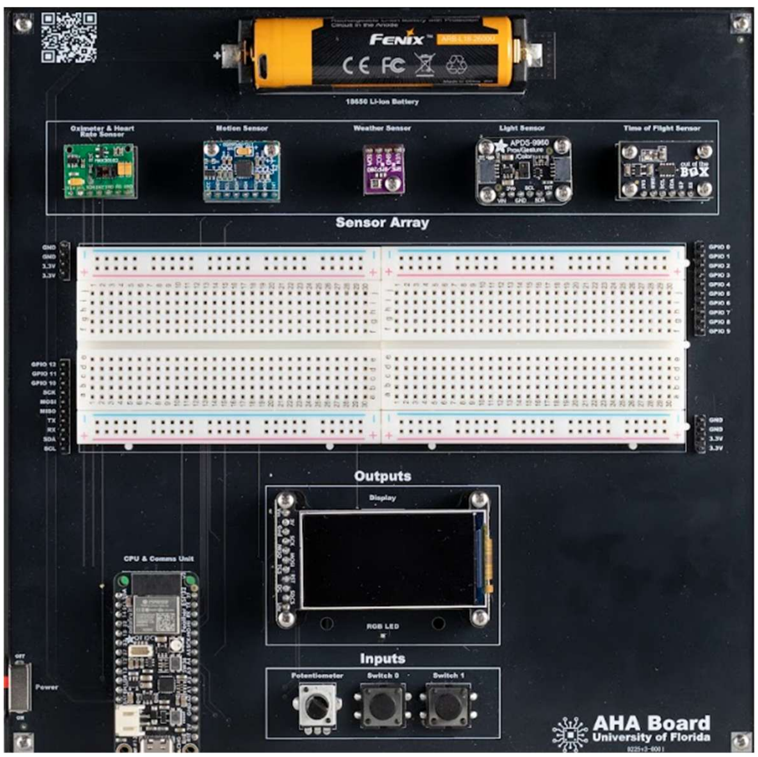


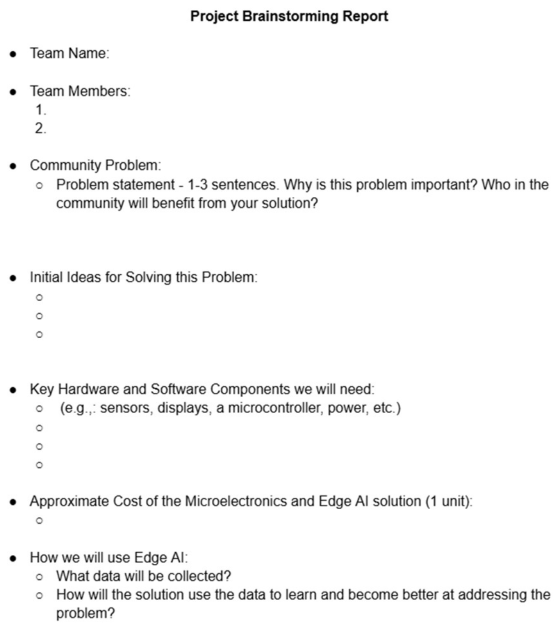
Figure 2. Educational Platform

Data Collection

To document participants' design process, we collected artifacts from the camp, including photos of prototypes, posters, and video recordings of final showcase presentations. Central to this collection were the scaffolds, intentionally designed to support CEED's emphasis on aligning technical development with community context. The primary scaffolds included:

- **Project Brainstorming Reports (Figure 3)**: Completed early in the design process, these reports captured each team's community problem statement and initial solution ideas.

- **Posters Template (Figure 4):** After initial facilitator feedback on brainstorming reports, participants completed structured templates to present their edge AI projects. Community feedback was gathered during the showcase through their final posters.



Project Brainstorming Report

- Team Name:
- Team Members:
  1.
  2.
- Community Problem:
  - Problem statement - 1-3 sentences. Why is this problem important? Who in the community will benefit from your solution?
- Initial Ideas for Solving this Problem:
  -
  -
  -
- Key Hardware and Software Components we will need:
  - (e.g.,: sensors, displays, a microcontroller, power, etc.)
  -
  -
  -
- Approximate Cost of the Microelectronics and Edge AI solution (1 unit):
  -
- How we will use Edge AI:
  - What data will be collected?
  - How will the solution use the data to learn and become better at addressing the problem?

