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Board 125: Taking an Experiential Learning Approach to Industrial IoT Implementation for Smart Manufacturing through Course Work and University-Industry Partnerships

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An Experiential Learning Approach to Industrial IoT Implementation of Smart Manufacturing through Coursework and University-Industry Partnerships

1. Introduction

As Internet of Things (IoT) and artificial intelligence (AI) continue to reshape industrial processes and product lifecycles, the need for retraining current workers and attracting future ones to the manufacturing industry has grown. Nationwide, The US manufacturing sector is expected to have 2.1M unfilled jobs by 2030, a shortage that will be led by gaps in filling and retaining skilled positions. The US Bureau of Labor Statistics shows that manufacturing jobs in Indiana grew back to pre-pandemic figures with a need for 526,000 workers in 2021, compared with 539,000 in 2019, resulting in the country's highest concentration of manufacturing jobs [1]. The problem further intensifies because although the manufacturing workforce growth results in new jobs and higher wages, manufacturers face challenges in recruiting well-qualified workers [2].

While reskilling and upskilling efforts will be needed for the current workforce, particularly in the plant floor, new jobs and occupations will emerge. These new jobs will require professionals and future managerial employees to have strong data science skills in order to effectively design and oversee future AI-enabled manufacturing systems. However, a critical gap exists between traditional analytic/numeric engineering education and computer science/AI development that can provide skills to effectively enact and manage the full data science cycle.

Specifically in Indiana, findings from the 2019 Indiana Manufacturing Survey [3] concluded that there is a serious shortage of skilled and unskilled laborers, with the expectation that the number of skilled jobs will increase; this skills gap impedes manufacturing growth. Furthermore, manufacturers, especially middle-size companies, have limited options for supporting their own workforce development and expect public secondary schools to help address this shortage [3].

To take steps toward preparing engineering graduates to effectively work with data, starting from data collection through sensors to data analysis and insight enabled by dashboards, [Midwestern] University designed and implemented a graduate course in partnership with local industries. This course has the dual purpose of training the next generation of manufacturing professionals and in the process supporting regional companies in addressing problems that could be solved with IoT or AI innovations. The goal of this study is to describe how the course was organized and delivered following design principles of Experiential Learning Theory, and as outcomes of the approach, we provide a description of the projects the students implemented within the regional manufacturing companies.

2. Pedagogical Framework

Kolb's Experiential Learning Theory (ELT) [4], [5] was used as an explanatory approach to describe the course design and implementation. ELT learning is "the process whereby knowledge is created through the transformation of experience. Knowledge results from the combination of [a] grasping and transforming experience" [4]. This form of learning is represented in a model (see Figure 1) that depicts two modes of grasping experience (i.e., concrete experience and abstract conceptualization) and two modes for transforming experience (i.e., reflective observation and active experimentation).

