

Exploring Situational Interest in Microelectronics and Edge AI Among Middle Schoolers in a Museum Program (Research to Practice)

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Introduction

The increasing significance of artificial intelligence (AI) in education has led to national policy efforts, such as the White House Task Force on Artificial Intelligence Education, aimed at fostering AI literacy, critical thinking, and early interest among educators and learners [1]. According to Adiguzel et al. [2], both learners and educators experience AI mostly as a software application, typically in the form of a chatbot. This creates important misconceptions around what AI is, how it works, and what its contributions and consequences for our society may be. A comprehensive conception of AI requires understanding the synergy between hardware and software applications. While AI software provides the algorithms that enable learning and decision-making, AI hardware brings these capabilities by executing computations and enabling AI systems to sense and act within the physical world [3] [4].

Despite its growing importance, AI hardware remains an underutilized domain in education, with most learners and educators primarily associating AI with software applications like chatbots or generative tools, overlooking the foundational role of microcontrollers, sensors, and embedded systems [5]. This gap in awareness presents a challenge: while the demand for professionals who can design and implement intelligent systems is rising [6], educational efforts often fail to emphasize the hardware side of AI. Encouraging exploration of both AI software and hardware empowers both learners and educators to understand AI's full potential.

Learning about AI hardware is closely connected to understanding Edge AI. Edge AI refers to AI running directly on local devices using microcontrollers, sensors, and embedded systems without relying on tethered or wireless internet access. Edge AI leverages various platforms for deployment, including Internet of Things (IoT), which connects physical objects with sensors to enable real-time data collection and analysis.

Developing expertise in AI hardware can significantly enhance career prospects, as it is a highly valued and rapidly growing skill in today's job market. As industries increasingly adopt AI-driven embedded system technologies, the demand for professionals who can design and implement intelligent hardware systems continues to rise. Bristow Holland reports that 250,000 AI hardware engineers will be required globally to meet industry demand by 2025 [6].

Focusing on AI hardware, in this study, middle-school aged youth learned about embedded systems and Edge AI using an innovative AHA! curriculum built around an inexpensive microcontroller platform called the AHA! board. The AHA! curriculum for middle schoolers is a hands-on, project-based learning experience designed for summer programs in informal educational settings. Our AHA! board uses a variety of sensors for multimodal data collection, a powerful ESP32 microcontroller, an OLED screen and RGB lights as outputs, as well as a breadboard for extensibility. It is used in conjunction with Arduino™ Integrated Development Environment (IDE) and Edge Impulse™ to allow children and adults to prototype novel AI

hardware applications in an intuitive manner (Figure 1). The AHA! can be described as a digital playground for supporting and encouraging engaging educational activities for young learners as they explore AI hardware applications through hands-on activities.

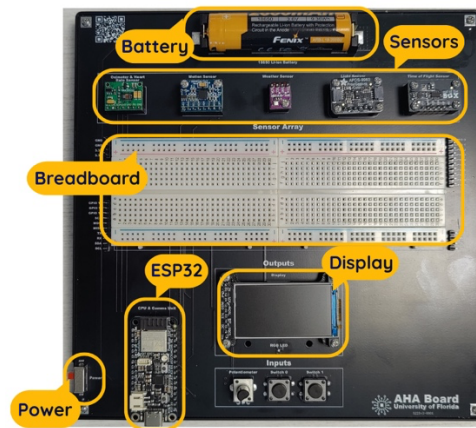


Fig 1. The AHA! Board Used as the Learning Platform

Supported by National Science Foundation (NSF DRK Award #2405373 and #1662976.), this two-week museum program engages middle schoolers in hands-on exploration of embedded systems, sensor technologies, and Edge AI through creative and tangible activities. Over approximately 30 instructional hours, the five-module curriculum guides students from basic computing concepts to designing and presenting Edge AI-powered solutions to solve local community challenges. This study examines how these experiences influenced learners' situational interest in Microelectronics and Edge AI during the program.

