

# **Exploring Outcome Expectations in Artificial Intelligence and Internet of Things in First-Year Engineering Students (Work in Progress)**

#### Ing. Andrea Ramirez-Salgado, University of Florida

Andrea is a doctoral candidate in Curriculum and Instruction at the University of Florida, specializing in Educational Technology. Her work centers on understanding the dynamics of teaching and learning approaches that shape the identity of computer engineers to support computer engineering career choices, particularly in women first-year engineering students. She is committed to designing inclusive curricula that cater to the needs of diverse learners, guided by principles of Universal Design for Learning and Culturally Responsive/Sustaining Pedagogies.

#### Dr. Pavlo Antonenko

Pavlo "Pasha" Antonenko is an Associate Professor of Educational Technology at the University of Florida. His interests focus on the design of technology-enhanced learning environments and rigorous mixed-method research on the effective conditions for tec

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# Introduction

For the United States to sustain its competitive edge and leadership in Artificial Intelligence (AI) and its intersection with Internet of Things (IoT) hardware technologies, a vital focus must be placed on fostering the growth and development of its specialized technical workforce in the Electrical and Computer Engineering (ECE) and other related fields [1]. This strategic focus is crucial given the escalating demand for proficiency in critical domains like embedded systems paired with machine learning, sensor-driven big data analytics, edge computing, and cybersecurity [2]. The combination of AI and IoT, known as AIoT, embodies the convergence of advanced technologies that rely on seamless collaboration between AI algorithms and IoT infrastructure. This integration drives innovation and efficiency across various industries, highlighting the urgent need for a skilled computing workforce to propel the nation's technological advancement [1]. However, many engineering students may lack exposure to AIoT concepts and may not fully grasp the potential career opportunities in this field. This lack of awareness could hinder their engagement and limit their ability to contribute effectively [3].

Our study aims to bridge this gap by examining first-year engineering students' outcome expectations (OE) after their participation in an undergraduate AIoT hands-on module. In this context, OE delineates individuals' anticipated beliefs regarding the outcomes or results they envision through their engagement in a specific activity [4] – in this instance, an AIoT module. These expectations would influence individuals' motivation, commitment, and perseverance within the field. Positive outcome expectations bolster motivation and commitment, whereas negative expectations may impede progress and discourage sustained involvement [4]. Our study investigates changes in OE before and after exposure to AIoT concepts and activities. We aim to understand how this exposure influences students' perceptions of career opportunities and motivates them to further explore these concepts throughout their undergraduate studies.

This work in progress is guided by the research question: How does an AIoT hands-on module impact first-year engineering students' outcome expectations? In the next phase of this study, we will explore potential differences in OE between women and men after their participation in the module. This future endeavor is imperative to support gender diversity in the field, aiming to unlock a wealth of untapped talent and perspectives, fostering innovation, and advancing social justice.

Keywords: AIoT education, outcome expectations, hands-on learning

#### **Theoretical Background**

Building upon the overarching theory of Social Cognitive Career Theory (SCCT) and its implications for career choice [5], this study's theoretical framework is grounded in the concept of OE. OE refers to an intrapersonal factor that is strongly tied to an individual's beliefs about the expected outcomes or results they expect to attain by participating in a particular activity [4]. Within the framework of SCCT, OE are fundamental cognitive factors that exert significant influence on individuals' career-related behaviors and decisions. These expectations function as anticipatory beliefs concerning the consequences of specific actions within a career context [5]. Positive OE bolsters motivation, shapes goal-setting processes, guide decision-making, and contributes to individuals' self-efficacy beliefs [4]. In essence, OE plays a pivotal role in shaping individuals' career trajectories and development by providing a cognitive framework through which they evaluate potential outcomes and make well-informed choices [4].

Bandura [4] delineated three types of OE, suggesting that positive outcomes can serve as incentives while negative outcomes may act as disincentives to persist in a certain behavior: performance outcomes, self-evaluative outcomes, and social outcomes[4]. In this study, we follow Bandura's multifaceted conceptualization of OE, as depicted in Figure 1.

