2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC

Host Sponsor UNC Charlotte

Paper ID #51088

From Sensors to AI: A Faculty View of a Project-Based Wearable Course in ECE

Ms. Peiran Wang, North Carolina State University at Raleigh

Peiran Wang is a Ph.D. student in Electrical and Computer Engineering at North Carolina State University, advised by Dr. Cranos Williams. Her research focuses on deep learning applications in agricultural data analysis and engineering education, with particular interest in improving student engagement and teaching strategies in large enrollment courses.

Dr. Laura Bottomley, North Carolina State University at Raleigh

Dr. Laura Bottomley is the Director of Engineering Education and Senior Advisor to WMEP at NC State University. She has been working in the field of engineering education for more than 30 years, having taught every grade level from kindergarten to engineering graduate school. She is a Fellow of the IEEE and ASEE and has been recognized with the PAESMEM award.

Mayur Sanap, North Carolina State University at Raleigh

Mayur Sanap is a Ph.D. student in Electrical Engineering at North Carolina State University. His research interests include edge AI, AI for healthcare, and embedded systems. In this paper, he contributed as a teaching assistant for the Wearable AI course, where he managed the course and supported student projects.

Dr. Edgar Lobaton, North Carolina State University at Raleigh

Edgar J. Lobaton is a Professor in the Department of Electrical and Computer Engineering (ECE) at North Carolina State University (NCSU). He joined the department in 2011. Lobaton earned his B.S. in Mathematics and Electrical engineering from Seattle University in 2004. He completed his Ph.D. in Electrical Engineering and Computer Sciences from the University of California, Berkeley in 2009. Lobaton was engaged in research at Alcatel-Lucent Bell Labs in 2005 and 2009. He was awarded the NSF CAREER Award in 2016. He was also awarded the 2009 Computer Innovation Fellows post-doctoral fellowship and conducted research in the Department of Computer Science at the University of North Carolina (UNC) at Chapel Hill from 2009 until 2011. In 2024, he received the University Faculty Scholars and the Outstanding Teacher Awards from NC State. His research focuses on the integration of AI, and physical and probabilistic modeling applied to cyber-physical systems in areas such as wearable health monitoring, rehabilitation robotics, agriculture and biological imaging.

From Sensors to AI: A Faculty View of a Project-Based Wearable Course in ECE

Abstract: This evidence-based practice full paper focuses on course design and evaluation for an undergraduate, project-oriented course on Wearables with AI Capabilities. The course follows a weekly format that begins with short lectures and transitions into team-based projects. It provides electrical and computer engineering students with a practical way to connect classroom concepts with hands-on design by developing health-focused wearable devices. These projects integrate sensors, microcontrollers with neural accelerators, and tiny machine learning tools while requiring students to evaluate trade-offs in power, computation, and communication across embedded, edge, and cloud systems.

From the educator's perspective, the paper presents results from a structured faculty survey used as the main assessment method. The survey asked instructors who have taught the course to describe expected learning outcomes, what students learn most effectively in practice, how the course links to future careers or advanced study, remaining gaps in student preparation, and how instructor guidance balances with student independence. We also plan to capture student perspectives through an end-of-semester survey to complement the faculty feedback and evaluate perceived learning gains and course impact.

The outcomes include the ability to connect AI and embedded hardware, frame and evaluate solutions to sensing problems, understand sensor interconnects and data flows, gain broad exposure to the full pipeline, and build depth in one area, such as communication, sensor integration, or on-device AI. Instructors observe significant gains in practical system integration, microcontroller programming, debugging, teamwork, and a clearer understanding of the big picture from concept to prototype. Identified gaps include project management, product development topics such as enclosure and regulatory steps, stronger data analytics and validation beyond proof of concept, and professional documentation and reproducibility. Faculty emphasize the importance of balanced guidance, authentic projects, interdisciplinary teams, iterative feedback through meetings and peer reviews, and public demonstrations as key components of course success.

This submission addresses ECE Division topics related to curriculum design and assessment, project-based learning, and creative uses of technology in the ECE classroom, including artificial intelligence, machine learning, big data, and real-time analytics.

Introduction and Motivation

With the development of artificial intelligence (AI), electrical and computer engineering programs have started to include it in undergraduate course. However, traditional embedded systems courses focus on microcontrollers, peripherals, and low-level programming, while machine learning courses usually focus on algorithms and software development [1]. How to combine these two areas so that students learn from real engineering problems has become a challenge [2].