Keywords: AI Hardware, Edge Intelligence, Microelectronics, Situational Interest

Purpose

Most learners are familiar with Artificial Intelligence (AI) through software applications like chatbots, leading to the limited understanding of AI as cloud-based generative systems. A major barrier to learning hardware-focused applications of AI such as smart Internet of Things (IoT) devices is not necessarily its complexity, but rather a lack of strategies and tools for learners and educators. As computer engineering becomes increasingly important in our society, it is essential to understand how young learners engage with microelectronics and specialized applications of AI like Edge AI. Importantly, there is limited research on how young people's interest in AI and its applications develops and changes over time. Situational interest plays a critical role in conceptual change and cognitive engagement [7]. This study, funded in part by the National Science Foundation, seeks to contribute to our collective knowledge relative to this gap and examine changes in informal learners' situational interest in microelectronics and Edge AI.

Theoretical Background

Conceptual Framework

This study took place at a community innovation museum in the Southeastern US and was grounded in the Four-Phase Model of Interest Development [8], [9] which describes how interest evolves from a brief, externally triggered spark to more sustained and personally meaningful engagement (Figure 2). The model includes four phases: triggered situational interest, maintained situational interest, emerging individual interest, and well-developed individual interest.

Each phase reflects increasing levels of personal relevance, emotional engagement, and cognitive investment, which are essential for sustained learning. Triggered situational interest occurs when an individual's interest is sparked by specific external stimuli, such as novel or surprising information. This type of interest is often short-lived and highly dependent on the immediate context [8]. Maintained situational interest is sustained over a longer period through continued engagement with the subject matter [8]. Emerging individual interest can develop into a more stable and enduring form of interest. This phase is characterized by a deeper personal connection to the subject, leading to increased motivation and effort to learn more about it [10]. In the final phase, well-developed individual interest drives sustained engagement and a commitment to mastering the subject matter [10].

According to Linnenbrink-Garcia et al. (2010), maintained situational interest consists of two distinct components: maintained-interest-feeling (MF) and maintained-interest-value (MV). MF reflects affective enjoyment, positive emotions, and sustained engagement whereas MV captures perceived usefulness, meaningfulness, and personal relevance.

The study also leveraged the Fredricks, Blumenfeld, and Paris engagement framework that operationalizes academic engagement as a) cognitive engagement, b) emotional engagement, and c) behavioral engagement [11]. Given the relatively short duration of the summer program (two weeks), it was reasonable to focus in this study on exploring the first two phases of interest development: triggered situational interest and maintained situational interest.

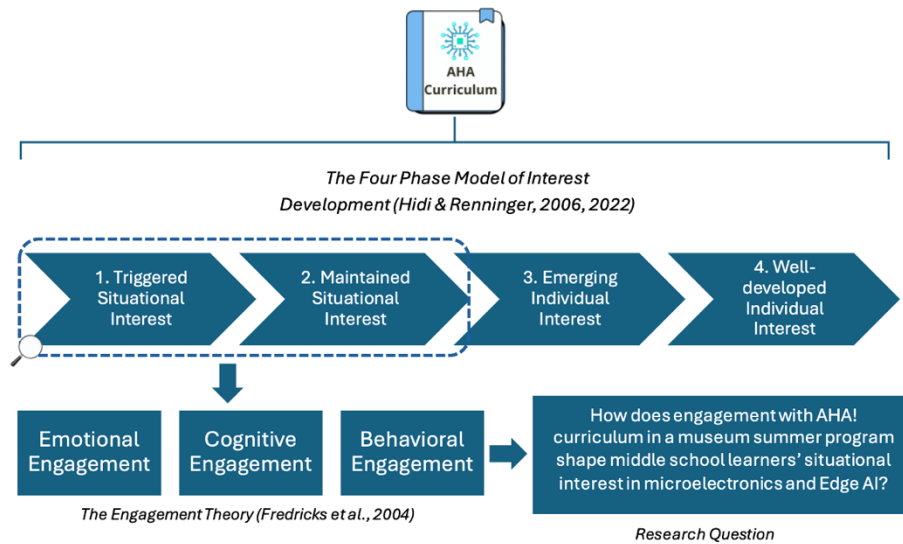


Fig 2. The Conceptual Framework-The Four-Phase Model of Interest Development [6], [7] and The Engagement Theory [8]

