5.2026

iJEP

International Journal: **Engineering Pedagogy**

Papers

Table of Contents

Papers

Online-Journals.org

iJEP International Journal of Engineering Pedagogy

iJEP | eISSN: 2192-4880 | Vol. 16 No. 5 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijep.v16i5.61389

PAPER

Multi-Modal Virtual Reality in Engineering Education: A Design Case Study of Fostering Situational Interest through Project-Based Learning

Daria Mizza[1] (✉),
Khalil Elkhodary[1],
Dhafer Malouche[2],
Mohammed Al-Mousa[1]

[1]American University in Cairo, Cairo, Egypt

[2]Qatar University, Doha, Qatar

daria.mizza@aucegypt.edu

ABSTRACT

Engineering students struggle with abstract concepts and theory-practice integration, yet few studies systematically examine how to design virtual reality (VR) learning environments that sustain engagement beyond initial novelty effects. Multi-modal approaches that strategically integrate different technological affordances offer promising but underexplored solutions. This design case study demonstrates the development and implementation of a multi-modal VR learning environment integrating immersive Cave Automatic Virtual Environments (CAVE), non-immersive MATLAB simulations, and artificial intelligence (AI) motion tracking within project-based learning (PjBL). We investigate how different technological modalities can be strategically orchestrated to support situational interest development in undergraduate engineering education. We designed and implemented a four-week "Biomechanics of a Pitch" project in a Strength of Materials course, engaging 20 undergraduate mechanical engineering students. Using an exploratory case study approach with convergent mixed-methods data collection, we measured presence, representation fidelity, and situational interest through validated instruments (α = 0.92–0.93) and focus groups. Data was analyzed through reliability analyses, descriptive statistics, and thematic analysis to understand design effectiveness and student experiences. The multi-modal design enabled distinct complementary technological affordances: CAVE excelled in spatial presence (α = 0.93) and immersive understanding (M = 4.2, SD = 0.8), MATLAB supported analytical thinking and pedagogical usefulness, while AI motion tracking created personalized connections. Student interest evolved from pre-experience curiosity through maintained engagement during multi-modal experiences to post-experience learning motivation. Qualitative data revealed how strategic modality transitions sustained engagement beyond novelty effects. We present an integrated framework synthesizing interest development theory with multi-modal VR design principles, demonstrating how theoretically grounded VR implementations move beyond novelty effects through strategic technological orchestration. The study contributes a design framework, evidence-based design checklist, and practical implementation guidelines for engineering educators seeking to create effective VR-enhanced learning experiences.

Mizza, D., Elkhodary, K., Malouche, D., Al-Mousa, M. (2026). Multi-Modal Virtual Reality in Engineering Education: A Design Case Study of Fostering Situational Interest through Project-Based Learning. *International Journal of Engineering Pedagogy (iJEP)*, 16(5), pp. 4–27. https://doi.org/10.3991/ijep.v16i5.61389

Article submitted 2026-03-05. Revision uploaded 2026-04-28. Final acceptance 2026-04-28.

KEYWORDS
virtual reality (VR), engineering education, multi-modal learning, situational interest, project-based learning (PjBL), student engagement, cave automatic virtual environments (CAVE)

1 INTRODUCTION

Numerous publications, including reports from the American Society for Engineering Education (ASEE) [1], [2] and other global research proceedings [3], [4], [5], [6], have explored state-of-the-art approaches in engineering education and identified critical challenges faced by engineering students. The abstract nature of engineering concepts and the need to integrate knowledge from multiple disciplines can create significant learning challenges [2], [5], often leaving students struggling to bridge the gap between theoretical knowledge and practical application [6]. These challenges stem from the complex, multidimensional nature of engineering education, which requires students to synthesize theoretical knowledge across various scientific and technical domains.

A collaborative report by ASEE and the National Academy of Engineering (NAE) further emphasized these challenges [1], identifying systemic barriers in undergraduate engineering education, including an overreliance on abstract mathematical prerequisites and discipline-specific silos that hinder students from connecting theory to practice and calling for a shift toward student-centered, active learning pedagogies to address these educational barriers.

Addressing these pedagogical barriers requires understanding how students develop engagement with complex, abstract content. Educational research has long recognized the cognitive demands placed on students when confronting abstract and interdisciplinary learning environments. Hidi and Renninger's [7] framework of interest development provides crucial insights into the learning process, distinguishing between situational interest, a temporary state of engagement triggered by environmental factors, and individual interest, which represents a more stable, long-term personal investment in a topic. Situational interest is characterized by its momentary nature, typically induced by external stimuli that capture a learner's attention and create a temporary state of cognitive engagement [8].

Building on this understanding of interest development, research has indicated that thoughtfully designed learning environments can effectively mitigate the challenges associated with complex, interdisciplinary concepts. A particularly promising approach involves leveraging situational interest to stimulate deeper cognitive engagement. As Krapp et al. [9] suggest, situational interest can serve as a catalyst for individual interest, transforming temporary engagement into a more enduring personal connection with the subject matter. Mitchell [10] further supports this notion, arguing that well-structured learning experiences can convert initial, externally triggered curiosity into intrinsic motivation.

Inspired by the aforementioned research, including Hidi and Renninger's frameworks and Schraw and Lehman's work on interest development, our research delves into the cognitive and affective mechanisms underlying engagement and interest development in engineering undergraduate education. Considering the challenges associated with teaching and learning abstract engineering concepts, virtual reality (VR) presents a promising solution by providing immersive and interactive experiences that can reduce perceived complexity [11] and stimulate motivation and curiosity [12], [13], [14]. The interactive nature of immersive technologies amplifies situational interest by providing contextualized, hands-on learning opportunities that traditional methods cannot replicate [15].

Through a design case study approach, our study investigates how carefully designed VR-enhanced learning environments can stimulate engagement and facilitate understanding by providing immersive and interactive experiences that reduce perceived complexity, laying the foundation for exploring the potential transformation of situational interest into sustained interest. To achieve this goal, we designed a multi-stage VR-based project integrating immersive and non-immersive elements, including an immersive Cave Automatic Virtual Environment (CAVE) and non-immersive VR simulations enhanced by artificial intelligence (AI) technologies. Through a mixed-methods case study design, we investigate how these carefully crafted experiences influence students' engagement and learning within the context of an undergraduate Strength of Materials course. We focus on four primary dimensions and nine sub-dimensions of situational interest. While recognizing the importance of contextually triggered engagement, this exploratory case study serves as an initial investigation with 20 mechanical engineering students. By drawing on our empirical findings, we aim to develop a foundational framework for future VR-enhanced educational experiences and provide evidence-based recommendations to foster both short-term and long-term engagement of undergraduate engineering students.

The remainder of this paper is organized as follows: Section 3 presents a comprehensive review of relevant literature, Section 4 details our case study methodology and research design, Section 5 presents our findings, Section 6 discusses the implications of our results, and Section 7 concludes with recommendations for future research and practice.

2 LITERATURE REVIEW

2.1 VR technologies in educational settings

The integration of immersive technologies along the reality-virtuality continuum, including augmented reality (AR), mixed reality (MR), and VR, represents a transformative approach to engineering education [16], [6]. These technologies address critical pedagogical challenges, specifically related to the gap between theory and practical application, by providing innovative mechanisms for conceptual visualization and interactive learning experiences. Ivanov [6] comprehensively outlines how these technologies enable students to visualize complex, abstract concepts through tangible, interactive representations, integrate virtual and physical components in real-time simulations, and create immersive learning environments that transcend traditional pedagogical boundaries. This transformation from passive to active, experiential knowledge construction offers unprecedented opportunities for reimagining engineering education [17], [18], particularly addressing fundamental challenges in understanding abstract, multidimensional systems [5].

While VR technologies demonstrate significant potential in engineering education, their effective implementation faces several challenges. Studies by Billinghurst et al. [16] and Pellas et al. [17] have demonstrated positive impacts on student engagement and spatial reasoning, yet educators must address key implementation barriers. These include managing cognitive load in complex virtual environments, addressing technical limitations of current VR systems, and optimizing design elements to support specific learning outcomes. The effectiveness of VR experiences ultimately depends on the quality of instructional design, the level of student engagement, and the alignment with intended learning outcomes [19].

2.2 The development of student interest

Interest, as an affective-cognitive construct, involves focused attention on specific objects or topics, leading to repeated engagement and increased persistence [20], [7], [21]. The distinction between situational and individual interest [9] provides a fundamental framework for understanding how learners develop sustained engagement with complex subjects. While situational interest represents temporary, context-specific engagement triggered by stimuli, individual interest develops as a more enduring connection rooted in personal values.

Research on situational interest has revealed its potential as a precursor to individual interest [9] suggesting that temporary engagement can evolve into enduring personal connection. Mitchell [10] demonstrated how well-designed learning environments can transform initial curiosity into intrinsic motivation, while Schraw and Lehman [8] showed that momentary engagement can facilitate significant cognitive processing and knowledge acquisition. Studies involving high school and college students have demonstrated that educators can intentionally design learning environments to trigger and sustain interest [22], [23], [24].

The theoretical insights into interest development have important implications for emerging educational technologies. VR presents a particularly promising avenue for stimulating situational interest through immersive and interactive experiences that can reduce perceived complexity [11] and enhance motivation and curiosity [12], [13], [14]. The interactive nature of VR technology provides unique opportunities to design learning environments that can effectively trigger and maintain situational interest, potentially facilitating its transformation into more sustained engagement.

2.3 VR's role in fostering undergraduate student interest

Recent research in university undergraduate education has demonstrated significant potential for VR to trigger situational interest and enhance learning experiences, particularly across STEM disciplines. In civil engineering education, Fink et al. [12] conducted a two-group experimental study with 64 university students learning about railroad bridges. Their findings revealed that VR environments, particularly those created through 3D modeling, can effectively increase student interest, with post-test interest significantly influenced by initial interest and sense of presence. In computer science education, Huang et al. [13] investigated the impact of different levels of immersion (Oculus Go and Oculus Rift) on learning and motivation. Their study introduced the Transitional Immersion Hypothesis, suggesting that a gradual increase in immersion can maintain or boost learner engagement. By starting with lower-immersion environments and progressively introducing more complex VR technologies, educators can leverage novelty effects, address navigation challenges, and sustain motivation across multiple learning sessions. This flexibility makes VR accessible to institutions with varying technological and budgetary constraints. In laboratory science education, Makransky et al. [25] provided compelling evidence for VR's effectiveness in laboratory simulations, demonstrating that head-mounted displays significantly increased student interest and engagement in chemistry experiments.

Beyond STEM disciplines, research has demonstrated VR's broad applicability. In humanities education, Chin et al. [26] explored VR's capacity to generate situational interest for historic sites by leveraging unusual multimedia stimuli to create compelling educational environments that transcend traditional teaching methods. Further validating VR's potential across disciplines, Chen et al. [11] found that VR learning enhanced students' creative thinking and motivation in design education. In library science, Lin et al. [27] compared VR and traditional library orientation methods, revealing that VR guides increased students' situational interest and cognitive engagement through novelty, challenge, and meaningful learning opportunities.

Recent discipline-specific applications have yielded promising results. In forensic science education, Chang [28] demonstrated VR's effectiveness in training, where VR platforms generated heightened situational interest through exploration and novelty while maintaining optimal cognitive load. Their study further found that VR can enhance learning outcomes, particularly in terms of immediate and long-term retention. These findings collectively highlight VR's significant potential to transform learning experiences across various undergraduate disciplines.

Despite these promising applications, the field of VR in undergraduate education faces significant methodological challenges. While VR interventions have been shown to improve student motivation across multiple disciplines [29]–[34], as demonstrated in Jiang and Fryer's [30] comprehensive review, many studies rely heavily on the novelty effect of VR technology rather than robust pedagogical frameworks. This gap between technological implementation and pedagogical theory highlights the critical need for interest-development frameworks in VR design. Educational technology researchers such as Makransky et al. [29] advocate for more sophisticated VR educational design, stressing the need for rigorous theoretical and methodological underpinnings. The crux of the issue lies not merely in technological innovation but in the quality of the instructional environment. Research by Hidi [35] and Krapp [21] underscores the significance of positive emotional responses in fostering student interest within effective learning environments. Radianti et al. [36] further highlight VR's unique capacity to stimulate situational interest through intentional, emotionally resonant instructional design, particularly in undergraduate STEM education.

2.4 Research gap and questions

The integration of VR in educational research represents a critical juncture, presenting a promising yet complex avenue for investigating situational interest in VR-enhanced learning environments [23], [37], [38]. While previous studies have explored VR's potential, there remains a critical need to systematically investigate the intricate mechanisms of educational engagement and the complex dynamics of situational interest in VR-enhanced learning environments [22], [24].

