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WIP: Leveraging Embedded Systems and Edge Intelligence to Enhance High-schoolers' Conceptual Change about AI

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Abstract

Embedded systems are foundational to electrical and computer engineering, requiring integrated knowledge of both hardware and software. As Artificial Intelligence (AI) becomes increasingly embedded in everyday systems, it is essential for future engineers to understand AI not only as algorithms but also as practical, system-level implementations. However, most pre-college programs emphasize computational thinking and AI algorithms rather than hands-on, embedded applications.

This work-in-progress presents an exploratory three-hour curriculum that introduces high school students to Embedded Systems, Tiny Machine Learning (TinyML), and AIoT through hands-on experience with an ESP32-based learning board with breadboard, a battery, five different sensors, and an OLED monitor. Using Arduino and Edge Impulse software, students witnessed the full TinyML workflow, from data collection and preprocessing to model training and deployment. This curriculum aims to help students conceptualize AI as a data-driven computational process within physical systems. Guided by the Cognitive Reconstruction of Knowledge Model (CRKM) of conceptual change, which highlighted the importance of affective and motivational factors in conceptual change process, this study investigates whether students revise their prior AI conceptions toward broader, system-level understanding.

One hundred and seventeen high-schoolers from four schools in the southeastern United States participated in the curriculum, with thirty four students completing the pre- and post-surveys. Quantitative analysis using paired t-tests and item-level diagnostics revealed meaningful gains in understanding AI's technical functioning (e.g., functioning without internet) and its societal roles. While the results are preliminary, they suggest that integrating Embedded Systems and Edge Intelligence can serve as an effective gateway for developing foundational AI literacy in pre-college engineering contexts. This paper presents the detailed curriculum design, exploratory assessment results, and a path for future psychometric validation of AI conception survey, contributing to the growing body of research on integrating Edge Intelligence into pre-college engineering education.

Introduction

While understanding and utilizing Artificial Intelligence (AI) has been the core skill set for students across wide disciplines, the question of how to develop the necessary skills still needs more research in terms of teaching and learning with AI. Hands-on, project-based learning has been identified to be effective in helping students build their attitudes, knowledge and skills for AI [1]. However, there has been little attention to the potential of Embedded Systems and Edge AI as learning tools for expanding students' and educators' conceptual understanding of AI and its application [2],[3].

Embedded Systems are foundational in electrical and computer engineering, requiring integrated knowledge of hardware and software. As AI becomes increasingly permeated in everyday life in the form of smart lights, cameras, locks, and other consumer products, it is essential for future engineers to understand AI not only as algorithms but as practical, integrated applications for social good. Unlike the general-purpose computers like laptops, using Edge AI as an AI learning tool may have several advantages considering accessibility, time-efficiency, integration of hardware and software, and community relevance.

To better understand the effectiveness of Edge Intelligence -based teaching and learning, this study investigated whether high-schoolers who engaged with an innovative Edge Intelligence-focused curriculum revise prior AI conceptions toward broader, system-level understanding while developing task value, interest, and engagement in AI-focused technologies and activities. Guided by the Cognitive Reconstruction of Knowledge Model (CRKM) of conceptual change, we designed and implemented an exploratory three-hour curriculum which addressed multivariable factors from cognitive to affective and motivational factors. This curriculum introduced participating high-schoolers to Embedded Systems, Tiny Machine Learning (TinyML), AIoT, and Edge Intelligence through hands-on experience with an ESP32-based learning board. This board includes a breadboard, a battery, five different sensors, and an OLED monitor. Using Arduino™ and Edge Impulse™ software, students witnessed the full TinyML workflow, from data collection and preprocessing to model training and deployment.