### Performance Outcomes

These pertain to the anticipated achievements and tangible results individuals expect to attain by participating in some situations [6]. In the realm of the hands-on module in AIoT, performance outcomes might include the mastery of specific technical skills, successful completion of projects, or the attainment of academic recognition. The focus is on measurable and task-specific accomplishments that contribute to one's overall career development.

### Self-Evaluative Outcomes

This category revolves around the personal satisfaction and intrinsic rewards individuals associate with their engagement [6]. It delves into the individual's perception of their own competence, fulfillment, and sense of accomplishment derived from participating in the AIoT module. Self-evaluative outcomes play a crucial role in shaping individuals' intrinsic motivation, commitment, and overall sense of well-being in the pursuit of their career goals.

#### Social Outcomes

Anticipated social outcomes refer to the expected recognition, respect, and validation individuals foresee receiving from others as a result of their involvement in some activity [6]. In the AIoT module context, social outcomes may involve acknowledgment from peers, instructors, or the broader community for contributions, innovations, or collaborative efforts. Social outcomes are integral to understanding the external validation and social aspects that influence an individual's career intentions and engagement.

This study explores changes in OE before and after participating in the module to elucidate the impact of hands-on learning experiences on students' perceptions and anticipations regarding AIoT technologies. Additionally, it seeks to understand how exposure to such activities influences students' motivation, confidence, and interests in the field of computer engineering. Ultimately, this study aims to inform educational practices and interventions to enhance students' preparedness and enthusiasm for AIoT technologies.

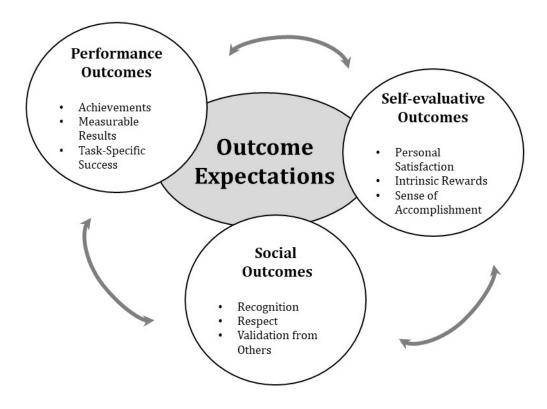


Figure 1. Primary forms of outcome expectations

### Methods

### **Study Context and Participants**

As part of a project funded by the NSF's Improving Undergraduate STEM Education (IUSE) program, our goal is to create a hands-on curriculum that fosters a stimulating and collaborative learning environment to increase interest among young students in hardware-related topics. In this curriculum, we designed an 8-week module centered on AIoT. This module, expanded upon later, specifically covers concepts related to data acquisition using sensors and microcontrollers, along with the implementation of machine learning models to address real-life scenarios. In Fall 2023, we implemented this module as the latter part of an elective course offered by the ECE department to first-year students enrolled in any engineering major at a large southeastern R1

institution. The course had no required prerequisites for enrollment, as we did not anticipate participants to have prior knowledge or skills.

Twenty-two (n=22) first-year engineering students participated in the class, of whom seventeen (n=17) provided informed consent. These students were requested to complete pre- and post-surveys at the beginning and end of the module to assess changes in their OE.

# **Curriculum Overview**

The activities throughout the 8-week module were centered around the AIoT learning board, as depicted in Figure 2. This standalone platform features an ESP32 microcontroller, a breadboard, a battery and power management unit, and an array of sensors, including motion, weather, heart rate, ultrasonic, and light sensors. The design of the learning board aimed to simplify the process of working with sensors by providing an abstraction layer, similar to assembling Lego pieces. Each pair of students in the course received an AIoT board along with a comprehensive manual. This manual detailed the sensors' components and technical specifications and provided code examples in Arduino for retrieving data from each sensor. This approach enabled students to comfortably manipulate both the software and hardware, even if they lacked prior experience in coding and digital design.

