



Volume 25, 2026

IoT-ENABLED POCKETLABS AND THE 5E INSTRUCTIONAL MODEL FOR ACTIVE LEARNING IN CONTROL SYSTEMS EDUCATION

Leonardo Enrique Bermeo Clavijo	Universidad Nacional de Colombia, Sede Bogotá, Facultad de Ingeniería, Departamento de Ingeniería Eléctrica y Electrónica, Bogotá, Colombia	lbermeoc@unal.edu.co
Edgar Hernando Sepúlveda-Oviedo	PROMES-CNRS (UPR-8521), Rambla de la thermodynamique, Tecnosud, Perpignan, France <i>and</i> Université de Perpignan Via Domitia, 52 Avenue Paul Alduy, Perpignan, France	edgar-hernando.sepulveda-oviedo@univ-perp.fr
Jhon Jairo Ramírez- Echeverry*	Universidad Nacional de Colombia, Sede Bogotá, Facultad de Ingeniería, Departamento de Ingeniería Eléctrica y Electrónica, Bogotá, Colombia	jiramireze@unal.edu.co

* Corresponding author

ABSTRACT

Aim/Purpose	This study investigates how integrating Internet of Things (IoT)-enabled Pocket Laboratories (PocketLabs) with the 5E instructional model can support active learning in undergraduate Control Systems education.
Background	Traditional Control Systems laboratories face challenges related to cost, availability, and access to hands-on experimentation. Although PocketLabs and IoT technologies offer promising alternatives, their pedagogical integration within structured instructional frameworks remains underexplored.
Methodology	An exploratory mixed-methods case study was conducted. A total of 55 undergraduate engineering students participated in the laboratory activities, and data

Accepting Editor Kathryn MacCallum | Received: March 22, 2026 | Revised: June 16, June 28, August 11, August 26, 2026 | Accepted: September 15, 2026.

Cite as: Bermeo Clavijo, L. E., Sepúlveda-Oviedo, E. H., & Ramírez-Echeverry, J. J. (2026). IoT-enabled PocketLabs and the instructional model for active learning in control systems education. *Journal of Information Technology Education: Research*, 25, Article 38. <https://doi.org/10.28945/5884>

(CC BY-NC 4.0) This article is licensed to you under a [Creative Commons Attribution-NonCommercial 4.0 International License](https://creativecommons.org/licenses/by-nc/4.0/). When you copy and redistribute this paper in full or in part, you need to provide proper attribution to it to ensure that others can later locate this work (and to ensure that others do not accuse you of plagiarism). You may (and we encourage you to) adapt, remix, transform, and build upon the material for any non-commercial purposes. This license does not permit you to use this material for commercial purposes.

	from a perception survey were collected from 40 of these students. The quantitative survey data were analyzed using descriptive statistics, while the qualitative responses were examined through thematic analysis.
Contribution	This study examines the pedagogical integration of IoT-enabled PocketLabs within a 5E instructional framework and presents a low-cost learning environment for in-person, remote, and hybrid Control Systems education.
Findings	Students reported positive perceptions of the learning environment. One hundred percent of survey respondents either agreed or strongly agreed that it supported their understanding of control concepts. Qualitative analysis identified five themes related to learning support, engagement, teamwork, self-regulated learning, and opportunities for improvement.
Recommendations for Practitioners	Engineering educators may consider combining portable experimental platforms, real-time visualization tools, and structured instructional frameworks to support active learning and increase access to hands-on laboratory experiences.
Recommendations for Researchers	Future studies should employ larger, more diverse samples, comparative research designs, and direct assessments of learning outcomes to evaluate further the educational effects of IoT-enabled PocketLabs and 5E-based instructional approaches.
Impact on Society	The proposed approach may expand access to practical engineering education by reducing infrastructure constraints and supporting flexible learning opportunities.
Future Research	Future research should employ longitudinal and comparative designs and explore adaptive learning, intelligent feedback, and learning analytics within IoT-enabled laboratory environments.
Keywords	Internet of Things, (IoT), 5E instructional model, control systems education, PocketLabs, active learning, engineering education

INTRODUCTION

In the domain of engineering education, including electrical engineering, conventional courses often incorporate laboratory sessions. These sessions bridge the gap between theoretical concepts and their practical applications, thereby facilitating a transition for comprehensive learning. These laboratory experiences offer several advantages. They promote the development of technical skills (Esposito et al., 2021), enhance both individual reasoning and collaborative reflection (Viegas et al., 2018), offer a broader learning perspective compared to lecture-only formats (Velosa, 2020), promote learning through experimentation and trial-and-error (Valencia de Almeida et al., 2022), and influence students' learning goals and strategies (Ma & Nickerson, 2006). In short, laboratories embody the learning-by-doing approach, enabling learners to construct knowledge and develop practical skills through direct interaction with physical systems and experiments rather than through passive instruction alone (Visioli, 2023).

Conventional laboratory equipment for control systems education typically consists of relatively complex platforms that integrate sensors, actuators, data acquisition hardware, real-time data processing capabilities, a physical plant, and supporting software. To address this need, several companies specializing in engineering education have developed control systems laboratory platforms (see, for instance, Quanser (n.d.) and Acrome (n.d.)). These platforms are carefully designed, validated, and tested by experienced engineers, providing students with comprehensive and reliable learning experience while minimizing the influence of unwanted experimental noise and implementation issues. In

addition, these platforms are often accompanied by carefully designed laboratory activities that help students explore and understand fundamental control concepts. However, the activities are generally designed to guide students toward predetermined experimental outcomes, leaving limited room for open-ended experimentation and inquiry.

Nonetheless, these platforms are expensive and require dedicated facilities. In practice, universities are often able to acquire only a limited number of these platforms for courses with large student enrollments, while laboratory space is likewise constrained. This challenge is common across many engineering disciplines that depend on specialized laboratory equipment. As a result, limited laboratory resources often require rigid scheduling schemes that may not effectively accommodate diverse learning paces and educational needs (Ghashim & Arshad, 2023; Kumar & Al-Besher, 2022).

Promoting self-directed learning and intrinsic motivation is a central objective of engineering education. However, students with a genuine interest in the subject who wish to design and test control systems beyond scheduled laboratory activities often have limited opportunities to do so. Access to advanced experiments is often restricted, limiting students' opportunities to explore a broader range of control-system phenomena (Insuasti et al., 2022; Takács et al., 2020). Consequently, limited availability of laboratory resources (both equipment and physical infrastructure) can become a significant obstacle to deeper exploration, independent learning, and sustained engagement with the subject matter.

In response to this challenge, several initiatives have integrated hybrid laboratories, which combine in-person and remote experiences, as a promising alternative in engineering education. Previous research suggests that different modes of laboratory access can influence students' learning experiences and educational outcomes, highlighting the importance of designing effective laboratory environments regardless of the delivery modality (Lindsay & Good, 2005). Hybrid laboratories have been increasingly adopted to expand access to practical learning experiences (Brinson, 2015; Klinger et al., 2018; Velosa, 2020). These advancements have been driven by contemporary technologies such as Pocket Laboratories (Insuasti et al., 2022; Oliveira et al., 2022), which can promote educational innovation by facilitating hands-on learning experiences (Terzieva et al., 2022) and IoT (Candelas et al., 2015; Sobota et al., 2013). Pocket Laboratories (hereafter referred to as PocketLabs) refer to portable, low-cost experimental setups designed for hands-on learning inside and outside traditional laboratory environments (Oliveira et al., 2022). These setups, often built with open-source software tools (and open hardware systems such as Arduino, Espressif 32-bit Microcontroller (ESP32), and Raspberry Pi), enable students to conduct experiments in flexible settings. IoT refers to a network of physical devices embedded with sensors, software, and connectivity features that enable the collection and exchange of data. IoT platforms facilitate the implementation of cost-effective hybrid laboratories by minimizing the need for expensive equipment and dedicated physical spaces (Ghashim & Arshad, 2023; Terzieva et al., 2022).

Specifically, in the domain of Control Systems, real-time data acquisition and remote manipulation enabled by PocketLabs and IoT technologies hold considerable potential to enhance students' understanding of abstract concepts. Control theory, a rather abstract branch of engineering, uses feedback, information processing, and computing mechanisms to produce a system behavior according to pre-defined requirements (Åström & Murray, 2021). For electrical engineering students, a solid understanding of this theory is essential for developing the cognitive and practical competencies required to apply it to physical systems relevant to Industry 4.0 (Vásquez, 2024). In response to this demand, current initiatives focus on incorporating technologies such as PocketLabs and IoT into control theory education. The integration of these technologies is considered an effective strategy for modernizing engineering curricula (Ghashim & Arshad, 2023; Oliveira et al., 2022). However, the impact of these technologies on students' learning processes still requires further empirical validation, underscoring the need for additional research in this area (Chacon et al., 2019).

Previous research has shown that the educational effectiveness of laboratory environments depends not only on the technological characteristics of the platform but also on the pedagogical strategies used to support experimentation, reflection, collaboration, and knowledge construction (Brinson, 2015; Feisel & Rosa, 2005; Ma & Nickerson, 2006; Van den Beemt et al., 2023; Viegas et al., 2018). While numerous studies have examined the technical feasibility and deployment of PocketLabs (Insuasti et al., 2022; Madritsch, 2022; Oliveira et al., 2022) and, separately, IoT-based educational technologies (Ghashim & Arshad, 2023; Sapale & Banerjee, 2023), the literature remains fragmented. Most existing studies focus on issues such as laboratory accessibility, hardware development, remote experimentation, or technological implementation. Comparatively less attention has been devoted to understanding how the combined use of IoT-enabled PocketLabs and structured instructional models can support students' conceptual understanding, engagement, and self-regulated learning in engineering education.

Moreover, evidence remains limited on how to integrate these technologies into a coherent pedagogical design that simultaneously addresses laboratory accessibility, active experimentation, collaborative learning, reflective knowledge construction, and the pedagogical implications of combining portable experimental platforms, IoT connectivity, and active-learning frameworks within a unified educational environment. Consequently, important questions remain regarding how these technologies can be systematically embedded into learning activities that guide students from initial engagement with physical phenomena to conceptual explanation, knowledge transfer, and performance evaluation. Addressing this gap is particularly relevant in Control Systems education, where students are required to connect abstract mathematical concepts with the behaviors of real physical systems.

RESEARCH AIM

Motivated by the pedagogical challenges posed by the limited accessibility of conventional Control Systems laboratories and by research gaps identified in the literature, this study investigates the integration of IoT-enabled PocketLabs into an undergraduate Control Systems course. To support this integration, a set of experimental learning activities was designed based on the 5E constructivist instructional model (Engage, Explore, Explain, Elaborate, and Evaluate) to extend laboratory experiences beyond traditional instructional settings (Bybee & Landes, 1990).

To the best of the authors' knowledge, the literature provides limited evidence of integrated implementations that simultaneously combine (i) portable PocketLabs specifically developed for Control Systems education, (ii) IoT-based communication and remote interaction capabilities, and (iii) learning activities systematically designed according to the 5E instructional model. Therefore, the novelty of this work lies not only in the technological architecture itself, but also in the pedagogical integration of these elements within a coherent active-learning framework.

