Engineering Educators Bringing the World Together
2025 ASEE Annual Conference & Exposition
Palais des congrès de Montréal, Montréal, QC • June 22–25, 2025
Paper ID #48170

WIP: Empowering First-Year Engineering Students for Career Choices through Hands-On AI Hardware Experiences

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Abstract

This manuscript is a work-in-progress paper. The semiconductor industry is making groundbreaking advancements, and hardware engineers play a pivotal role in driving these technological innovations and industrial progress. Despite this, engineering education programs often struggle to attract and retain enough students to sustain a robust cadre of next-generation hardware engineers. A significant number of first-year computer science and engineering students gravitate toward software-focused academic and career trajectories, frequently due to their limited exposure to hardware-specific issues and trends. With this context in mind, our research began with the question of how we can support first-year engineering students in broadening their perspectives and discovering opportunities in hardware-related engineering professions. To address this question, we leverage the Social Cognitive Career Theory (SCCT) based on Bandura's social cognitive theory.

This paper discusses a novel hardware AI curriculum and its implementation aimed at improving students' hardware engineering self-efficacy beliefs, outcome expectations, and interest in the hardware industry. Within this project-based 8-week curriculum, students engage with a custom-made AIoT learning board that includes an ESP32 microcontroller, a breadboard, a battery, power management components, and several sensors. The activities of this curriculum encourage students to collect data using the board's sensors and leverage edge artificial intelligence (edge AI)—that is, AI performed on the local device—for the design of a personally relevant embedded systems project. With guidance from the instructors and detailed activity scaffolds, students can experiment with the provided code that uses multiple sensors and machine learning models on the microcontroller. They then adapt these applications to address problems and scenarios relevant to both their personal interests and societal issues.

The results of this study indicate a noticeable difference in students' self-efficacy, outcome expectations, and interest in AIoT before and after the implementation of the hands-on, project-based, personalized, and culturally responsive curriculum. In future research, we hope to further provide essential insights on how to support diverse student groups in the field, with the goal of unlocking their talents, broadening their perspectives, fostering more innovative ideas in engineering, and contributing to the sustainable development.

Introduction

The semiconductor industry is experiencing rapid transformations driven by revolutionary developments in Artificial Intelligence (AI), Internet of Things (IoT), cybersecurity, and a renewed emphasis on sustainable technologies. These technologies are not only enhancing manufacturing efficiency and sustainability but also introducing new challenges, particularly in national and global workforce development.

While hardware engineers create the essential physical elements and systems that power these advancements, there is a deficit of hardware engineers [1]. This engineer shortage is attributed to several issues including declining interest among undergraduate students for pursuing careers in hardware engineering or the educational gaps condition where structural opportunities for students to develop practical skills in hardware engineering are limited. Trevelyan [2] highlighted that there has been a severe lack of curricula in higher education to improve employability and prepare engineers for sustainable development goals.

To address this social and educational problem, this study focuses on a particular curriculum innovation for first-year engineering students' career choice. According to Trafford et al. [3], first year students' course experience is closely associated with the student's identity in the Electrical and Computer Engineering field. Engineering students are more inclined to follow software career paths, frequently due to their minimal exposure to hardware issues and trends.

With this context in mind, our research explored the issue of how we can support first-year engineering students in broadening their perspectives and discovering opportunities in hardware-related academic pathways and professions. Building on the foundations of Social Cognitive Career Theory's (SCCT) choice-making model [4], this research focuses specifically on how to assist first-year engineering students' career choices by engaging them in hands-on AI hardware experiences in an elective first-year-embedded systems course. This work-in-progress paper discusses a novel hardware AI curriculum and research on its implementations aimed at improving students' hardware engineering self-efficacy beliefs, outcome expectations, and interest.

Theoretical Background

Social Cognitive Career Theory (SCCT) by Lent et al. [4] has been used to explain and predict career choices considering both environmental and individual factors which influence students' career decision making. SCCT is rooted in Bandura's social cognitive theory that emphasizes the role of cognitive processes, personal backgrounds, self-efficacy beliefs, and learning experiences [5]. Figure 1 illustrates the process of SCCT's career choice model. Based on SCCT framework, this study focuses on the impact of first-year college students' learning experience in terms of self-efficacy beliefs, outcome expectations, and interest as factors to lead their career goals and choices.