The module encouraged students to gather environmental data using sensors and utilize machine learning algorithms in cloud-based services like ThingSpeak to predict or classify different conditions. This approach was meticulously designed with Universal Design for Learning (UDL) principles in mind [7], aiming to promote inclusivity and engagement among all students. UDL emphasizes providing multiple means of representation, expression, and engagement to cater to diverse learners, facilitating success in specific tasks and measurable achievements, thereby enhancing overall performance outcomes. Throughout the module, we incorporated these principles by offering students various pathways to access information, express their understanding, and engage with the material effectively. For example, instead of relying solely on traditional lectures, we began each lesson with hands-on explanations of the sensor devices, followed by data collection and interpretation activities. We provided the necessary codes and libraries for each activity, allowing students to manipulate them freely, similar to a playground. Additionally, we encouraged students to demonstrate their understanding of AIoT concepts through a variety of mediums, such as project-based assignments, presentations, group discussions, and coding exercises. This approach empowered students to choose methods that aligned with their strengths and interests.

For the module's final project, students worked in groups to develop solutions using the AIoT learning board sensors and apply machine learning algorithms to tackle real-world scenarios. Through collaborative efforts in this challenge, we offered students opportunities for recognition and validation from their peers, fostering positive social outcomes. Within the framework of

Culturally Sustaining Pedagogies (CSP) [8], we encouraged students to integrate their own cultures and personal backgrounds into their project solutions, fostering a sense of belonging and promoting critical thinking. By using the AIoT board as a hands-on tool, students could experiment with culturally relevant AIoT scenarios drawn from real-world contexts. This practical approach allowed them to apply their learning in tangible settings, enhancing their understanding and readiness for real-world challenges in AIoT applications. This process also fostered self-evaluative outcomes through intrinsic rewards and a sense of accomplishment.



Figure 2. AIoT learning board

#### Measures and data sources

Before and after completing the AIoT module, the seventeen (n=17) consenting participants were administered an Instructional Technology Outcome Expectation (ITOE) adapted survey [6]. The survey aimed to measure participants' expectations regarding performance outcomes, self-evaluative outcomes, and social outcomes associated with their learning experience in the module. The survey was delivered electronically using the Qualtrics survey platform.

Niederhauser and Perkmen [6] developed and validated the ITOE scale to assess instructional technology OE among preservice teachers. Their validation process yielded a Cronbach's alpha coefficient of .93, signifying strong internal consistency [6]. Construct validity was further supported through Confirmatory Factor Analysis (CFA), showing acceptable fit indices for the three-factor model comprising performance, self-evaluative, and social outcomes [6].

Our study adapted the ITOE items to measure first-year engineering students' AIoT technology OE. Close-ended items were utilized, employing a 5-point Likert scale ranging from "strongly disagree" to "strongly agree" to capture participants' responses. A sample of the modified items is provided in Table 1.

This survey instrument served as both a pre-test and post-test measure, enabling us to assess changes in participants' OE before and after their engagement with the AIoT module.

Original Item	Modified Item		
<i>Performance outcome expectations:</i> Using instructional technology in the classroom will increase my effectiveness as a teacher	Using AloT technologies will increase my effectiveness as an engineer		
Self-evaluative outcome expectations: Using instructional technology in the classroom will make my teaching more exciting	Using AloT technologies will make my career more exciting		
Social outcome expectations: Effectively using instructional technology in the classroom will increase my status among my colleagues	Effectively using AloT technologies will increase my status among my colleagues		

Table 1. Examples of original and modified survey items

Descriptive statistics, including means, medians and standard deviations, were calculated separately for each factor/ OE facet (performance outcomes, self-evaluative outcomes, and social outcomes) for the pre-module and post-module surveys. Paired samples t-tests were then performed to assess changes in OE from pre-module to post-module. This analysis specifically addressed the research question: How does an AIoT hands-on module impact first-year engineering students' outcome expectations?

The use of paired samples t-tests was appropriate for this analysis. Both skewness and kurtosis values fell within the range of -1 to 1, suggesting approximate normality, even with a relatively small sample size [9].

Future work in this study will analyze qualitative data from semi-structured interviews that have already been conducted. These interviews explored students' perceptions of the AIoT module and career choices and interests, complementing the quantitative data collected from pre- and post-surveys. Additionally, the analysis will investigate nuanced differences in OE between women and men. This exploration will provide insights to support efforts toward equity and inclusion.

# **Results and Discussion**

This study included seventeen (n=17) first-year engineering students: thirteen men (n=13), three (n=3) women, and one (n=1) non-binary individual. They were distributed among three majors: computer engineering (n=13), computer science (n=3), and mechanical engineering (n=1). The average age of the participants was 18 years old. Predominantly, the racial ethnicity of the participants was white (n=13), followed by Asian (n=3), with one Hispanic student.