Methods

Research Design

The program involved 11 middle-school aged summer camp participants (11-13 years old) engaged with five curriculum modules: (1) embedded systems, (2) data acquisition, (3) multimodal sensing, (4) AI and Edge AI, and (5) Edge AI for social good. Module 1 introduced microelectronics and embedded systems through hands-on exploration of components, sensors, and input-processing-output relationships. Module 2 built on these foundations by unpacking analog and digital signals, binary representation, and the role of sensors in data conversion on the AHA! Board. Module 3 shifted toward data collection and multimodal sensing by asking students to investigate each AHA! Sensor, combine data sources, and ideate sensor-based applications. Module 4 introduced artificial intelligence concepts, including supervised and unsupervised learning, Edge AI workflows, and model training using Edge Impulse™. Module 5 supported students in applying these skills to develop a real-world problem-solving project, create code logic for Edge AI and Arduino components, design a poster, and present their solutions at a final showcase.

A mixed method convergent parallel design combined quantitative and qualitative approaches [12]. Quantitatively, participants completed a pre- and post-Situational Interest Scale (SIS) adapted from Linnenbrink-Garcia et al. [13]. Qualitatively, data sources included structured observations and semi-structured interviews analyzed using Braun and Clarke's six-phase thematic analysis [14]. Inter-observer reliability (IOR) was assessed using the percentage agreement method across two configurations: two-observer and three-observer.

Before implementation, core program activities were piloted with four youth (two girls and two boys) ages 11-15 to explore the relevance and developmental appropriateness of the curriculum. Adjustments were made to the program to include more hands-on activities,

creative play and production-focused activities, particularly early in the program (e.g., a basic PC assembly activity to introduce key microelectronics components).

Research Question

Informed by the conceptual framework, this study addressed the following research question: How does engagement with AHA! curriculum in a museum summer program shape middle school learners' situational interest in microelectronics and Edge AI?

Participants

The program involved 11 middle-schoolers, aged 11 to 13, whose parents or caregivers voluntarily enrolled them in a summer program hosted at a museum in the Southeastern United States. The participants were recruited through community outreach and represented various ethno-cultural and socio-economic backgrounds. Participation in the program was free of charge and open to the public. Pseudonyms were used in this research report to protect participants' identities, key demographic, and learning characteristics are summarized in Table 1.

TABLE 1
PARTICIPANT DEMOGRAPHICS WITH PSEUDONYM

Pseudonym	Age	Grade	Race/ Ethnicity	School Type	Key Learner Characteristics
Aeron	13	7	White	Private (Montessori)	Curious; enjoys computers and hands-on inquiry
Sage	11	7	African American	Public magnet (technology)	Creative; socially engaged; interdisciplinary interest
Zane	12	7	Asian	Private independent	Prior robotics/IoT experience; collaborative
Elara	12	7	Asian	Public (gifted)	Focused; interested in AI; prefers structured tasks
Nova	11	6	Asian	Private independent	Robotics experience; persistent; design-oriented
Luna	10	6	White	Public (gifted)	Ambitious; STEM-oriented; hands-on learner
Orion	11	6	African American	Public (advanced/gifted)	Reserved; benefits from structured roles
Thorne	13	7	Hispanic	Public middle school	Energetic; leadership-oriented; creative
Skye	12	7	African American	Public magnet (gifted)	Reflective; goal-oriented; collaborative

Kael	12	6	African American	Public magnet (gifted)	Dependable; team-oriented
Jax	13	7	African American	Public school	Practical; enjoys sensor-based projects

Measures and Data Sources

Methodological triangulation in this study was achieved using three complementary data collection methods: structured observations, semi-structured interviews, and survey. This approach aligns conceptualization of triangulation as the use of multiple methods to examine the same phenomenon to enhance the credibility and depth of finding [15].

1. Structured Observations

Qualitative data were systematically gathered through structured daily observations using an open-ended observational protocol. The protocol was designed to document both positive and negative evidence of interest and engagement within a real-time informal learning context. Three trained observers documented learners' behaviors, interactions, and verbal expressions that reflected the constructs of interest, that is, situational interest and engagement.