Wearable systems provide a natural platform for addressing this gap because their functionality depends on the integration of sensors, embedded processors, communication interfaces, and on-device machine learning. Prior work in engineering education has shown that project-based learning can support system thinking and professional skill development when students are given real design problems and sustained mentorship [1], [3]. However, many project-based courses report student works without clearly documenting how learning outcomes are assessed.

This paper presents an evidence-based practice study of an undergraduate, project-oriented course on Wearables with AI Capabilities in electrical and computer engineering (ECE). The course follows a weekly format combining short lectures with team-based projects and emphasizes system-level integration from sensing to embedded AI inference. Rather than focusing solely on student deliverables, this study centers on a structured faculty assessment of learning outcomes, observed gains, and remaining gaps.

The contributions of this paper are primarily in three areas. First, it documents a replicable course design that integrates sensors, embedded systems, and on-device AI through open-ended projects. Second, it presents a faculty-targeted assessment framework based on structured open-ended survey questions aligned with course objectives. Third, it analyzes observed learning gains and limitations and maps these outcomes to ABET student outcomes to support curriculum alignment in ECE programs.

Background and Related Work

Project-Based Learning in ECE

To promote active learning, teamwork, and the connection between theory and practice, project-based learning (PBL) has been widely used in engineering education. Prior studies indicate that PBL is most effective when projects require students to reason about system behavior, make design trade-offs among multiple alternatives, and iteratively refine their solutions based on feedback [4]. In ECE, PBL has traditionally been used mainly in senior design and graduate-level courses, where students are expected to integrate knowledge gained from multiple prerequisite courses [5].

Priorly, the adoption of PBL in undergraduate ECE courses has been limited due to concerns about system complexity, variation in students' mathematical preparation, and the instructional workload associated with organizing and assessing open-ended projects [6], [7]. As a result, many foundational courses have emphasized analytical problem solving rather than system-level exploratory activities.

Teaching Embedded AI and Wearable Systems

Recent efforts to introduce embedded AI, TinyML, and IoT concepts into undergraduate course have primarily focused on isolated tools rather than full system integration experiences [8]–[10]. Warden and Situnayake [8] describe instructional uses of TensorFlow Lite Micro on Arduino-class microcontrollers, where students typically learn how to use a pre-trained keyword spotting or gesture recognition model as an individual exercise. Such activities are often embedded in introductory embedded systems or signals courses. However, the co-design part is always overlooked in prior work. Similarly, benchmarking-focused studies such as Banbury et al. [9] are sometimes incorporated into graduate-level courses to teach students how to evaluate TinyML models under hardware constraints. While these modules strengthen students' understanding of performance trade-offs, they remain largely analytical and do not require students to integrate sensing hardware, firmware, learning models, and application logic into an end-to-end system. In the project-oriented wearable courses reported by Boaventura et al. [10], students often complete functional subsystems, yet system-level behaviors such as timing mismatches, data pipeline failures, or resource contention are rarely addressed as part of the course design.

Across these approaches, assessment also tend to focus on final demonstrations with limited mechanisms for instructors to evaluate students' learning progress at intermediate stages. This gap makes it difficult to assess how well students understand the interactions among embedded AI components, which are essential for designing robust wearable systems.

Gap Addressed by This Study

Although courses on AI-related embedded systems have increased in recent years, existing studies mainly focus on course design or student technical outputs, with limited attention to how instructors assess learning. In such courses, project's topic is varied, and traditional exams are not the primary assessment tool. This study addresses this gap by examining assessment practices in a wearable systems course, with the goal of evaluating their feasibility and value in a real instructional setting.

Course Context and Learning Objectives

Course Context

The course examined in this study is an undergraduate special topics project course in ECE that centers on wearable systems with AI functions. It is offered for one to three credits and attracts students from the sophomore through senior years. The course follows a Vertically Integrated Project (VIP) course framework [13] where students are initially engaged in a 1-credit course while they get exposed to the projects and learn the basics from more senior students, and then sign up for 2-credit course to perform their main work, and possibly a follow-up 3-credit course to gain further depth and potential contribute to some research. There is a total of four instructors in this course whose expertise cover sensor design, embedded system integration and AI model development and deployment. The class meets once a week for a 50 minute in person session. After a short introduction period, most of the semester is organized around team-based projects.