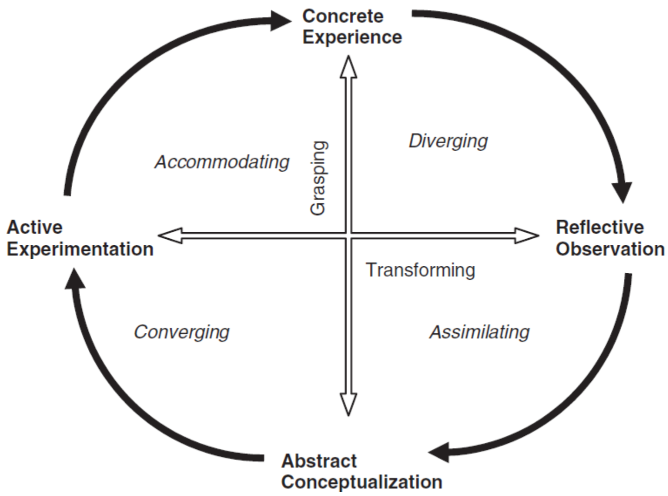


Figure 1 Kolb's experimental learning cycle

According to the cycle shown in Figure 1, learning occurs when learners construct knowledge by experiencing the tensions among the four learning modes, concrete experience, reflective observation, abstract conceptualization, and active experimentation, created by contextual demands. Thus, ELT's implications for the course's design consisted of guiding learners through recursive processes of experiencing, reflecting, thinking, and acting to respond to the learning situation. That is, "immediate or concrete experiences are the basis for observations and reflections. These reflections are assimilated and distilled into abstract concepts from which new implications for action can be drawn. These implications can be actively tested and serve as guides in creating new experiences" [5]. Specifics of how ELT guided the course implementation are described in the section below.

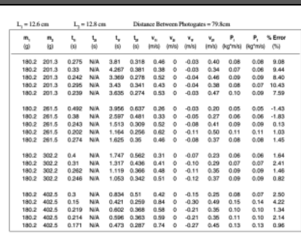
3. The Course

The course titled Industrial IoT Implementation for Smart Manufacturing provides an introduction to the industrial internet of things (IIoT) implementation on real production machines for smart manufacturing. It is a practical lab/project course that allows engineering students to implement IoT sensors and devices on real production machines at local manufacturing companies, collect data, perform data analytics for the company's benefit, and demonstrate the visualization of the analyzed data. Students worked with local Indiana manufacturing companies and institutes to support the implementation of deployment of sensors and devices to a production machine, collection of data, analytics, and visualization. The partnering manufacturing companies are small and medium sized enterprises (SMEs). A significant number of SMEs may not be equipped to cope with the forthcoming alterations in Industry 4.0 due to a scarcity of qualified personnel or their reluctance or uncertainty towards technology strategies, which are still uncharted territory for them [6]. The collaboration projects might be a favorable opportunity for local manufacturing companies to try IIoT on their shop floor. Students can gain valuable experiential learning opportunities by applying the theoretical and technological skills acquired in the course to real-world industrial settings.

Specifically, the course had five specific objectives, including (LO1) formulating a framework for managing collected sensor data from production machines; (LO2) describing communication protocols for implementing wired and wireless connections to machines; (LO3) identifying proper sensors for measurement of desired data; (LO4) implementing data analytics and machine learning tools for extraction of desired information; and (LO5) demonstrating personal and professional development in communication and management in the context of smart manufacturing. The course was coupled with laboratory reports, written reports, and oral presentations to achieve these objectives and capture evidence of students' learning and skills development.

Of particular relevance for this course was the integration of ELT principles to coordinate and orchestrate the laboratory assignments that built the necessary skills and practices so students would successfully complete their semester-long projects and, at the same time, address a company's needs. Table 1 presents a description of how ELT principles guided the implementation of the course. Specifically, students acquired *concrete experiences* by working directly with IoT sensors in the process of installing them, implementing wired and wireless connections to machines, and acquiring the data. These experiences were then used as the basis for *observations and reflections* that further prompted the students to create frameworks for managing collected sensor data from production machines. These reflections were then further assimilated and distilled into *abstract concepts* in the form of visualizations or dashboards representing data. These dashboards were used to gather insight and interpret the data from which new implications for action and recommendations were drawn. These implications can be *actively tested* and serve as guides for improvements and recommendations.

Table 1 Course orchestration following principles of ELT

Concrete Experience	**Reflective Observation**	**Abstract Conceptualization**	**Active Experimentation**
			
Learner actively *installs and configures sensors and acquires data* with IoT equipment	Learner consciously reflects back on that experience by *cleaning, processing, and storing the data by* creating a database framework.	Learner conceptualizes a model of what is observed by *generating visualizations of the data.*	Learner *interprets visualizations*, *gathers insights*, and offers recommendations accordingly.

The course implemented nine laboratories organized into four main topics to build a foundation of knowledge and skills. The first topic was around IoT and data collection, consisting of three labs. The second topic was related to connectivity and middleware, consisting of two labs. The third topic focused on data storage and visualization tools, also consisting of two labs, and the fourth and last topic focused on machine learning composed of two labs. Each lab assignment consisted of two parts: (1) a prelab assignment to introduce concepts and prepare for (2) the main lab assignment. Students completed the prelab assignment asynchronously before coming to the in-person lab meeting time to work on the main lab assignment.