We concur with Radianti et al. [36], who emphasize VR's unique potential to generate situational interest through purposeful, emotionally resonant instructional design. This perspective underscores the need to transcend a purely technological approach and adopt a more strategic, pedagogically and psychologically informed approach to learning environment design. Building upon this foundation and aligning with researchers like Makransky et al. [29], we stress the importance of robust theoretical frameworks in creating learning environments that deliberately generate situational interest. Our overarching goal is to fundamentally transform our understanding of VR, elevating it from a complementary technological tool [14] to a sophisticated medium for cognitive and emotional engagement.

With this goal in mind, a fundamental consideration is how VR environments can be designed to leverage established learning theories. An important one, assimilation theory [39], highlights how crucial the process of anchoring new knowledge to existing mental models is, based on the fact that building on prior knowledge is fundamental to effective instruction [39], [40], [41].

VR can facilitate this process by activating existing knowledge and creating connections to new information. In VR instructional design, this can be achieved by diagnosing learners' prior knowledge, creating scaffolded interactions that bridge familiar and novel concepts, and enabling learners to reconstruct and expand their understanding through interactive, contextually rich virtual environments. Cognitive science research underscores the role of mental representations in shaping conceptual understanding. By strategically connecting new information with learners' prior knowledge, VR creates a unique opportunity to make complex concepts more accessible. Loewenstein's [42] information-gap theory further suggests that VR can deliberately create cognitive tensions that motivate learning by revealing and addressing knowledge gaps.

The effectiveness of VR-based learning environments is further enhanced by the concept of presence. As explored by Jelfs and Whitelock [43] and Slater [44], presence in virtual environments represents a complex psychological and perceptual experience, encompassing spatial presence, social presence, and psychological involvement. While psychological involvement, the mental absorption in the virtual environment, is distinct from engagement, Dubovi [45] suggests that this deep psychological immersion can foster both cognitive and emotional engagement by creating conditions where learners are more receptive to and invested in the learning material. Empirical research by Petersen et al. [46] demonstrates that varying degrees of presence significantly affect situational interest development, with higher levels of immersion and interactivity positively correlating with situational interest.

High-fidelity representations serve as a crucial bridge between presence and understanding. As Mikropoulos and Natsis [47] emphasize, accurate and realistic representations can significantly enhance learners' comprehension and retention of information. These representations increase cognitive elaboration, enhance learner motivation, and facilitate deeper conceptual understanding by providing authentic and contextually relevant learning experiences [25]. However, as Fowler [19] cautions, it is essential to balance detailed representations with cognitive accessibility to avoid overloading learners. The psychological research conducted by Hidi [35] and Krapp [21] confirms that learning environments generating positive emotional responses, such as those facilitated by high-fidelity VR experiences, are particularly effective in inducing student interest.

Furthermore, student engagement emerges as a critical factor in successful learning, supported by Bandura's [48] social cognitive theory and self-determination theory [49], [50]. These theories highlight how VR can stimulate curiosity, foster intrinsic motivation, and enhance learners' self-belief, leading to deeper engagement and improved learning outcomes. This heightened engagement, in turn, contributes to the development of sustained interest in both the learning process and specific tasks.

Building upon these theoretical foundations, this design case study investigates the impact of a multi-staged VR-based simulation on students' situational interest through the following overarching research question: "To what extent does a multi-staged VR-based project set, combining immersive experiences (VR-based simulation in CAVE and learner motion tracking) and non-immersive experiences (Biomechanics of Bodies MATLAB software), influence students' situational interest through dimensions of presence, involvement, and representation fidelity?"

To address this comprehensive question, our investigation features a comprehensive workflow incorporating:

a) Immersive VR-based simulations in the CAVE and learner motion tracking
b) Non-immersive experiences using the Biomechanics of Bodies plug-in on MATLAB software
c) AR experiences using a depth-sensing camera for student motion tracking

Thus, through our exploratory case study, we examine three key constructs and conduct reliability analyses where appropriate:

1. *Presence*: Spatial presence (feeling of being there); Psychological involvement (mental absorption); Overall perceived realness.
2. *Technical Fidelity*: Visual quality; Spatial accuracy of the simulation.
3. *Learning Engagement*: Cognitive engagement; Emotional engagement; Situational interest; Motivation for further exploration.

These variables inform our specific sub-questions within the VR-based project set:

- Sub-Question #1: "How does the VR environment's presence impact students' situational interest?"
- Sub-Question #2: "How does representation fidelity of the VR simulation influence students' situational interest?"
- Sub-Question #3: "Which aspects of the overall VR experience most effectively engage, generating curiosity and learning motivation to learn more about the topic?"

Inspired by our literature review, we draw on the theoretical insights of Krapp et al. [9] and Hidi and Renninger [7] to focus on the development of situational interest and its transition into deeper engagement. By combining immersive and non-immersive experiences, we aim to capitalize on the novelty effect, address navigation challenges, and sustain motivation, as suggested by Huang et al. [13]. Following Chin et al.'s [26] approach to transcend traditional teaching methods, we incorporate PjBL strategies [51] to create an adaptable and innovative learning environment that supports diverse learning styles and preferences.

3 RESEARCH METHODS

3.1 Research approach and case context

This study employs a design case study approach [52] to systematically document and evaluate the development of a multi-modal VR learning environment within an authentic educational context. Case study research is particularly appropriate when investigating contemporary phenomena in real-world settings where design decisions, technological affordances, pedagogical strategies, and student experiences interact in complex ways [53]. We selected this approach for several methodological reasons: (1) our exploratory goal is to understand *how* multi-modal VR environments can be designed to support situational interest development, rather than to establish generalizable causal relationships; (2) the design complexity of integrating three distinct technological components (CAVE, MATLAB, and AI tracking) within a project-based learning (PjBL) framework requires examination of how these components interact and contribute complementary affordances; and (3) implementing the intervention within an authentic required course ensures ecological validity and practical relevance, while accepting the trade-off of reduced experimental control [54].

The case study focuses on a project-based course (MENG 2112: "Strength of Materials") offered in the Department of Mechanical Engineering at the School of Sciences and Engineering of the American University in Cairo. In the spring 2024 semester, twenty undergraduate students participated in a four-week mandatory course project, "Biomechanics of a Pitch," which required them to collaborate on calculating stress in a baseball pitcher's arm and reconstructing key phases of the pitching motion. Through this bounded case, we investigated the impact of a multi-stage, VR-based project on undergraduate engineering students' situational interest in learning new concepts in strength of materials.

We employed a convergent parallel mixed-methods design within the case study framework [55]. Quantitative data provides systematic measurement of presence, representation fidelity, and situational interest dimensions across the sample, while qualitative data from focus groups and open-ended responses provides rich descriptions of student experiences and explanatory insights into *how* and *why* design features influenced engagement. Integration occurs through triangulation during interpretation, using qualitative themes to explain quantitative patterns and quantitative patterns to contextualize the prevalence of qualitative themes.

Given the exploratory nature of this design case study, the sample size of 20 students is appropriate and aligns with established case study methodology. As Yin [52] emphasizes, case studies prioritize depth of understanding over breadth of generalization. This sample size allows for detailed qualitative analysis of student experiences while providing sufficient data for preliminary quantitative patterns. The goal is not statistical generalization to larger populations, but rather analytical generalization, developing theoretical insights and design principles that can inform future VR implementations in similar educational contexts [56].

3.2 Multi-stage VR implementation

To investigate our research questions, we strategically employed a project-based and VR-enhanced learning approach. This approach aimed to enhance student understanding, critical thinking, and problem-solving skills through a combination of non-immersive, immersive, and interactive VR experiences throughout the course project. By applying theoretical knowledge to real-world scenarios, students were expected to develop a deeper appreciation for and understanding of engineering principles.

The project implementation consisted of four sequential key stages, as illustrated in Figure 1, where both immersive and non-immersive VR were used to visualize and analyze the complex biomechanical movements of a baseball pitch, compute stress and strain in the pitcher's arm, and gain a deeper understanding of the underlying principles.

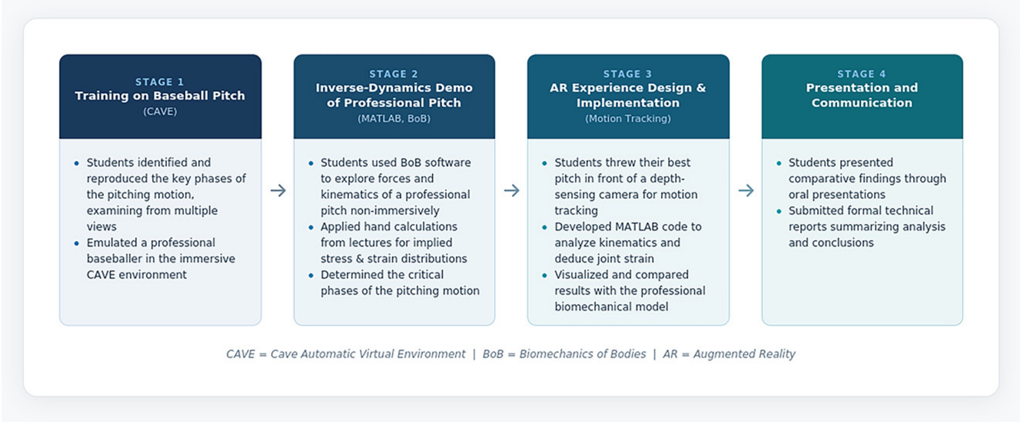

Fig. 1. Key stages of the project "Biomechanics of a Pitch"

Table 1 outlines the VR experiences that were integrated into the project. These experiences comprised two main components:

1. Immersive VR experience, in which students observed a professional baseballer's pitch in 3D within a CAVE, emulating the pitcher's movements and experiencing the corresponding muscle strain and joint stress firsthand.
2. Non-immersive VR experience, in which students analyzed a 3D skeletal view of a baseballer's pitch using Biomechanics of Bodies MATLAB software, identifying key planes of motion, timeframes of interest, and maximum internal forces and moments at each joint.

Each component included instructional tasks specifically designed for enhancing understanding, increasing engagement, and fostering learning. By integrating VR with PjBL, we aimed to create a dynamic and engaging learning environment that fosters deep learning and critical thinking.

Table 1. Alignment of instructional task design aims with VR experience types

Instructional Task Design Aim	VR Experience Type
Enhance Understanding: Provide intuitive visualizations, real-world context, and interactive exploration of complex spatial relationships and stress distribution.	Immersive
Increase Engagement: Engage multiple senses, evoke emotional connections, and make the material personally relevant.	Immersive
Foster Learning: Combine comprehensibility, vividness, and interactive exploration to create a memorable learning experience.	Immersive and non-immersive

3.3 Surveys and focus groups

This study employed a mixed-methods approach, combining quantitative and qualitative research methods to comprehensively investigate the impact of the VR-based learning experience. The research design involved the administration of two surveys and the conduct of focus group discussions. The statistical analysis in this study was conducted using R version 4.3.2, with the *psych* package (version 2.2.5) employed for reliability analyses. Cronbach's alpha coefficients were calculated to assess the internal consistency of the scales measuring presence, representation fidelity, and situational interest. Inter-item correlation matrices were generated to evaluate the coherence of the items within each scale. Descriptive statistics, including means and standard deviations, were computed to summarize participant responses, and correlation analyses were performed to explore the relationships between key variables, such as presence, representation fidelity, and situational interest. These analyses were conducted to ensure the reliability and validity of the measurement scales used in the study.

Survey # 1. Survey #1, also referred to as "Baseline Survey," provided foundational data to inform the design of the VR-based project set. While primarily focused on preliminary assessment, this survey's sections on prior knowledge, interest, curiosity, and motivation align with our theoretical framework on situational interest development [7] and helped establish baseline measures for understanding how students might experience presence and engagement in subsequent VR environments. Additionally, the survey explored the potential of collaborative learning within the VR environment, helping to inform the design of team-based problem-solving tasks. The survey consisted of eight sections (refer to Table 2), combining closed-ended and open-ended questions to gather both quantitative and qualitative data. Most questions were Likert scale questions, requiring participants to rate their responses on a 5-point scale ranging from "strongly disagree" to "strongly agree."