Projects account for 50% of the final grade, with the remaining credit coming from assignments and class participation. Usually, three students work as a team, and each team includes members with different skills. Lead mentors meet with teams regularly to provide guidance and feedback, while teams are free to decide on their design approach, set milestones, and manage their work.

Learning Objectives

As stated in the course syllabus, the learning objectives of this course emphasize practical system-level knowledge rather than a single technology. Upon completion of the course, students should be able to:

1. Understand the design of multimodal wearable devices.
2. Design systems using microcontrollers with neural accelerators.
3. Apply TinyML tools for programming embedded devices.
4. Evaluate trade-offs among power consumption, computation, and communication across embedded, edge, and cloud platforms.

These objectives guided both course activities and the assessment framework described in the following sections.

Course Design and Project Framework

The course follows a project-centered structure in which short lectures introduce technical concepts as needed, and most instructional time supports project development. Early sessions focus on sensing, embedded platforms, and AI deployment constraints. As the semester progressed, the focus of classroom discussions and instruction naturally shifted to evaluating design proposals, addressing problems encountered during system debugging, and tackling the practical challenges revealed during the overall integration process.

Sample projects topic including embedded audio analysis, on-device health monitoring, sensor calibration, custom PCB design, and power and energy benchmarking are listed in Table1. Despite their diversity, all projects follow a common system pipeline: sensing and data acquisition, embedded processing or AI inference, communication or storage, and evaluation under real constraints. Student documentation shows iterative development, trade-off analysis, and partial failures that inform redesign decisions

Table 1. Representative Student Project Themes and Learning Emphases in the Wearables with AI Course

Project Theme	Project Focus and Technical Scope	Hardware / Platform	Primary Learning Emphases
Embedded ML for Respiratory Health Monitoring	Real-time cough detection using Convolutional Neural Networks (CNNs),	MAX78000 microcontroller (low-power embedded platform with an	On-device AI inference, embedded signal processing, model deployment

	mel-spectrogram preprocessing, model quantization, and deployment on hardware accelerators	integrated neural network accelerator)	constraints, accuracy vs. resource trade-offs
Edge ML for Audio Analysis	Streaming wearable audio data to an edge device for speech analysis and transcription. Evaluation of communication methods	ESP32 wireless microcontroller (embedded sensing and communication platform) with NVIDIA Jetson Orin Nano (GPU-based edge AI device)	System partitioning across embedded and edge platforms, latency and bandwidth constraints, edge–device communication
Sensor Calibration and Environmental Monitoring	Integration and calibration of gas, humidity, temperature, and light sensors. Controlled experiments and error analysis	Edge AI microcontroller platform: MAX78000 FTHR board or ESP32 microcontroller, integrated with ENS160 air-quality sensor and SHT45 temperature-humidity sensor	Sensor interfacing, experimental design, data validation, environmental effects on sensor measurements
Custom Printed Circuit Board (PCB) Design for Wearable Devices	Design, revision, and testing of custom PCBs integrating MCU, microphones, Audio CODEC (signal encoding and decoding for audio input/output), and wireless modules	Custom MAX78000-based PCB designed in KiCAD (an open-source PCB design suite)	Hardware design workflow, schematic and layout trade-offs, manufacturability and debugging
Power, Energy, and Performance Benchmarking	Measurement of energy consumption, latency, and memory usage for embedded AI workloads using internal and external tools	MAX78000 evaluation kit with external Source Measure Unit (SMU) (instrument for precise current and voltage measurement) and TFT display (thin-film transistor screen for visual output)	Power-aware system design, performance profiling, optimization under resource constraints

Multimodal Sensing and System Integration	End-to-end integration of sensing, processing, and evaluation components within a wearable prototype	Mixed platforms across MAX78000, ESP32, and peripheral sensors	System-level integration, debugging across hardware and software boundaries, full pipeline understanding

Assessment Design and Research Questions

In project-based courses, instructors have continued and direct access to students' learning processes. Therefore, this study selects instructor evaluation as the primary perspective for assessing learning outcomes [12]. To build this evaluation framework, we conducted a survey with six open-ended questions involving three instructors who had taught the course. All instructors were actively engaged in mentoring student teams throughout the semester.

Research Questions

This assessment was guided by four research questions, which align with the course learning objectives in project-based engineering courses.