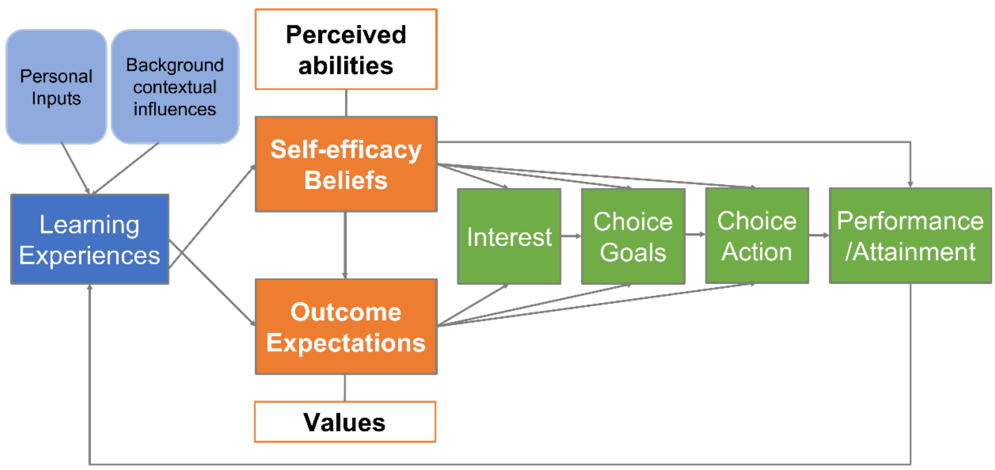

Figure 1. Framework of the career choice model based on social cognitive career theory (SCCT)

Personal/Contextual Influences

Personal input and contextual influences are crucial factors in the SCCT framework. Personal input refers to individual characteristics including gender and ethno-cultural background. Environmental factors include affordances that individuals feel or derive from the environment about support systems or the availability of resources [4]. These elements are grouped as cultural influences, which interplay to shape cognitive influences (i.e., self-efficacy beliefs and outcome expectations). Our curriculum considered these students' cultural influences to help the students' career choices. For instance, in a final project, students should not only employ AIoT technology considering sensors, data transmission, and machine learning components employ, but also provide solutions to the real-world issues in their community and social problems that they personally think important.

Self-efficacy Beliefs

Self-efficacy is defined as an individual's perception of their ability to successfully perform a specific task or achieve a particular goal [5]. In the context of SCCT, self-efficacy is an important outcome of learning experiences, along with outcome expectation. Self-efficacy belief is shaped by several sources, such as individuals' mastery experiences (e.g., performance accomplishments), vicarious learning, social persuasion, along with physiological and affective states [4].

Outcome Expectations

Outcome expectations involve beliefs about the consequences or outcomes of performing specific behaviors, and it is also affected by individual's self-efficacy [4]. Within SCCT, these expectations along with self-efficacy beliefs influence an individual's career choices by affecting their perceived feasibility of certain career paths. Positive outcome expectations can encourage individuals to pursue careers with higher expectations on the outcome, while negative expectations might stop them from having a certain career pathway. As suggested by Bandura [5], this study included the three types of outcome expectations: performance outcome expectations, self-evaluative outcome expectations, and social outcome expectations.

Interest

SCCT posits that both outcome expectations and self-efficacy influence a person's interest in a particular career domain. In other words, when individuals feel competent and expect positive outcomes in a field, they are more likely to develop interest in the area. This development of interest is a critical step that leads to the formation of career goals and the intended pursuit of any specific career paths [4].

Choice of Goals, Action and Performance

In SCCT, the result of increased interest translates into concrete career goals, actions, and performance. Individuals set career goals based on their social and cognitive influences from self-efficacy beliefs and outcome expectations. These modified goals guide their behaviors and efforts towards achieving desired career goals. To sum up, this interplay of personal/contextual influences and cognitive factors leads to the pursuit and the attainment of career success as defined by the individual's aspirations and environmental realities.

Guided by SCCT, this study was designed to explore the important outcomes of students' self-efficacy and outcome expectations before, during, and after engaging with a hands-on curriculum that provides project-based hardware engineering and AIoT learning experiences. Specifically, this work-in-progress study is guided by the following research question:

- Do the AIoT hands-on hardware learning modules have an impact on first-year engineering students' self-efficacy, outcome expectations, and interest in AIoT?