Table 2. Structure and thematic focus of the baseline survey (Survey #1)

Main Sections	Section Description	Key Features
Section 1	Familiarity with engineering concepts and procedures: Assesses participants' prior knowledge of engineering concepts related to strength of materials.	Exploration of the role of prior knowledge in shaping engagement with the topic.
Section 2	Prior VR experience: Gathers information about participants' previous exposure to VR technology.	Evaluation of participants' experiences with VR technology and collaborative learning.
Section 3	Experience with collaborative and cooperative work: Evaluates participants' experience with group projects, role-taking, teaching, and sharing experiences.	Evaluation of participants' experiences with VR technology and collaborative learning.
Section 4	Interest: Measures participants' interest in learning about various engineering concepts related to the strength of materials.	Focus on situational interest by assessing factors like perceived complexity, understanding, confidence, curiosity, and motivation.
Section 5	Curiosity: Assesses participants' curiosity about learning these engineering concepts.	Focus on situational interest by assessing factors like perceived complexity, understanding, confidence, curiosity, and motivation.
Section 6	Motivation: factors motivating participants to learn about the strength of materials.	Focus on situational interest by assessing factors like perceived complexity, understanding, confidence, curiosity, and motivation.
Section 7	Attitudes Towards Collaboration and Cooperation: Evaluates participants' comfort level with group work and collaboration.	Evaluation of participants' experiences with VR technology and collaborative learning.
Section 8	Learning preferences: Explores participants' perceptions of how VR could enhance their learning of engineering concepts.	Evaluation of participants' experiences with VR technology and collaborative learning.

Building on these survey sections, we identified five key focal points that informed the design and implementation of the VR-based project set:

- The relationship between prior knowledge and situational interest: By assessing students' existing knowledge and interest in engineering concepts, the survey provided insights into how prior knowledge can influence engagement and learning.
- The impact of VR on motivation and engagement: By comparing students' responses to questions about VR and their interest in engineering, the survey explored the potential of VR to enhance motivation and engagement.
- The effectiveness of collaborative learning in VR: The survey assessed students' experiences with collaborative work and their attitudes towards team-based projects, providing information on the potential benefits of collaborative learning in VR-enhanced learning environments.
- Students' perceptions of VR as a learning tool: By understanding students' beliefs about how VR can enhance learning, the survey helped to inform the design of the VR-based project set.
- The specific factors within VR that contribute to student engagement: The survey identified key VR features, such as immersion, interactivity, and realism, that can stimulate interest and motivation.

Survey # 2. Survey #2 was strategically administered in two phases to address our research questions about presence, representation fidelity, and engagement. The first section, the "VR Survey," administered after the immersive CAVE experience, focused on two key dimensions central to our research questions:

- *Presence* (addressing sub-question #1): measuring participants' sense of involvement, perceived realness, and spatial presence. This dimension assesses three key aspects of the VR experience:
  - Involvement: The participant's psychological immersion in the virtual environment
  - Realness: The perceived authenticity of the virtual experience
  - Spatial Presence: The feeling of being physically present in the virtual space
- *Representation Fidelity* (addressing sub-question #2): assessing the realism and precision of the virtual environment through:
  - Visual quality and clarity of the 3D simulation
  - Spatial accuracy of movements and distances
  - Overall realism of the baseball pitcher's movements

This section particularly examined how representation fidelity supported understanding of five key engineering concepts:

- Understanding how forces affect structural elements differently according to element strength
- Finding weakest points in a structure under different loads in 3D
- Calculating critical stresses and potential failure modes
- Measuring structural deformation under load using strain measures
- Presenting engineering results clearly

The second section, "Engagement and Learning: Stress Computation," was administered after both the non-immersive VR experience on MATLAB software and the AR-based motion tracking of student movement. This section investigated engagement factors (addressing sub-question #3) through nine dimensions that collectively measured how different aspects of the VR simulation influenced situational interest and learning motivation:

- *Prior Knowledge*: Assessed participants' existing knowledge of stress computation
- *Initial Interest*: Measured participants' initial level of interest in biomechanics
- *Curiosity*: Evaluated participants' desire to explore stress analysis further
- *Enjoyment*: Measured participants' enjoyment of the VR experience
- *Motivation*: Assessed participants' drive to learn stress computation
- *Focus and Attention*: Measured participants' ability to concentrate during the simulation
- *Pedagogical Usefulness*: Evaluated the educational value for understanding stress concepts
- *Personal Relevance*: Assessed how participants connected the experience to their engineering goals
- *Potential Future Engagement*: Measured interest in further exploring biomechanics and stress analysis

Both sections employed 1–5 Likert scales for quantitative measurement, supplemented by open-ended responses collected in focus groups for qualitative insights.

This survey design strategically connects with Survey #1, tracking key changes across:

- Prior understanding of stress computation concepts (linking to Survey #1's engineering concepts section)
- Changes in situational interest, curiosity, and motivation throughout the project
- Alignment between expected and actual VR learning experiences
- Impact of previous VR and collaborative work experience on project outcomes

Through these complementary surveys and their interconnected sections, we aimed to comprehensively assess how our multi-stage VR project set influenced students' engagement and understanding of stress computation concepts while tracking changes in their interest, motivation, and learning preferences throughout the experience.

4 FINDINGS

4.1 Survey #1

The Survey #1, or "Baseline Survey" results, informed the three-fold approach to tailoring instruction during the course project:

1. *Targeted Instruction*: By assessing students' prior knowledge of engineering concepts, the instructor was able to tailor VR-based tasks within the project set to specific learning outcomes and address areas where students needed more explanation. Students showed lower familiarity with core concepts, particularly deformation and stress distribution, with key misconceptions around how structures change shape under load. For example, students expressed curiosity about understanding how forces affect the strength of a structure, rating it as their highest area of interest, so a VR simulation was developed to allow them to experiment

with different force scenarios. The simulation incorporated color-coded visualizations for stress distribution and interactive tools to observe and manipulate deformation, addressing both interest and knowledge gaps. The survey revealed detailed patterns of situational interest, with students showing highest interest in finding weak points in structures and solving real-world engineering problems, which directly informed the design of interactive scenarios.
2. *Level of Guidance*: Understanding students' prior experience with VR helped the instructor determine the appropriate level of guidance and support needed, ensuring a smooth learning experience. Survey results revealed mixed prior VR exposure, primarily gaming-based, and some concerns about physical comfort. This led to implementing a graduated introduction to VR technology, incorporating comfort breaks, and providing alternative viewing options. Students' perceptions of VR's potential for learning were particularly enthusiastic about visualization capabilities, with many responses highlighting the value of "seeing inside" structures and experiencing "3D visualization" of concepts. These preferences directly shaped the development of visualization tools and immersive experiences in the project.
3. *Collaborative Learning*: Assessing students' comfort levels with collaborative work informed the instructor's choice of teaching approaches and technology support to promote effective teamwork. Students demonstrated high comfort with group work (4.24/5 rating), strong experience in role-taking (4.43/5 rating), and positive attitudes toward peer teaching (4.1/5 rating). This led to incorporating role-based team structures and peer-teaching components in VR activities. The survey revealed that students particularly valued the opportunity to deepen their understanding through explaining concepts to others and sharing different perspectives, which informed the design of collaborative VR tasks.

Aligned with these insights, the project comprised a multi-staged VR-based project set that included a combination of an immersive baseballer movement simulation in the CAVE, a non-immersive demo using Biomechanics of Bodies MATLAB software, and an immersive motion-tracking component, as well as the related instructional tasks. This integrated approach was specifically designed to address identified knowledge gaps—particularly in understanding stress distribution, deformation before failure, and identifying structural weak points—through visual and interactive learning, maintain student interest through practical applications (which rated 4.38/5 as a motivator), and support collaborative learning while accommodating different learning preferences. The design particularly responded to students' expressed desire for interactive experimentation and real-world applications, as revealed in Section 8 of the survey, where students emphasized the potential of VR for enhancing their understanding through hands-on experimentation with forces and materials.

4.2 Survey #2

Reliability analysis. To ensure the rigor of Survey #2, we conducted a comprehensive reliability analysis of the measurement scales used to assess presence, representation fidelity, and situational interest. Cronbach's alpha, a statistical measure used to assess the internal consistency reliability of a scale, was employed. The Presence, Representation Fidelity, and Situational Interest scales demonstrated excellent internal consistency, with Cronbach's alpha coefficients of 0.93, 0.88, and

0.92, respectively. These high reliability coefficients indicate that the scales reliably measure the intended constructs.

The Presence scale encompasses three key aspects aligned with our theoretical framework: involvement, realness, and spatial presence. To ensure the reliability of this scale, which directly measures one of the primary dimensions influencing situational interest, we utilized the statistical software R and the psych package to calculate Cronbach's alpha. This measure assesses the internal consistency of the scale items, determining whether they reliably capture the construct of presence as experienced by students in the VR environment. A reliable scale provides confidence that subsequent analyses linking presence to situational interest are based on sound measurements. The Presence scale showed strong reliability, with a Cronbach's alpha of 0.93. This indicates that the scale effectively measures the construct of presence, encompassing involvement, realness, and spatial presence.

The representation fidelity scale measuring VR simulation quality initially included four items:

- "When you visualize the movements in a 3D space, how realistic does the VR-based simulation look and feel?"
- "When you visualize the movements in a 3D space, how clear and high-quality are the visuals?"
- "When you visualize the movements in a 3D space, do you experience any motion sickness or discomfort while looking at the simulation?"
- "When you visualize the movements in a 3D space, how accurately does the VR-based simulation represent real-world spatial relationships and distances?"

However, we removed the motion sickness item, as it did not align with the other items' positive focus. The results indicated excellent internal consistency, with a Cronbach's alpha of 0.88. This suggests that the three items coherently measure the construct of representation fidelity. The inter-item correlation matrix (refer to Table 3) further supports this reliability, showcasing strong positive correlations between all item pairs. Additionally, each item's correlation with the total scale score was substantial, ranging from 0.71 to 0.87, underscoring the meaningful contribution of each item to the overall construct. These findings establish the reliability of the Representation Fidelity scale, enabling its effective use in examining the impact of representation fidelity on students' situational interest.

Table 3. Inter-item correlation matrix for the representation fidelity scale

	Q9	Q11	Q15
Q9	1.00	0.75	0.62
Q11	0.75	1.00	0.81
Q15	0.62	0.81	1.00

Note: Correlations are Pearson's r coefficients.

To enhance the reliability and the validity of the situational interest scale, we conducted a thorough analysis and refinement. The initial eleven-item scale was revised to a nine-item scale by removing items Q31 and Q35, which exhibited lower item-total correlations and misalignment with the underlying construct. The revised nine-item scale demonstrated excellent internal consistency, with a Cronbach's alpha of 0.92, and effectively captures key dimensions of interest, including attention, enjoyment, motivation, focus, and personal relevance. A correlation matrix (see Figure 2) further supports the scale's validity. The strong internal consistency and the meaningful contribution of each item establish the scale as a reliable and valid tool for assessing students' interest in VR-based learning experiences.

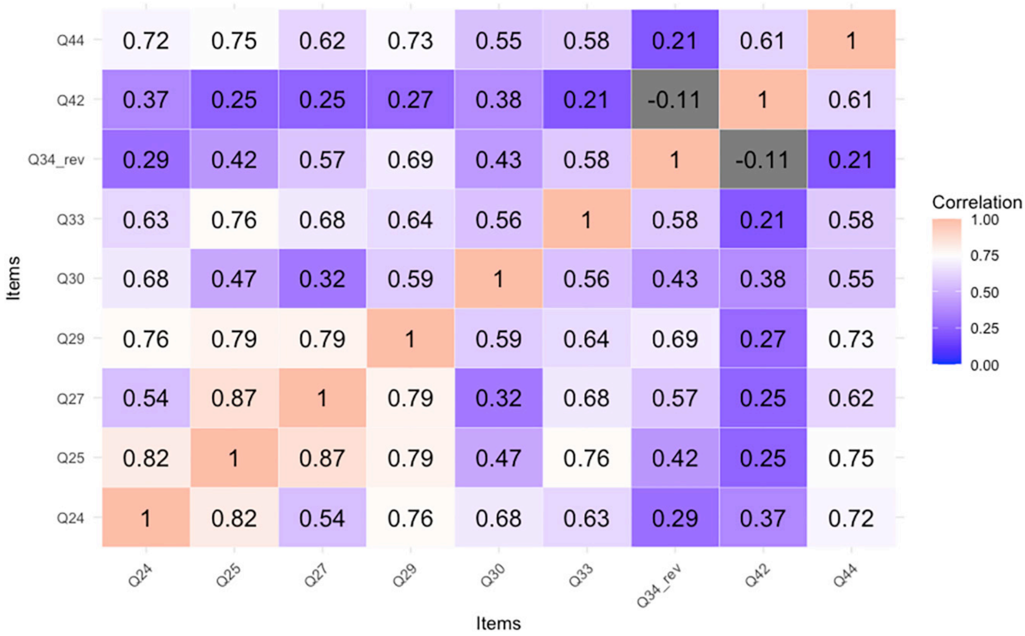

Fig. 2. Inter-item correlation matrix for the situational interest scale

Results. Based on the analysis of the results of Survey #2, we were able to address each of the research sub-questions posed in our study.

a) **Presence and situational interest.** A key sub-question in our study was: "How does the VR environment's presence impact students' situational interest?" To address this question, we analyzed the presence scale and found a high level of immersion among participants. The Cronbach's alpha of 0.93 indicates excellent internal consistency, suggesting that the scale effectively measures the construct of presence. The strong inter-item correlations further confirmed the reliability and validity of the scale. These findings suggest that the VR environment successfully transported participants to a virtual world where the student interacted with the critical phases of a pitcher's movements and where their emulations could be effectively compared. Also, students got the opportunity to "feel" in their own muscles the "strain and stress" they were asked to compute, rendering the involvement a first-hand experience. Specifically, participants reported high levels of involvement ($M = 4.2$, $SD = 0.8$), realness ($M = 4.1$, $SD = 0.7$), and spatial perception ($M = 4.3$, $SD = 0.6$). These factors contributed to a sense of presence, driven by the immersive design of the baseballer movement simulation in the CAVE. The realistic 3D graphics, interactive elements, and spatial and sensory experiences that mimicked real-world interactions effectively captured students' attention, minimized distractions, and optimized their cognitive processing. For a more detailed analysis of the presence scale, please refer to Tables 4 and 5. Figures 3 and 4 provide visual representations of the distribution of the scale scores and item responses, respectively.