Survey results revealed a positive increase in participants' overall OE regarding AIoT technologies after the module. A paired samples t-test demonstrated a statistically significant difference in AIoT OE before (M=3.49, SD=.43) and after the module (M=3.88, SD=.78; t(16)= -2.25, p<.05). The effect size, Cohen's d, was estimated at .550, indicating a moderate effect. Table 2 provides descriptive statistics for each of the three factors/OE facets in the survey, detailing means, medians, and standard deviations. Notably, the scale ranges from 1 to 5, with 3 representing a neutral score. The medians, less influenced by extreme values, provide a more accurate measure of central tendency.

	Performance outcomes		Self-evaluative outcomes		Social outcomes	
	Pre	Post	Pre	Post	Pre	Post
Median	3.57	4.00	4.00	4.00	3.33	4.00
Mean	3.50	4.04	3.55	3.90	3.33	3.67
Std. Deviation	.44	.71	.81	.93	.77	.88

As previously noted, thematic qualitative data will be utilized to reinforce these findings. However, the quotes from the interview transcripts provided below further support the increase in OE across all dimensions.

- <u>Social outcomes Validation from others:</u> "My dad doesn't have an engineering background, but, you know, he enjoys working with his hands and figuring things out, so I was, you know, very proud when I brought the board home during break and showed him how to sense the environment and make decisions.... That was really cool."
- <u>Self-evaluative outcomes Personal satisfaction:</u> "I loved to see that my code in fact worked and to show the results in the app, I mean..."
- <u>Performance outcomes Achievements:</u> "I use AI all the time, like ChatGPT is part of my life and now I feel it is less of a buzzword, like I can explain what really it is"
- <u>Self-evaluative outcomes Intrinsic rewards:</u> "I wish I knew all of this stuff in my robotics competiton in high school!"
- <u>Social outcomes Recognition:</u> "It was very simple sometimes because we always had the code ready but I think it could lead to bigger things. Every small amount of experience will help me get to entry levels"

The observed increase in students' OE concerning AIoT technologies highlights the effectiveness of infusing UDL, CSP, and collaborative project work in the instructional module design. These approaches have proven to significantly enhance students' performance, social, and self-evaluative outcomes. The qualitative data extracted from interview transcripts elucidate the multifaceted ways in which the instructional module impacted their perceptions and attitudes toward AIoT technologies, aligning with the survey results. Guided by the SCCT approach [4], cultivating positive OE about AIoT in the early stages of undergraduate engineering programs plays a pivotal role in guiding career decisions and fostering specialized career development in AIoT. Ultimately, this contributes to the expansion of the AIoT workforce.

While the findings of this study are promising, it is crucial to acknowledge the limitations associated with the small sample size. A larger and more diverse sample could offer a more comprehensive understanding of the generalizability of the results across various populations and contexts. The deliberate focus on first-year engineering students aimed to introduce AIoT topics early in their program. However, due to the scaffolded hands-on instructional approach, we anticipate that the module could also benefit other groups of students, such as non-engineering majors or junior/high school students.

# Significance

This study holds significance beyond the classroom, impacting both workforce development and societal progress. Our instructional approach focuses on equipping students with the confidence to navigate AIoT technologies, enabling them to effectively tackle real-world challenges and fostering early interest in the field. Through the integration of hands-on learning boards within a UDL-enhanced learning environment, we were able to nurture students' performance and social

outcomes. This has the potential to play a pivotal role in sustaining their engagement with the subject matter over time.

By incorporating CSP approaches, our module facilitated inclusive participation in culturallyrelevant AIoT projects for students from diverse backgrounds. This proactive approach not only promotes diversity and equity but also encourages the development of a workforce that values inclusivity. By prioritizing such initiatives, we ensure that the benefits of technological advancements are accessible to everyone, thereby contributing to the creation of a more inclusive and socially responsible society. This aligns with the enhancement of self-evaluative outcomes, as individuals from various backgrounds can cultivate positive attitudes and expectations toward AIoT technologies, thus fostering a more inclusive and equitable future.

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