3.1. Topic 1: IoT sensor communication and data collection.

Table 2 describes the three laboratory assignments associated with the first topic of IoT sensors and data collection, along with the learning objectives for the prelab and lab assignments. Figure 2 illustrates the schematic of this topic. During the 10 lab assignments, students frequently interacted with a Raspberry Pi computing device [7], external hardware connections and sensors, and software configurations. As such, Section 1 of this course was focused on how IoT sensors can collect and communicate data.

To begin, Lab 2 briefs students on the Python programming used to interact with the temperature and humidity sensor, DHT11. Then, the students are asked to connect the DHT11 sensor to their Raspberry Pi which then interacts with Python programming code to collect data. Next, Lab 3 follows suit with a lesson on accelerometer and signal processing, and how frequency domain plots are useful for analyzing sensor data from machining equipment. For the completion of this lab, students need to wire an accelerometer to a fan and input the time/frequency-domain data into their Raspberry Pi environment, which then they analyze using Python programming code. Finally, Lab 4 wraps up the IoT sensor section by introducing machining standards and protocols for power meter equipment and computer numerical control (CNC) industry controllers. In this lab, students are asked to configure power meter hardware to communicate with their Raspberry Pi system. Then, students do the same for a Haas CNC [8] controller and analyze the data to report industry standard metrics. In conclusion, this section briefs students on popular manufacturing oriented IoT sensors and applies real-world sensors to real data analytics, resulting in a fundamental understanding about how manufacturing equipment can interact with computers and provide useful insight and input.

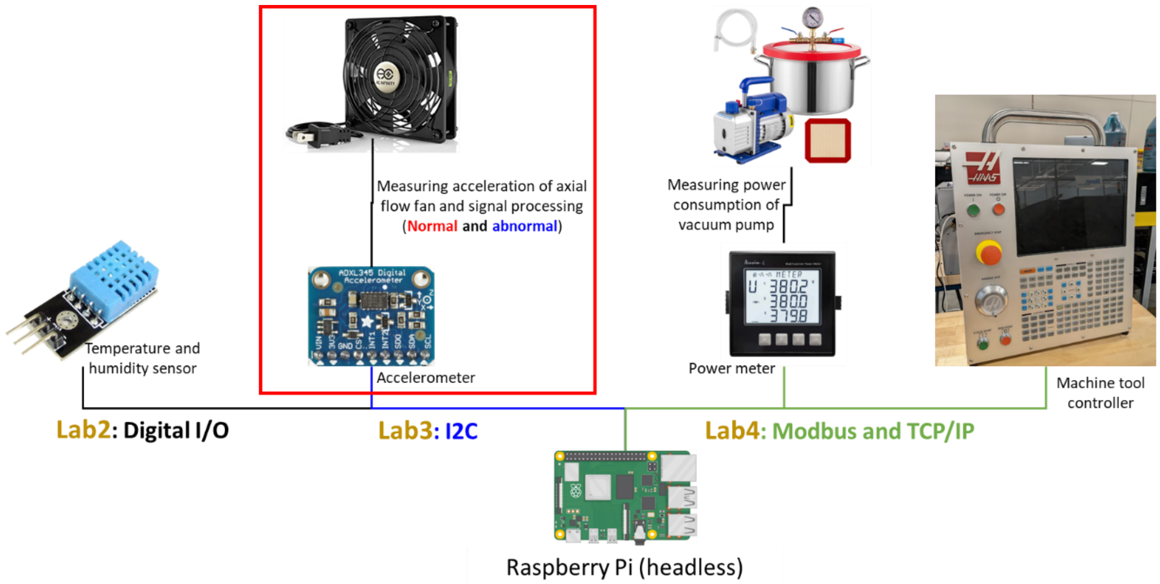


Figure 2 Schematic of Topic 2: IoT sensor communication and data collection

Table 2 Primary learning objectives for each prelab and lab assignment for Topic 1