Figure 3. Project Brainstorming Report

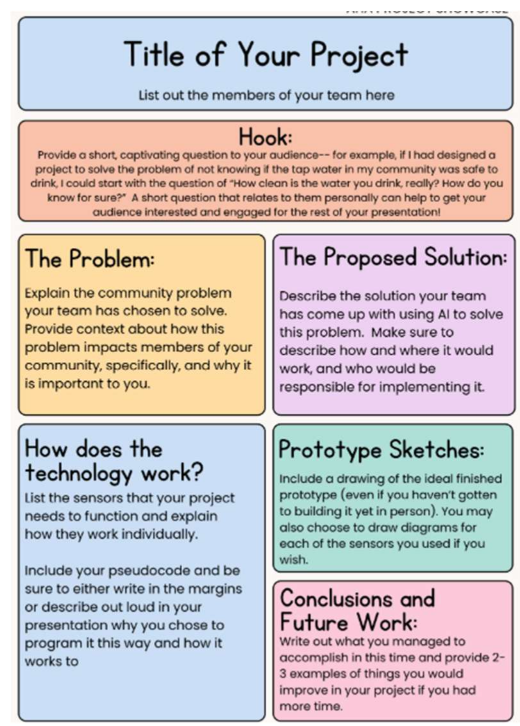


Figure 4. Poster Template

Data Analysis

Analysis followed a three-stage approach grounded in the CEED framework. The scaffolds enabled extraction of comparable data across three teams regarding community framing, edge AI integration, and stakeholder (facilitator) consideration.

1. **Design Narrative Reconstruction**
   We analyzed each team's design journey—problem framing, concept development, sensor use, logic design, and final presentation—using their brainstorming reports, observation notes, and posters [19].
2. **Mapping to CEED Quadrants**
   Artifacts and activities were coded within the CEED framework to identify *topic vs. concept-driven* work and moments of *facilitation* or *steering*, including facilitator prompts and poster reflections.
3. **Cross-Case Synthesis**
   Coded data from all teams were compared using an authentic assessment rubric (Table 1, [20]) that evaluated community relevance, edge AI integration, stakeholder perspective, and clarity of the proposed solution.

For this study, understanding of edge AI is operationalized as artifact-based evidence that learners could articulate (a) which sensors collect relevant data, (b) how that data maps to a decision or inference, and (c) why that decision matters for a specific community user. This definition excludes general or abstract references to AI without corresponding sensor-inference-user logic.

IAP2 levels were assigned analytically: inform was coded when framing drew entirely on general awareness with no evidence of stakeholder dialogue; consult was coded when teams demonstrated awareness of a specific user group and responded to facilitator-simulated stakeholder prompts, but without direct community input or iterative co-design.

Table 1. Cross-case synthesis

Team	Community Problem Framing	Stakeholder Framing	Edge AI Integration	Technical Feasibility	Overall Alignment
Deforestation Monitor (Team 1)	Global environmental framing of deforestation and reforestation strategies	Indirect — generalized need, no local user specified	Edge AI used with sensors (LIDAR, cameras) and automated drone logic	Technically imaginative, unclear real-time logic	**Strong technical concept, low local grounding**
Trash Bot (Team 2)	Urban pollution and public littering in cities and shared spaces	Moderate — general public, city users implied	Mentions motion, sound, and GPS sensors; Edge AI loosely referenced	Feasible physical logic, vague learning model	**Moderately aligned**
Sleep Monitoring System (Team 3)	Focus on personal comfort, sleep health, and sensory-driven feedback loops	Strong — specific user (deep sleepers, deaf people), personalized context	Edge AI used to interpret sensor thresholds for sleep events. Vibration (not necessarily a sensor) to act as an alarm system for deaf people	Well-scoped design with clear sensor logic	**Highly aligned**

Findings

Across three teams, findings reveal how community-framing quality shaped the coherence of edge AI design, and how scaffolded artifacts mediated learners' movement between problem understanding and technical solution development.

RQ1: Community Problem Framing

Initial brainstorming reports showed emerging civic awareness rooted in personal experience or familiar settings, but community framing specificity varied substantially across teams. This variation, as shown below, predicted the coherence of teams' edge AI integration.