RQ1: What learning outcomes do instructors expect students to achieve in a wearable systems course integrating embedded hardware and AI?

RQ2: What knowledge and skills do instructors observe students learning most effectively through project-based work?

RQ3: What gaps remain between students' project experiences, and the knowledge or skills needed for future coursework, research, or professional practice?

RQ4: How do instructors balance guidance and student independence in an open-ended project environment, and what instructional conditions support course success?

Faculty Survey

This faculty survey is designed to collect practice-based reflective observations.

1. Expected learning outcomes of the course
2. Learning outcomes most strongly observed in practice
3. Connections to students' future careers or academic goals
4. Gaps between current learning and future needs
5. Balance between instructor guidance and student independence
6. Factors contributing to the success of special projects courses

We selected open-ended short-answer questions so that faculty could describe learning outcomes across different project themes without restricting their responses to predefined categories. In

Table 2, we list the faculty survey questions and their alignment with research questions and course learning objectives.

Table 2. Alignment Between Faculty Survey Questions, Research Questions, and Assessment Focus

Faculty Survey Question	Research Question(s) Addressed	Primary Assessment Focus
What are the main learning outcomes you expect from this course?	RQ1	Instructor expectations regarding system integration, embedded AI, and wearable design fundamentals
In practice, what do you find students learn the most from it?	RQ2	Observed learning gains in hands-on system integration, embedded programming, debugging, and teamwork
How do you see this course connecting to students' future careers or academic goals?	RQ2	Perceived relevance to industry roles, research preparation, and emerging hardware–AI career paths
What gaps, if any, remain between what students learn here and what they need later?	RQ3	Limitations in project management, depth of evaluation, data validation, documentation, and product development
How do you balance your guidance with students' independent learning in the project?	RQ4	Instructional scaffolding, degree of student autonomy, and mentorship strategies
Looking back, what makes a special projects course most successful in your view?	RQ4	Structural factors supporting project-based learning, including real scope and feedback loops

We explore the three faculty responses. It started by organizing comments around the four research questions, then compared answers across instructors to see where their views matched and where they differed. We focused on repeated ideas in how instructors described student learning, strengths they observed, and challenges that remained.

Faculty Assessment Results and Alignment with ABET Student Outcomes

Observed Learning Gains

Three instructors agreed that the course significantly improved students' learning outcomes in system level thinking and applied engineering skills. Although project topics varied across teams, the resulting student work showed a high degree of consistency in overall outcomes. For example, in the Embedded ML project, students applied signal processing and machine learning concepts from the course to a real system by completing the full pipeline from audio data collection and Mel spectrogram feature extraction to convolutional neural network training, quantization, and deployment on the MAX78000 microcontroller. The system achieved real time cough detection with approximately 90% inference accuracy on hardware. In the Edge ML with Jetson Orin Nano project, students further connected embedded devices with an edge computing platform, transmitted audio data to the Jetson system through wireless communication, and implemented speech analysis and real time transcription, forming an end-to-end data collection, transmission, and analysis system. Instructors noted that students no longer treated sensing, embedded hardware, and AI as isolated components, but instead integrated them into a fully functioning system prototype. Through this process, students gained experience working with real engineering constraints, including communication bandwidth limits, data flow organization, timing coordination, and embedded hardware resource limitations. This type of concept to prototype experience allowed students to engage with engineering practice that is typically reserved for graduate-level design courses much earlier in the curriculum.

Instructors also highlighted significant improvement in students' embedded programming skills, particularly in microcontroller-based development and debugging. This progress was evident in projects such as Wireless Communication Between the MAX78000 and the Adafruit, where students implemented and tested low level communication protocols including SPI, UART, and I2C, developed custom firmware for packet-based data transfer, and debugged timing and synchronization issues between microcontrollers. Students designed data buffers, verified byte level transmission correctness, and adjusted communication frequency to achieve stable operation under hardware constraints. Faculty noted that these tasks required students to work directly with peripheral drivers, interrupt behavior, and protocol level details, providing clear evidence that students had moved beyond abstract programming toward practical embedded system development grounded in real hardware behavior.

Teamwork was identified as a key outcome of the course. Instructors stated that the collaborative project structure required students to coordinate across hardware and software. Working toward shared goals and deadlines strengthened students' communication skills and their ability to solve problems collectively, especially when facing system integration challenges. In Figure1, we could retrieve the faculty evaluation stages.