Title of Lab	Prelab Learning Objective	Lab Learning Objective
Lab 2 – IoT Sensor Data Collection: Humidity & Temperature	Students will be able to prepare a Python programming environment on the Raspberry Pi to measure sensor data	Students will be able to program Python code to read, save, and format data from a DHT11 atmospheric sensor
Lab 3 – IoT Sensor Data Collection: Accelerometer & Signal Processing	Students will be able to visualize time- and frequency-domain datasets by calculating and plotting data using Python	Students will be able to build and accelerometer that processes data using physical sensors and time-/frequency-domain graphs
Lab 4 – IoT Sensor Data Collection: Power Meter & CNC	Students will be able to define and describe power meter and CNC standards and protocols	Students will be able to calculate power meter effectiveness metrics by building a pipeline into a Raspberry Pi

3.2. Topic 2: Connectivity and middleware.

Table 3 describes the two laboratory assignments associated with the second topic of connectivity and middleware, along with the learning objectives for the prelab and lab assignments. Figure 3 illustrates the schematic of this topic. A typical manufacturing environment runs different types of equipment, sensors, and standards, a middleware is required to appropriately aggregate and handle data. The second topic of this course focuses on how to use the MTConnect standard.

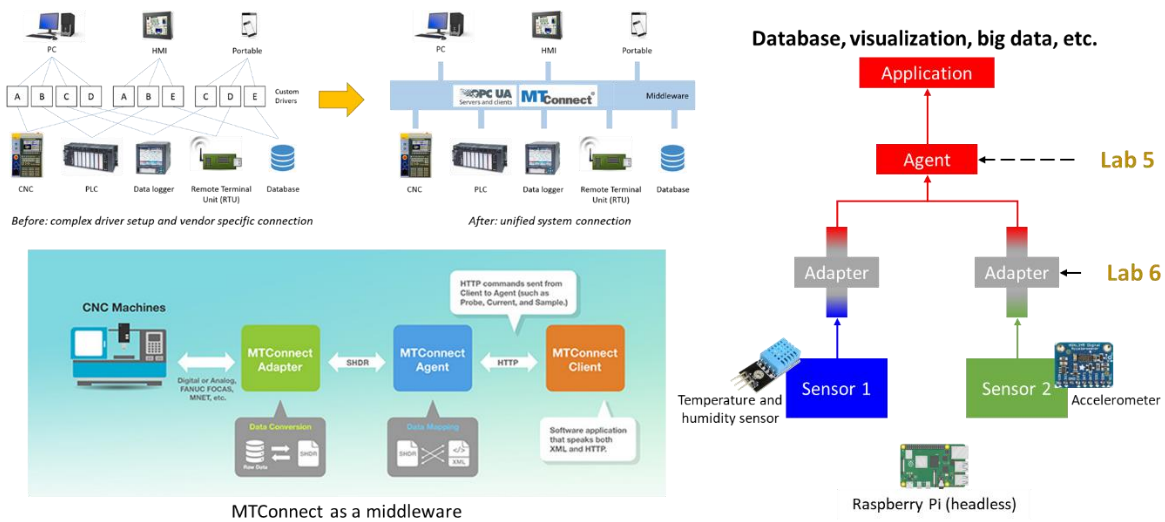


Figure 3 Schematic of Topic 2: Connectivity and middleware

Students will begin with Lab 5 introducing the concepts of middleware and how the MTConnect Agent is a critical part to bridge hardware sensors and adapters into an application-ready data stream [9]. In this lab, students are asked to run an MTConnect Agent on their Raspberry Pi and simulate the MTConnect data pipeline. Then in Lab 6, students are introduced to the MTConnect Adapater. There are hands-on activities to prepare students to work with multiple adapters, and multiple agents, and connect those to computing devices. During this lab, students become familiar with how to parse and interpret incoming data to then present in database management tools. As it is seen, this section prepares students to handle complex manufacturing environments by using middleware to interact with various types of manufacturing equipment.