One hundred and seventeen high-schoolers from four schools in the southeastern United States participated in the curriculum implementation. Thirty-four out of the students completed both pre- and post-surveys about AI conceptions that focused on the domains of AI, uses of AI technology, ubiquity of AI technology, and reasons for AI uses. Students' conception shift was captured after their engagement with the learning boards in terms of their emotion toward AI, and fact-based understanding. The results demonstrate that instruction integrating Embedded Systems and Edge Intelligence can serve as a gateway for developing and expanding foundational AI literacy in pre-college engineering contexts.

At the same time, this study has several limitations as a work-in-progress paper, which should be addressed in the later phases of our design-based research project [4]. In the following sections, we will introduce the theoretical background to support this study, and provide details regarding the curriculum design, assessment instruments, and anticipated results, contributing to the growing body of research on integrating Edge Intelligence into pre-college engineering education.
Keywords: AI Conception, conceptual change, Edge AI, Embedded Systems

Theoretical Background

Conceptual change theory posits that students' prior conceptions shape their interpretation about a topic or subject that they learn[5]. Building on this foundational premise, models of conceptual change have been developed to explain how these prior conceptions or beliefs can be revised incrementally or, more ambitiously, how entire cognitive structures can be restructured or replaced [6], [7].

The classical theories on the nature or conceptual change process have focused on the rational and cognitive factors that lead to actual change in conception about a topic or subject [5]. However, an important turning point was made around 1993. Pintrich et al. [6] highlighted that the literature prior to 1993 theories of conceptual development mostly focused on knowledge representations. In his assertion, this "cold" perspective might have ignored the affective and motivational factors that may lead to students' actual conceptual change. Pintrich's approach recognized that conceptual change is influenced by "warm", affect-driven factors such as students' goals and motivational beliefs [8], which results in a re-conceptualization of conceptual change to incorporate both cognitive and epistemic aspects of students' conceptual development.

Similar to this viewpoint, Dole and Sinatra [9] provided another lens that incorporates social psychological perspectives and suggested Cognitive Reconstruction of Knowledge Model (CRKM) as an alternative model. In terms of conceptual change process, CRKM highlighted the role of affective and motivational factors, involving dissatisfaction, or personal relevance. This model also distinguished between the central route and the peripheral route to get to the eventual conceptual change. The former involves deep, thoughtful processing leading to lasting change in terms of message, while the latter results in quick, superficial changes based on cues like an attractive or credible source of information. Based on the distinction, CRKM suggests that conceptual change can come not only through the central route, but also through the peripheral route with an arousal of situational interest. CRKM also supported that conceptual change is influenced by multivariable factors encompassing cognitive, affective and motivational factors.

While conceptual change has been used as a key theoretical framework in science or math education, in the past few years it has been increasingly applied in other domains including AI education. Educational researchers agree that understanding of AI requires conceptual change, because misconceptions or limited understandings about AI abound [10]. Those include but are not limited to such notions as a) AI is ChatGPT, b) AI requires cloud computing, c) AI devices are expensive, d) AI engineers are mostly motivated by high salaries, and that e) using AI will cause loss of jobs for human workers and is therefore unethical. A few recent studies have explored misconceptions about AI [11],[12], producing results that imply a strong need for shifting our society's conceptions about AI.

Mertala and colleagues [13], [14] emphasize the need for quantitative analyses of AI conceptions in the K-12 context. They leveraged several AI conception models and analyzed students' AI conceptions relative to four dimensions: domains, uses, ubiquity, and reasons, incorporating both affective and cognitive factors. Guided by these four dimensions of AI conceptions and CRKM that highlights multivariable factors influencing conceptual change, this study was designed to explore students' evolving AI conceptions as they engage with a hands-on, project-based learning curriculum on Embedded Systems and Edge Intelligence . Specifically, this work-in-progress study is guided by the following research question:

• To what extent does an Edge Intelligence-focused, hands-on curriculum influence high-schoolers' conceptions about AI?