Team 1 (Inform Level). Team 1 framed deforestation as a global environmental challenge, proposing an edge AI-powered monitoring tower using cameras, LIDAR, radar, and a seed-distribution system. Their problem statement cited aggregate statistics ("35% of all trees have been lost through deforestation"), reflecting general environmental awareness rather than a locally situated community need. Within the CEED framework, this framing placed Team 1 in the concept-driven/steering quadrant: they arrived with a strong technical vision and pursued it rather than beginning from stakeholder dialogue. The IAP2 engagement level was coded as *inform*, as no specific community user was identified and problem framing did not evolve in response to stakeholder perspectives. This framing had direct consequences for their AI design: without a defined local user, the team could not specify what the image classifier needed to distinguish or why.

Team 2 (Consult Level). Team 2 framed public littering as a civic problem, describing their Smart Trash Bot as a solution for urban spaces. Their poster identified a plausible user group (city residents, non-English speakers) and proposed inclusivity features such as multilingual audio feedback. However, their community framing remained aspirational and broad: the problem was stated as general urban pollution rather than a specific, locally situated need. Facilitator prompts (simulating city planner and resident perspectives) helped the team refine their sensor selection, but these interactions reflected facilitation-supported, topic-driven work rather than co-design. The IAP2 level was coded as *consult*: the team responded to structured prompts representing community perspectives but did not initiate or sustain direct stakeholder dialogue. As with Team 1, the absence of a specific user constrained the specificity of their AI logic.

Team 3 (Consult Level, Strongest Community Alignment). Team 3 addressed oversleeping among heavy sleepers and Deaf and Hard of Hearing (DHH) users. Their problem statement explicitly named a user population and articulated why standard alarm solutions were inadequate: "many people sleep through or ignore [loud alarms which can lead to] missed appointments or feeling groggy all day." This framing reflected attention to user experience and accessibility from the outset. Within CEED, their process moved from topic-driven/facilitation-supported work in the brainstorming phase to concept-driven reasoning during prototyping, as facilitator scaffolding helped translate empathetic concern into a concrete technical specification. The IAP2 level was coded as *consult*: engagement was based on reasoned assumptions about DHH users rather than direct community input, though it was the most contextually grounded of the three teams.

Cross-team pattern. The contrast across teams supports the claim that community framing specificity functions as a cognitive scaffold for edge AI design: teams with a named user and a locally situated problem produced more coherent sensor-inference logic. Importantly, no team reached IAP2 levels above consult, indicating that the two-week camp structure, while sufficient to produce meaningful design work, was not sufficient to support authentic co-design with community members.

RQ2: Sensor-Inference Integration through Scaffolded Activities

Brainstorming reports and prototyping activities served different but complementary functions in supporting edge AI integration. Reports helped teams externalize and organize sensor-inference logic; prototypes helped them test and communicate that logic physically. The quality of integration, specifically whether teams could articulate a coherent sensor → data → inference → action → community need chain, varied by team.

Team 1. Team 1's brainstorming report included pseudocode and an explicit plan to train an image classifier using Edge Impulse™, demonstrating the most technically elaborated understanding of inference as a process. The report specified inputs (camera images of tree canopy), the decision the model would make (healthy vs. deforested), and the action triggered (drone seed deployment). This sensor-inference chain was coherent, though it was not grounded in a community context. The prototype was symbolic (a physical mock-up representing the tower structure) but reflected systematic sensor planning. The AI component was understood as the decision-making core, not merely a named feature.

Team 2. Team 2's report identified sensor inputs (motion, GPS, camera) and a servo-based response mechanism, but inference logic was not elaborated. The team described what their AI system would do ("detect the trash") without specifying how a model would be trained to distinguish trash from other objects, what training data would be needed, or how confident classifications would trigger responses. This gap between naming AI and understanding AI inference represents what we term nominal AI integration: AI is invoked as a capability label rather than a design specification. The humanoid robot prototype effectively communicated the input-output behavior of the system (approach trash, collect it), but did not represent the inference layer. Facilitator prompts helped the team clarify sensor selection but did not fully bridge the gap to inference elaboration.

Team 3. Team 3's report described rule-based threshold logic in which sensor readings (movement cessation, absence of sound response) would be interpreted as indicators of deep sleep, triggering a vibration alarm. Their report explicitly connected sensor thresholds to DHH user characteristics: the vibration mechanism was chosen because it did not rely on auditory feedback. This represents the tightest coupling between AI inference logic and community need across the three teams. The prototype, a mattress-frame model with an embedded vibration motor, physically instantiated the sensor-to-action chain and served as a communication artifact during the showcase. Facilitation helped translate the team's empathetic framing into a concrete design specification.