Table 3 Primary learning objectives for each prelab and lab assignment for Topic 2

Title of Lab	Prelab Learning Objective	Lab Learning Objective
Lab 5 – Middleware: MTConnect Agent	Students will be able to install the MTConnect Agent and describe its functionality for a manufacturing use case	Students will be able to run the MTConnect Agent in configuration to see the data stream in the MTConnect adapter
Lab 6 – Middleware: MTConnect Adapter	Students will be able to configure the MTConnect Adapter and identify its components	Students will be able to manage multiple MTConnect Adapters and extract information from incoming HTTP requests

3.3. Topic 3: Data storage and visualization tools.

Table 4 describes the two laboratory assignments associated with the third topic regarding data storage and visualization tools, along with the learning objectives for the prelab and lab assignments. Figure 4 illustrates the schematic of this topic. Once IoT sensors can interact with an edge computing device like the Raspberry Pi, and MTConnect can appropriately aggregate the multiple data streams, then database and visualization techniques are required to gain meaningful insight for manufacturing. As such, the third topic of this course covers how SQL and Grafana are utilized to interact with data in a database and visualize it for application-use [10], [11].

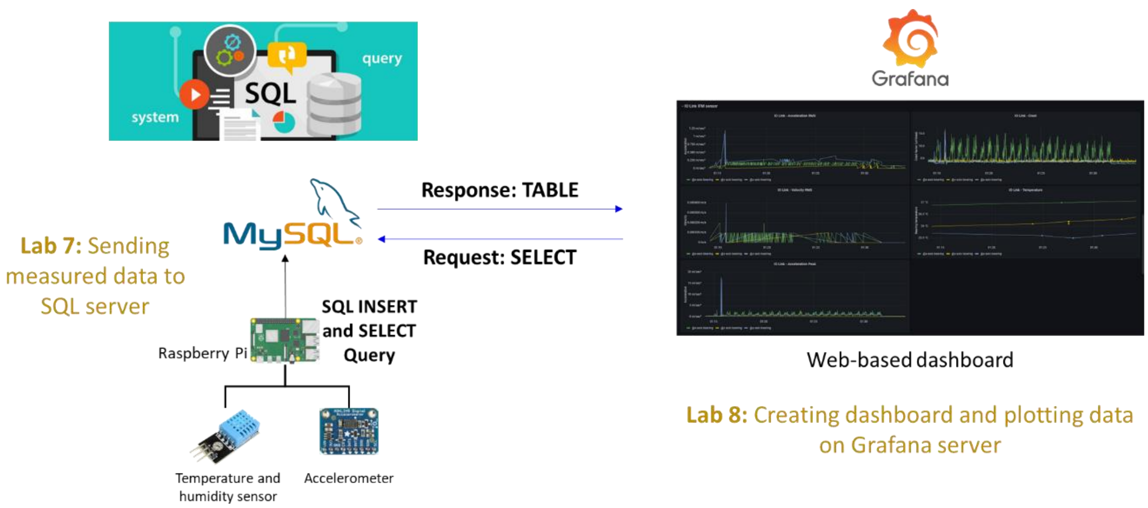


Figure 4 Schematic of Topic 3: Data storage and visualization

To do this, Lab 7 covers introductions and basics to SQL programming. Students learn about basic SQL scripts to write functions to interact with data. Then, Lab 8 showcases how the Grafana visualization tool creates dynamic and rich visualizations of input data. Students will learn how to integrate multiple technologies and concepts learned up to this point and build a monitoring system to simulate a manufacturing environment. Through completion of this lab assignment, students will understand how large amounts of raw data can aggregate into human-readable formats.