Table 4. Reliability statistics for the presence scale

Statistic	Value
Number of Items	3
Cronbach's Alpha	0.93
Average Inter-Item Correlation	0.83
Mean of Scale	3.5
Standard Deviation of Scale	1.1

Table 5. Item statistics for the presence scale

Item	Item-Total Correlation	Mean	Standard Deviation
Q3	0.87	3.9	1.1
Q5	0.88	3.4	1.2
Q7	0.85	3.1	1.2

Note: Q3 = Involvement, Q5 = Realness, Q7 = Spatial Presence. See Section 4.3.2 for full item descriptions.

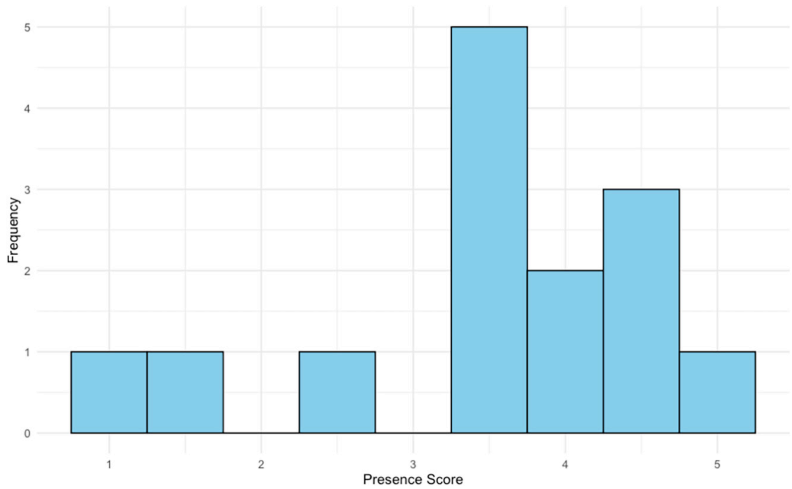

Fig. 3. Distribution of presence scale scores

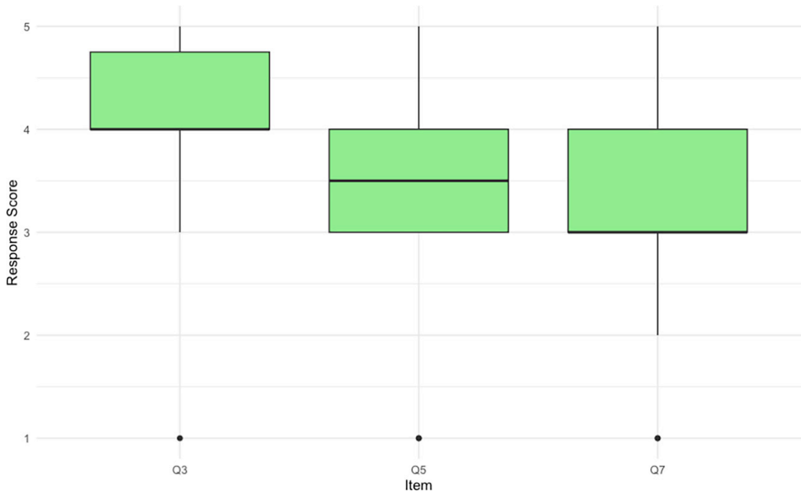

Fig. 4. Distribution of responses for presence scale items

b) **Representation of fidelity and situational interest.** Our second key sub-question asked: "How does the representation fidelity of the VR simulation influence students' situational interest?" To answer this question, we analyzed the representation fidelity scale and found good reliability (Cronbach's alpha = 0.88) after removing the motion sickness item. The strong correlations between items such as visual realism (r = 0.75) and spatial accuracy indicated that the baseballer movement simulation in the CAVE provided a high-quality and immersive experience. These factors contributed to improved understanding and retention of information. The project set utilized a high-fidelity 3D model of a professional pitch, allowing students to interactively explore its complex kinematics from multiple viewpoints. This immersive experience facilitated rapid training and emulation of the pitch for motion tracking analysis. By comparing stress and strain in 3D, students gained a deeper understanding of how forces affect structural elements differently based on their strength. They were able to identify weak points, calculate critical stresses and potential failure modes, measure deformation under load, and effectively present their engineering findings. This contextually relevant simulation helped students develop a strong grasp of real-world scenarios and the above engineering concepts. Additionally, the use of high-quality visuals made the learning process engaging and memorable.
c) **Situational interest and learning.** Our last sub-question asked: "Which aspects of the overall VR experience most effectively engage, generating curiosity and learning motivation to learn more about the topic?" The situational interest scale, with a Cronbach's alpha of 0.92, exhibited excellent reliability. The analysis revealed that the VR overall exposure successfully captured students' attention, generated curiosity, and motivated students to learn more about strength of materials. The high mean scores for items such as attention capture (M = 3.4), motivation to explore (M = 3.6), and desire to know more (M = 3.9) indicate that the VR overall experience was highly engaging and stimulating. The strong correlations between items on the situational interest scale further support its reliability and validity. For example, the correlation between attention capture and motivation to explore was 0.823, suggesting a strong relationship between these two constructs. This indicates that the VR experience not only captured students' attention but also motivated them to delve deeper into the subject matter.

This finding was corroborated by focus group discussions conducted at the end of the semester, where themes of increased motivation and persistence emerged. Learners reported feeling more interested and engaged than at the beginning of the course, as evidenced by the respective responses in Survey #1 and in the second section of Survey #2. Consequently, they were motivated to actively participate in learning activities, seek out additional information, and apply their knowledge to real-world problems. In answering the main research question of this study: "To what extent does a multi-staged VR-based project set, combining immersive experiences (VR-based simulation in CAVE and learner motion tracking) and non-immersive experiences (Biomechanics of Bodies MATLAB software), influence students' situational interest through dimensions of presence, involvement, and representation fidelity?" the strong reliability of these scales provides confidence in the validity of the findings. The high levels of presence, representation fidelity, and situational interest reported by participants highlight the potential of VR to create engaging and effective learning experiences.

4.3 Implications

This study offers a significant contribution to the field of educational technology, particularly in the domain of VR-enhanced learning environments. By employing a rigorous methodological approach and systematically examining item-total correlations and content validity, this study demonstrates a sophisticated approach to scale development. This empirical support for the multidimensional nature of presence, representation fidelity, and situational interest in VR environments extends existing theoretical frameworks and provides valuable insights into the psychological processes underlying VR-based learning.

The findings have profound implications for the design and implementation of effective VR-based learning experiences across various disciplines. While this study specifically focuses on undergraduate engineering education, the principles and insights gained can be applied to a wide range of educational contexts, including other disciplines within higher education, various subjects in K-12 education, and industries like healthcare, manufacturing, and aviation in corporate training.

This study provides a solid foundation for educators and training professionals seeking to understand the underlying mechanisms of VR-based learning, ultimately optimizing the design and delivery of VR experiences to maximize their impact on student and employee learning and engagement. Educators and trainers, for example, can apply these findings by prioritizing the development of VR experiences that offer high levels of presence and representation fidelity, ensuring that the virtual environments are not only visually appealing but also accurately reflect real-world phenomena. Incorporating elements that foster collaboration and peer-to-peer learning within VR environments can enhance student engagement and deepen understanding.

5 CONCLUSION

Through this design case study combining PjBL strategies and a multi-dimensional framework, we investigated the mechanisms of interest generation and the development of situational interest across various stages of a VR-based project. Our findings highlight the importance of designing VR experiences that are not only immersive but also intellectually stimulating and that align with well-established pedagogical principles.

This study addresses two significant gaps in the field of educational technology, particularly in the context of VR-based learning. First, the research addresses the challenge of teaching abstract and interdisciplinary engineering concepts. By leveraging the immersive capabilities of VR, this study explores how to create engaging and effective learning experiences that can help students overcome these challenges. The multi-dimensional framework proposed in this study can serve as a valuable tool for designing VR-based learning experiences that can support student learning and motivation.

Second, the study responds to the need for a more purposeful and emotionally resonant approach to VR-based instructional design. By drawing on theories of motivation, engagement, and cognitive psychology, this study provides a framework for designing VR experiences that can effectively capture and sustain student interest, leading to deeper learning. The study highlights the importance of considering factors such as personal relevance, pedagogical usefulness, and potential engagement when designing VR-enhanced learning environments. By addressing these two key gaps, this study contributes to a more nuanced understanding of the potential of VR as an educational tool, targeting the engineering undergraduate educational context. This study represents a significant step toward a more nuanced understanding of VR as an educational tool. By shifting the focus from technology-centric approaches to a learner-centered perspective, we have explored the potential of VR to foster deep, meaningful learning experiences. VR, when thoughtfully integrated into education, can create innovative and engaging learning environments that enhance student motivation and learning outcomes.

5.1 Limitations and future research and practice

As with any exploratory case study, this study, while providing valuable insights into the potential of VR for undergraduate engineering education, presents certain limitations that should be acknowledged. Firstly, while the study demonstrates a positive overall impact of the VR project set on student interest, further research is needed to investigate the dynamics of interest over time. Tracking student responses to key questions (e.g., interest, motivation) across different stages of the VR project set would provide valuable insights into how student interest evolves throughout the learning process. Secondly, the reliance on self-reported measures may introduce potential biases. As is characteristic of case study research, the goal is analytical generalization to theory rather than statistical generalization to populations [52]. The findings provide theoretical insights and design principles that can inform implementations in similar contexts, though validation in diverse settings would strengthen these contributions. To address these limitations, future research should consider integrating motivational theories like SDT. By designing environments that support students' psychological needs and creating experiences that transform temporary interest into sustained motivation, researchers can enhance the effectiveness of VR-based learning. Thirdly, as a bounded case study, the research focused on a specific course in mechanical engineering at one institution. The design principles and theoretical insights may transfer to other STEM disciplines and institutional contexts, though such transferability should be investigated through additional case studies and comparative research. Finally, the study primarily focused on the immediate impact of the VR experience. Future research could explore the long-term effects of VR on student learning outcomes, such as retention of knowledge, application of skills, and overall academic performance. Additionally, future research could investigate the optimal design principles for VR-based learning experiences, considering factors such as instructional design, pacing, and the level of learner autonomy.

5.2 Abbreviations

AI – Artificial Intelligence
AR – Augmented Reality
ASEE – American Society for Engineering Education
BoB – Biomechanics of Bodies
CAVE – Cave Automatic Virtual Environment
MATLAB – Matrix Laboratory MR Mixed Reality
NAE – National Academy of Engineering
NSF – National Science Foundation

PjBL – Project-Based Learning
SDT – Self-Determination Theory
STEM – Science, Technology, Engineering, and Mathematics
VR – Virtual Reality

5.3 Statements and declarations

Data availability statement. To protect participant privacy and comply with research ethics protocols, the data that support the findings of this study are available upon reasonable request from the corresponding author. The dataset contains sensitive information from a small group of undergraduate engineering students (N = 20) that could potentially make participants identifiable. Access to anonymized data may be granted following review of research purposes and signing of a data sharing agreement.

Conflict of interest statement. The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Statement of AI. By submitting this manuscript, we confirm that we have adhered to appropriate ethical guidelines or approvals for the human subjects' research conducted in this study, including taking into consideration any federal requirements and institutional guidelines concerning the use of AI in human subjects' research.