Observers independently coded observation data using the codebook that was developed through an iterative process that combined patterns emerging from the observation data with theoretical frameworks, rather than being predetermined [16]. Positive evidence included focused attention, active participation, enthusiastic responses, persistence in tasks, curiosity-driven behaviors, and meaningful peer interactions. Conversely, signs of disinterests such as yawning, off-task behavior, fidgeting, lack of participation, disengaged facial expressions, and early task abandonment were recorded as negative evidence of engagement and situational interest. Contextual factors such as time of day, activity type, and group dynamics were noted to enrich the interpretation of observed behaviors. The codes were aligned with the Four Phases of Interest Development to interpret learners' engagement [6] [7]. By aligning specific emotional, cognitive, and behavioral codes with each phase of interest, this provides a framework for classifying observation notes into corresponding interest types.

Observations were conducted unobtrusively to minimize distraction and ensure authenticity of student engagement. This technique represents a non-participant observation method, which is widely used in educational research to ensure validity of the data collection method and authenticity of data [17]. IOR was calculated across two configurations, two-observers and three-observers, to compare coding consistency.

2. Situational Interest Scale

The instrument was developed by Linnenbrink-Garcia et al. and contained a 12-item, previously validated Likert-response scale [12]. The purpose of the original survey is to measure situational interest across academic domains [12]. In alignment with the Hidi and Renninger Four Phase of Interest Development [6] [7], it captures three dimensions

of interest: triggered situational interest, maintained situational interest (feeling), and maintained situational interest-value. Triggered situational interest refers to the initial spark of interest that occurs when the material is presented in an engaging or stimulating way. Maintained Situational Interest-feeling involves a deeper and ongoing interest sustained by a personal emotional connection to the content. Maintained Situational Interest-Value is driven by the learners' recognition of the material's significance and relevance to one's goals or life.

3. Semi-Structured Interviews

Interviews were conducted with participants to gain deeper insight into their experiences and evolving interest in microelectronics and Edge AI based on a semi-structured interview protocol. The interview protocol consists of four main open-ended questions that explore learners' overall perceptions of the program (Q1), activities they found most engaging (Q2), activities they perceived as less interesting (Q3), and their motivation to pursue microelectronics or AI-related careers (Q4). This qualitative data enriched the observational and survey findings by revealing personal narratives and contextual factors influencing interest development.

Results and Discussion

This study explored how engagement with AHA! curriculum within a museum summer program shaped middle school learners' situational interest in microelectronics and Edge AI. In the following sections, results of the Situational Interest Scale, observational, and interview data are presented to describe changes in situational interest across the program.

The Situational Interest Scale (SIS), adapted from Linnenbrink-Garcia et al. [12], was conducted right before and after the program. Given the nature of our research question and a limited sample size (for a quantitative study), all quantitative data were analyzed using descriptive statistics.

TABLE 2
SITUATIONAL INTEREST SCALE (SIS) RESULTS

Interest Level	Pre-Test (M $\pm$ SD)	Post-Test (M $\pm$ SD)
Triggered Situational Interest	13.1 $\pm$.63	13.3 $\pm$.60
Maintained Situational Interest – Feeling (MF)	13.6 $\pm$.91	13.2 $\pm$.56
Maintained Situational Interest – Value (MV)	12.8 $\pm$.91	13.2 $\pm$.68

Six of the research participants (4 girls and 2 boys) completed all quantitative instruments, therefore quantitative data are reported descriptively and analyzed as supplemental to the qualitative data. Pre and post data from the Situational Interest Scale [12] indicated that participants' triggered situational interest slightly improved ($M_{pre} = 13.1$, $M_{post} = 13.3$), and so did perception of the value of the experience as part of the maintained interest factor ($M_{pre} = 12.8$, $M_{post} = 13.2$) whereas situational interest-maintained feeling slightly decreased ($M_{pre} =$

13.6, $M_{\text{post}} = 13.2$). The slight divergence between MF and MV reflects prior work showing that affective enjoyment (MF) may fluctuate while perceived value (MV) increases.