Table 4 Primary learning objectives for each prelab and lab assignment for Topic 3

Title of Lab	Prelab Learning Objective	Lab Learning Objective
Lab 7 – Database and Visualization: SQL Database	Students will be able to explain the basic functions of SQL and common SQL statements	Students will be able to write SQL statements to modify, edit, and extract data from a database table
Lab 8 – Database and Visualization: Grafana Dashboard	Students will be able to explain how SQL database management allows for Grafana visualization	Students will be able to build a monitoring system in Grafana that connects and visualizes all of the components in the lab thus far

3.4. Topic 4: Machine Learning.

Table 5 describes the two laboratory assignments associated with the fourth topic on machine learning, along with the learning objectives for the prelab and lab assignments. Figure 5 illustrates the schematic of this topic. Prior to topic 4, students have been able to interact with data and interpret data visualizations, but now machine learning techniques allows for more complex data analytics and deeper insights for manufacturing processes and efficiency. The fourth topic of this course introduces students to machine learning (ML) basics and how ML can be implemented in the manufacturing data pipeline. Throughout this section, students are introduced to basics of ML and neural networks, classification techniques, edge device TinyML computing using TensorFlow [12], and monitoring systems using TinyML.

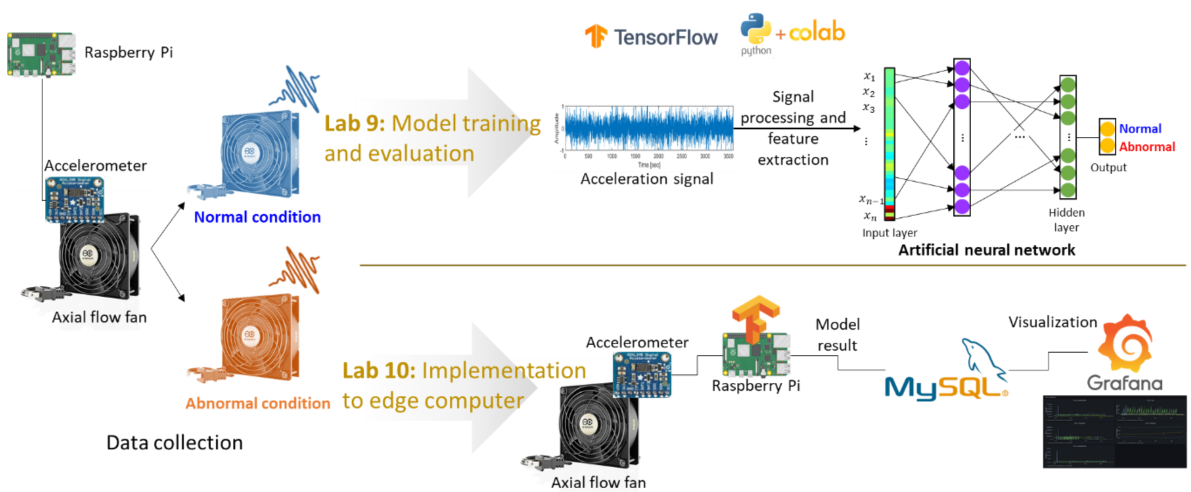


Figure 5 Schematic of Topic 4: Machine learning

To begin, Lab 9 briefs students on ML fundamentals, then scaffolds students through building a machine learning model to classify and analyze time- and frequency-domain data from Lab 3. Students experience extensive hands-on learning for utilizing ML in manufacturing equipment. Then, Lab 10 explains how technologies surrounding TinyML allow for machine learning models to be installed on small and low power devices in a manufacturing environment. To do this, students learn about and install TensorFlow on a Raspberry Pi to prepare for loading the ML model they developed in Lab 9 [12]. Students complete Lab 10 by integrating the TinyML data streams into a monitoring system discussed in Section 3. This section of the course introduces students to practices and concepts encompassed by Industry 4.0 revolution which redefines the way organizations have utilized technology to optimize operations and production [12]. In conclusion, it is essential for students to understand these Industry 4.0 technologies to help transform manufacturing practices and stay ahead of global competition.