IRB case #: 2023-2024-139

6 REFERENCES

[1] G. R. Bertoline, Ed., *The Engineering Mindset Report: A Vision for Change in Undergraduate Engineering and Engineering Technology Education,* American Society for Engineering Education (ASEE) and National Academy of Engineering (NAE), Washington, DC, 2024. [Online]. Available: https://mindset.asee.org

[2] M. Borrego and L. Newswander, "Journal clubs as pedagogy for interdisciplinary graduate education," in *Proc. 2008 ASEE Annual Conf. & Exposition,* American Society for Engineering Education, 2008, pp. 13–822. https://doi.org/10.18260/1-2--3665

[3] M. Abdulwahed, "Technology Innovation and Engineering Education and Entrepreneurship (TIEE) in engineering schools: Novel model for elevating national knowledge based economy and socio-economic sustainable development," *Sustainability,* vol. 9, no. 2, p. 171, 2017. https://doi.org/10.3390/su9020171

[4] S. Kochekseraii and L. Osgood, "Lifelong learning: A skill needed today for the engineers of the future," in *Proc. 2016 Canadian Engineering Education Association Conf. (CEEA),* 2016. https://doi.org/10.24908/pceea.v0i0.6445

[5] A. Kolmos and E. De Graaff, "Problem-based and project-based learning in engineering education: Merging models," in *Cambridge Handbook of Engineering Education Research,* A. Johri and B. M. Olds, Eds., Cambridge: Cambridge University Press, 2014, pp. 141–161. https://doi.org/10.1017/CBO9781139013451.012

[6] V. Ivanov, "Exploring the potential of virtual reality as part of the training of students in the self-defense elective course," *Strategii na Obrazovatelnatai Nauchnata Politika,* vol. 31, no. 5s, pp. 52–61, 2023. https://doi.org/10.53656/str2023-5s-5-exp

[7] S. Hidi and K. A. Renninger, "The four-phase model of interest development," *Educational Psychologist,* vol. 41, no. 2, pp. 111–127, 2006. https://doi.org/10.1207/s15326985ep4102_4
[8] G. Schraw and S. Lehman, "Situational interest: A review of the literature and directions for future research," *Educational Psychology Review,* vol. 13, no. 1, pp. 23–52, 2001. https://doi.org/10.1023/A:1009004801455
[9] A. Krapp, S. Hidi, and K. A. Renninger, "Interest, learning, and development," in *The Role of Interest in Learning and Development,* K. A. Renninger, S. Hidi, and A. Krapp, Eds., Hillsdale, NJ: Erlbaum, 1992, pp. 3–25.
[10] M. Mitchell, "Situational interest: Its multifaceted structure in the secondary school mathematics classroom," *Journal of Educational Psychology,* vol. 85, no. 3, pp. 424–436, 1993. https://doi.org/10.1037/0022-0663.85.3.424
[11] Y. C. Chen, Y. S. Chang, and M. J. Chuang, "Virtual reality application influences cognitive load-mediated creativity components and creative performance in engineering design," *Journal of Computer Assisted Learning,* vol. 38, no. 1, pp. 6–18, 2022. https://doi.org/10.1111/jcal.12588
[12] M. C. Fink, D. Sosa, V. Eisenlauer, and B. Ertl, "Authenticity and interest in virtual reality: Findings from an experiment including educational virtual environments created with 3D modeling and photogrammetry," *Frontiers in Education,* vol. 8, p. 969966, 2023. https://doi.org/10.3389/feduc.2023.969966
[13] W. Huang, R. D. Roscoe, M. C. Johnson-Glenberg, and S. D. Craig, "Motivation, engagement, and performance across multiple virtual reality sessions and levels of immersion," *Journal of Computer Assisted Learning,* vol. 37, no. 3, pp. 745–758, 2021. https://doi.org/10.1111/jcal.12520
[14] P. Sureephong, S. Chernbumroong, K. Intawong, K. Jansukpum, N. Wongwan, and K. Puritat, "The effect of virtual reality on knowledge acquisition and situational interest regarding library orientation in the time of Covid-19," *The Journal of Academic Librarianship,* vol. 49, no. 6, p. 102789, 2023. https://doi.org/10.1016/j.acalib.2023.102789
[15] S. Kavanagh, A. Luxton-Reilly, B. Wuensche, and B. Plimmer, "A systematic review of virtual reality in education," *Themes in Science and Technology Education,* vol. 10, no. 2, pp. 85–119, 2017.
[16] M. Billinghurst, A. Clark, and G. Lee, "A survey of augmented reality," *Foundations and Trends in Human-Computer Interaction,* vol. 8, nos. 2–3, pp. 73–272, 2015. https://doi.org/10.1561/1100000049
[17] N. Pellas, A. Dengel, and A. Christopoulos, "A scoping review of immersive virtual reality in STEM education," *IEEE Trans. Learn. Technol.,* vol. 13, no. 4, pp. 748–769, 2020. https://doi.org/10.1109/TLT.2020.3019405
[18] C. Dede, "Immersive interfaces for engagement and learning," *Science,* vol. 323, no. 5910, pp. 66–69, 2009. https://doi.org/10.1126/science.1167311
[19] C. Fowler, "Virtual reality and learning: Where is the pedagogy?" *British Journal of Educational Technology,* vol. 46, no. 2, pp. 412–422, 2015. https://doi.org/10.1111/bjet.12135
[20] J. M. Harackiewicz, J. L. Smith, and S. J. Priniski, "Interest matters: The importance of promoting interest in education," *Policy Insights from the Behavioral and Brain Sciences,* vol. 3, no. 2, pp. 220–227, 2016. https://doi.org/10.1177/2372732216655542
[21] A. Krapp, "Structural and dynamic aspects of interest development: Theoretical considerations from an ontogenetic perspective," *Learning and Instruction,* vol. 12, pp. 383–409, 2002. https://doi.org/10.1016/S0959-4752(01)00011-1
[22] D. I. Cordova and M. R. Lepper, "Intrinsic motivation and the process of learning: Beneficial effects of contextualization, personalization, and choice," *Journal of Educational Psychology,* vol. 88, no. 4, p. 715, 1996. https://doi.org/10.18260/1-2--3665

[23] P. Siklander, J. Kangas, S. Ruhalahti, and P. Korva, "Exploring triggers for arousing interest in online learning," in *Proc. 11th Int. Technology, Education and Development Conf. (INTED2017),* 2017, pp. 9081–9089. https://doi.org/10.21125/inted.2017.2150

[24] T. Verhagen, F. Feldberg, B. van den Hooff, S. Meents, and J. Merikivi, "Understanding users' motivations to engage in virtual worlds: A multipurpose model and empirical testing," *Computers in Human Behavior,* vol. 28, no. 2, pp. 484–495, 2012. https://doi.org/10.1016/j.chb.2011.10.020

[25] G. Makransky, S. Borre-Gude, and R. E. Mayer, "Motivational and cognitive benefits of training in immersive virtual reality based on multiple assessments," *Journal of Computer Assisted Learning,* vol. 36, no. 5, pp. 691–707, 2020. https://doi.org/10.1111/jcal.12285

[26] K. Y. Chin, Y. C. Kao, and H. C. Hsieh, "A virtual reality learning system to support situational interest in historic site courses," in *Proc. Int. Congress on Advanced Applied Informatics (IIAI-AAI),* 2018, pp. 960–961. https://doi.org/10.1109/IIAI-AAI.2018.00201

[27] H. C. S. Lin, S. J. Yu, J. C. Y. Sun, and M. S. Y. Jong, "Engaging university students in a library guide through wearable spherical video-based virtual reality: Effects on situational interest and cognitive load," *Interactive Learning Environments,* vol. 29, no. 8, pp. 1272–1287, 2021. https://doi.org/10.1080/10494820.2019.1624579

[28] R. C. Chang, "Using virtual reality to enhance forensic science education: Effects on CSI learning achievements, situational interest and cognitive load," *Journal of Criminal Justice Education,* vol. 37, no. 1, pp. 99–118, 2024. https://doi.org/10.1080/10511253.2024.2372860

[29] G. Makransky, N. K. Andreasen, S. Baceviciute, and R. E. Mayer, "Immersive virtual reality increases liking but not learning with a science simulation and generative learning strategies promote learning in immersive virtual reality," *Journal of Educational Psychology,* vol. 113, no. 4, pp. 719–735, 2021. https://doi.org/10.1037/edu0000473

[30] J. Jiang and L. K. Fryer, "Multi-user extended reality simulation-based learning and training: A systematic review (protocol)," *OSF Preprints,* 2022. https://doi.org/10.17605/OSF.IO/A7XSW

[31] E. Akman and R. Çakır, "The effect of educational virtual reality game on primary school students' achievement and engagement in mathematics," *Interactive Learning Environments,* vol. 31, no. 3, pp. 1–18, 2020. https://doi.org/10.1080/10494820.2020.1841800

[32] D. Allcoat and A. von Mühlenen, "Learning in virtual reality: Effects on performance, emotion and engagement," *Research in Learning Technology,* vol. 26, 2018. https://doi.org/10.25304/rlt.v26.2140

[33] Y. C. Chen, Y. S. Chang, and M. J. Chuang, "Exploring the specification of educational compatibility of virtual reality within a technology acceptance model," *Australasian Journal of Educational Technology,* vol. 37, no. 1, pp. 16–30, 2021. https://doi.org/10.14742/ajet.5786

[34] J. Q. Guan, L. H. Wang, Q. Chen, K. Jin, and G. J. Hwang, "Effects of a virtual reality-based pottery making approach on junior high school students' creativity and learning engagement," *Interactive Learning Environments,* vol. 31, no. 4, pp. 2016–2032, 2023. https://doi.org/10.1080/10494820.2021.1871631

[35] S. Hidi, "Interest and its contribution as a mental resource for learning," *Review of Educational Research,* vol. 60, no. 4, pp. 549–571, 1990. https://doi.org/10.3102/00346543060004549

[36] J. Radianti, T. A. Majchrzak, J. Fromm, and I. Wohlgenannt, "A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda," *Computers & Education,* vol. 147, p. 103778, 2020. https://doi.org/10.1016/j.compedu.2019.103778

[37] A. Krapp, "Interest, motivation and learning: An educational-psychological perspective," *European Journal of Psychology of Education,* vol. 14, no. 1, pp. 23–40, 1999. https://doi.org/10.1007/BF03173132

[38] W. Yan, V. L. Lowell, and L. Yang, "Developing English language learners' speaking skills through applying a situated learning approach in VR-enhanced learning experiences," *Virtual Reality,* vol. 28, no. 4, pp. 1–23, 2024. https://doi.org/10.1007/s10055-024-01061-5

[39] D. P. Ausubel, "Facilitating meaningful verbal learning in the classroom," *The Arithmetic Teacher,* vol. 15, no. 2, pp. 126–132, 1968. https://doi.org/10.5951/AT.15.2.0126

[40] M. T. Chi, M. Bassok, M. W. Lewis, P. Reimann, and R. Glaser, "Learning problem solving skills from studying examples," *Cognitive Science,* vol. 13, no. 2, pp. 235–241, 1989. https://doi.org/10.1207/s15516709cog1302_4

[41] D. E. Alvermann and S. A. Hague, "Comprehension of counterintuitive science text: Effects of prior knowledge and text structure," *Journal of Educational Research,* vol. 82, no. 1, pp. 197–202, 1989. https://doi.org/10.1080/00220671.1989.10885893

[42] G. Loewenstein, "The psychology of curiosity: A review and reinterpretation," *Psychological Bulletin,* vol. 116, no. 1, p. 75, 1994. https://doi.org/10.1037/0033-2909.116.1.75

[43] A. Jelfs and D. Whitelock, "The notion of presence in virtual learning environments: What makes the environment 'real'," *British Journal of Educational Technology,* vol. 31, no. 2, pp. 145–152, 2000. https://doi.org/10.1111/1467-8535.00143

[44] M. Slater, "Place illusion and plausibility can lead to realistic behaviour in immersive virtual environments," *Philosophical Transactions of the Royal Society B: Biological Sciences,* vol. 364, no. 1535, pp. 3549–3557, 2009. https://doi.org/10.1098/rstb.2009.0138

[45] I. Dubovi, "Cognitive and emotional engagement while learning with VR: The perspective of multimodal methodology," *Computers & Education,* vol. 183, p. 104495, 2022. https://doi.org/10.1016/j.compedu.2022.104495

[46] G. B. Petersen, G. Petkakis, and G. Makransky, "A study of how immersion and interactivity drive VR learning," *Computers & Education,* vol. 179, p. 104429, 2022. https://doi.org/10.1016/j.compedu.2021.104429

[47] T. A. Mikropoulos and A. Natsis, "Educational virtual environments: A ten-year review of empirical research (1999–2009)," *Computers & Education,* vol. 56, no. 3, pp. 769–780, 2011. https://doi.org/10.1016/j.compedu.2010.10.020

[48] A. Bandura, "Self-efficacy: Toward a unifying theory of behavioral change," *Psychological Review,* vol. 84, no. 2, pp. 191–215, 1977. https://doi.org/10.1037/0033-295X.84.2.191

[49] E. L. Deci and R. M. Ryan, *Intrinsic Motivation and Self-Determination in Human Behavior.* New York: Plenum, 1985. https://doi.org/10.1007/978-1-4899-2271-7

[50] R. M. Ryan and E. L. Deci, "Self-determination theory of intrinsic motivation: A review," *American Psychologist,* vol. 55, no. 1, pp. 68–78, 2000. https://doi.org/10.1037/0003-066X.55.1.68

[51] O. Halabi, "Immersive virtual reality to enforce teaching in engineering education," *Multimedia Tools and Applications,* vol. 79, no. 3, pp. 2987–3004, 2020. https://doi.org/10.1007/s11042-019-08214-8

[52] R. K. Yin, *Case Study Research and Applications: Design and Methods,* 6th ed. Thousand Oaks, CA: Sage Publications, 2018.