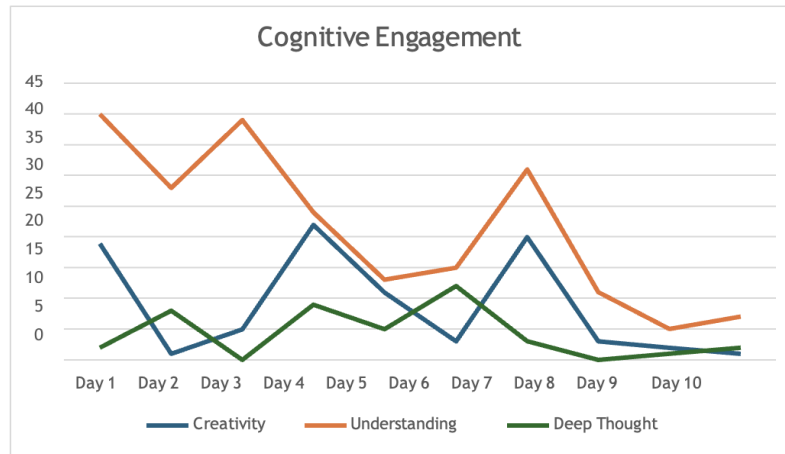


Fig 3. Daily cognitive engagement

These data are supported by qualitative analyses of daily observations. Cognitive engagement data revealed that the predominant processes and indicators of information processing during the summer program included creativity, understanding, and deep thought (Figure 3). In this study, deep thought is indicated by deliberate analytical actions such as asking thoughtful questions, proposing sensor ideas, or reasoning through sensor functions. Understanding is marked by accurate concept interpretation, clear explanations, and correct demonstrations of comprehension. Creativity and understanding peaked early in the camp when participants engaged in a variety of creative production activities, including making a binary conversion bracelet and composing lyrics to a song about smart technologies. Cognitive engagement peaked again on Day 8 of the camp when participants started actively conceptualizing their community-related projects, which reflected their understanding of embedded systems, microelectronics, and Edge AI. Interestingly, both creativity and understanding levels dropped in the middle of the camp when the youth started learning more about cloud AI versus Edge AI whereas “deep thought” indicators peaked at this time. Participants commented a number of times that activities during the middle of the camp felt too academic for a summer camp and our data on emotional engagement (Figure 4) reflects that this is where the campers also experienced some boredom.

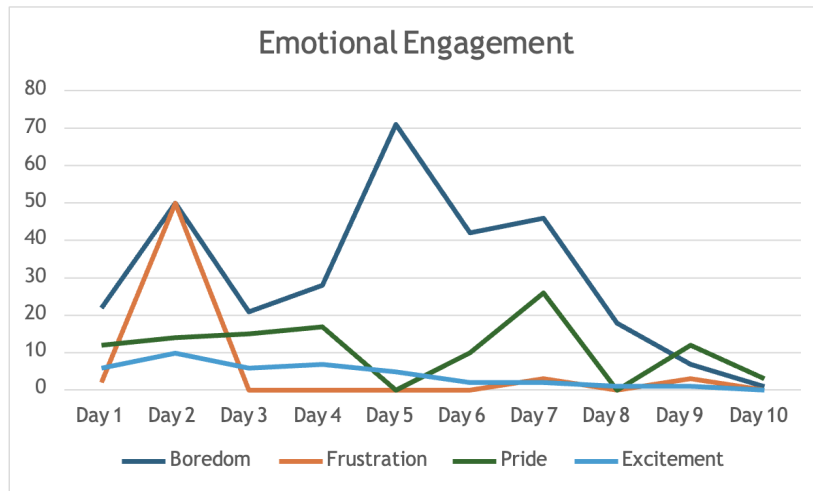


Fig 4. Daily emotional engagement

Figure 4 summarizes the dynamics of the predominant emotions observed during the 10 days of the camp. Notably, boredom was the overall predominant emotion peaking in the middle of the camp, on Day 5, when participants were asked to engage in activities like watching and discussing videos that they referred to as, “too much like school.” Pride was the key positive emotion that dropped in the middle of the camp but peaked on Day 7 when the participants started working on their community-relevant Edge AI projects and when they presented them on Days 9 and 10. Pride was coded when students showed confidence, like volunteering, making positive remarks about their work, or taking leadership, and coded negatively when they avoided presenting or minimized their role.