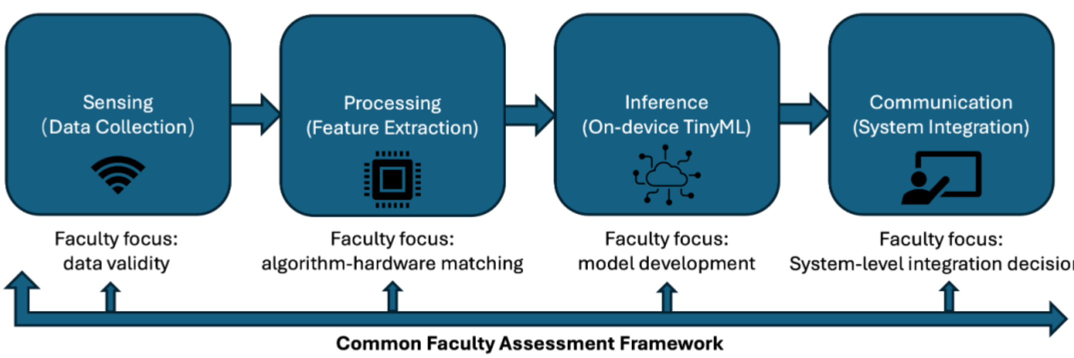

Figure1. System Pipeline Assessment Framework. This framework also served as a common reference for faculty during project review meeting across diverse teams.

Student Survey Evidence

To complement the faculty perspective, a short anonymous student survey was conducted at the end of the course to collect student feedback on learning outcomes and course experiences. Four students completed the survey using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The questions were designed to reflect several of the course learning objectives, including system integration, embedded programming, AI deployment, teamwork, and project management. Table 3 summarizes the average student ratings for each survey item.

Table 3. Student Perception of Learning Outcomes in the Wearables with AI Course

Survey Item	Mean Score (1–5)
Integration of sensors, embedded hardware, and AI into a complete system	3.5
Understanding trade-offs among power, computation, and communication	3.25
Ability to design and debug microcontroller software	4.5
Confidence deploying AI models on embedded platforms	3.0
System-level engineering thinking	3.75
Collaboration in interdisciplinary teams	3.25
Technical communication through presentations and reports	3.5
Relevance to future academic or career goals	3.25
Planning and managing long-term projects	4.0

Student responses indicate strong perceived gains in embedded software development and debugging, which received the highest average score (4.5). Students also reported improvement in system-level thinking and project planning skills. Lower scores were observed in deploying AI models on resource-constrained embedded platforms, suggesting that this topic may require additional instructional support in future offerings.

Open-ended feedback also highlighted several areas for improvement, including clearer communication of project requirements, stronger coordination across teams, and additional support for debugging complex systems. These comments align with faculty observations regarding the challenges students face during system integration and project planning.

Identified Gaps and Limitation

Although the instructors gave positive evaluations of the course, they also pointed out that several limitations remained at the end of the semester. One recurring issue was that students' project management and planning skills were still underdeveloped. For example, in the PCB Design project, students focused primarily on whether the initial board design was functionally connected, with limited consideration of debugging convenience or future system expansion. As a result, during later testing phases, students frequently relied on jumper wires and external modules to compensate for design limitations. Instructors noted that students did not initially treat verification as distinct phases in their project timeline but instead assumed they would naturally follow design completion. In response, instructors guided students during the middle of the semester to revisit the design workflow, clearly distinguishing between schematic design, and debugging. It illustrated how insufficient early planning directly increased time costs in later stages.

Instructors also identified clear challenges in verification and analysis, particularly when assessing the depth of students' understanding of experimental results. In the Sensor Calibration project, students conducted multiple sensor experiments in a systematic manner, recorded time-series data for temperature, humidity, and gas concentration, and identified significant sensor errors under different environmental conditions. However, instructors observed that some students focused mainly on stating that errors existed, with limited discussion of the underlying mechanisms, such as environmental coupling or limitations of the experimental setup itself. Although the project outcomes were strong, the final reports alone made it difficult to determine whether students had developed a comprehensive understanding of the experimental system. As a result, instructors often relied on oral discussions and process-level observations to supplement grading decisions.