[53] S. B. Merriam and E. J. Tisdell, *Qualitative Research: A Guide to Design and Implementation,* 4th ed. San Francisco: Jossey-Bass, 2015.

[54] R. E. Stake, *The Art of Case Study Research.* Thousand Oaks, CA: Sage Publications, 1995.

[55] J. W. Creswell and V. L. Plano Clark, *Designing and Conducting Mixed Methods Research,* 3rd ed. Thousand Oaks, CA: SAGE Publications, 2018.

[56] K. M. Eisenhardt, "Building theories from case study research," *Academy of Management Review,* vol. 14, no. 4, pp. 532–550, 1989. https://doi.org/10.5465/amr.1989.4308385

7 AUTHORS

Daria Mizza teaches Curriculum and Instruction and Educational Technology in the Department of Applied Linguistics and Educational Studies at the American University in Cairo. Her research focuses on the transformative impact of educational technology on curriculum and instruction across higher education and K-12 settings, emphasizing research-driven planning and pedagogically sound innovation. Her publications explore the intersection of technology and teaching, grounded in instructional design frameworks and Universal Design for Learning (UDL) principles (E-mail: daria.mizza@aucegypt.edu).

Khalil Elkhodary is a Professor of mechanical engineering and currently serves as associate dean for undergraduate studies in the School of Sciences and Engineering and as founding co-director of its Educational Virtual Environment (EVE). His teaching interests include transitioning from traditional lecture-based engineering instruction to collaborative, project-based learning (PjBL) to foster teamwork and high-road knowledge transfer. He is currently focused on integrating AI and virtual reality (VR) into structured teamwork strategies that promote engagement, equitable participation, and individual accountability among students.

Dhafer Malouche is a Professor of Statistics in the Department of Mathematics, Statistics, and Physics at Qatar University. His research interests include Bayesian networks and graphical models, biostatistics, causal inference, multivariate analysis, and stochastic processes. He has authored numerous peer-reviewed publications and collaborates broadly across health and many other applied fields, contributing statistical expertise to solve real-world problems. His work bridges methodological development and applied research with partners from a wide range of disciplines and institutions.

Mohammed Al-Mousa is a technical instructor and consultant in the field of Computer Science Education. He holds a BSc in Software Engineering from Baghdad University and an MA in Education from the American University in Cairo. His research and professional work focus on project-based learning in computer science, with particular emphasis on developing chatbots and AI applications, as well as Arabic conversational agents.

Online-Journals.org

iJEP International Journal of Engineering Pedagogy

iJEP | eISSN: 2192-4880 | Vol. 16 No. 5 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijep.v16i5.60763

PAPER

Strategic Importance of Education in Cybersecurity

Pavel Beňo[1] (✉),
Roman Hrmo[2]

[1]Comenius University in Bratislava, Bratislava, Slovakia

[2]DTI University, Dubnica nad Váhom, Slovakia

pavel.beno@uniba.sk

ABSTRACT

This paper examines the strategic importance of cybersecurity education as a pedagogical and managerial mechanism for strengthening organisational resilience. Responding to the need for practice-orientated engineering pedagogy, the paper formulates a guiding research question: How can role-specific cybersecurity education be selected, justified, and evaluated so that it supports resilient behaviour across organisational levels? The study combines a structured narrative review of cybersecurity education and awareness approaches with a transparent SWOT-based analytical framework. SWOT is used as a managerial self-assessment tool for identifying strengths, weaknesses, opportunities, and threats in both the general cybersecurity environment and the human-factor dimension. The paper distinguishes gamification from games, explains the rationale for selecting educational approaches, and proposes operational criteria for translating SWOT findings into training requirements. The contribution is intended for educators, cybersecurity managers, and organisational leaders who design or evaluate cybersecurity awareness programmes in engineering-orientated, technical, and socio-technical environments.

KEYWORDS

cyber security, cybersecurity education, engineering pedagogy, SWOT, security awareness

1 INTRODUCTION – CYBERSECURITY AS A STRATEGIC PRIORITY

We constantly speak of the growing trend of cybercrime, and new reports of attacks on various sectors appear in the media on a regular basis. The most recent large-scale example is the company Jaguar, which has been unable to restore its production lines distributed across the globe for more than three weeks. In today's digitally interconnected world, the dependence of organisations on information technologies is growing almost exponentially. Along with this dependence, cyber threats are also intensifying.

Nextech [1] reports a twofold increase in attacks in the first half of 2025. These include sophisticated phishing attacks and ransomware, as well as threats stemming from employee errors. In today's world—the world of AI—such attacks are becoming increasingly sophisticated, with hackers making ever greater use of AI-based tools.

Beňo, P., Hrmo, R. (2026). Strategic Importance of Education in Cybersecurity. *International Journal of Engineering Pedagogy (iJEP)*, 16(5), pp. 28–45. https://doi.org/10.3991/ijep.v16i5.60763

Article submitted 2026-01-26. Revision uploaded 2026-05-31. Final acceptance 2026-06-21.

Security incidents are no longer merely an issue for the IT sector; their consequences can disrupt the daily operations of a company, jeopardise its reputation, undermine financial stability, and erode customer trust [2].

Companies adopt various forms of protection. Most commonly, they safeguard themselves by implementing modern firewalls, so-called next-generation firewalls, and by deploying new antivirus solutions. Organisations also increasingly rely on the encryption of sensitive data; backup through non-rewritable storage known by the acronym WORM (Write Once – Read Many); introduce multi-level authentication; and regularly test the resilience of their systems through penetration testing and diverse simulations of cyberattacks.

Another crucial element of cybersecurity is the education of employees and management. This must be carried out systematically, starting from basic awareness of risks, through training in phishing recognition, to the strategic management of incidents. ESET, as one of the globally recognised leaders in the field of cybersecurity, posed the following questions regarding the necessity of cybersecurity training [3]:

- You educate employees and foster security awareness within the organisation.
- You protect your company against the threats and pitfalls of cyberspace.
- You increase your company's ability to withstand cyber threats.
- You minimise the chances of attackers succeeding in their attempts.

According to the IBM *Cost of a Data Breach Report 2025* [4], a data breach in 2025 costs organisations an average of 4.44 million USD, while in the United States alone the figure has risen to as much as 10.22 million USD. The report also highlights the growing risks associated with artificial intelligence (AI) and so-called *shadow AI*, referring to unauthorised implementations of AI within organisations. Similarly, the National Security Authority of the Slovak Republic (NBU SR) [5] has issued warnings regarding threats linked to the use of certain AI models.

Already two years ago, the same IBM report [6] stated that the most common causes of data breaches were employee errors or misconfigured systems. Summarising the findings, it becomes evident that as many as 82% of incidents involve elements of the human factor. This indicates that technological solutions alone are insufficient when confronted with mistakes or a lack of employee awareness. Building a security culture and investing in education have therefore become indispensable.

For the reasons mentioned above, the role of the cyber security manager (CSM) in building security awareness is strategically irreplaceable. The CSM sets security standards and cyber security policies but, above all, fosters a culture in which cybersecurity becomes an integral part of the daily work of all employees. According to the ISACA *People, Processes and Behaviours 2022* report [7], it is crucial for companies that leadership actively supports a security culture and employee education, since the human factor remains one of the main causes of security incidents.

The objective of this article is to strengthen the pedagogical framing of cybersecurity education in organisations and to provide a transparent approach for linking educational interventions to organisational resilience. The paper addresses the following research question: RQ1: Which role-specific cybersecurity education approaches can be selected and justified through SWOT-based organisational self-assessment in order to improve resilience and security culture? Two supporting questions guide the analysis: RQ1a: What educational approaches are suitable for management, administrative staff, and technical employees? RQ1b: Which criteria should managers use when translating SWOT findings into actionable training requirements? The target audience consists of engineering educators, cybersecurity managers, adult-learning designers, and decision-makers responsible for building security awareness in organisations. The contribution is not an experimental evaluation of one training programme; rather, it is a practice-orientated pedagogical framework that connects related work, organisational analysis, and implementation guidelines.

2 RELATED WORK AND PEDAGOGICAL POSITIONING

Cybersecurity education has increasingly been studied as a socio-technical and pedagogical challenge rather than only as a matter of technical control. Systematic reviews show that organisations use a wide range of approaches, including awareness campaigns, e-learning, microlearning, simulations, phishing exercises, cyber ranges, serious games, and blended learning. However, the effectiveness of these approaches depends on context, learner characteristics, timing, feedback, and the extent to which training is connected with real work tasks [8] [9] [10].

For this reason, the paper positions cybersecurity education within engineering pedagogy as a form of competence-orientated learning. In technical and engineering environments, employees must not only know rules but also understand systems, risks, dependencies, and consequences. This corresponds with the NIST NICE Framework, which describes cybersecurity work through tasks, knowledge, skills, and abilities and can therefore support role-specific training requirements [11].

The literature also cautions against treating security awareness training as automatically effective. Phishing simulations, for example, may improve recognition and reporting when they are embedded in a broader learning process with timely feedback, but isolated or punitive simulations can produce limited learning effects, stress, or even mistrust. Therefore, such simulations should be used as diagnostic and reflective tools rather than as stand-alone proof of competence [9] [12].

Finally, it is important to distinguish gamification from games. Gamification refers to the use of game design elements, such as points, feedback, badges, progression, or challenges, in a non-game context; serious games are complete game-based learning environments. Both may support motivation and engagement, but they require explicit learning objectives and evaluation criteria [13] [14]. This distinction is used in the present paper when discussing interactive cybersecurity education.

3 WHY MANAGERS MUST CARE ABOUT EDUCATION IN THE FIELD OF CYBER SECURITY

As outlined in the introduction, this work sets the direction of our research and its focus area. The times when cybersecurity was perceived merely as an issue of the IT department are long gone. Over the past decade, cybersecurity has increasingly become a strategic component of the management of every organisation. For managers, this means that education in the field of cybersecurity is essential not only for employees but also for senior management.

It can be stated that although managers may delegate a significant portion of responsibilities to the CSM, they still bear their own accountability for the organisation. This accountability translates into several reasons why managers must be aware of the state and level of cybersecurity within their organisation:

- Responsibility for risk management
- Reputation, business continuity and legislation
- Financial consequences of incidents and the importance of the human factor

3.1 Responsibility for risk management

The ultimate responsibility for risk management—encompassing not only financial and operational aspects within the company—rests with the managers themselves. Cyber incidents can affect the entire business, causing operational disruptions, data loss, or the misuse of sensitive information. The ability to identify vulnerabilities, understand the types of threats, and implement appropriate measures enables managers to make decisions that minimise the impact of such incidents. Risk management in the context of cybersecurity involves several key areas:

- Identification and threat assessment – A manager must be able to identify potential sources of risk, whether external (malware, phishing, etc.) or internal (user errors, unauthorised access to data, etc.). Equally important is the ability to understand the likelihood of an incident and its potential impact on the company's operations, finances, and overall reputation.
- Prioritisation and Resource Allocation – A manager must determine which risks are critical and require immediate attention, which can be addressed later, and which may be acceptable to leave unresolved. This is referred to as the level of residual risk. To this end, the manager must also ensure the adequate allocation of resources—whether in the form of investments in technologies, external audits, the engagement of specialised consultants, or employee training.
- Implementation of Security Measures and Policies – This involves direct actions aimed at eliminating risks. The manager establishes guidelines that define how sensitive data is handled, how systems are monitored, and how incidents are to be addressed in the event they occur.
- Monitoring and Continuous Improvement – It is essential to ensure that the implemented measures are regularly reviewed in terms of their effectiveness, that new and constantly evolving threats are assessed, and that company strategies are adapted accordingly. This represents an ongoing process of improvement.
- Accountability in the Event of Incidents – It must be recognised that in the case of incidents, the manager bears both legal and moral responsibility for the decisions that influence their impact on the company.