The contributions of this work are outlined as follows:

- The study presents two PocketLabs developed for Control Systems instruction: a DC motor platform for speed and position control experiments and a temperature control system. Both platforms are low-cost, reproducible, and easy to maintain, making them suitable for addressing the resource constraints commonly encountered in Control Systems laboratories. Their portability enables their deployment outside conventional laboratory facilities. Moreover, since the platforms are powered directly via a USB connection, students need only a laptop to conduct experiments, thereby facilitating access to hands-on learning experiences in different places.
- PocketLabs reported in this study that they function as IoT devices, supporting the implementation of learning activities across in-person, remote, and hybrid instructional modalities and thereby extending access to laboratory experiences beyond traditional facilities. By providing access to experimental platforms and real-time data from diverse locations, these systems are intended to enhance the flexibility and availability of laboratory resources. Fur-

thermore, the networked architecture enabled by IoT technology is designed to support collaborative learning through shared access to resources and coordinated experimental activities.

- The study presents a set of learning activities systematically designed in accordance with the 5E instructional model. It provides detailed examples illustrating the implementation of each phase of the model from Engage and Explore to Explain, Elaborate, and Evaluate within the context of Control Systems education. The application of the 5E model leverages the educational potential of the PocketLabs and their underlying IoT technology by organizing the learning experience into progressive stages that promote direct engagement with physical phenomena, critical reflection, conceptual understanding, and the application of knowledge.
- The study analyzed both quantitative and qualitative data collected through a student perception survey to explore students' perceptions regarding the educational value of the implemented practical experiences across several dimensions of learning, including the understanding of theoretical concepts, perceived learning efficiency, the application of theory to real-world systems, learning motivation and engagement, and the promotion of peer-learning interactions.

Consequently, this study is guided by the following research question: "What are students' perceptions of the educational effects of integrating IoT-enabled PocketLabs with the 5E instructional model in Control Systems education?" This study adopts an exploratory approach to provide preliminary empirical evidence on the educational benefits students perceive from this integration. The purpose of this evidence is to inform future curriculum design. The research proposal for this study was reviewed and approved by the Research Ethics Committee of the Faculty of Engineering at the National University of Colombia in Bogotá under approval number 25347, granted in 2025.

This work is structured as follows: first, the text introduces related work on the use of PocketLabs, IoT, and the 5E instructional model in engineering education. The following section describes the architecture of the integrated learning environment for Control Systems reported in this study. Subsequently, the research design is outlined, including descriptions of active learning activities, participants, and data collection instruments. The subsequent section presents the quantitative and qualitative results obtained. Subsequently, the findings are discussed, and their implications for educational design are analyzed. In conclusion, the final section summarizes the key findings and discusses the study's limitations and potential future directions.

BACKGROUND AND RELATED WORKS

In recent years, there has been growing interest in integrating innovative technologies, such as PocketLabs and IoT platforms, into engineering education. These tools are of value in the domain of control systems instruction, as they facilitate real-time data acquisition and remote system interaction. Moreover, they can support self-regulated and active learning models, making them well-suited to constructivist pedagogical frameworks (Candelas et al., 2015), including the 5E instructional model.

THE 5E INSTRUCTIONAL MODEL

The 5E Model, originally developed by Bybee and Landes (1990), is a constructivist framework designed to promote active, student-centered learning through five sequential phases: Engage (E1), Explore (E2), Explain (E3), Elaborate (E4), and Evaluate (E5). In the Engage phase, instructors use brief activities or questions to stimulate students' curiosity and connect to their prior knowledge. In the Explore phase, students collaborate on hands-on tasks or problem-solving activities to investigate novel concepts. In the subsequent phase of the instructional cycle, known as the Explain phase, students and instructors participate in a collaborative discussion to clarify and refine the key concepts and findings derived from the initial inquiry. The Elaborate phase involves learners applying concepts to new situations or real-world problems. The Evaluate phase is characterized by the implementation

of both formal and informal assessments to evaluate comprehension and provide feedback (Bybee & Landes, 1990). The 5E model, a widely adopted approach in science and engineering education, has exhibited notable advantages (Melgarejo et al., 2024). For instance, Lee et al. (2024) found that integrating the 5E model with Learning by Evaluating (LbE) in engineering design education promoted deeper engagement, enhanced problem-solving abilities, and improved communication skills among students. However, the study also highlighted challenges in self-evaluation and the need for structured guidance during assessment (Lee et al., 2024). Moreover, comparative research indicates that the 5E model increases student interest, supports scientific inquiry, and leads to higher academic achievement compared to traditional instructional methods. However, effective implementation by teachers requires careful instructional planning and contextual adaptation (Hu et al., 2017; Lee et al., 2024). Despite these challenges, the 5E model is recognized for its capacity to transform passive learning environments into dynamic spaces where students actively construct and apply knowledge, specifically in engineering and technology disciplines (Lee et al., 2024).

POCKETLABS FOR CONTROL SYSTEMS EDUCATION

Research indicates that PocketLabs promote self-paced, exploratory learning and increase access to practical experiences for students lacking traditional lab resources (Insuasti et al., 2022; Oliveira et al., 2022). Klinger and Kreiter (2018) describe a two-year experience at Carinthia University of Applied Sciences (CUAS) integrating PocketLabs into engineering education. They aimed to provide students with portable hardware and software solutions, allowing greater flexibility in time and location for laboratory exercises. Their findings suggest that students highly appreciated the flexibility offered by PocketLabs and emphasized PocketLabs as an effective tool for enhancing access to hands-on learning beyond traditional environments. Zhou et al. (2024) introduce Mathematics to Practice Laboratory (M2PLab), a flexible framework for control systems education powered by a Raspberry Pi. Their study finds that the M2PLab enables students to conduct experiments across various locations, significantly enhancing accessibility. Students report high satisfaction with the flexibility and effectiveness of the M2PLab in an Automatic Control Theory course. The authors conclude that M2PLab can improve both the learning experience and students' practical skills in engineering education.

Anishchenko and Zaleskyi (2020) describe a PocketLab developed for studying DC motors using the NI myDAQ data acquisition device. Their study finds that integrating virtual instruments in NI LabVIEW enhances students' understanding of motor control concepts. They conclude that PocketLabs offer a practical and accessible alternative to traditional labs when integrated into the curriculum. Juchem et al. (2020) discuss the development of pocket-sized Proportional–Integral–Derivative (PID) experimental setups for control engineering courses. Their study finds that active learning with these mobile setups improves student engagement and comprehension of control concepts. They conclude that portable setups such as these can significantly enhance control education by making learning more interactive and accessible.

IoT TECHNOLOGIES IN CONTROL SYSTEMS EDUCATION

IoT enables the gathering and processing of real-time data, supports personalized learning, and enables continuous monitoring of student progress (Kumar & Al-Besher, 2022; Terzieva et al., 2022). The accessibility and flexibility of IoT-based laboratories are particularly valuable in current educational contexts, as they promote both collaboration and remote learning opportunities (Chacon et al., 2019; Oliveira et al., 2022). By integrating hardware and software into real-time applications, IoT-based experiments can deliver immediate feedback to students, thereby enhancing the learning experience (Ghashim & Arshad, 2023). In addition, the capacity for remote access to laboratories fosters dynamic learning environments (Chacon et al., 2019), effectively addressing the spatial and temporal limitations that often hinder hands-on experimentation (Ghashim & Arshad, 2023).

Several studies have examined IoT's role in teaching control systems. Hossain et al. (2019) explored IoT-based applications for managing power and energy through remote substation monitoring and control. Their study developed an IoT-based network strategy that enhanced efficiency by reducing

human intervention. IoT improves accuracy and resource management, suggesting its value for training in educational settings. Carli et al. (2020) presented an IoT-based architecture for Model Predictive Control implementation in smart buildings. Their study shows how IoT sensors and actuators combined with remote interfaces optimize energy consumption and thermal comfort. Tested on a real campus, the system improved energy efficiency and satisfaction. The authors conclude that IoT-based control systems provide valuable real-world applications for engineering students learning predictive control methods.

Verma et al. (2017) proposed a smart computing framework that uses IoT technologies to assess student performance in engineering education. The system under discussion collects real-time activity data from students via sensors and processes it using advanced algorithms. The findings indicate that IoT-based monitoring enhances assessment accuracy and facilitates timely interventions. The authors concluded that IoT-driven solutions have the potential to transform control systems and engineering education by offering deeper insights into student performance. Akbar et al. (2018) developed a cost-effective, industrial-standard training system for undergraduate and postgraduate control labs that integrates IoT technologies, including controller programming and machine-to-machine communication. Their study demonstrated that this system significantly enhances student engagement and learning outcomes, underscoring the importance of hands-on and practical environments in preparing future IoT professionals.

Similarly, Sapale and Banerjee (2023) explored the role of IoT in improving accessibility and personalized learning in educational settings. Through case studies of universities implementing IoT, they found that these technologies foster greater student-educator interaction and engagement. However, concerns regarding privacy and security persist. The study's conclusions underscore the important role that IoT can play in helping educational institutions maintain their competitive edge in a rapidly evolving digital educational landscape.

RESEARCH GAP AND MOTIVATION

The reviewed literature demonstrates the growing interest in PocketLabs, IoT technologies, remote laboratories, and active-learning approaches in engineering education. Previous studies have reported benefits related to accessibility, flexibility, student engagement, and opportunities for hands-on experimentation (Klinger & Kreiter, 2018; Oliveira et al., 2022; Zhou et al., 2024). More recent evidence also suggests that the educational value of remote and hybrid laboratories depends strongly on the active-learning strategies and pedagogical structures used to support student interaction, experimentation, and reflection (Van den Beemt et al., 2023). However, the literature also highlights several challenges, including technical troubleshooting requirements, hardware reliability concerns, unequal access to digital infrastructure, increased instructor workload, and difficulties associated with the assessment of learning outcomes in remote or hybrid laboratory settings (Brinson, 2015; Ghashim & Arshad, 2023; Ma & Nickerson, 2006; Van den Beemt et al., 2023).

Moreover, most studies have focused on technological development, laboratory deployment, or accessibility improvements. Comparatively less attention has been devoted to investigating how portable IoT-enabled experimental platforms can be pedagogically integrated within structured instructional frameworks that actively support conceptual understanding, engagement, reflection, and self-regulated learning. Evidence remains limited on integrating IoT-enabled PocketLabs with the 5E instructional model in the context of Control Systems education.

Accordingly, this study addresses this gap by investigating an integrated educational environment that combines low-cost PocketLabs, IoT technologies, and learning activities designed according to the 5E instructional model. Rather than focusing exclusively on technical feasibility, the study explores students' perceptions regarding the educational value of this integrated approach. Consequently, the present work contributes to the literature by examining the pedagogical implications of integrating IoT-enabled PocketLabs within a structured 5E instructional framework for Control Systems education. From a methodological perspective, the study integrates quantitative survey data with qualitative

evidence from students' open-ended responses, providing complementary perspectives on students' perceptions of the learning experience.