Table 5 Primary learning objectives for each prelab and lab assignment for Topic 4

Title of Lab	Prelab Learning Objective	Lab Learning Objective
Lab 9 – Machine Learning: Artificial Neural Networks and Classification	Students will be able to develop an ML model and assess metrics of performance as it detects anomalous data	Students will be able to implement an artificial neural network to classify incoming real-world data
Lab 10 – Machine Learning: Implementation to Edge Devices	Students will be able to install TensorFlow and load a ML model	Students will be able to deploy a TinyML model using TensorFlow and build a monitoring system using TinyML

4. Impact and Outcomes of the Course

A primary delivery of the course consisted of a team-based semester-long project consisting of implementing an IoT solution for a local company. From the beginning of the semester, representatives from each company and institute delivered presentations during lectures as a form of a seminar. In the presentations, they had a speech about the importance of IoT technology and applications in the real field as well as they explained the scope and details of the collaboration project. If the project scope is undecided, the company and students came up with the project subject together based on course contents and company needs. To perform the projects, 2 or 3 students consisted of a team. There were one research institute, one education institute, and six companies, participated in the collaboration projects. After the presentations from the companies and institutes, students put in for a project upon their interests.

Table 6 summarizes the participating company/institute and project goals. In Table 6, the first column, No., means the assigned team number. To make project progress, students had meetings in-person or virtually with the company once or twice a week for two months. They also had several visits to deploy sensors, edge devices, and/or other implementation procedures. Part of the students' visits were also meant to determine implementation schedules with the company to ensure the company can minimize downtime and continue their production. As these were semester-long projects, students conducted project work alongside lab work. And, as such, students had regular meetings with the instructor and lab TA to discuss approach, progress, feasibility, difficulty, and so on. If they were stuck on technical or practical issues, TA and instructor gave feedback and suggested solutions. The main focus of these projects was to take the IIoT and AI learning outcomes and apply what they learned to the real shop floor.

Table 6 Type of participating company/institute and collaboration project goal

No.	Company/Institute Type	Project Goal
1	Research institute 1	Establish digital twin and power consumption analysis for injection molding machine
2	Research institute 1	Develop an AI model to predict machine tool running state based on sound and power meter
3	Education institute 1	Establish digital twin for welding lab equipment monitoring
4	IT company 1	Develop an AI model to predict machine state from manufacturing sound data
5	Manufacturing company 1	Deploy a IoT system for agitator gearbox health monitoring using sound
6	Manufacturing company 2	Develop an AI model for failure prediction of heating element of furnace
7	Manufacturing company 3	Develop an MTConnect adapter for a laser cutter
8	Manufacturing company 4	Develop an AI model to predict machine tool state using sound
9	Manufacturing company 5	Develop part measurement platform using edge device

There were two presentation days: midterm presentation and final presentation. For each presentation, students submitted reports. In the midterm presentation, the instructor gave feedback and evaluated the progress. In the final presentation day (Figure 2), all teams presented their project. Representatives from the company/institute joined and discussed each project in Q&A session. The category of the project subject, outcome, and benefit of company are summarized in Table 7. Projects were categorized in ‘Monitoring system deployment’, ‘AI application’, and ‘Software development’. Throughout the project, not only do students learn how IoT techniques and knowledge are able to be applied to the real field but also company take benefits of the collaboration project.

Figure 6 Final presentation day

Table 7 Project category, outcome, and benefit

No.	Category	Outcome and Benefit
1	Monitoring system deployment	• Real-time monitoring system for injection molding machine • Empirical power consumption model based on constructed system
2	AI application	• An AI model to predict running state of machine tool based on sound and power consumption
3	Monitoring system deployment	• Real-time monitoring system for welding lab equipment • Ventilation motor running state and vibration monitoring
4	AI application	• Real-time monitoring system for gearbox condition
5	Monitoring system deployment	• An AI model for spindle speed prediction of milling machine based on sound sensor
6	AI application	• AI models and comparison results for failure prediction of heating element of furnace
7	Software development	• MTConnect adapter software
8	AI application	• An AI model to predict cutting state of machine tool based on sound
9	Software development	• MTConnect adapter software development for measuring workpiece in CNC machine using linear encoder