The Ability to Respond Quickly and Effectively – A manager's capacity to activate a crisis plan and communicate with all stakeholders can significantly minimise damages and help maintain the trust of customers and partners.

3.2 Reputation, business continuity and legislation

A security incident can significantly damage the trust of a company's customers and partners. Corporate clients, business partners, and investors expect that their data—particularly sensitive information—is adequately protected and that the company is capable of managing risks. In the commercial world, a company's reputation carries direct financial value, and a data breach or major service outage can lead to a loss of customer trust, which may translate into reduced revenues. According to PwC's Annual Global Digital Trust Insights Survey [15], among the damages organisations have suffered over the past three years as a result of cyberattacks or data breaches are customer loss (27%), loss of client data (25%), and damage to reputation or brand (23%).

Since cyberattacks can paralyse critical systems and disrupt the entire operation of a company, managers must be able to ensure business continuity (BC). BC is achieved through the implementation of disaster recovery plans (DRP) and the regular testing of backup systems and procedures, as well as by increasing the resilience of processes against cyber threats.

Moreover, legislative frameworks such as GDPR [16] or the more recent NIS2 Directive [17] impose obligations on companies in the areas of data protection and incident prevention. Compliance with legislation is not only a legal requirement but also a mechanism that fosters trust among customers and business partners. Conversely, non-compliance with these regulations can result in significant fines and legal consequences, thereby increasing the pressure on management to actively support security education. A manager who understands the regulatory framework is able to ensure the alignment of internal processes with legal requirements, minimise the risk of substantial penalties, and proactively plan investments in security technologies and training.

3.3 Financial consequences of incidents and the meaning of the human factor

Cyberattacks, as well as internal errors, often have both immediate and long-term financial impacts. These include not only the direct costs of remediation but also indirect damages that may arise over time. Among them are expenses related to system recovery, legal services, fines, and the long-term consequences of customer loss. We can therefore state that this represents a form of:

- Direct Costs – These are associated with the restoration of IT systems, servers, and data, as well as legal services and court fees, payments for security audits, or the services of external specialists.
- Indirect Costs – These include the loss of customers or business partners and revenue declines caused by operational disruptions, as well as damage to brand and reputation, which may negatively affect future business opportunities.
- Long-Term Consequences – Reported incidents may result in fines related to legislation, for example, in cases of personal data theft; increased premiums for cyber risk insurance; as well as long-term internal investments directed toward technologies and training aimed at minimising future risks.

A significant share of cybersecurity incidents stems from human errors linked to insufficient awareness, commonly referred to as the human factor. This clearly demonstrates that technological solutions alone are insufficient; rather, education and a strong security culture within the company are considered essential.

An educated manager is capable not only of responding to incidents but, above all, of preventing them, implementing effective policies, and fostering a culture in which security is not merely a rule but a natural part of every employee's work.

4 METHODOLOGY AND ANALYTICAL PROCEDURE

The paper uses a conceptual and practice-orientated methodology. First, it summarises relevant literature on cybersecurity education, adult learning, gamification, simulations, and organisational security culture. Second, it derives role-specific educational requirements for three learner groups: management, administrative staff, and technical employees. Third, it applies SWOT analysis as a structured self-assessment tool for identifying educational and organisational priorities. Fourth, it translates the SWOT findings into operational recommendations that can be used when selecting training formats.

The SWOT analysis is not presented as a statistical measurement. Its purpose is to support reproducible managerial reasoning by making explicit which factors are considered internal strengths and weaknesses and which factors are interpreted as external opportunities and threats. In practice, each item should be scored by an organisation according to likelihood, impact, and current control maturity. The resulting priorities should then be validated through security audits, incident records, phishing-reporting statistics, employee surveys, and interviews with process owners.

To improve transparency, the following criteria guided the selection of educational approaches: role relevance, transfer to daily work, measurability of learning outcomes, feasibility for the organisation, alignment with legal and governance requirements, and contribution to resilience. These criteria provide a rationale for the recommendations and reduce the risk that the proposed measures appear arbitrary.

Table 1. Criteria for selecting and evaluating cybersecurity education approaches

Criterion	Meaning for Selecting Cybersecurity Education	Example of Operational Indicator
Role relevance	The approach fits the tasks and risk exposure of the learner group.	Separate learning paths for management, administrative staff, and technical staff.
Transfer to daily work	Training must support behaviour employees can apply immediately.	Ability to report suspicious emails, use MFA correctly, or follow incident procedures.
Measurability	The outcome can be evaluated without relying only on attendance.	Pre/post tests, reporting rates, exercise performance, observed compliance.
Feasibility	The approach is realistic in terms of time, cost, and available expertise.	Short modules for all staff; deeper simulations for high-risk roles.
Governance alignment	Training supports policies, legislation, and managerial accountability.	Coverage of GDPR, NIS2, incident reporting, and internal procedures.
Resilience contribution	The approach strengthens prevention, detection, response, or recovery.	Lower repeated errors; faster escalation; improved crisis coordination.

5 SWOT ANALYSIS OF CYBERSECURITY FROM THE PERSPECTIVE OF THE ORGANISATION

As we have noted, cybersecurity is currently one of the key areas influencing not only the technological resilience of a company but also its reputational and legal accountability. The size of the organisation is by no means a decisive factor. Statistically, attacks are more often directed at small and medium-sized enterprises, which generally lack well-developed protective mechanisms. Attackers attempt to exploit a wide range of technical and configuration vulnerabilities, as well as human ignorance, in order to infiltrate systems, gain access to devices and sensitive data, and ultimately disrupt the company's operations.

A good manager sets as a goal the regular evaluation of the state of cybersecurity and the following:

- Determine the actual state of security within the company
- Identify the greatest risks and vulnerabilities
- Propose specific measures to minimise risks
- Strive to raise awareness among employees and management about the importance of security measures within the organisation

In this work, we employ the well-known SWOT analysis, a tool familiar to managers, which makes it possible to evaluate the state of cybersecurity comprehensively and clearly through four categories:

- S – Strengths: It addresses what we do well and which security mechanisms are functioning effectively.
- W – Weaknesses: It identifies where deficiencies or vulnerabilities exist.
- O – Opportunities: It defines the opportunities for improvement or innovation.
- T – Threats: It is a list of factors that may threaten us, whether from external or internal sources.

In this work, we present two SWOT analyses that we developed and applied in assessing the state of cybersecurity within organisations. Due to the limited scope of this contribution, we will not provide a specific analysis of a selected company but will instead describe a practical approach to the activities required to achieve a thorough analysis. The first is a SWOT analysis of the general level of cybersecurity within a company, while the second is a SWOT analysis focused on the human factor, that is, the determination of awareness and knowledge of cybersecurity within the organisation. It is the latter analysis that interests us most, as this work is orientated toward the strategic significance of education. Naturally, it is possible to create a dedicated SWOT methodology for each distinct area of cybersecurity.

The context assumed for the SWOT examples is a small- or medium-sized organisation that depends on digital services, processes personal or business-critical data, and must comply with internal governance and external cybersecurity requirements. The listed factors should therefore be interpreted as a reusable analytical template rather than as findings from one named organisation. To apply the template reproducibly, organisations should document the evidence for each item, assign a priority score, identify the responsible owner, and define a related educational or technical response.

5.1 SWOT analyses – General level of the state of cyber security

S – strengths

- Use of modern IT infrastructure and regular renewal
- Existence of an internal team with certifications (ISO27001, CISSP, etc.)
- Implemented security policies
- Centralisation at the level of identity and access management (SSO, MFA, etc.)
- Cooperation with external companies for audits and consultations
- Regular penetration testing and the presence of SIEM monitoring

W – weaknesses

- Lack of professional staff for cybersecurity and overall IT
- Absence of an Incident Response Plan (IRP)
- Outdated, unpatched applications and unsupported hardware
- Underestimation of risks related to cloud services
- Low level of cybersecurity awareness, especially outside the IT department
- Non-compliance with applicable legislation (GDPR, Cybersecurity Act, and NIS2)

O – opportunities

- Availability of grants or state support for cybersecurity
- Integration of cybersecurity training as part of corporate culture
- Cooperation with CSIRTs or other MSSPs (Managed Security Service Providers)
- Automation of security processes, such as patch management
- Reduction of reputational risk through preventive measures

T – threats

- Ransomware, phishing, BEC (business email compromise)
- Leakage of sensitive or personal data
- Increase in fraud facilitated by AI (deepfake, voice spoofing, etc.)
- Deliberate as well as unintentional insider threats
- Stricter regulations arising from legislative changes
- Suppliers as a weak link in the chain

5.2 SWOT analyses – human factor

S – strengths

- High willingness of employees to participate in organised training
- Opportunity to utilise both internal and external training programmes
- Employees are aware and understand the value of corporate data.
- Security campaigns aimed at raising risk awareness

W – weaknesses

- Responses to fraudulent emails (phishing)
- Reusing the same passwords across multiple platforms
- Delaying device updates
- Failure to comply with internal policies
- Exposure to social engineering
- Low involvement of departments outside IT (finance, HR, etc.)

O – opportunities

- Implementation of simulated phishing campaigns
- Interactive training (gamified, e-learning, etc.)
- Internal cyber security ambassadors

- Integration with the company's social responsibility initiatives
- Feedback from real incident, so-called case studies

T – threats

- Employees as the "weakest link" (human factor)
- Attacks targeting specific individuals (spear phishing, whaling)
- Unintentional data leaks, use of public Wi-Fi
- Unsecured home office setups
- Employee overload leading to mistakes and inattentiveness
- Employees facing personal difficulties being more prone to errors

Table 2. Example of translating SWOT findings into education requirements

SWOT Finding	Evidence to Document	Training Requirement	Evaluation Measure
Low awareness outside IT	Survey results, helpdesk tickets, audit findings	Role-specific microlearning and workshops for non-IT departments	Knowledge test and incident-reporting rate
Responses to phishing emails	Simulation results and real reports	Reflective phishing exercises with immediate feedback	Click rate, report rate, repeated-error rate
Management crisis decisions	Incident drill observations	Table-top exercises for leadership and communication	Time to decision and quality of escalation
Unsecured home office	Remote-access audit, BYOD inventory	Short modules on MFA, secure Wi-Fi, and device updates	Compliance checks and policy acceptance
AI-enabled fraud	Threat intelligence and incident examples	Scenario-based learning on deepfakes and voice spoofing	Scenario recognition and escalation accuracy

The advantage of using SWOT analysis is that it:

- Enables the integration of technical and non-technical aspects of security
- Provides a clear presentation of results for both management and company leadership
- Supports strategic planning of security measures and investments
- Can be easily adapted to various segments, from infrastructure to employee training.

Thus, the use of SWOT analysis in assessing the state of cyber security (including self-assessment pursuant to §29, paragraph 1 of Act No. 69/2018 Coll. on Cyber Security and on Amendments to Certain Acts of the Slovak Republic) can provide companies with a clear and effective tool for identifying key areas requiring management's attention. At the same time, it can serve as a starting point for the implementation of concrete measures and for raising cybersecurity awareness across the entire organisation.

6 HOW TO EFFECTIVELY EDUCATE EMPLOYEES

One of the key pillars of building a resilient and adaptable organisation is effective employee education. We believe that all global experts on cybersecurity would agree with this statement. Simply conveying new information is far from sufficient; rather, it is essential to ensure its transfer into everyday practice, resulting in the long-term development of internal teams. Naturally, the educational needs of employees differ depending on their job position and level of responsibility. These can be categorised by level and role:

- Technical staff, who require more practical training and detailed procedures in order to respond more quickly to specific situations and to effectively use targeted tools.
- Administrative staff, who need to acquire skills in processes, communication, and the use of documentation while also focusing on the ability to coordinate and support other teams.
- Management, which must be orientated toward strategic leadership, decision-making in crisis situations, and the ability to create an environment in which knowledge is effectively disseminated among all employees.

Effective corporate education must be grounded in the principles of andragogy (adult learning) [18] [19], which emphasise practicality, immediate applicability, and the connection to the professional experience of course participants. Modern methods therefore aim to create interactive and experiential forms of learning that replace outdated, unengaging approaches based on passive information intake.

- Microlearning encompasses learning activities that are carried out on a small scale or within a limited time frame [20]. Information is delivered in short, thematically coherent modules, typically lasting 2 to 5 minutes, which increases retention rates and enables more flexible learning. For cybersecurity, this format is more effective in quickly adopting factors, procedures, and updates that might otherwise be lost within the vast volume of information in traditional, more extensive training [21]. *Practical application*: Short videos or learning modules can be used for the rapid adoption of new security rules, familiarisation with software updates, or changes in internal regulations.