METHODS

ARCHITECTURE OF THE IoT-ENABLED POCKETLABS LEARNING ENVIRONMENT FOR CONTROL SYSTEMS

The architecture of the active IoT learning environment for Control Systems proposed in this work is shown in Figure 1. It integrates the following key elements: students, PocketLabs based on ESP32 microcontrollers, a Python-based Application Programming Interface (API) for interacting with the physical systems through Jupyter Notebooks, and a Message Queuing Telemetry Transport (MQTT) broker service for IoT communication.

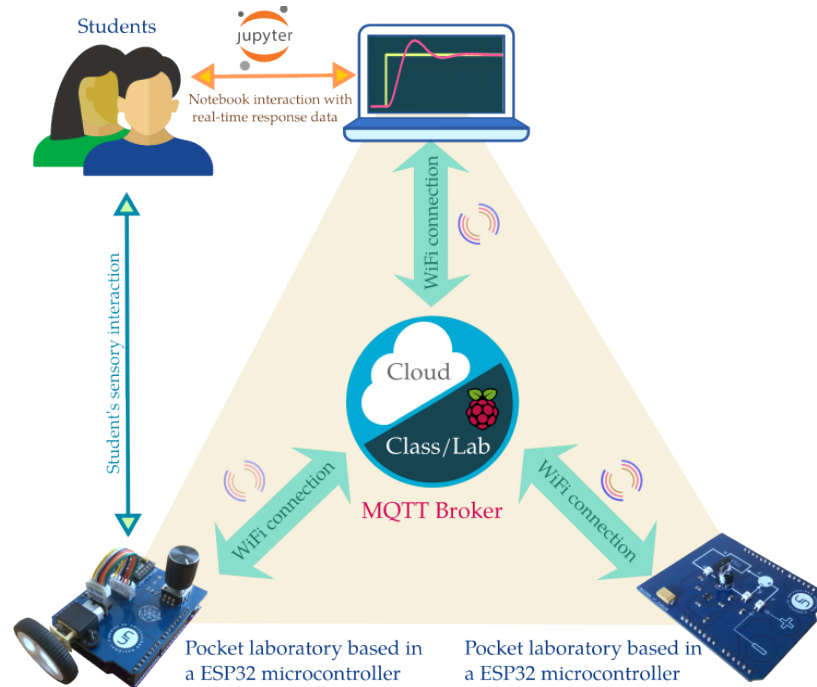


Figure 1. General architecture of the proposed system for learning control systems

Students

As central actors in an active learning environment, students engage in hands-on experimentation with PocketLabs through two modalities: a basic hardware interface and Python-based Jupyter Notebooks. They can operate the PocketLabs either in person or remotely (or even in a hybrid format).

PocketLabs

They are complete and compact experimental setups designed to support students' active learning of fundamental Control Systems principles. In this study, two different PocketLabs are designed:

1. *Characterization and Control of a DC Motor:* This PocketLab, illustrated at the lower-left vertex of Figure 1, integrates all the required electronic components (including a driver and an encoder) to enable experiments on DC motor speed and angle control. It also includes basic user interface elements, such as capacitive buttons (to adjust setpoint or voltage), a smart RGB LED, a knob, and a wheel. For a more detailed overview, please refer to the image available at the provided link: <https://github.com/nebisman/UNDCMotor/blob/main/docs/WorkingDiagramMotorDC.png>

2. *Temperature Control System*: This PocketLab, depicted at the lower-right vertex of Figure 1, integrates all the required electronic components (including sensing and analog current control) to perform experiments on precise temperature control of a power transistor. It also includes basic user interface elements, such as capacitive buttons (to adjust setpoint) and three smart RGB LEDs. For a more detailed overview, please refer to the image available at the provided link: <https://github.com/nebisman/UNThermal/blob/main/docs/Working-DiagramThermalSystem.png>

Two key requirements for the PocketLabs were a compact form factor and USB-C power compatibility. To reduce size, the devices were designed using the extended Arduino form factor (68.6 mm × 53.4 mm), ensuring long-term hardware compatibility. These PocketLabs comply with the USB 3.0 specification, allowing them to be powered by a laptop, smartphone, or standard USB-C charger.

The PocketLabs use a dual-core ESP32-S3 microcontroller that enables data acquisition, processing, and wireless connectivity to a MQTT broker. The ESP32-S3 firmware was developed using the real-time operating system FreeRTOS (Barry & The FreeRTOS Team, 2023).

As indicated by the blue arrow on the left side of Figure 1, students can directly observe and interact with the controlled variables for each module. For example, in the DC motor system, the controlled angle is observable through the movement of a wheel, whereas in the thermal system, the current temperature and power levels are represented by heat maps displayed using smart RGB LEDs. The reference values of these variables can also be adjusted using capacitive buttons or a knob.

Python-based API and Jupyter Notebooks

A Python-based API is provided for interacting with the ESP32-S3 firmware of the PocketLabs. The API includes several functions that allow students to perform different experiments. For example, students can obtain the step response of the PocketLab by calling the simple command `step_closed(system)`, as shown in the help documentation provided at this link: https://nebisman.github.io/UNThermal/step_closed.html

As depicted at the top of Figure 1, Jupyter Notebooks (which use the Python-based API) are the primary interface for student interaction with the PocketLabs. These notebooks serve as interactive guides for conducting different experimental activities and acquiring real-time response data. For instance, one learning activity involves experimenting with different PID control tuning methods for both the DC motor and the temperature PocketLab (the corresponding notebook for this activity can be reviewed at this link: [https://github.com/nebisman/UNThermal/blob/main/docs/Notebook for PID TUNING.ipynb](https://github.com/nebisman/UNThermal/blob/main/docs/Notebook%20for%20PID%20TUNING.ipynb))

Broker MQTT

The core of the communication architecture is the open-source MQTT Mosquitto broker (Light, 2017), depicted as a blue circle at the center of Figure 1. The figure is horizontally divided to illustrate the two key modes of operation of the environment, in-person and remote, which are depicted in Figure 2.

- *In-person mode*: Students have a PocketLab available at the site where the activity takes place. The broker service is provided by a laptop or by a compact single-board computer (SBC), such as a Raspberry Pi, located at the same site. As shown in Figure 2(a), this mode is typically used for active learning activities in laboratory or classroom settings, owing to the PocketLabs' compact size and low power consumption. It is important to note that, due to the architecture of the IoT-based communication system, all students in a workgroup can interact simultaneously with the same PocketLab (and with the instructor, if required).
- *Remote-hybrid mode*: In this mode, some or all students in a workgroup can interact with the PocketLabs remotely via Jupyter Notebooks. This mode requires the MQTT broker service

to be hosted in the cloud or on an on-premises server. As shown in Figure 2(b), a typical application involves a subset of students remotely operating a PocketLab located at one participant's home. Another important application is the deployment of one or more plants in a university laboratory, allowing students to perform experiments at their convenience from any location.

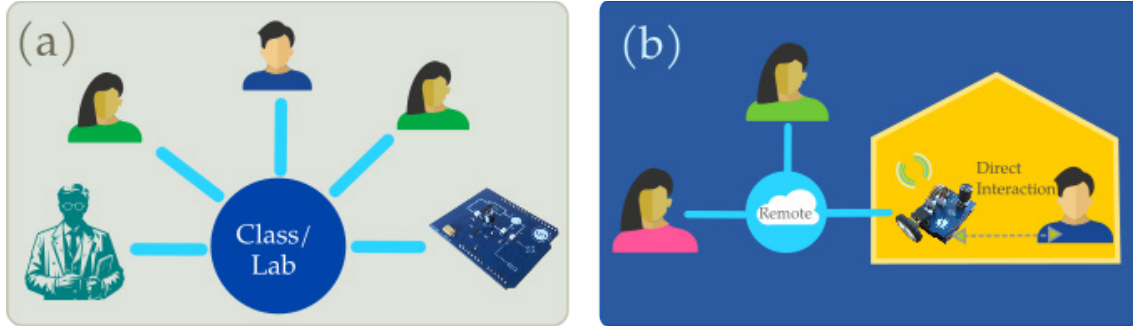


Figure 2. Modes of operation of the proposed environment:
(a) In-person mode; (b) Remote-hybrid mode

DESIGN OF EDUCATIONAL RESEARCH

This study adopted an exploratory mixed-methods case study design to examine the initial implementation of an IoT-enabled educational intervention within a single-institution engineering education context. Given the first-time integration of PocketLabs into our Electrical, Electronics, and Mechatronics Engineering programs, an exploratory approach was appropriate for capturing diverse student experiences. The case study design was selected because the intervention was implemented within an existing mandatory course, which limited the possibility of random assignment or the formation of equivalent control and experimental groups. Consequently, the present study focuses on an empirical investigation of a convenience sample to generate preliminary evidence to inform future curricular improvements.

The educational intervention replaced the traditional laboratory methodology based on static PDF guides and linear procedures with a constructivist 5E instructional framework. IoT-enabled PocketLabs supported real-time experimentation and iterative learning processes. The intervention was implemented in three phases:

- *Familiarization*: Introduction to the hardware and software tools through hands-on activities.
- *Implementation*: Completion of five laboratory activities involving DC motor and thermal plant systems using Jupyter Notebooks.
- *Assessment*: Student perceptions were collected via an online survey designed to gather both quantitative and qualitative data on the learning experience.

Course and setting

The course selected for implementing the integrated environment was Control Systems. In this course, the learning goals are as follows:

- Discuss the fundamental properties of feedback in engineering systems.
- Build experimental models of linear dynamical systems.
- Apply PID tuning techniques commonly used in industrial processes.
- Design and test linear controllers using linear models of dynamical systems.

The distribution of laboratory activities using PocketLabs and the topics addressed are presented in Table 1.

Table 1. Practice development in the Control Systems course, with activity descriptions

ID#	PocketLabs used	Activity	Week	Duration (hours)
1	Thermal and DC Motor	Identify the basic elements of a feedback control system	1	2
2	Thermal and DC Motor	Build first-order models using the reaction curve method (step response)	2	2
3	Thermal and DC Motor	Tune Proportional–Integral (PI) and PID controllers using First-Order Time Delay (FOTD) models	3-4	4
4	DC Motor	Design and test PI and PID controllers from Pseudo-Random Binary Sequence (PRBS) models using algebraic methods	5-6	4
5	DC Motor	Design and test a linear controller subject to multiple requirements and constraints	7-10	8

All activities are organized into instructor-guided sessions lasting two hours and conducted once per week. Accordingly, Activities 1 and 2 each require a single two-hour session and are completed within one week. Activities 3 and 4 each require two two-hour sessions, for a total of four hours distributed over two weeks. Activity 5 spans four two-hour sessions, totaling eight hours over four weeks. These scheduled sessions are intended primarily to provide students with access to instructor support and guidance throughout the learning process. However, students are free to use the PocketLabs outside the scheduled sessions to complete assigned tasks, repeat experiments, or engage in open-ended exploration.

The 5E Model (Bybee & Landes, 1990) is the instructional model used to design the active learning activities in the Control Systems course, which are supported by the integrated learning environment represented in Figure 1. In this regard, Figure 3 depicts the five phases of the 5E instructional model as applied in the Control System course. As indicated in Table 1, Activity 1 is specifically designed to engage students at the course's outset, while Activity 5 is primarily focused on the Elaboration phase. Activities 2 to 4 integrate the phases of the 5E model to varying degrees. The following section describes the implementation of the 5E learning phases within the activities designed for the Control Systems course.