Context and Participants

This project was funded by NSF, so its goal is to improve STEM education aligned with our funder. Specifically, this project aimed to design, test, and study the uses and effects of a curriculum that engages high-schoolers in hands-on learning experiences using Edge Intelligence to promote their interest, conceptual understanding as well as career choice in computer engineering. As a joint effort by the Electrical and Computer Engineering, Engineering Education, and Teaching and Learning faculty, this three-hour curriculum was adapted for the high-schoolers from an existing undergraduate course about AI and microelectronics. The curriculum did not make any assumption about participants' prior knowledge, experience or skills.

The study participants consisted of 117 high school students recruited from four schools in the southeastern United States. These students were enrolled in STEM elective courses, specifically Computer Science or Environmental Science, and they were taught by four in-service high school teachers. The four teachers had participated in a specialized professional development institute in September 2025 and volunteered to implement the three-hour curriculum between September and December 2025 in their classrooms. While 117 students participated in the instructional sessions, only 34 students completed both the pre- and post-surveys required for the final analysis. Despite the full classroom implementation, this discrepancy in participation for the research can be attributed to the voluntary process of returning signed parental consent forms required for data collection in a pre-college setting, and this might serve as a potential source of selection biases.

Curriculum

This three-hour curriculum has been designed as a guided exploratory experience to introduce high-schoolers to Edge Intelligence through hands-on experience with an ESP32-based learning board (Figure 1) with breadboard, a battery, five different sensors (i.e. weather sensor, heart-rate sensor, oximeter sensor, light sensor, and time-of-flight sensor) and an OLED monitor.

In Module 1, students are introduced to key concepts such as Embedded Systems, the Internet of Things (IoT), AIoT, and Edge Intelligence, and they investigate the input-processing-output cycle by engaging with the learning board focusing on light sensor. Module 2 facilitates the full TinyML workflow—from data collection to on-device deployment—using Edge Impulse to solve real-world problems like fruit-ripeness detection. The final modules encourage students to apply the engineering design process to ideate and prototype Edge AI solutions for community-relevant challenges. The specific instructional prompts and activities provided to students are detailed in Appendix A