For the next phase of this study, our team is planning to explore potential individual differences of the students' career goals and actions after participating in the module, focusing on genders, ethno-cultural groups, and learning preferences. We believe that this future endeavor will provide crucial information on how to support diverse groups of students in the field, aiming to unlock the students' talent and perspectives not only for more innovative ideas in the field of engineering but for ensuring sustainable development of the world.

Methods

Study Context and Participants

Supported by the NSF Improving Undergraduate STEM Education (IUSE) program, our project designed and developed an innovative AIoT curriculum that engaged first-year undergraduate engineering students in hands-on learning experiences to promote their interest as well as career choice in hardware-focused engineering. The curriculum was offered by the Electrical and Computer Engineering (ECE) department at a large public university in the US Southeast. This 8-week curriculum was implemented during two Fall semesters (2023 and 2024) with two cohorts of students as part of an elective engineering course. The same instructors facilitated students' learning in both cohorts. The course requires no prerequisites, making no assumptions about participants' prior knowledge, experience or skills. This study was approved for the expedited review by the Institutional Review Board (IRB) by the authors' institution (IRB 202301130).

Forty-five first-year engineering students enrolled in this elective course ($n = 22$ for Fall 2023 and $n = 23$ for Fall 2024). Since this course was elective and experimental in terms of curriculum, we could not recruit a whole class for a control/comparison group experiment. As a result, twenty of the enrolled students completed both pre- and post-surveys ($n = 17$ from Fall 2023 and $n = 3$ from Fall 2024). The twenty study participants represented four different majors: Computer Engineering ($n = 13$), Electrical Engineering ($n=3$), Computer Science ($n = 3$), and Mechanical Engineering ($n = 1$). Most of the participants identified as men ($n = 16$), followed by women ($n = 3$), and non-binary ($n = 1$). Ethnoculturally, most participants identified as White ($n = 15$), followed by Asian ($n = 4$), and Latine ($n = 1$).

Curriculum Features

Table 1 provides an overview of the weekly structure of the AIoT curriculum designed to trigger and sustain first-year students' interest in hardware engineering and support their engineering self-efficacy and outcome expectations.

Table 1. Overview of AIoT curriculum

Week	Topic	Projects
1	AHA board tour	
2	RGB sensor modules and predictions	Fruit ripeness monitor
3	Methods to measure distances	Range detection
4	Smart light bulb	Controlling Smart light bulb
5	Measures of temperature	Temperature Measurement
6	Motion detection	Movement Recognition
7	Project Work	Project - Steps 1 &2
8	Project Work	Final Project Reports

On the first day of the 8-week curriculum, students form teams (usually pairs) and receive a custom-made AIoT learning board (also called the AHA board) along with a comprehensive manual on how to use it. The board includes an ESP32 microcontroller, a breadboard, a LED screen, a battery, power management components, and various sensors (an oximeter and heart rate sensor, a motion sensor, a light sensor, a weather sensor, a potentiometer, and an ultrasonic sensor.). Figure 2 illustrates the AHA board used in the curriculum. The board features clear labeling and a Lego-like organization with removable sensors and a breadboard that provides extensibility for a number of embedded systems projects.