E1: Engage. The hardware design of the PocketLabs is intended to facilitate this phase. Some tasks designed to capture students' interest and activate their prior knowledge are presented below:

- In Activity 1, students should interact with PocketLabs through their basic user interface elements. They manually set different setpoints for the controlled variable using the knob and capacitive buttons, and apply external disturbances by attempting to change the DC motor wheel's angle by hand or by altering the transistor's temperature with a fan cooler.
- In Activity 3, students physically generate (by touch) and experience the system's response to external disturbances under different PI tuning methods using PocketLabs (see the video at this link: <https://youtu.be/gvQ6wkzJHOs>).

E2: Explore. In this phase, students conduct several experiments to develop models and test controllers using code implemented in Jupyter Notebooks. Some examples are presented below:

- In Activity 2, students perform experiments to obtain static and dynamic models for both PocketLabs at different operating points based on their step responses.
- In Activity 3, students test PI and PID controllers for both PocketLabs using different empirical tuning rules proposed in the literature.

- In Activity 4, without prior explanation, students configure a controller that deliberately generates instability in the DC motor angle to observe the resulting phenomena.

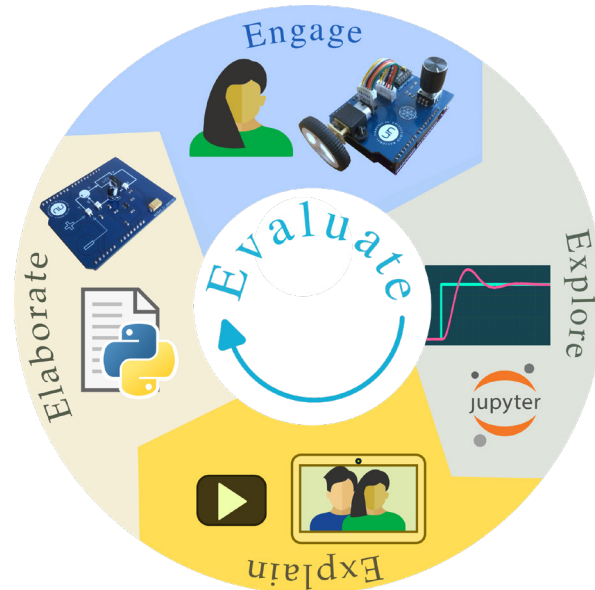


Figure 3. The 5E instructional model applied to the Control Systems course

E3: Explain. This phase is developed through the combined efforts of students and the instructor, with the support of the course materials. In this regard, throughout all activities in Table 1, students are presented with guiding questions that are discussed during the laboratory session. They are encouraged first to discuss these questions among peers and, if necessary, consult the instructor for conceptual clarification. Some examples are presented below:

- Once students have obtained dynamic models for the PocketLabs (E2 in Activity 2), the explanatory material that develops the mathematical models of the PocketLabs (see the related material at: https://github.com/nebisman/UNThermal/blob/main/docs/modelo_matematico_unthermal.pdf) and the procedure for obtaining first-order models is reviewed (see the related material at: https://github.com/nebisman/UNThermal/blob/main/docs/metodo_2_puntos.pdf). Students are then asked to explain why control can be more challenging at certain operating points than at others (see the video at: <https://www.youtube.com/watch?v=cSEKfjeJms4>).
- Once students have tested different tuning methods (E2 in Activity 3), they are required to discuss which method yields the best response based on speed, overshoot, and disturbance-rejection criteria.
- Once students have configured an unstable system (E2 in Activity 4), the related theoretical concepts are reviewed, and students are required to explain why instability was observed in the previous experiment.

As a deliverable, students working in pairs must submit a video report in which they discuss their responses to the questions in each activity.

E4: Elaborate. Activities 2–5 in Table 1 each conclude with a task designed to extend the concepts learned one step further, as described below:

- In Activity 2, students are required to design and conduct experiments to estimate the uncertainty in the DC motor parameters.

- In Activity 3, students are required to improve PID controller tuning by combining previously tested methods with heuristic tuning rules.
- In Activity 4, students are required to program a self-tuning PID control algorithm for the DC motor angle based on the reviewed mathematical theory (see the video at: https://youtu.be/1ruEt_AREpw).
- Activity 5 is strongly focused on the elaboration phase. Students are required to design and test a controller for the DC motor angle. Their design must account for trade-offs among multiple requirements and constraints. The Python-based API provides a dedicated function for programming general linear controllers, thereby expediting students' testing of their designs. This function can be accessed at https://nebisman.github.io/UNThermal/set_control-ler.html.

E5: Evaluate. This phase includes both formative and summative evaluation components. Formative evaluation consists of peer-to-peer discussions and informal instructor assessment. The summative evaluation component includes video reports (the videos linked above were produced using student-generated material) and demonstrations of the results achieved by each group in response to the tasks proposed during the elaboration phase.

Details of course implementation

Three instructors supervised the students participating in this study. Each instructor was assigned to a group of approximately 15 students and was responsible for guiding that group throughout all the laboratory activities described above.

It is important to note that the instructors participating in this study were trained in the 5E instructional model and actively involved in designing and developing the laboratory activities presented in Table 1 and the accompanying instructional materials. Prior to implementation, the activities underwent pilot testing with the support of two teaching assistants, who completed all laboratory activities, verified the estimated completion times, evaluated the Jupyter Notebooks, and reported any issues or errors encountered during testing. This pilot-testing phase facilitated the refinement of both the instructional materials and the technical resources before their deployment in the course.

Participants

Participation in the study was voluntary and anonymous. A convenience sample was used because course enrollment is based on institutional scheduling and students' academic interests rather than on researcher selection. A total of 55 students participated in the laboratory activities, and 40 (72.7% response rate) completed a perception survey. The survey respondents included 36 male students (90%) and four female students (10%), reflecting the historical gender imbalance in these engineering disciplines at the institution. The selected Control Systems course is a mandatory component of the undergraduate curriculum. It is typically taken by students in the seventh semester of a ten-semester program in mechatronics, electronics, and electrical engineering at the National University of Colombia (Universidad Nacional de Colombia). Students entering this course are required to have completed the "Signals and Systems" course, which provides a baseline of theoretical knowledge for modeling dynamic systems.

Measurement instrument

Quantitative and qualitative data on student perceptions were collected via an online survey administered immediately after the final laboratory session (Week 10) to ensure that participants had engaged with all phases of the 5E model. Prior to participation, students received an informed consent form detailing the study objectives, ensuring the confidentiality of responses, and emphasizing that participation was voluntary. Explicit consent for the use of responses in this study was also obtained. The study integrated quantitative and qualitative data sources to strengthen the analysis:

- Quantitative component: A 6-point Likert scale (ranging from strongly disagree (1) to strongly agree (6)) collected student perceptions about five learning dimensions: (1) topic comprehension, (2) learning facilitation, (3) task engagement (perseverance and interest), (4) application of theory to a physical system, and (5) peer collaboration.
- Qualitative component: Each Likert item included an open-ended question requiring justification of the selected rating. Responses were analyzed through thematic analysis to identify themes that facilitated or hindered learning.

The survey statements were as follows:

The following questions refer to your experience using the IoT-enabled pocket laboratories:

- Statement 1: The use of the hardware-software environment helped me understand the control concepts of the course. Why?
- Statement 2: The use of the hardware-software environment allowed me to learn the control concepts of the course more quickly. Why?
- Statement 3: The control theory concepts presented through the hardware-software environment were easy to understand. Why?
- Statement 4: The hardware-software environment used in the lab contributed to my perseverance in achieving good performance in controller design. Why?
- Statement 5: The hardware-software environment encouraged collaboration with my peers to enhance my learning. Why?
- Statement 6: The hardware-software environment helped me understand how control theory is applied in a real physical system. Why?
- Statement 7: The hardware-software environment enhanced teamwork. Why?
- Statement 8: The overall experience provided by the hardware-software environment was interesting. Why?

The Likert scale facilitated a structured quantification of students' perceptions, while open-ended justifications offered deeper qualitative insights into their experiences. This combination enabled a comprehensive analysis of the perceived effects of the IoT-enabled PocketLabs environment on student learning. For reference, the full survey is available at the following link:

<https://forms.gle/CjxNk1R8so8VCGvk8>.

The survey instrument was specifically developed for this study based on a review of the literature on engineering education and laboratory-based learning. The review enabled the identification of key dimensions potentially affected by the intervention. To ensure content validity, the instrument was reviewed by experts in engineering education and control systems. The review focused on the representativeness, clarity, and relevance of the survey items. Feedback obtained during this process was incorporated into the final version of the instrument. Internal consistency metrics, such as Cronbach's alpha, were not calculated because the survey items were designed to assess independent, distinct dimensions of the learning experience rather than a single unidimensional latent construct.

Data analysis

Responses were obtained from 40 participants, and quantitative Likert-scale data were analyzed using descriptive statistics. Qualitative data from open-ended survey responses were examined using thematic analysis (Bryman, 2012). Each student response served as the unit of analysis, and the process comprised three stages: open, axial, and selective coding. During open coding, relevant words and phrases describing students' experiences were identified. In axial coding, related codes were grouped into categories and organized into higher-level themes. Iterative refinement of coding and categorization enabled a comprehensive interpretation of responses. Finally, selective coding contextualized the findings by examining relationships among themes and categories to address the research question. The coding process was directed by a researcher specializing in engineering education and qualitative methodologies, who did not serve as the course instructor. This methodological decision was made

to mitigate potential social desirability bias in the interpretation. To ensure the reliability of the findings, the study employed a collaborative peer-review process. Following the initial coding phase, the results were shared and critically reviewed by a second researcher with expertise in control systems engineering. This collaborative triangulation entailed formal peer-checking sessions and multiple iterations of the coding structure to resolve any conceptual discrepancies and refine the thematic categories. The 40 students provided 320 individual comments (eight open-ended responses per participant), which served as the primary units of analysis.

RESULTS

STUDENT RESPONSES TO THE POCKETLABS ENVIRONMENT

Figure 4 presents the response distribution for each survey item. Across all statements, responses were concentrated in the highest levels of agreement, with “Strongly agree” being the most frequent category. Negative responses were nearly non-existent, while items associated with collaboration and teamwork exhibited slightly greater variability than the rest of the responses.