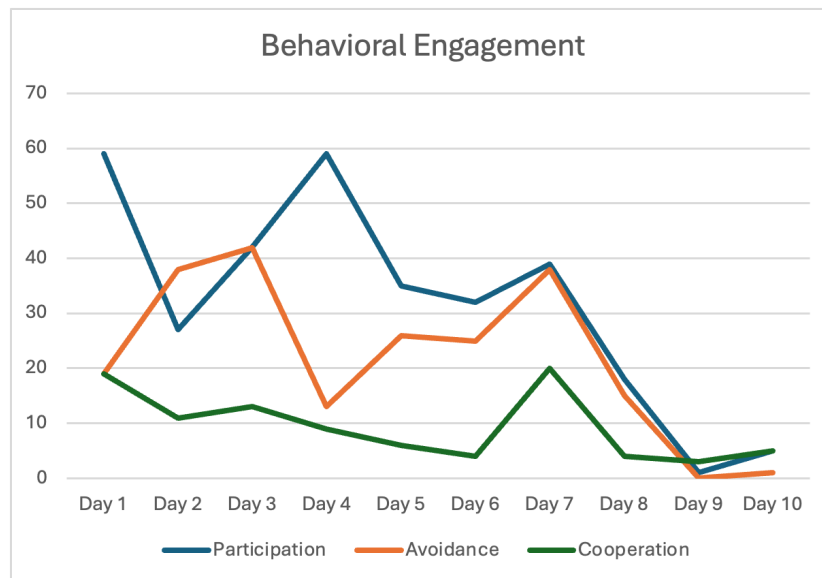


Fig 5. Daily behavioral engagement

The most common indicators of behavioral engagement included participation, avoidance, and cooperation (Figure 5). Important in these data are the peak in participation as well as a drop in avoidance on Day 4 when the campers engaged in hands-on station-based activities working with the board and exploring multimodal sensing. Surprisingly, all three indicators of behavioral engagement, including avoidance, peaked again on Day 7 when the participants started working on the design of their community-relevant Edge AI projects. A closer examination of avoidance data suggests that while the girls in our sample actively participated in project brainstorming and poster design on Days 7 and 8, boys put together their posters relatively quickly and avoided spending additional time discussing and fine-tuning their ideas and posters.

Thematic analysis of daily observation data suggests that across the 10-day camp, hands-on, collaborative, and creative tasks (e.g., PC assembly, AI drawing, sensor prototyping) consistently triggered and maintained situational interest, often helping students transition toward emerging individual interest. Most participants, especially Zane, Luna, and Nova, demonstrated sustained curiosity, leadership, and initiative, while others, like Aeron and Sage, showed fluctuating engagement shaped by energy levels and task format. Fatigue was a recurring theme, with students often yawning or fidgeting towards lunch time but remaining cognitively engaged, suggesting resilience and some level of intrinsic motivation. Peer collaboration proved crucial, with group projects, skits, and poster work fostering teamwork, peer learning, and shared problem-solving.

A summary of IOR across the 10 observation days showed consistently high agreement among observers. For two observers, IOR values ranged from .91 to 1.00, with an overall mean of .97 (SD = .09), indicating strong consistency. Similarly, for three observers, IOR values ranged from .95 to 1.00, with an overall mean of .99 (SD = .09), reflecting near-perfect agreement. These results demonstrate that the coding process was reliable and that observer training effectively minimized discrepancies when interpreting student behaviors.

The interview data revealed that participants entered the program with curiosity and enthusiasm, particularly during hands-on activities. This initial engagement was evident in their reflections on sensor-based projects and creative tasks.

For example, Zane was captivated by the real-world applications of AI technology:

“It’d be good in a house... if you put AI in it, it’ll be nice... it can tell you the weather... you can also see your heart rate.”