5. Discussion and Conclusion

At the end of the semester, course evaluation was conducted anonymously by the students. Table 8 shows the evaluation items related to the project and lab activities and score. The score was calculated based on responses of each evaluation item. Response options (score) are Strongly Agree (5), Agree (4), Neither Agree nor Disagree (3), Disagree (2), and Strongly Disagree (1). Therefore, the maximum and minimum scores are 5 and 1, respectively. The enrollment of the course was 21 and the response rate for the course evaluation was 57.14%. Students mostly responded positively to the course, and specifically, the learning content included in the lab portion of this course. Moreover, students indicated that the combination of the semester-long project work and lab work helped them achieve practical and applicable skills—even asking to expand the content within the lab.

Table 8 Course evaluation and score relevant to lab and project

Evaluation item	Score Mean	Standard Deviation
The course is well organized.	4.58	0.67
The assignments aid me in achieving the class objectives.	4.83	0.39
The projects or laboratories aid me in achieving the class objectives.	4.83	0.39
Lab procedures are clearly explained to me.	4.67	0.89
Prelab lectures are helpful in my understanding of the lab experiments	4.67	0.89
The content of the lab is a worthwhile part of this course.	4.92	0.29

On top of that, in the course evaluation, we also asked students to share comments about lab. The sentence to ask for comments was “We welcome your comments below. What is something/are some things that the instructor does well, e.g., something you hope that the instructor will continue to do in the class in the future?” All responses were as follows.

- The prelab and lab material were extremely helpful for learning. The assignments made me understand the tasks better. Everything was ready when we arrived to the lab, it was well-structured.
- Lab activities are very helpful for students to experience a broad range of course topics which include sensor implementation, data collection, data storage, data analysis with machine learning models, and visualization. I hope the lab activities will be continued in the class.
- The class instructor did an excellent job during the semester. I consider the class structure outstanding; all the assignments, the laboratories, and the presentations of the industry sponsors made the class develop in an excellent way and increased my interest.
- He does a good job relating the material to real-world use. Also, I would like to highlight TA (because I don't see a specific spot for him) because he has been an incredibly valuable resource for the lab portion of this class. He has been the most attentive and

helpful TA I have ever had. He will always help you understand the material and has done a great job supporting the students.

In addition, Students suggested to improve the course. The suggestion request sentence was “Make a suggestion(s) for improving the course.” All the responses were as follows.

- The lab sessions can be extended. I really liked the content and the material during lab sessions. The only improvement could be having more time to practice with more lab sessions.
- I would recommend the instructor to maintain the projects with the industry sponsors, as well as the laboratories. Personally, those were my favorite things about the class.
- Maybe doing less labs overall and making them bigger. Some of the steps were repeated between labs, but I think if there were less labs were we didn't repeat steps as much then the extra time could be used effectively for the project.

To summarize, students preferred to perform lab activities over other course material even when the topics seemed broad and extensive. This may be a result of their motivation to complete the semester-long project, as they saw the connections between that and each lab. By doing industry-collaboration projects, students were able to apply IoT and AI technologies learned from the lab activities to the real field. While the learning outcomes for each lab (indicated in Tables 2-5) were not directly measured, the intentions were to prepare students for real-world work. And, as it is seen, the students' perceived the lab/course material to help them complete the project. Vice versa, the skills and experience gained during the project helped them achieve the course and lab learning outcomes. As part of future work, we will explore the feasibility of adapting the course for undergraduate students and scaling it up to wider audiences. A potential strategy we will explore is to repurpose the final projects as case studies and laboratory assignments and provide students with the real data already collected in previous years. Ultimately, by taking an experiential learning approach, students effectively learned IIoT knowledge in smart manufacturing settings to apply their knowledge in real-world practice.

6. Acknowledgments

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