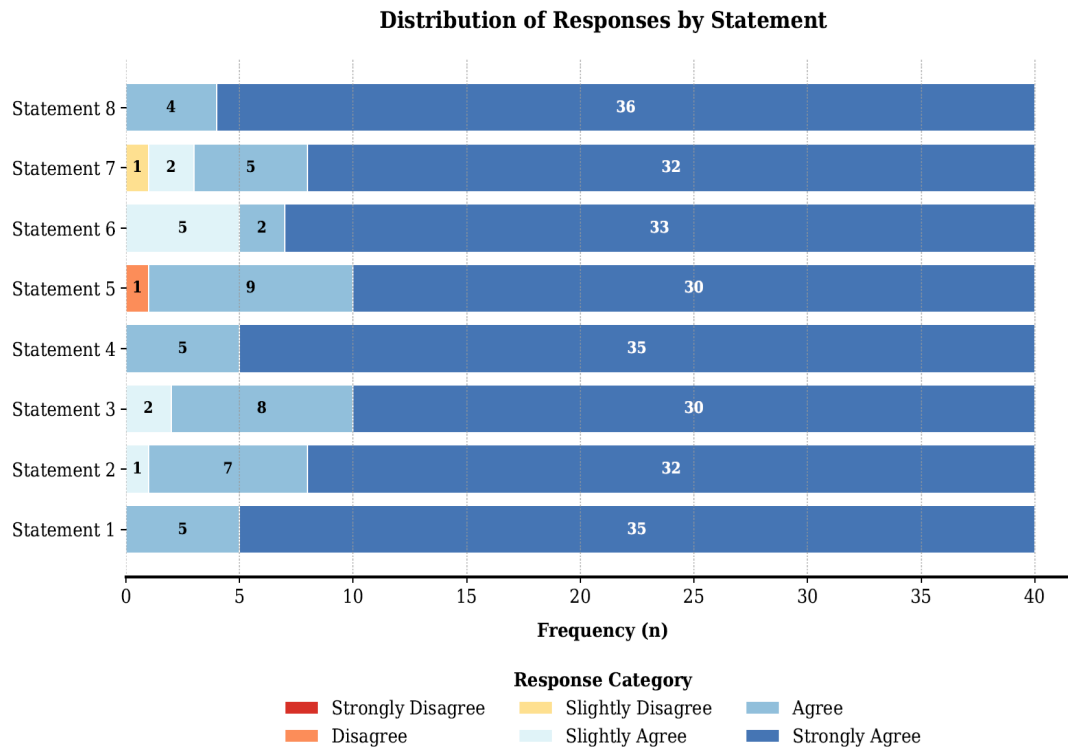


Figure 4. Quantitative results of student perceptions of the learning experience with the IoT-enabled PocketLabs environment for Control theory

As presented in Table 2, all statements received high ratings, with mean scores exceeding 5.6 on a six-point scale. The aspects that received the highest ratings were support for understanding the subject matter, perseverance in controller design, and overall experience. Conversely, peer collaboration received the lowest rating, although it was still classified as highly positive ($M = 5.68$). The variability was found to be low across items, indicating substantial agreement among participants. These consistently high ratings should be interpreted primarily as evidence of strong student acceptance and positive perceptions of the learning environment, rather than as direct evidence of improved learning outcomes.

Table 2. Descriptive statistics of student perceptions of the learning experience with the IoT-enabled PocketLabs environment for control theory

Statement		Mean	Standard deviation
1	Understanding of the subject matter	5.88	0.33
2	Perceived faster understanding of concepts	5.78	0.48
3	The ease of understanding control theory concepts presented through the environment	5.70	0.56
4	Perseverance in controller design	5.88	0.33
5	Encouraged peer collaboration	5.68	0.73
6	Clarified real-world applications of control theory	5.70	0.69
7	Teamwork	5.70	0.69
8	Overall experience	5.90	0.30

On the other hand, qualitative data analysis offers detailed insights into students' perspectives on the environment, including perceived strengths, overall reception of the tool, and areas for improvement. From the 320 initial comments, the thematic analysis identified 565 distinct text segments, each categorized into at least one of the identified themes. This indicates that many student responses were multifaceted, contributing to the understanding of different dimensions of the learning experience. Analysis of these segments identified five core themes: (1) hardware–software features enhancing teaching and learning (213 segments), (2) effects on teaching and learning processes (156 segments), (3) features promoting teamwork and peer learning (92 segments), (4) features supporting self-regulation in learning (69 segments), and (5) aspects for improvement (35 segments).

Table 3 presents the macro-categories and categories identified within Theme 1. The symbol *n* represents the total number of mentions (text segments) associated with each macro-category. The table also summarizes the main characteristics of the hardware–software environment and provides representative student comments.

1. *Characteristics that Impact Conceptual Deepening:* With 101 total mentions, this dimension emerged as the most relevant benefit. Students perceived that integrating real-time observation with structured Python-based guidance helped them move beyond abstract mathematical modeling to tangible engineering applications. Participants emphasized that the environment provided a manifestation of control concepts. Furthermore, Jupyter Notebooks appeared to serve as scaffolding, fostering a reflective and collaborative environment in which peer-to-peer feedback became an integral part of the learning process.
2. *Technical Usability and Operational Efficiency:* The second macro-category (87 mentions) highlights the reduction of cognitive load regarding non-essential tasks. Students reported that they were able to focus exclusively on control strategies rather than hardware troubleshooting by utilizing predefined system models and an intuitive interface. This efficiency appeared to enable a “fail fast” approach, which encourages rapid experimentation. As stated by a participant: “We are commonly asked to design models and circuits, which is a high effort... Having the study systems and focusing on the control tools seems very wise.” This shift from “building” to “analyzing” was perceived by students as increasing the time dedicated to high-level iteration and parameter optimization.
3. *Visual Analytics and Optimization:* Finally, the students perceived that synergy between interactive visualization and iterative tuning (25 mentions) addressed the emotional and analytical aspects of learning. Real-time graphical feedback was perceived as a bridge between theoretical stability criteria and practical system response. This immediate reinforcement reportedly

mitigated frustration during the tuning process, transforming trial and error into a methodical, data-driven experience. Students perceived that the interface enabled “progressively better controllers” as they began to internalize the relationship between parameter adjustments and system behavior.

Table 3. Hardware-software features of the environment that enhance teaching and learning

#	Macro-category	Frequency (n)	Categories	Examples of opinions
1	Characteristics that Impact Conceptual Deepening	101	Real-time observation, Jupyter Notebooks /Python guidance, didactic structure	“Being able to observe so clearly how different controllers act on the plant allows for a better understanding of control concepts.”
2	Technical Usability and Operational Efficiency	87	Ease of use, rapid iteration, predefined models	“Because the software is so user-friendly and lets us see everything we’re doing, what we still need to correct and improve, and what we’re aiming to achieve.”
3	Visual Analytics and Optimization	25	Interactive visualization, iterative tuning	“The iterative process allows progressively better controllers to be obtained as the system response to parameter adjustment is understood.”

Table 4 presents the categories and their definitions, along with examples of comments for each category in the second theme: effects on teaching and learning processes. The definitions were derived from the interpretation of students’ responses.

1. *Empirical Validation and Gap Bridging:* The most prevalent macro-category (83 mentions) in this theme concerns the reconciliation of mathematical abstraction with physical constraints. The students reported that the environment allowed them to identify the “limitations and differences between reality and theory,” a critical skill in control engineering. Beyond simple confirmation, this category highlights the role of the laboratory in correcting misconceptions. As noted by one participant, the hands-on interaction helped “correct some concepts that I had wrong,” suggesting that the real-time feedback of the labs serves as a self-correcting pedagogical tool that theory alone cannot provide.
2. *Perceived Learning Efficiency and Intuition:* With 47 mentions, students reported that the environment appeared to support a faster conceptual assimilation. The “interactive nature” of the environment transformed static theoretical blocks into dynamic, observable behaviors. Students attribute this acceleration to the immediate feedback loop between parameter manipulation and system response. Participants reported that “seeing concepts presented and tested immediately” allowed them to intuitively understand technical variables that would otherwise require extensive cognitive effort to visualize through traditional methods.
3. *Holistic Knowledge Synthesis:* Finally, 26 segments emphasized the environment’s ability to foster a “holistic understanding” of the curriculum. Students perceived that they could connect “apparently unconnected knowledge,” suggesting that the laboratory promotes high-level relational thinking. The observation of a complete control loop appeared to facilitate students’ transition from a fragmented understanding of individual topics, such as the Laplace transform or stability criteria, to a unified mental model of how these components interact within a real-world system.

Table 4. Effects on teaching and learning processes

#	Macro-category	Frequency (n)	Categories	Examples of opinions
1	Empirical Validation and Gap Bridging	83	Theory vs. reality, system limitations, and misconception correction	“Practical [interaction] helped me to better understand the concepts and to correct some concepts that I had wrong.”
2	Perceived Learning Efficiency and Intuition	47	Rapid assimilation, intuitive visualization, feedback loop	“Interacting with a plant while quickly varying parameters ... allows knowledge to be assimilated more clearly and quickly.”
3	Holistic Knowledge Synthesis	26	Interdisciplinary links, curriculum integration, mental mapping	“... seeing how the process is applied makes one relate [concepts] better, and even other apparently unconnected knowledge can be connected.”

The third theme (92 comments), features of the learning environment that promote teamwork and peer learning, encompasses students’ perceptions that the practices could foster collaborative learning and structured team discussions, encourage cooperation through shared resources, and facilitate easy accessibility to instructor support for concept clarification. The students perceived that the environment facilitates active collaboration, enabling them to work in teams to analyze experiments, respond to notebook questions, and create video reports, thereby promoting knowledge sharing, diverse perspectives, and collective problem-solving. Moreover, they reported that the lab environment supported teamwork both within groups and across the course, as shared physical spaces and online resources facilitated equitable task distribution and idea exchange. Additionally, students underscored the pivotal role of instructor guidance in understanding complex control and dynamic systems concepts, with real-time support and structured explanations enhancing their theoretical and practical understanding. The following are illustrative examples of student comments:

- *“Thanks to the fact that the two plants could be managed simultaneously, the teamwork was optimized and allowed for more of an atmosphere in which impressions were shared rather than instructions.”*
- *“In addition to the hardware-software environment, it was also made easier to understand the theory concepts due to assertive guidance from the professor.”*

The fourth theme (69 comments), Learning environment features that support self-regulation, encompasses students’ perceptions that laboratory practices enhanced motivation, supported time management and autonomous learning, promoted experimental flexibility and self-efficacy, reduced frustration, and consolidated learning. The students perceived that the interactive laboratory structure stimulated curiosity and engagement, increasing interest in Control Systems while reinforcing theoretical concepts through hands-on experimentation. The laboratory design was perceived as supporting iterative controller adjustments, fostering a deeper understanding of control theory, and encouraging performance-oriented refinement. Students reported efficient time use, accelerated learning, and increased autonomy in mastering key concepts such as modeling, plant identification, and controller design.