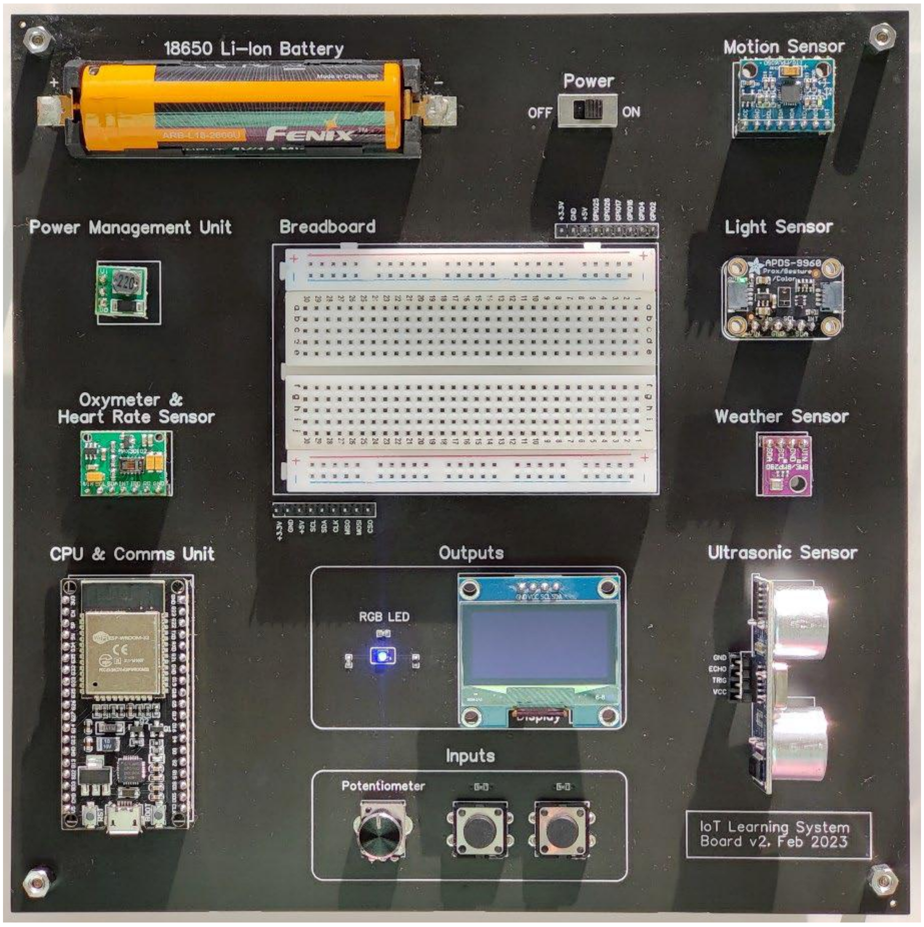

Figure 2. AHA (AI-Hardware Adventure) board

The curriculum engages students in multiple iterations of hands-on project-based learning. After being introduced to the concepts of IoT, AIoT, and Edge AI, each weekly activity guides students through the iterative process of the following stages. First, students attend short lessons on how the sensor works. Second, students are encouraged to collect data using the board's sensors. Third, with guidance from the instructors and detailed scaffolds, students can experiment with the provided code that makes use of edge intelligence, that is, machine learning models that are run on the local ESP32 microcontroller. Fourth, students use a pre-developed AI model and deploy it such that it can be run on the board. Finally, they use the AHA board to predict the new input. The process is repeated whenever students in teams are introduced to a new sensor. For their final project, student teams adapt the code and apply their knowledge of AIoT and edge AI to address a real-world problem within scenarios relevant to both their personal interests and broader societal issues. Through these multiple activities, students not only understand AIoT concepts more effectively but also apply knowledge in a variety of contexts and personalize their learning through their final project.

In this project-based, personalized learning [6] curriculum, each project can be tailored for individual students' leaning needs, pace, and interests in relation to the sensor devices and coding for adapting machine learning. Students are encouraged to monitor and regulate their own learning by letting them choose their own goals and manage their projects toward the final project outcomes considering their knowledge, interests and needs. Since all projects are conducted in teams in the classroom, individualized and differentiated feedback can be provided to the students based on their learning paths.

Our curriculum design also reflects the principles of Culturally Sustaining Pedagogy (CSP) [7], encouraging students to integrate their cultural backgrounds in identifying the social problems and evaluating whether and how these problems can be tackled using edge AI solutions. Students are encouraged to engage in projects with the final projects in mind so that they can regard their cultural backgrounds and experiences as valuable assets to create feasible solutions for their community issues. In this process they can critically evaluate the societal inequities and injustices, which empowers the students to question and challenge the status quo and allow active participation.

Instrument and Data collection

To assess SCCT factors, 21 items were adapted from Niederhauser and Perkmen's study [8]. The original instrument aimed to identify teachers' self-efficacy, outcome expectations and interest in integrating technology for students learning. We modified each item by replacing the word "instructional technology" with "AIoT" along with adjusting the context. For instance, an original item was: "Using instructional technology in the classroom will increase my effectiveness as a teacher. (item 5)" The modified version was: "Using AIoT technologies will increase my effectiveness as an engineer." The instrument asked the three components: self-efficacy (6 items), outcome expectations (9 items), and interest (6 items). Respondents expressed their agreement with each statement using a five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5).