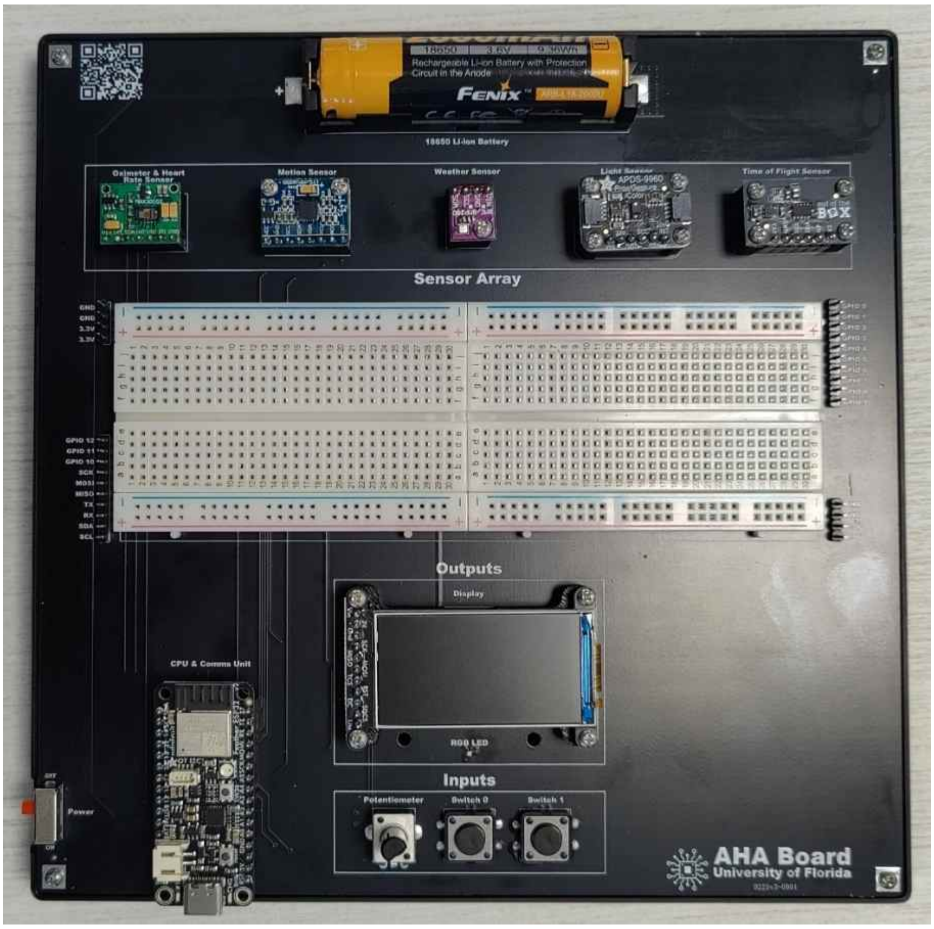

Figure 1. Edge Intelligence-embedded board

Instrument

The AI Conception Survey (AICS) used in this study is a 20-item instrument designed to assess respondents' conceptions of AI across four domains: (1) Domains of AI (Q1-4), (2) Uses of AI Technology (Q5-10), (3) Ubiquity of AI Technology (Q11-15), and (4) Reasons for AI Use (Q16-20). The question items in AICS were adapted from author's paper [11] considering the context using Edge Intelligence. The full items in AICS are included in Figure 2. This instrument reflects both accurate and inaccurate conceptions of AI. Students responded to each item using a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), with 3 representing a neutral stance. Items marked with an asterisk (*) represent conceptually incorrect statements and are therefore reverse-scored during data analysis. To this end, all items in the statements were expected to increase after the curriculum implementation.

Due to the nascent nature of AI literacy research, this adapted version of the AICS is currently in the process of psychometric validation. Rather than serving as a standardized diagnostic tool to make conclusive judgments, we used AICS as an exploratory instrument to capture broad shifts in students' conceptual landscapes following exposure to AI and Edge Intelligence.

Results

In this pilot study (n = 34) we observed a mean increase in the total score from 65.61 to 67.27. The descriptive results of the pre- and post-survey data are summarized in Figure 2. A paired-samples t-test controlling the school effect indicated that this improvement slightly missed the statistical significance in a two-tailed test, $t = -2.01$, $p = .053$. Given the directional hypothesis that post-test scores would exceed pre-test scores, however, a one-tailed test reached statistical significance ($p = .026$). The effect size for the change was small to medium (Cohen's $d = 0.34$), suggesting a modest impact of the curriculum on students' AI conceptions.