Similar assessment challenges were observed in the Power, Energy, and Performance Benchmarking project. Students successfully built a framework for measuring power consumption and monitoring performance, and they were able to present inference latency and energy usage under different model configurations. While instructors considered these results successful at the presentation levels, they also noted that some analyses remained at the level of metric comparison, without deeper explanations related to hardware resource allocation, peripheral activation, or differences in inference workflows. These projects showed that students could effectively use tools and produce results, but interpreting those results into an understanding of internal system behavior remained further instructional support.

These limitations provide clear direction for future course improvement: instructors should introduce more explicit project phases to help students develop executable engineering plans, while also encouraging students to focus not only on whether a system works, but on understanding the underlying engineering principles and system behavior.

Instructional Balance: Guidance, Independence, and Course Success

Two instructors viewed the course as seeking a balance between instructor guidance and student autonomy, while another instructor viewed the course as mainly student driven. Despite this difference, all instructors agreed that in an open-ended project setting, continuous guidance is critical for student success. Rather than prescribing fixed solutions, instructors emphasized motivating students to take responsibility for their own projects while setting clear deliverable requirements. Project progress can be monitored through presentations to keep students on schedule. Instructors also mentioned that project proposals, interdisciplinary teams, and frequent feedback are key factors that support student learning.

Alignment with ABET Student Outcomes

The faculty-assessed learning outcomes align closely with ABET student outcomes for accredited ECE programs. Table 4 presents the alignment between course learning outcomes, faculty assessment evidence, and ABET student outcomes. This table synthesizes the qualitative assessment results and situates the course within established accreditation frameworks.

Table 4. Alignment Between Course Learning Outcomes and ABET Student Outcomes

Course Learning Outcome (Wearables with AI Course)	Evidence from Course Design / Faculty Assessment	ABET Student Outcome
Integrate sensors, embedded hardware, and AI models into a functional wearable system	Faculty report strong gains in hands-on system integration, from concept to prototype	(1) Ability to identify, formulate, and solve complex engineering problems
Analyze and evaluate trade-offs among power, computation, and communication across embedded, edge, and cloud platforms	Faculty emphasize students' understanding of design trade-offs and system-level constraints in real-world wearable applications	(2) Ability to apply engineering design to produce solutions that meet specified needs
Design and implement embedded software for microcontrollers with neural accelerators	Student projects demonstrate deployment of TinyML models and low-power inference on resource-constrained MCUs	(1), (2)
Work effectively in interdisciplinary teams combining hardware, software, and AI skills	Faculty identify teamwork, collaboration, and shared ownership as major learning outcomes	(5) Ability to function effectively on a team
Communicate design decisions, experimental results, and system limitations through reports, demos, and reviews	Course deliverables include project documentation, presentations, and public demonstrations	(3) Ability to communicate effectively with a range of audiences
Understand wearable and embedded AI systems in health, industry, and research pathways	Faculty connect course outcomes to industry-relevant skills and preparation for research or graduate study	(4) Ability to recognize ethical and professional responsibilities and make informed judgments
Reflect on project limitations, remaining gaps, and areas for improvement	Faculty identify gaps in project management, validation, and documentation as areas for growth	(7) Ability to acquire and apply new knowledge as needed

Discussion, Implications and Limitations

Wearable and AI Projects as a Platform for System Thinking

Instructor evaluations indicate that integrating embedded AI into wearable systems provides an effective instructional setting for supporting systems-level learning among ECE students. In these course projects, students are no longer focused on a single algorithm or hardware module. They started to consider the interactions among sensing, computation, and performance evaluation. For example, during project development, students repeatedly discussed whether computation should be performed on the device or at the edge, and they had to make trade-offs among limited computational resources and power constraints. And they solved issues related to constrained embedded hardware resources and noise in sensor data. As instructors guided these design decisions, they observed that students increasingly explained their choices from a system-level perspective rather than focusing only on individual components.

These observations provide course-level evidence that supports existing engineering education research on the development of systems thinking. Prior studies suggest that when students engage with real engineering constraints and cross-module trade-offs, rather than isolated exercises, they are more likely to develop an integrated understanding of system behavior [3], [5]. In this course, system-oriented thinking emerged early in the project timeline. Compared with traditional course, where problems of similar system complexity are often encountered only during senior design.

Implications for Assessment in Project-Based ECE Courses

This study shows that in open-ended project courses, assessment reflects learning outcomes more effectively than standardized exams. Because course uses staged project reviews rather than a single final grade and includes peer review. In addition, multiple instructors from different areas take part in the evaluation process, providing feedback from several perspectives and supporting the development of students' engineering decision making skills.