While 45 first-year engineering students participated in the activities, 20 students (17 from Fall 2023 and 3 from Fall 2024) completed both pre- and post-surveys. For both cohorts, pre-survey data were collected during the first week of the curriculum and post-survey were asked after the final project presentations. Through the surveys, we assessed the influence of hands-on AIoT experience on the outcomes in students' self-efficacy, outcome expectations, and interests.

Results and Discussions

The descriptive results of the pre- and post-survey data are summarized in Table 2.

Table 2. Descriptive statistics of Pre- and Post-test results

Variable	Pre-test N	Pre-test Mean (SD)	Pre-test Min.-Max.	Post-Test N	Post-test Mean (SD)	Post-test Min.-Max.
AIoT self-efficacy	20	3.15(0.96)	1.00-4.83	20	3.75(0.68)	2.17-5.00
AIoT outcome expectation	20	3.72(0.54)	2.5-4.88	20	3.96(0.73)	1.88-5.00
AIoT interest	20	3.71(0.74)	1.71-5.00	20	3.91(0.85)	1.43-5.00

Our team observed a noticeable discrepancy among students' pre- and post-survey results in self-efficacy compared to outcome expectations and interest. To further investigate the differences, we conducted the Wilcoxon signed-rank test, a non-parametric alternative to a paired samples t-test due to following reasons. First, the sample size was limited. Second, the data was not normally distributed as shown in the results of Shapiro-Wilk's test in AIoT self-efficacy ($W=0.95$, $p = 0.42$) and outcome expectations ($W = 0.96$, $p = 0.60$).

The result of Wilcoxon signed-rank test in Table 3 shows the impact of the intervention on participants' self-efficacy, outcome expectations, and interest. It reveals statistically significant changes across all three constructs.

Table 3. Wilcoxon Signed-rank Test Results of Pre- and Post-tests

Variable	Z-value	V-value	P-value
AIoT self-efficacy	-3.40	14	0.01*
AIoT interest	-2.80	26.5	0.02*
AIoT outcome expectation	-2.93	30	0.03*

* $p < 0.05$

Self-efficacy showed the most substantial and consistent change ($Z = -3.40$, $V = 14$, $p = 0.01$), indicating a significant improvement in students' self-efficacy belief. AIoT Interest also demonstrated a significant increase ($Z = -2.80$, $V = 26.5$, $p = 0.02$), after the intervention. Outcome expectations, while still significant, showed a slightly less noticeable change ($Z = -2.93$, $V = 30$, $p = 0.03$). The lower V value for self-efficacy, compared to the other constructs, indicates a more uniform positive change in the variable.

In the data analysis, we did have ties and zero differences in responses for certain participants. This is assumed to be ceiling effects, where some participants may have already had high scores before taking this course. Despite these ties, the overall significant results across all three constructs provide robust evidence for the impact of the learning modules.

These findings strongly support the effectiveness of the hands-on AIoT curriculum intervention in enhancing key psychological factors related to career choice in hardware engineering, aligning with SCCT's postulation that personally/culturally relevant learning interventions can positively influence these interconnected variables.

Conclusion and Future Work

The results indicate a noticeable difference in students' self-efficacy, outcome expectations, and interest in AIoT between before and after the implementation of the curriculum. Our hands-on, project-based, personalized, and culturally responsive curriculum aims to improve students' self-efficacy, outcome expectations, and interest, which are crucial elements in career decision-making and development according to SCCT. This work-in-progress paper provides evidence suggesting that such curriculum-based approaches can enhance first-year engineering students' interest and broaden their perspectives in AIoT hardware-related issues and trends.

Future research could further investigate the long-term stability of these changes in the students' actual career choices by incorporating other factors both during their engineering studies and after graduation, such as job type, salary, and job prospects. Increasing the number of participants in this curriculum and study would enable us to examine potential moderation factors that might influence the intervention's effectiveness across diverse groups of students, including gender, major, ethno-cultural background, and other contextual variables. Previous studies show that the first-year career choice can vary based on race and gender; future research could examine these differences so that engineering programs can create personalized learning environments that support the career choices of targeted groups of students. We believe that this endeavor will yield essential insights on how to support diverse student groups in the field, with the goal of unlocking their talents, broadening their perspectives, fostering more innovative ideas in engineering, and contributing to the sustainable development.

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