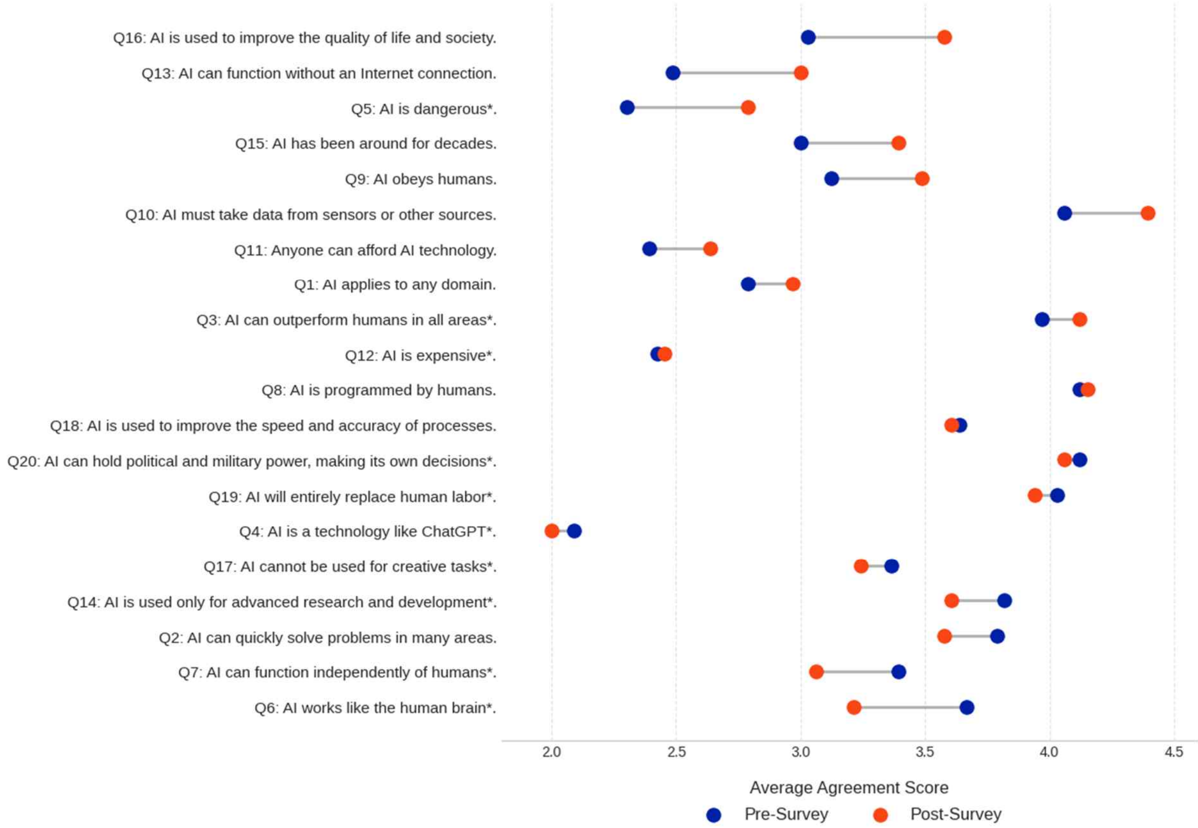

Figure 2. Change in AI Conception

Item-level analyses (Figure 2) revealed that changes were not evenly distributed across the scale. The three items showing the largest positive gains were Q16 (AI is used to improve the quality of life and society; +0.545), Q13 (AI can function without an Internet connection; +0.515), and Q5 (AI is dangerous*; +0.485). These increases suggest greater awareness of both the societal role of AI and certain technical realities and risks.

In contrast, four items showed declines: Q2 (AI can quickly solve problems in many areas.), Q6 (AI works like the human brain*; -0.455), Q7 (AI can function independently of humans*; -0.333), and Q14 (AI is used only for advanced research and development*; -0.212). All remaining items changed by less than 0.35 points, indicating relatively stable conceptions across most areas.

The internal consistency of the scale was low at both time points (Cronbach's $\alpha = 0.39$ pre-test; 0.51 post-test), suggesting limited coherence among the items as a single construct. Item-level diagnostics identified Q11 (Anyone can afford AI technology.) and Q12 (AI is expensive*) as problematic, with weak item–total correlations. Removing either item increased reliability modestly (pre-test $\alpha = 0.44$-0.50; post-test $\alpha = 0.56$-0.57).

Discussion

The results indicate a small but meaningful improvement in participants' AI conceptions following instruction. Although the two-tailed test narrowly missed significance, the significant one-tailed result and the observed effect size support the interpretation that participants' understanding of AI improved in the intended direction.

The strongest gains were observed in items related to AI's societal role (Q16: AI is used to improve the quality of life and society) and technical functioning (Q13: AI can function without an Internet connection). The increase in Q13 can be attributable to the curriculum's focus on Edge Intelligence, where students witnessed the AI model functioning on a battery-powered ESP32 board after disconnecting it from their computer. The change in Q16 reflects the curriculum, where students are asked to design and prototype their own solutions for community challenges with Edge Intelligence. This suggests that the curriculum may have been particularly effective in clarifying why it is used and how AI operates. The increase in endorsement of Q5 (AI is dangerous*) may reflect increased positive attitude and reduced random concerns related to AI, which has been increasingly emphasized in AI education.