Although this study uses a wearable systems course as its example, the underlying course design principles and assessment methods are not limited to this specific topic and have broad applicability across ECE. For ECE programs that aim to introduce AI content at the undergraduate level, embedded platforms provide a practical pathway. Such platforms directly link algorithms and data processing with real physical systems, allowing students to understand the application of AI at the level of an integrated system.

Limitations and Future Work

This study has several limitations that should be noted. The evaluation in this study is primarily based on instructors' perspectives, supplemented by a small student survey conducted at the end of the course. Although the survey provides preliminary insight into student perceptions of learning outcomes, the number of respondents remains limited. While instructors offered useful observations based on their long-term teaching and mentoring experience, additional student feedback would help further validate these findings from multiple perspectives. In the future, the course will include broader student evaluations to address this limitation. Second, the number of instructors who participated in the survey is small. To make the approach applicable to general engineering classes, future work will consider studying project-based courses across multiple disciplines. Finally, instructors pointed out challenges related to preserving project documentation and ensuring the long-term sustainability of student projects. These limitations suggest that there is still room for improvement in the course design and addressing them will be an important direction for future work as the course continues to develop.

References

[1] B. Hur, “Machine learning and Vision Based Embedded Linux System Education,” ASEE Annual Conference & Exposition, Mar. 2025.

[2] P. Naidoo and M. Sibanda, “Integrating Artificial Intelligence in Electrical Engineering Education: A Framework for the Fourth Industrial Revolution,” *Atlantis Press – Advances in Social Sciences, Education and Humanities Research*, vol. 313, pp. 314-319, 2024.

[3] M. Prince and R. Felder, “Inductive teaching and learning methods: Definitions, comparisons, and research bases,” *J. Eng. Educ.*, vol. 95, no. 2, pp. 123–138, 2006.

[4] A. Kolmos, F. K. Fink, and L. Krogh, *The Aalborg PBL Model: Progress, Diversity and Challenges*. Aalborg, Denmark: Aalborg Univ. Press, 2004.

[5] Mills, Julie E.. “Engineering Education, Is Problem-Based or Project-Based Learning the Answer.” (2003).

[6] J. D. Lang, S. Cruse, F. McVey, and J. McMasters, "Industry expectations of new engineers: A survey to assist curriculum designers." Journal of Engineering 88(1), 43-51,1999.

[7] C. L. Dym, A. M. Agogino, O. Eris, D. D. Frey, and L. J. Leifer, “Engineering design thinking, teaching, and learning,” Journal of Engineering Education, vol. 94, no. 1, pp. 103–120, 2005.

[8] Sheppard, Sheri. “Educating Engineers: Designing for the Future of the Field.” Choice Reviews Online, 2009. doi:10.5860/CHOICE.47-0304.

[9] P. Warden and D. Situnayake, *TinyML: Machine Learning with TensorFlow Lite on Arduino and Ultra-Low-Power Microcontrollers*. Sebastopol, CA, USA: O’Reilly Media, 2020.

[10] C. R. Banbury, V. J. Reddi, M. Lam, W. Fu, A. Fazel, J. Holleman, X. Huang, R. Hurtado, D. Kanter, A. Lokhmotov, D. Patterson, D. Pau, J.-S. Seo, J. Sieracki, U. Thakker, M. Verhelst, and P. Yadav, ‘‘Benchmarking TinyML systems: Challenges and direction,’’ 2020, arXiv:2003.04821.

[11] A. Boaventura *et al*., “Collaborative course development for applications of artificial intelligence and wearable devices in healthcare,” in *Proc. ASEE Annu. Conf.*, 2022.

[12] H. M. Paiva, F. Maria Santoro, V. T. Hayashi and B. C. Lima, "PBL Student Assessment: Consistency of Different Evaluation Methods in a Computing Faculty," in *IEEE Transactions on Education*, vol. 68, no. 2, pp. 215-223, April 2025, doi: 10.1109/TE.2025.3545314

[13] Marshall, S., Coyle, E., Krogmeier, J. V., Abler, R. T., Johnson, A., & Gilchrist, B. E. (2014). The Vertically Integrated Projects (VIP) program: Leveraging faculty research interests

to transform undergraduate STEM education. In Transforming Institutions: 21st Century Undergraduate STEM Education Conference.