Additionally, the students reported that opportunities for repeated trials and progressive adjustments helped them strengthen their confidence and self-efficacy in learning control theory. The structured yet flexible environment appeared to minimize errors and frustration, supporting persistence and sustained motivation during design refinement. Further integrating hands-on experimentation with theoretical reinforcement could enhance the effective application and consolidation of concepts in practical contexts. The following are illustrative examples of student comments:

- *“It was a really innovative method which gave comfort and even high interest to attend classes.”*
- *“Sure, because together with the development of one’s own script and the very simple implementation provided by the environment, one is motivated to get the best possible controllers.”*

Finally, the fifth theme concerned aspects of laboratory practices requiring improvement (35 comments). Students noted that the time allocated to laboratory work limited deeper exploration of certain concepts and suggested extending the session duration, as the laboratory component spanned ten weeks. They also expressed a strong interest in greater engagement with plant configuration and sensor integration to strengthen practical design skills beyond software-based modeling. In addition, students emphasized the need for clearer links between software commands and physical system responses, highlighting the importance of stronger theoretical–practical integration. The following are illustrative examples of student comments:

- *“I agree with the implementation of the software and hardware; it was very interactive and appropriate. However, it would have been good to learn more about the programming and the implementation of how the code relates to the transfer functions, that is, more about the software.”*
- *“The hardware-software environment helped me understand how control theory is applied to a real physical system because we used actual plants rather than just simulations. However, I think we could have gone further in learning how to set up the plant and the sensors — for example, by starting with just the motor and building the measurement circuit and everything else.”*

DISCUSSION

This study addressed the research question: “What are students’ perceptions of the educational effects associated with the integration of IoT-enabled PocketLabs and the 5E instructional model in Control Systems education?” Overall, the quantitative and qualitative evidence suggests that students found the IoT-enabled PocketLabs environment supportive of their conceptual understanding of control theory, engagement with laboratory tasks, and capacity to connect theoretical models to the behavior of physical systems when embedded within the 5E instructional framework. Specifically, all survey respondents agreed or strongly agreed that the environment supported their understanding of complex concepts (Statement 1, $M = 5.88$), and mean scores exceeded 5.6 across all eight survey items. Five interconnected themes emerged from the thematic analysis: Hardware and software features that were perceived as enhancing teaching and learning (Theme 1); effects on teaching and learning processes (Theme 2); features that promote teamwork and peer learning (Theme 3); features that support self-regulation in learning (Theme 4); and aspects for improvement (Theme 5). It is important to note that these findings reflect student perceptions of their learning experience rather than direct assessments of learning outcomes. The study did not include a control group, pre- and post-performance assessments, or comparative outcome data; therefore, claims regarding a causal improvement in learning are not supported. The evidence supports students’ perception that the environment fosters engagement, conceptual exploration, and the progressive construction of understanding, all of which are valuable process-level indicators in educational research and align with the constructivist foundations of the 5E Model.

A cross-cutting interpretation of the findings reveals a coherent alignment between the five qualitative themes and the sequential phases of the 5E instructional framework. The Engage and Explore phases were supported primarily by the hardware–software features reported in Theme 1 and by the self-regulatory behaviors found in Theme 4: the physical interactivity of the PocketLabs, including the direct manipulation of controlled variables through capacitive buttons, knobs, and observable plant outputs, was perceived as stimulating students’ curiosity and activating prior knowledge, while the flexibility of the environment to support repeated, risk-free experimentation appeared to support the iterative inquiry that characterizes the Explore phase. The Explain and Elaborate phases were supported by the processes documented in Theme 2 and Theme 3: real-time data visualization func-

tioned as a shared empirical referent that grounded theoretical discussions, enabling students to transition from a fragmented understanding of individual topics, such as the Laplace transform or stability criteria, to an integrated mental model of how these components interact within a complete control loop. This is consistent with the holistic knowledge synthesis macro-category.

Collaborative discussion during these phases was facilitated both by access to the same physical setup and by the structured guidance of the Jupyter Notebooks, which oriented students toward collective analysis and peer explanation. The Evaluate phase was underpinned by the instructor's guidance, documented in Theme 3: students consistently described the professor's immediate support and clear conceptual explanations as essential for consolidating experimental observations into theoretically coherent conclusions. These results align with Vinayachandra and Krishna Prasad (2020) regarding the role of IoT in enhancing student–teacher interaction. Finally, the feedback reported in Theme 5 (aspects for improvement) provides an empirical basis for the iterative refinement of the 5E instructional design itself. It suggests future adjustments in session duration and hardware-level task complexity.

THE ENVIRONMENT AS A PEDAGOGICAL MEDIATOR

The most consistent finding across both data sources was that students perceived the environment as facilitating the transition from mathematical abstraction to tangible engineering application. Importantly, the educational value perceived by students cannot be attributed exclusively to the PocketLabs' technological characteristics. Rather, the findings suggest that the observed benefits arose from the interaction between the technological environment and the pedagogical structure of the 5E instructional model. The portability of the PocketLabs, the real-time feedback enabled by IoT connectivity, and the progressive sequence of engagement, exploration, explanation, elaboration, and evaluation collectively shaped the learning experience. This observation reinforces the view that educational effectiveness depends not only on technological innovation but also on the pedagogical design through which technology is integrated into the learning process.

Theme 1 accounted for approximately 47% of all qualitatively identified text segments (213 out of 565), indicating that students attributed pedagogical value to the platform beyond its functional aspects. Within this theme, the macro-category of characteristics fostering conceptual deepening (101 mentions) was the most frequently reported benefit. Students described how real-time observation of controllers' effects on a physical plant, made visible through interactive graphical interfaces in Jupyter Notebooks, enabled them to move beyond abstract mathematical models and interact directly with the dynamic behavior of control systems. These results align with those reported by Insuasti et al. (2022), who found that the ability to swiftly modify parameters and promptly observe system responses fostered a deeper understanding of complex concepts. Furthermore, Nunes et al. (2014) and Takács et al. (2020) found that features such as real-time visualization and interactive parameter manipulation allowed for the immediate application of theory to clarify abstract concepts.

These perceptions are further supported by Theme 2, in which empirical validation and gap bridging (83 mentions) emerged as the dominant learning effect. Students reported that hands-on interaction with PocketLabs helped them identify discrepancies between theoretical predictions and actual system responses. In several cases, this interaction corrected persistent misconceptions that formal instruction alone had not resolved. The laboratory environment's self-correcting function is consistent with the constructivist foundations of the 5E instructional model (Bybee & Landes, 1990) and aligns with findings from analogous active-learning studies in control engineering education (Insuasti et al., 2022; Juchem et al., 2020).

On the other hand, the availability of predefined system models and the abstraction provided by the Python-based API were perceived as reducing the cognitive load associated with hardware implementation. This enabled students to focus on higher-order tasks, such as controller tuning and comparative method analysis. The transition from constructing experimental setups to analyzing system behavior is a pedagogical design choice that directly supports the Explore and Explain phases of the

5E model. The adoption of low-cost, reproducible hardware has also been shown to alleviate the constraints typically associated with specialized laboratory platforms (Ghashim & Arshad, 2023; Oliveira et al., 2022). This extended experimentation beyond the scheduled sessions, which students reported as valuable for autonomous exploration.

However, it is important to note that although perceptions of conceptual understanding were high overall, the item assessing ease of understanding (Statement 3, $M = 5.70$, $SD = 0.56$) showed the greatest dispersion among the comprehension-related items. Approximately 25% of respondents selected “slightly agree.” This variability suggests that, although the environment appears to support exploration and the construction of incremental knowledge, the complexity of control theory, especially its reliance on advanced mathematical formalisms, remains a significant challenge that cannot be resolved by the laboratory environment alone. This finding aligns with the feedback under Theme 5 (Aspects for Improvement), where students expressed the need for stronger theoretical–practical integration and clearer connections between software-level commands and their underlying mathematical models. Thus, the environment may be better understood as a tool that supports students in persevering through conceptual difficulty rather than as a mechanism that simplifies the theory itself. This distinction has important implications for instructional design.

The iterative dynamic of rapid experimentation closely aligns with the structure of the 5E instructional model. In the Explore phase, PocketLabs enabled students to conduct multiple rapid experiments without the setup friction associated with conventional laboratory platforms, thereby supporting open-ended inquiry. During the Explain phase, real-time visualization provided a shared empirical reference for instructor-guided discussions of theoretical concepts, facilitating the collaborative construction of explanatory frameworks. In the Elaborate phase, particularly in Activity 5, which required students to design and test a controller subject to multiple competing requirements over eight hours of laboratory work, students reported that the iterative nature of the environment sustained their motivation and perseverance, even as the task became more complex. Overall interest in the learning experience was high (Statement 8, $M = 5.90$, $SD = 0.30$), indicating that the environment was perceived as engaging throughout the instructional cycle. Theme 2’s macro-category of cognitive acceleration and intuition (47 mentions) further illustrates this process: students described how adjusting control parameters and observing immediate system responses transformed static theoretical concepts into observable, dynamic phenomena. This enabled an intuitive grasp of relationships that would otherwise require extensive analytical effort. These findings align with prior literature documenting the value of immediate feedback in engineering laboratory contexts (Chacon et al., 2019; Klinger et al., 2018; Takács et al., 2020).

THE ENVIRONMENT AS MEDIATOR FOR SELF-REGULATED LEARNING

The present study has identified a theoretical finding, Theme 4, which concerns features that appeared to support self-regulation in learning and were mentioned 69 times. However, it requires careful epistemic qualification. Students perceived that the laboratory environment enhanced motivation, promoted autonomous time management, supported iterative self-correction, and reduced frustration during design tasks. These perceptions describe behaviors associated with self-regulated learning, particularly regarding learning motivation, such as self-efficacy expectations in learning, effort self-regulation (persistence), and the application of learning strategies, such as efficient time management and the application of theory to solve problems (critical thinking) (Pintrich, 2000). These perceptions should be interpreted as indicators consistent with self-regulated learning processes rather than as direct assessments of self-regulation. The reported increases in engagement and motivation are consistent with the conclusions of Candelas et al. (2015) and Sobota et al. (2013) regarding the advantages of interactive laboratory frameworks, as well as with the results reported by Juchem et al. (2020). Specifically, active learning environments have been shown to improve engagement with abstract control concepts.

Within the 5E framework, conditions that most directly support self-regulation occur during the Explore and Elaborate phases. During these phases, students must manage their own experimental trajectories and make successive design decisions based on the observed behavior of the physical system. The combination of rapid feedback, flexible repetition of experiments, and open-ended task structures created an environment in which students could develop and reinforce regulatory strategies without experiencing the performance pressure of summative evaluation tasks.

Additionally, students reported correcting misconceptions and integrating previously isolated concepts into unified mental models through experimentation (Theme 2: Holistic Knowledge Synthesis, with 26 mentions). These perceptions align with learning strategies such as metacognitive monitoring and elaboration of ideas. However, the survey instrument was not designed to explicitly assess these strategies, and the thematic analysis did not yield dedicated categories for them. Consequently, these results are emergent findings. The environment appears to have created conditions conducive to metacognitive monitoring and idea-elaboration strategies. This was achieved through the iterative feedback structure of the Explore and Elaborate phases and the extent to which students engaged in reflective self-monitoring and evaluated the adequacy of their conceptual models. Nevertheless, more research is necessary to confirm these hypotheses. Future studies should investigate these dimensions using instruments specifically designed to assess self-regulated learning and metacognitive development.

PEER COLLABORATION, TEAMWORK, AND AN UNEXPECTED DIVERGENCE

One of the more insightful findings of this study concerns the social dimension of the learning experience. Although Theme 3 (Features Promoting Teamwork and Peer Learning, 92 mentions) indicates that the environment was generally perceived as supportive of collaborative activity, a critical examination of the quantitative data reveals a divergence between peer collaboration and formal teamwork. Statement 5 (encouraged peer collaboration, $M = 5.68$, $SD = 0.73$) and Statement 7 (enhanced teamwork, $M = 5.70$, $SD = 0.69$) recorded the lowest mean scores and highest standard deviations in the survey results, and both included responses in the lower range of the scale. Statement 7 received the most variable response distribution of all items, including “Slightly Disagree” ratings that did not appear for any other statement. While these results generally indicate positive perceptions, this pattern represents a meaningful departure from the near-uniform high agreement observed for the comprehension, engagement, and perseverance items. Further research is necessary to understand these findings better.