Cross-team pattern. Brainstorming reports were most effective as inference scaffolds when teams had a specific user context to anchor design decisions. Prototyping supported communication and iteration, but its impact on inference elaboration was limited when community framing remained abstract. The finding that Team 3's community specificity enabled more precise sensor-inference logic, and that Team 2's broad framing corresponded to nominal AI integration suggests that the scaffolds worked in interaction with community framing quality, not independently of it.

Discussion

These findings extend prior work on computing education by demonstrating that community relevance in youth AI design serves a dual function: motivational and cognitive. Existing literature has emphasized the motivational value of culturally-relevant problem contexts for broadening participation in computing [5]. This study adds evidence that specificity of community framing also shapes the technical quality of AI design: it scaffolds learners' ability to define what their AI needs to sense, decide, and do for a particular user. This has implications for how AI education researchers conceptualize the relationship between social and technical dimensions of learning.

The finding that all teams remained at the *inform* or *consult* level of the IAP2 spectrum is consistent with the constraints of a two-week informal learning setting, but it also surfaces a structural tension that the community-engaged engineering education field has recognized more broadly: authentic co-design requires sustained relationships with community stakeholders that are difficult to establish within bounded program formats [17]. This tension is particularly consequential in AI education contexts, where the ethical stakes of community misalignment (building AI systems for a community without that community's input) are high. Future curriculum designs should explore how to push participation toward higher IAP2 levels, for example through pre-camp community interviews that establish user relationships before design begins, or post-camp deployment and feedback cycles that return finished prototypes to community members for evaluation.

The identification of nominal AI integration in Team 2's work is a theoretically useful construct for the field. We define nominal AI integration as invoking AI as a capability label ("it will use AI to detect trash") without specifying the underlying sensing, training, or inference logic that would make such detection possible. This contrasts with elaborated AI integration, in which learners can specify what data the system will collect, how the model will learn to classify or predict from that data, and why the resulting inference addresses a particular community user's need. Team 3's sleep monitor exemplifies elaborated integration; Team 2's trash bot does not, despite both teams demonstrating genuine engagement with the design challenge. This distinction mirrors findings in the broader K–12 AI literacy literature suggesting that awareness of AI as a category does not necessarily entail understanding of how AI systems learn or decide. The CEED framework's explicit linkage of sensor inputs to community outcomes provides a structural prompt for moving learners from nominal to elaborated integration, but the present findings suggest that prompt works most effectively when community framing is already specific enough to anchor the inference specification.

This study's use of the CEED framework as both an instructional and analytic tool is a methodological contribution. Using the same framework for design and analysis creates coherence between what is taught and what is measured, but it also introduces the risk of confirmation bias, specifically seeing CEED alignment because the analysis was structured to find it. Future studies should consider complementing CEED-based analysis with additional analytic lenses (e.g., computational thinking frameworks, learning progression analyses) to triangulate interpretations.

Limitations

Several limitations bound the scope of these findings. First, the sample of twelve participants across three teams in a single two-week camp limits transferability. These findings describe what was possible in this specific context and should not be generalized to edge AI education broadly. Second, the CEED framework itself was developed by the research team; independent replication using the same framework in other settings is needed to assess its robustness as an analytic tool. Third, no pre/post learning assessments were administered, so claims about learning gains are necessarily limited to observable artifact evidence rather than demonstrated knowledge change.

Significance and Conclusion

This study contributes a model for integrating edge AI education with community-engaged engineering design in informal learning settings. Using the CEED framework as both instructional scaffold and analytic lens, we documented how three teams of youth navigated the intersection of community problem framing and AI system design across a two-week summer camp. Key findings indicate that community framing specificity functions as a cognitive scaffold for edge AI design, that scaffolded artifacts (brainstorming reports and prototypes) support sensor-inference integration most effectively when paired with specific user contexts, and that stakeholder engagement in short-format programs tends to plateau at the consult level without structural mechanisms for authentic community contact.

For informal learning practitioners and AI education researchers, this study offers a replicable curriculum model, an integrated analytic framework, and a vocabulary, including the construct of nominal AI integration, for describing how youth engage with AI as a design material. Future work should explore how to extend the IAP2 engagement spectrum toward involve, collaborate, and empower within informal AI learning contexts, and should examine how learners' edge AI understanding develops over longer program durations or across multiple design iterations.

Acknowledgements

This material is based upon work supported by the National Science Foundation under Grants No. 2405373 and No. 1662976.

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