Interestingly, decreases in Q6 (AI works like the human brain*), and Q7 (AI can function independently of humans*) may seem like a movement more toward the anthropomorphic conceptions of AI considering both are reversely coded. However, this shift could be interpreted positively along with the decrease in Q2 (AI can quickly solve problems in many areas.), as it may reflect a more nuanced understanding. The result in Q2 may mean that students understood that AI cannot solve problems quickly. It suggests they have moved beyond a "magic box" view of AI and now appreciate that generating a solution is a complex, multi-step process, not an instantaneous event. Through the hands-on experience of training and testing data in Edge Impulse, students may have realized that generating an AI solution is an iterative engineering task rather than an instantaneous event. The decrease in Q14 (AI is used only for advanced research and development*) likewise shows that students may have noticed the complex process of AI applications beyond anthropomorphism. Therefore, decrease in the two reversely coded items, Q6 or Q7, can be re-framed. Rather than viewing the results as a move toward a literal, biological perception of AI, it likely signifies their surprise and awe at the sophisticated processes they had just learned about.

Limitations and Future Work

As a Work-in-Progress study, several limitations must be addressed in future research phases. First, the low response rate for the surveys, primarily due to the voluntary nature of parental consent, introduces a potential self-selection bias that may serve as a source of confounding. Second, the instrument, AICS, is still under development. Future studies should refine and further validate the AI conception survey. Its low internal consistency suggests that while it captures broad conceptual shifts, it requires further psychometric validation, such as factor analysis, to refine problematic items like Q11 and Q12. Third, the short duration of the three-hour curriculum may limit the depth of conceptual change compared to longer interventions. Future studies will focus on longitudinal designs with more diverse and larger samples to enhance generalizability Additionally, we aim to improve the alignment between instructional prompts, survey items, and expected results to more accurately capture the nuanced transitions from narrow to accurate and systematic AI understanding.

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Appendix A. Overview of Three-hour Curriculum on AI and Microelectronics

Unit A: Hardware Exploration and Non-AI Logic

Task A.1: Hardware Audit. Students visually identify the ESP32 microcontroller, OLED display, and the sensor array (weather, heart-rate, oximeter, light, and time-of-flight) on the learning board. Students define key concepts such as the Internet of Things (IoT), AIoT, Edge Intelligence, Embedded systems based on their exploration.

Task A.2: Raw Data Observation. Using the Arduino IDE and the Light Sensor-based Arduino file, students observe raw RGB values and ambient light intensity (0–255 range) in the Serial Monitor.

Task A.3: Algorithmic Testing. Students use RGB color cards to test the limitations of manual threshold-based rules under varying lighting conditions.

Unit B: TinyML Workflow and AI Application

Task B.1: Model Exploration. Students walk through the "Impulse Design" in Edge Impulse, including data cleaning (flattening), defining the classification model, and verifying model testing accuracy.

Task B.2: AI-Model Flashing. Students import the deployed .zip library into Arduino and flash the fruit ripeness classification firmware onto the ESP32 board.

Task B.3: Model Testing. Students use the board without internet or PC connection to test the AI model's real-time performance on fruit color detection with the existing fruit cards.

Unit C: Sensor Stations

Task C.1: Station Rotation. Students rotate through four stations to compare Non-AI versions (e.g., raw temperature reading) with AI-enabled versions (e.g., weather pattern prediction). Students record the functional differences and perceived accuracy of AI versus non-AI logic for motion, heart rate, weather, and distance detection

Unit D: Design for Community Solutions

Task D.1: Design & Prototyping. Students identify a local community challenge (e.g., energy waste) suitable for Edge AI. Following the engineering design process (ask, imagine, plan), students provide a solution using the board's sensors to address the identified problem.