A reasonable hypothesis for this discrepancy is the PocketLabs interface’s individual-centered design. Although students worked in pairs and shared access to the same physical plant, the interaction paradigm of the Jupyter Notebook environment is fundamentally individual. Each student operates a personal computational interface and can independently execute experiments. Under this configuration, collaborative activity tends to take the form of informal impression sharing and parallel observation rather than structured, coordinated group management of a joint task. This interpretation is corroborated by qualitative evidence in Theme 3, where students noted that having two plants available simultaneously optimized teamwork by creating an atmosphere of shared impressions rather than instructions, a description that reflects collaboration at the level of discourse rather than coordinated action.

Additionally, in the remote-hybrid modality, where some students interacted with the PocketLabs from separate locations, the logistical demands of synchronizing experimental activities may have introduced further friction in formal teamwork, although asynchronous peer exchange remained productive. These findings align with the broader observation in STEM education literature that access to shared digital resources does not automatically translate into structured collaborative learning without explicit pedagogical scaffolding for group coordination (Sapale & Banerjee, 2023). Future iterations of the instructional design should incorporate more deliberate structures for group problem-

solving, such as differentiated roles during the Elaborate phase or structured peer-review protocols during the Evaluate phase, to better leverage the environment’s collaborative potential.

IMPLICATIONS FOR EDUCATIONAL DESIGN

When considered as a whole, the findings suggest several implications for the design of laboratory-based engineering instruction. First, the integration of high-iteration hardware–software environments within structured constructivist frameworks appears to be a viable approach for supporting students’ engagement with abstract theory, particularly in domains such as control systems, where the gap between mathematical formalism and physical behavior is substantial. The deliberate reduction of implementation complexity, through predefined system models and an accessible Python-based API, allowed instructional attention to be redirected toward higher-order cognitive activities, including system identification, controller evaluation, and comparative method analysis. This design principle aligns with the broader active learning literature, which emphasizes reducing cognitive load when processing schemas. This shift from “building” to “analyzing” is a critical innovation in educational training, as highlighted by Hossain et al. (2019) in their discussion of the integration of IoT into real-world applications.

Second, student feedback under Theme 5 (aspects for improvement, 35 mentions) highlights a tension inherent in software-assisted modeling environments: while the abstraction they provide lowers the initial barrier to entry and facilitates conceptual exploration, it may also limit students’ development of competencies related to physical plant configuration, sensor integration, and the translation between hardware behavior and mathematical representations. Several students expressed a desire for greater exposure to the electronics-level mechanics of the PocketLabs and a clearer understanding of how software commands correspond to physical control actions. Future instructional designs should therefore consider the strategic introduction of hardware-oriented tasks in later phases of the 5E cycle, particularly within the Elaborate phase, to extend students’ practical engineering competencies beyond software-mediated modeling, without reintroducing the cognitive burden that the current design was intended to reduce.

Third, the portability of the PocketLabs and their compatibility with the IoT-based MQTT communication architecture enabled both in-person and remote-hybrid modalities, thereby extending access to hands-on laboratory experiences beyond the spatial and temporal constraints of conventional facilities (Brinson, 2015; Klinger et al., 2018). This aligns with Sapale and Banerjee (2023) regarding the role of IoT in facilitating personalized and accessible learning. Furthermore, the inherent portability of PocketLabs offers the flexibility required for out-of-class exploration (Anishchenko & Zaleskyi, 2020; Madritsch, 2022; Zhou et al., 2024). This feature is of relevance for institutions facing resource constraints, as it supports more democratized access to high-quality engineering laboratory instruction without requiring significant infrastructure investment (Insuasti et al., 2022; Oliveira et al., 2022). Finally, the instructor’s role emerged as a critical complementary element of the learning environment. Students in Theme 3 described instructor guidance as pivotal for consolidating experimental observations into theoretically coherent explanations, suggesting that the environment functions most effectively not as a replacement for expert pedagogical intervention but as a medium through which such intervention can be made more contextually grounded and empirically referential.

CONCLUSIONS

This exploratory study investigated the integration of IoT-enabled PocketLabs within a 5E instructional framework for Control Systems education. The findings suggest that students perceived the proposed environment as a valuable support for connecting abstract control theory with the behaviors of real physical systems. Quantitatively, 100% of survey respondents reported that the environment helped them understand the concepts addressed in the course, while all survey dimensions obtained high levels of agreement. Qualitatively, five complementary themes emerged from student responses: hardware–software features that enhance teaching and learning; effects on teaching and

learning processes; features that promote teamwork and peer learning; features that support self-regulated learning; and aspects for improvement.

The results further suggest that educational value may emerge from the interaction between the technological environment and the pedagogical structure provided by the 5E instructional model. The combination of portable experimental platforms, IoT connectivity, real-time feedback, and structured learning activities appears to support students' engagement, reflection, experimentation, and application of theoretical concepts. From an educational perspective, the results indicate that low-cost, portable laboratory environments may be a promising strategy for expanding access to hands-on learning experiences in Control Systems courses and other resource-constrained engineering disciplines.

LIMITATIONS AND FUTURE WORK

While the findings of this exploratory study are encouraging, several constraints warrant consideration regarding the generalizability of the results. First, the perception survey (on which most of the study's quantitative and qualitative findings are based) was completed by only 40 students from a single institutional context (out of the 55 who participated in the laboratory activities), which limits the generalizability of the findings to other disciplines and educational settings. In addition, the sample exhibited a marked gender imbalance (90% male). Although this distribution reflects the current enrollment in the engineering program where the study was conducted, the findings primarily represent male learning experiences. Second, the study relied primarily on self-reported perceptions collected immediately after the intervention. Consequently, the results may have been influenced by response bias, novelty effects, or students' subjective appreciation of the learning environment. Moreover, the study did not include a control group, pre-post assessments, or direct measures of learning outcomes. Therefore, the findings provide preliminary evidence of students' perceived benefits rather than demonstrating causal improvements in learning. As an exploratory study, the primary objective was to provide an in-depth empirical account of the intervention within its specific educational context rather than to establish broad generalizability.

Future research should examine the proposed approach using larger and more diverse samples, comparative and longitudinal research designs, and objective assessments of learning outcomes. Incorporating direct measures of conceptual understanding alongside evaluations of self-regulated learning, collaboration, and metacognitive development would provide a more comprehensive assessment of the educational effectiveness of IoT-enabled PocketLabs and help establish the generalizability of this approach across diverse engineering education contexts.

On the other hand, despite the effectiveness of the 5E framework, student feedback underscored a need for even tighter coupling between theoretical models and the mechanics of physical hardware. This suggests that while software-assisted modeling lowers the initial barrier to entry, it may inadvertently bypass certain granular complexities of sensor configuration and hardware interfacing that are essential for comprehensive engineering mastery.

Looking ahead, future research could investigate the potential of evolving the proposed architecture into a hybrid intelligent learning system. The combination of IoT-based real-time data acquisition and the extensibility of the Python-based API may create opportunities to explore machine learning (ML) techniques for analyzing student interaction patterns and supporting adaptive educational interventions. In addition, larger collections of textual data generated through student reflections, reports, and open-ended responses could motivate the exploration of computational approaches for large-scale corpus analysis. In other research domains, bibliometric methods have been used to characterize large scientific corpora and identify major research trends (Sepúlveda-Oviedo et al., 2023), while more recent natural-language-based approaches combining topic modeling, dimensionality reduction, and expert analysis have been proposed to uncover latent thematic structures in large document collections (Sepúlveda-Oviedo et al., 2025). Although these studies were conducted in the context of photovoltaic fault diagnosis rather than education, their analytical strategies provide a methodological

basis for exploring analogous approaches to educational textual data. Such methods could potentially support the identification of latent learning patterns and emerging educational themes and, in the longer term, contribute to personalized feedback and scaffolding mechanisms during the Explore and Explain phases of the 5E instructional model. However, their application and educational effectiveness would require dedicated methodological and empirical validation.

REFERENCES

- Acrome. (n.d.). *Linear inverted pendulum*. <https://acrome.net/product/linear-inverted-pendulum>
- Akbar, M. A., Rashid, M. M., & Embong, A. H. (2018). Technology based learning system in Internet of Things (IoT) education. *Proceedings of 7th International Conference on Computer and Communication Engineering, Kuala Lumpur, Malaysia*, 192-197. <https://doi.org/10.1109/ICCCE.2018.8539334>
- Anishchenko, M., & Zaleskyi, V. (2020). Pocket labs development using NI myDAQ data acquisition device. *Proceedings of IEEE Problems of Automated Electrodrive. Theory and Practice (PAEP), Kremenchuk, Ukraine*, 1-4. <https://doi.org/10.1109/PAEP49887.2020.9240823>
- Åström, K., & Murray, R. (2021). *Feedback systems: An introduction for scientists and engineers* (2nd ed.). Princeton University Press.
- Barry, R., & The FreeRTOS Team. (2023). *Mastering the FreeRTOS™ real time kernel – a hands-on tutorial guide* (1.1.0 ed.). FreeRTOS. <https://github.com/FreeRTOS/FreeRTOS-Kernel-Book/releases/download/V1.1.0/Mastering-the-FreeRTOS-Real-Time-Kernel.v1.1.0.pdf>
- Brinson, J. (2015). Learning outcome achievement in non-traditional (virtual and remote) versus traditional (hands-on) laboratories: A review of the empirical research. *Computers & Education*, 87, 218-237. <https://doi.org/10.1016/j.compedu.2015.07.003>
- Bryman, A. (2012). *Social research methods* (4th ed.). Oxford University Press.
- Bybee, R., & Landes, M. (1990). Science for life & living: An elementary school science program from biological sciences curriculum study. *The American Biology Teacher*, 52(2), 92-98. <https://doi.org/10.2307/4449042>
- Candelas, F., García, G., Puente, S., Pomares, J., Jara, C., Pérez, J., Mira, D., & Torres, F. (2015). Experiences on using Arduino for laboratory experiments of automatic control and robotics. *IFAC-PapersOnLine*, 48(29), 105-110. <https://doi.org/10.1016/j.ifacol.2015.11.221>
- Carli, R., Cavone, G., Ben Othman, S., & Dotoli, M. (2020). IoT based architecture for model predictive control of HVAC systems in smart buildings. *Sensors*, 20(3), 781. <https://doi.org/10.3390/s20030781>
- Chacon, J., de la Torre, L., & Dormido, S. (2019). The air levitation system. *IFAC-PapersOnLine*, 52(9), 33-35. <https://doi.org/10.1016/j.ifacol.2019.08.119>
- Esposito, G., Mezzogori, D., Reverberi, D., Romagnoli, G., Ustenko, M., & Zammori, F. (2021). Non-traditional labs and lab network initiatives: A review. *International Journal of Online and Biomedical Engineering*, 17(5), 4-32. <https://doi.org/10.3991/ijoe.v17i05.20991>
- Feisel, L., & Rosa, A. (2005). The role of the laboratory in undergraduate engineering education. *Journal of Engineering Education*, 94(1), 121-130. <https://doi.org/10.1002/j.2168-9830.2005.tb00833.x>
- Ghashim, I., & Arshad, M. (2023). Internet of Things (IoT)-based teaching and learning: Modern trends and open challenges. *Sustainability*, 15(21), 15656. <https://doi.org/10.3390/su152115656>
- Hossain, M., Rahman, M., Sarker, M., Haque, M., & Jahid, A. (2019). A smart IoT based system for monitoring and controlling the substation equipment. *Internet of Things*, 7, 100085. <https://doi.org/10.1016/j.iot.2019.100085>
- Hu, J., Gao, C., & Liu, Y. (2017). Study of the 5E instructional model to improve the instructional design process of novice teachers. *Universal Journal of Educational Research*, 5(7), 1257-1267. <https://doi.org/10.13189/ujer.2017.050718>