Luna connected the final project to her past science fair experience, saying:

“It reminds me of my science fair project that I did a couple years ago”

And further emphasized her enjoyment of working with sensors, noting,

“I really liked when we worked with the sensors... the heart rate sensor... We got to do jumping jacks and stuff.”

Similarly, Skye described strong engagement with creating and prototyping, explaining,

“We got to make it... and the one with the AHA! boards... they put new things into it,”

Elara also reported interest in the culminating experience, noting that she enjoyed the final project because it *“allows her time to think about the projects and sensors.”*

Several participants described positive emotional shifts over time. Skye, who initially felt anxious, described a positive shift in comfort and engagement:

"It's been good. Was scared at first... but now that I know everyone here, I feel fine."
Adding that the program exceeded her expectations:
"At first it would be more like daycare... but this is good too."
Even Sage, who expected to be bored, admitted:
"It was more enjoyable than I imagined, I thought I'd be very bored."
Aeron expressed enjoyment in being part of the group and engaging with technology:
"Um, they're pretty good. Yeah. Um... I just liked to hang out."
"Going to use the computer and learn about it. Or playing with the laptop... and do some research." adding that
"The computer always surprises me with new stuff."

These responses reflect the program's success in triggering situational interest, especially through interactive and personally meaningful activities.

Conclusion and Future Work

This study explored how a museum program about microelectronics and Edge AI shaped middle schoolers' situational interest. The survey results showed slight increases in triggered situational interest and perceived value, while maintained feeling decreased slightly. Observation data confirmed that hands-on, collaborative, and creative tasks such as sensor prototyping, binary bracelet making, and skit project design most strongly triggered and sustained interest. In contrast, activities perceived as "too much like school" led to increased boredom and decreased emotional engagement. Pride and participation rose sharply once students began community-relevant projects and presentations. Interviews showed that learners developed stronger curiosity, confidence, and personal relevance over time, suggesting early signs of emerging individual interest. Overall, situational interest developed most effectively when activities were active, meaningful, and socially interactive.

Several limitations should be acknowledged. The two-week duration of the intensive museum summer program limited the study to the early phases of interest development which triggered and maintained situational interest, precluding observation of longer-term individual interest development that typically requires sustained engagement. In addition, participants self-enrolled on a first-come, first-served basis, reflecting convenience sampling and limiting transferability, as the sample may overrepresent students with prior interest in engineering and AI. Detailed demographic and contextual information are therefore provided to address this limitation.

Future research should focus on longer-term interest development and conduct follow-up measures after program completion. Additionally, studies should explore how activity timing, fatigue, and cognitive load influence engagement throughout the day. Increasing sample size could improve quantitative robustness. Additionally, future work should explore the specific triggers of situational interest using approaches such as micro-level discourse analysis [18] and examination of the project artifacts produced by the participants [19]. Our work demonstrates the typical pedagogical challenges with creating and maintaining emotional engagement in summer camp activities on microelectronics, multimodal sensing, and Edge AI. This study also shows the importance of engaging youth with a variety of applications of AI beyond chatbots, and the use and effects of these alternative approaches should be further explored.

Significance

Our research contributes to the emergent body of literature on young people's interest in AI in general and situational interest dynamics during an Edge AI focused summer program. This investigation relies mostly on qualitative data aligning interest development with the common indicators of emotional, cognitive and behavioral engagement in educational settings as a useful alternative when quantitative data collection is not feasible or meaningful.