- Insuasti, S., Paredes, J., & Camacho, O. (2022). Controllers and compensators design for undergraduate control students: Testing with TCLab Arduino kit. *Proceedings of IEEE Sixth Ecuador Technical Chapters Meeting, Quito, Ecuador*, 1-6. <https://doi.org/10.1109/ETCM56276.2022.9935740>
- Juchem, J., Chevalier, A., Dekemele, K., & Loccufier, M. (2020). Active learning in control education: a pocket-size PI(D) setup. *IFAC-PapersOnLine*, 53(2), 17276-17281. <https://doi.org/10.1016/j.ifacol.2020.12.1805>
- Klinger, T., & Kreiter, C. (2018). Experiences with the use of pocket labs in engineering education. In M. E. Auer, D. Guralnick, & I. Simonics (Eds.), *Teaching and learning in a digital world* (pp. 665-670). Springer. https://doi.org/10.1007/978-3-319-73204-6_72
- Klinger, T., Zutin, D., & Madritsch, C. (2018). Parallel use of remote labs and Pocket Labs in engineering education. In M. E. Auer, & D. Zutin (Eds.), *Online engineering & Internet of Things* (pp. 452-458). Springer. https://doi.org/10.1007/978-3-319-64352-6_42
- Kumar, K., & Al-Besher, A. (2022). IoT enabled e-learning system for higher education. *Measurement: Sensors*, 24, Article 100480. <https://doi.org/10.1016/j.measen.2022.100480>
- Lee, W., Mentzer, N., Clevenger, A., Jackson, A., & Bartholomew, S. R. (2024). Board 68: Integration of Learning by Evaluating (LbE) within the 5E instructional model in engineering-design education. Paper presented at the *ASEE Annual Conference & Exposition, Portland, Oregon*. <https://doi.org/10.18260/1-2--48365>
- Light, R. (2017). Mosquitto: Server and client implementation of the MQTT protocol. *Journal of Open Source Software*, 2(13), 265. <https://doi.org/10.21105/joss.00265>
- Lindsay, E., & Good, M. (2005). Effects of laboratory access modes upon learning outcomes. *IEEE Transactions on Education*, 48(4), 619-631. <https://doi.org/10.1109/TE.2005.852591>
- Ma, J., & Nickerson, J. (2006). Hands-on, simulated, and remote laboratories: A comparative literature review. *ACM Computing Surveys*, 38(3), 7. <https://doi.org/10.1145/1132960.1132961>
- Madritsch, C. (2022). Embedded systems engineering education using cost effective pocket labs platform. *Proceedings of 45th Jubilee International Convention on Information, Communication and Electronic Technology, Opatija, Croatia*, 1347-1350. <https://doi.org/10.23919/MIPRO55190.2022.9803660>
- Melgarejo, T., Atanacio, L., Leandro, A., Faustino, L., Rivarola, M., López, J., & Chavez, J. (2024). The 5E instructional model in the meaningful learning of science and technology. *Frontiers in Education*, 9, 1435530. <https://doi.org/10.3389/educ.2024.1435530>
- Nunes, E. P. S., Nunes, F. L. S., Tori, R., & Roque, L. G. (2014). An approach to assessment of knowledge acquisition by using three-dimensional virtual learning environment. *Proceedings of IEEE Frontiers in Education Conference, Madrid, Spain*, 1-8. <https://doi.org/10.1109/FIE.2014.7044239>
- Oliveira, P., Soares, F., & Cardoso, A. (2022). Pocket-sized portable labs: Control engineering practice made easy in COVID-19 pandemic times. *IFAC-PapersOnLine*, 55(17), 150-155. <https://doi.org/10.1016/j.ifacol.2022.09.272>
- Pintrich, P. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451-502). Academic Press. <https://doi.org/10.1016/B978-012109890-2/50043-3>
- Quanser. (n.d.). *QUBE-Servo 3*. <https://www.quanser.com/products/qube-servo-3>
- Sapale, S., & Banerjee, S. (2023). Empowering education: Exploring the impact of IoT in smart learning environments. *International Journal for Multidisciplinary Research*, 5(5), 1-11. <https://doi.org/10.36948/ijfmr.2023.v05i05.7474>
- Sepúlveda-Oviedo, E., Travé-Massuyès, L., Subias, A., Pavlov, M., & Alonso, C. (2023). Fault diagnosis of photovoltaic systems using artificial intelligence: A bibliometric approach. *Heliyon*, 9(11), e21491. <https://doi.org/10.1016/j.heliyon.2023.e21491>
- Sepúlveda-Oviedo, E., Travé-Massuyès, L., Subias, A., Pavlov, M., & Alonso, C. (2025). Artificial intelligence in photovoltaic fault diagnosis: A natural language-based topic-tSNE fusion analysis. *Energy and AI*, 21, 100558. <https://doi.org/10.1016/j.egyai.2025.100558>

- Sobota, J., PiŚl, R., Balda, P., & Schlegel, M. (2013). Raspberry Pi and Arduino boards in control education. *IFAC Proceedings*, 46(17), 7-12. <https://doi.org/10.3182/20130828-3-UK-2039.00003>
- Takács, G., Chmurciak, P., Gulán, M., Mikulás, E., Kulhánek, J., Penzinger, G., Vdolecek, M., Podbielančik, M., Lučan, M., Šálka, P., & Šroba, D. (2020). FloatShield: An open source air levitation device for control engineering education. *IFAC-PapersOnLine*, 53(2), 17288-17295. <https://doi.org/10.1016/j.ifacol.2020.12.1807>
- Terzieva, V., Ilchev, S., & Todorova, K. (2022). The role of Internet of Things in smart education. *IFAC-PapersOnLine*, 55(11), 108-113. <https://doi.org/10.1016/j.ifacol.2022.08.057>
- Valencia de Almeida, F., Hayashi, V., Arakaki, R., Midorikawa, E., Canovas, S., Cugnasca, P., & Corrêa, P. (2022). Teaching digital electronics during the COVID-19 pandemic via a remote lab. *Sensors*, 22(18), 6944. <https://doi.org/10.3390/s22186944>
- Van den Beemt, A., Groothuijsen, S., Ozkan, L., & Hendrix, W. (2023). Remote labs in higher engineering education: Engaging students with active learning pedagogy. *Journal of Computing in Higher Education*, 35, 320-340. <https://doi.org/10.1007/s12528-022-09331-4>
- Vásquez, M. C. (2024). Control and automation education: Academia and industry together. *Proceedings of 28th International Conference on System Theory, Control and Computing, Sinaia, Romania*, 379–384. <https://doi.org/10.1109/ICSTCC62912.2024.10744639>
- Velosa, J. (2020). *Diseño de laboratorios híbridos para la enseñanza de ingeniería de manufactura* [Design of hybrid laboratories for teaching manufacturing engineering. Doctoral dissertation, EAN University]. <http://hdl.handle.net/10882/10110>
- Verma, P., Sood, S., & Kalra, S. (2017). Smart computing based student performance evaluation framework for engineering education. *Computer Applications in Engineering Education*, 25(6), 977-991. <https://doi.org/10.1002/cae.21849>
- Viegas, C., Pavani, A., Lima, N., Marques, A., Pozzo, I., Dobboletta, E., Atencia, V., Barreto, D., Calliari, F., Fidalgo, A., Lima, D., Temporão, G., & Alves, G. (2018). Impact of a remote lab on teaching practices and student learning. *Computers & Education*, 126, 201-216. <https://doi.org/10.1016/j.compedu.2018.07.012>
- Vinayachandra, & Krishna Prasad, K. (2020). Application of IoT in the development of intelligent education system – A thematic literature review. *International Journal of Management, Technology, and Social Sciences*, 5(1), 124–146. <https://doi.org/10.47992/IJMTS.2581.6012.0086>
- Visioli, A. (2023). Control education: TC 9.4 developments and vision. *IFAC-PapersOnLine*, 56(2), 332–335. <https://doi.org/10.1016/j.ifacol.2023.10.1589>
- Zhou, X., Liu, G., Hu, W., & Lei, Z. (2024). M2PLab: A pocket laboratory with unified and flexible framework applied in engineering education. *IEEE Transactions on Industrial Electronics*, 71(3), 3208-3218. <https://doi.org/10.1109/TIE.2023.3270544>

AUTHORS



Leonardo Enrique Bermeo Clavijo received the BSc degree in Electronics from the Universidad Distrital Francisco José de Caldas, Bogotá, Colombia, the MSc degree in Industrial Automation from the Universidad Nacional de Colombia, Bogotá, Colombia, and the DSc degree in Electrical Engineering from the Universidade Federal de Rio de Janeiro, Rio de Janeiro, Brazil. He is currently an Associate Professor in the Department of Electrical and Electronics Engineering at the Universidad Nacional de Colombia, Bogotá, Colombia. His research interests include engineering education, immersive virtual reality in education, simulation in medicine and neonatology, and applications of discrete-event systems theory.



Edgar Hernando Sepúlveda-Oviedo received the Mechatronics Engineering degree and the MSc degree in Industrial Automation from the Universidad Nacional de Colombia, Bogotá, Colombia, in 2016 and 2019, respectively, and the PhD degree in Electrical Engineering from Université Toulouse III – Paul Sabatier, Toulouse, France, in 2023. He is currently an Associate Professor of Industrial Engineering and Maintenance at Université de Perpignan Via Domitia, Perpignan, France, and a researcher at PROMES-CNRS. His research interests include fault diagnosis, prognostics, predictive maintenance, artificial intelligence, renewable energy systems, digital twins, and biomedical systems modeling.



Jhon Jairo Ramírez-Echeverry received the BSc degree in Electronics Engineering from the Universidad Nacional de Colombia, Manizales (Caldas), Colombia, the MSc degree in Telecommunications Engineering from the Universidad Nacional de Colombia, Bogotá, Colombia, and the PhD degree, cum laude, in Engineering of Projects and Systems from the Universitat Politècnica de Catalunya, BarcelonaTech, Spain. He is currently an Associate Professor in the Department of Electrical and Electronics Engineering at the Universidad Nacional de Colombia, Bogotá, Colombia. His primary research area is engineering education, with a particular focus on self-regulated learning.