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Reference

- [1] AI.gov, "AI education," Apr. 2025. [Online]. Available: <https://www.ai.gov/initiatives/education>
- [2] T. Adiguzel, M. H. Kaya, and F. K. Cansu, "Revolutionizing education with AI: Exploring the transformative potential of ChatGPT," *Contemporary Educational Technology*, vol. 15, no. 3, pp. 429, 2023. doi: 10.30935/cedtech/13152.
- [3] IBM, "What is AI hardware?" IBM Think, 2024. [Online]. Available: <https://www.ibm.com/think/topics/ai-hardware>
- [4] D. Randle, A. Rasheed, D. Cotting, and R. Pivovar, "Physical AI: Building the next foundation in autonomous intelligence," AWS Spatial Computing Blog, Dec. 2, 2025. [Online]. Available: <https://aws.amazon.com/blogs/spatial/physical-ai-building-the-next-foundation-in-autonomous-intelligence>
- [5] A. Ramirez-Salgado and P. Antonenko, "Developing an Equity-Centered Hands-On Curriculum to Support Hardware Engineering Learning," presented at the 2024 AECT International Convention, Kansas City, MO, USA, Oct. 2024.
- [6] Bristow Holland, "The rise of AI and its impact on hardware engineering," Bristow Holland, Feb. 24, 2025. [Online]. Available: <https://www.bristowholland.com/insights/industry-insights/the-rise-of-ai-and-its-impact-on-hardware-engineering/>
- [7] C. L. Thomas and L. A. J. Kirby, "Situational interest helps correct misconceptions: An investigation of conceptual change in university students," *Instructional Science*, vol. 48, pp. 223–241, 2020. doi: 10.1007/s11251-020-09509-2.
- [8] S. Hidi and K.A. Renninger, "The four-phase model of interest development," *Educational Psychologist*, vol. 41, no. 2, pp. 111-127, 2006. doi: 10.1207/s15326985ep4102_4.
- [9] S. Hidi and K.A. Renninger, "Interest development and learning," in *The Cambridge Handbook of Motivation and Learning*, 2nd ed., A. Renninger and S. Hidi, Eds.

- Cambridge, U.K.: Cambridge University Press, 2022.
- [10] K. A. Renninger and S. E. Hidi, "Interest development, self-related information processing, and practice," *Theory Into Practice*, vol. 61, no. 1, pp. 23–34, 2022, doi: 10.1080/00405841.2021.1932159.
 - [11] J. A. Fredricks, P. C. Blumenfeld, and A. H. Paris, "School engagement: Potential of the concept, state of the evidence," *Review of Educational Research*, vol. 74, no. 1, pp. 59–109, 2004. doi: 10.3102/00346543074001059.
 - [12] J. W. Creswell and V. L. Plano Clark, *Designing and Conducting Mixed Methods Research*, 3rd ed. Thousand Oaks, CA, USA: SAGE Publications, 2018
 - [13] L. Linnenbrink-Garcia, A. M. Durik, A. M. Conley, K. E. Barron, J. M. Tauer, S. A. Karabenick, and J. M. Harackiewicz, "Measuring situational interest in academic domains," *Educational and Psychology Measurement*, vol. 70, no. 4, pp. 647–671, 2010. doi: 10.1177/0013164409355699.
 - [14] V. Braun and V. Clarke, "Using thematic analysis in psychology," *Qualitative Research. Psychology*, vol. 3, no. 2, pp. 77–101, 2006.
 - [15] N. K. Denzin, *The Research Act: A Theoretical Introduction to Sociological Methods*, 2nd ed. New York, NY, USA: McGraw-Hill, 1978.
 - [16] K. Roberts, A. Dowell, and J.-B. Nie, "Attempting rigour and replicability in thematic analysis of qualitative research data: A case study of codebook development," *BMC Medical Research Methodology*, vol. 19, no. 1, Art. no. 66, 2019, doi: 10.1186/s12874-019-0707-y.
 - [17] J. Fielding, N. Fielding, and G. Hughes, "Opening up open-ended survey data using qualitative software," *Quality & Quantity*, vol. 47, pp. 3261–3276, 2012. doi: 10.1007/s11135-012-9716-1.
 - [18] R. K. Sawyer and S. Berson, "Study group discourse: How external representations affect collaborative conversation," *Linguistic Education*, vol. 15, pp. 387–412, 2004.
 - [19] P. Bhattacharya and M. Brown, "Bee-Bot for Computational Thinking: An Artifact Analysis," in *Proc. Soc. for Information Technology & Teacher Education International Conference*, Online, 2020, pp. 2–7. [Online]. Available: <https://www.learntechlib.org/primary/p/215724/>. [Accessed: Jul. 30, 2025].