The educational value of microlearning is highest when short modules are connected to concrete behaviours and repeated over time. Therefore, microlearning should not replace deeper training for high-risk roles but should serve as a reinforcement mechanism for rules, updates, and recurring mistakes identified through audits or incident reports.

- Simulation exercises are based on the concept of experiential learning, where participants acquire knowledge through experience, reflection, and application of insights in a controlled environment. A typical example requiring adaptation of the real work environment includes tasks whose mastery—or even learning their basics under operational conditions—disproportionately increases risk [22]. In the case of cybersecurity, the risk of potential system compromise is substantial, which makes it appropriate to train users and managers in a simulated environment where such risks do not exist. *Practical application*: In the field of cybersecurity, two teams can be created (the so-called red team vs blue team) to test each other's preparedness and response capability during an attack. Similarly, model exercises can be designed to practise correct procedures in the event of a data breach, for crisis management leadership, and, most importantly, for the simulation of strategic decision-making.

In this paper, phishing simulations and table-top incident exercises are treated as pedagogical interventions only when they include preparation, feedback, reflection, and follow-up learning. Their purpose is not to shame employees but to identify risky situations, support reporting behaviour, and provide evidence for targeted training improvements [23] [26].

- Internal workshops enable colleagues to share experiences and foster a so-called community of practice. This concept, introduced by Wenger [23], describes a setting where knowledge spreads organically and new procedures are developed, tailored to the specific context of the organisation. Workshops also serve as a highly effective managerial tool for supporting corporate culture and strengthening team identity. *Practical application*: They are ideal for sharing experiences across departments. For example, the IT department may present new security procedures, or company leadership may introduce new strategies and discuss their implementation with teams.
- Blended learning combines physical and digital learning in a conscious and integrated way. The aim of blended learning is to shape education in such a way that it becomes more effective, efficient and flexible with the help of IT [24]. In cybersecurity education, this approach is grounded in the theory of blended learning, which combines the advantages of self-directed study—such as learning pace and flexibility—with those of collective learning, where feedback and discussion with the instructor provide significant opportunities for knowledge transfer. *Practical application*: A typical example may be the combination of an e-learning module (e.g., a Moodle course) on GDPR, NIS2, or the Cyber Security Act, together with a workshop where employees practise solving specific case studies.
- Gamification of education refers to the use of game elements in a non-game context [25]. In teaching, gamification is applied as a stimulating tool for learners, aiming to make the learning process more engaging, interactive, and enjoyable. By incorporating gamification, it is possible to increase interest in cybersecurity training and make the learning experience more entertaining [26]. For managers, it is important to carefully plan the introduction of such games. This plan must be based on clearly defined goals, since all objectives and tools work effectively only if participants experience genuine engagement and motivation from the game [27]. In the context of cybersecurity education, this represents one of the manager's most important tasks. *Practical application*: An example we use is the implementation of company challenges, where employees collect points for completing security quizzes. This serves as a motivational tool for fostering a culture of continuous learning.

For clarity, gamification does not mean that the whole training becomes a game. It means that selected game design elements are added to a non-game learning process. Serious games or cyber-range games are separate formats that require more extensive design, scenarios, and evaluation. Managers should therefore select gamification when the aim is motivation and reinforcement, and serious games or simulations when the aim is deeper experiential learning.

- Mentoring and coaching as personalised approaches provided by more experienced colleagues or an external coach are based on Bandura's principles of social learning [28] [29], where observation, modelling, and feedback form the foundation. Coaching fosters self-reflection and critical thinking, while mentoring also transfers cultural and informal organisational knowledge, which then reflects the overall perception of cybersecurity within the company. *Practical application*: New employees are assigned a mentor who guides them and imparts not only knowledge but also corporate values. Coaching is used primarily in leadership, aimed at developing leadership competencies, the ability to make quick decisions under pressure, and crisis management skills.

By combining these forms appropriately, it is possible to achieve greater retention and transfer of knowledge into practice than would be the case with traditional training. The manager must evaluate the benefits of education and establish measurable indicators. In this way, they can implement the following:

Table 3. Linking learner groups, education approaches and measurable outcomes

Learner Group	Main Learning Need	Suitable Approach	Measurable Outcome
Top management	Strategic risk ownership, legal duties, crisis decisions	Table-top exercises, executive briefings, incident simulations	Decision quality, escalation time, approval of resources
Middle management	Policy implementation and team behaviour	Workshops, case studies, peer discussion	Team compliance, reporting culture, completed action plans
Administrative staff	Recognition of phishing, data handling, reporting	Microlearning, blended learning, reflective phishing simulations	Reporting rate, lower repeated mistakes, test results
Technical staff	Incident response, configuration, secure operations	Hands-on labs, cyber ranges, mentoring	Exercise performance, recovery time, reduced misconfiguration
New employees	Onboarding into security culture	Mentoring, short modules, role-specific checklists	Completion of onboarding and correct use of procedures

- Regular knowledge testing
- Monitoring success in solving model situations
- Gathering feedback from participants as well as their supervisors
- Evaluating team collaboration during stress-related tasks

Naturally, the manager must evaluate not only individuals but also sub-teams and the team as a whole. A suitable approach in this regard is the use of exercises that test employees' ability to function under pressure, collaborate effectively, and maintain process continuity even during unexpected events.

Today, the possibilities for employee education are highly diverse—ranging from internal workshops, e-learning platforms, and mentoring to cooperation with external experts or universities. The foundation for securing qualified employees is laid primarily within the educational process at universities, which shape young people (potential employees) and provide high-quality education in the field of security [30]. For a manager, it is essential to establish a systematic framework in which educational methods are appropriately combined and adapted to the needs of different employee groups and, subsequently, to the company as a whole. Only in this way does education become not merely an obligation but a natural part of corporate culture and a key factor in the organisation's long-term competitiveness.

7 SECURITY CULTURE AS A PART OF STRATEGY OF A COMPANY

Effective employee education forms the foundation for building resilient teams and, consequently, a resilient organisation as a whole. However, the process does not end with the one-time acquisition of knowledge; it is equally important to verify it, conduct regular testing, and create conditions in which employees can retain new insights and apply them in practice. For this reason, the next step is to focus on methods of measuring learning outcomes and evaluating the readiness of teams to face real-world challenges.

Security culture is increasingly becoming an inseparable part of corporate strategy. It can be understood as a set of fundamental assumptions, values, norms, rules, symbols, and beliefs that shape the perception of challenges, opportunities, and risks, as well as the ways in which security is understood and considered. This also encompasses the related methods and patterns of learned behaviour and interaction among social actors, aimed at ensuring the safe continuity and development of all reference entities and of society as a whole [31].

In the field of security, it is no longer just about technical measures or rules in internal guidelines, nor is it solely a matter for IT departments. All measures and their effectiveness depend—and will continue to depend—primarily on people's attitudes, their motivation, their stance, and their everyday behaviour. The task of the organisation is therefore to create an environment in which security becomes a natural value and an integral part of corporate identity. The manager plays a key role in building security culture, demonstrating through their own behaviour the importance of compliance with rules and the proper approach to risks. If a leader disregards internal procedures, they cannot expect employees to respect them. Conversely, if a manager actively communicates about security topics, supports employees in reporting incidents, and rewards safe behaviour, they foster an atmosphere of trust. In such a setting, security becomes a shared responsibility rather than an imposed obligation.

Security culture in a company does not emerge solely through top-down management. It requires acceptance, commitment and support (buy-in) across the entire organisation. In short, employees at all levels must understand why security matters, what it means for their daily work and what it implies for them personally. For this reason, communication must be clear, understandable, and focused on benefits, not just sanctions. Likewise, it is important to employ modern methods such as gamification, interactive training, and simulations, which actively engage people in security issues. This also helps ensure that security measures are not perceived as an administrative burden but rather as a natural part of business processes.

The security culture of a company is closely connected to the concept of ESG—environment, social and governance. The core idea of ESG may bring tangible benefits in the financing of sustainable activities, which is also reflected in EU legislation. This gradually creates pressure for ESG reporting even among entities not directly bound by such legal obligations [32]. Within the "governance" dimension, emphasis is placed on transparency, risk management, and ethical conduct. In the Slovak Republic, this is embedded in Act No. 69/2018 on Cyber Security [33], as amended by Act No. 366/2024 Coll. [34], effective from January 1, 2025, along with NBU Decree No. 226/2025 Coll. [35] on reporting requirements and NBU Decree No. 227/2025 Coll. [36] on security measures. All of these laws and decrees reflect Directive (EU) 2022/2555 on measures for a high common level of cybersecurity across the Union, amending Regulation (EU) No. 910/2014 and Directive (EU) 2018/1972, and repealing Directive (EU) 2016/1148 (NIS2 Directive) [37]. Organisations that work systematically on building security awareness thereby, strengthen not only their internal stability but also their credibility with customers, partners and investors, while also ensuring compliance with legal requirements.

Responsibility in the field of cybersecurity also carries a broader social dimension in preventing incidents that could negatively affect communities or harm the public interest. In this sense, security culture becomes not only an internal tool but also part of the organisation's social responsibility. Security culture is a long-term process that requires leadership commitment, the involvement of all employees, and strategic anchoring within corporate policy. An organisation that understands security as a value rather than merely an obligation gains not only higher resilience against risks but also a competitive advantage in the eyes of the market and society at large.

8 DISCUSSION AND THREATS TO VALIDITY

The analysis suggests that cybersecurity education should be understood as a continuous pedagogical process linked to organisational risk management. The central result is not a universal list of training formats but a set of criteria for selecting and evaluating formats according to learner roles, organisational weaknesses, and resilience objectives. This addresses the practical problem that many organisations conduct security training as a formal compliance activity without demonstrating how it changes behaviour or supports incident readiness.

The SWOT framework is useful because it creates a common language for managers, technical staff, and educators. Nevertheless, SWOT has limitations. It can oversimplify complex socio-technical problems and may reflect the perceptions of the people involved in the assessment. Therefore, a SWOT analysis should be treated as a starting point and combined with empirical evidence such as audit logs, incident data, exercise results, and employee feedback.

The validity of the proposed framework is limited by the fact that it is conceptual and has not been tested in one controlled organisational case. The paper therefore does not claim causal evidence that a particular training method will reduce incidents in every context. Future work should apply the framework in a specific organisation, collect pre- and post-training data, and compare the effectiveness of different educational interventions across roles.

9 WHAT IS POSSIBLE TO DO IMMEDIATELY?

Building a security culture within a company is a long-term process, yet there are steps that managers can implement immediately. These activities not only strengthen the level of cybersecurity within the organisation but also send a clear signal that education and awareness are of strategic importance for stability and competitiveness.

First and foremost, it is necessary to create a systematic training plan that should cover not only technical staff, administrative employees, and management but also the CSM himself or herself. Leaders who actively educate themselves in cybersecurity set an example for others and demonstrate that it is a priority for the entire organisation. After all, an organisation's security is only as strong as its weakest link. Although this comparison may not be pleasant, it unfortunately reflects reality.

A weakness in the form of a user disclosing their login credentials in a phishing campaign can bring down any company, just as a misconfiguration caused by a technical oversight can. Therefore, it is essential to identify weaknesses in time, whether in technical knowledge, appropriate responses to phishing campaigns, or understanding of internal procedures. Identifying such weaknesses enables education to be targeted where it delivers the greatest benefit.

For better managerial orientation, it is advisable to begin with a security awareness audit. Such an audit provides an objective picture of how well employees understand risks and whether they are able to respond adequately. In addition to a traditional security audit, which can be carried out through self-assessment or by an external entity, managers can conduct phishing simulations, short questionnaires, or incident drills. What matters most is the outcome of these evaluations, which must serve as a basis for targeted training and the improvement of processes.

Another key point is the support of the security specialist—ideally, the cybersecurity manager. It is important that the manager not only formally approves but also actively supports their work. This involves ensuring that the CSM has space to communicate with the team, that leadership legitimises their recommendations and that sufficient resources are allocated for the implementation of measures. Such support reinforces the perception of security as a strategic priority and helps reduce the risk of measures remaining only on paper.

Even small and immediate measures can have a profound impact on the future preparedness of an organisation. Training, audits, and systematic support of specialists create the foundation on which long-term development can be built. Companies that implement security activities without delay gain a significant advantage: not only do they achieve better protection against incidents, but they also build stronger credibility with clients, partners and regulatory authorities.

The answer to the question of what an organisation can do immediately is the following:

- Develop a role-specific training plan based on risk exposure, legal duties and prior incident evidence.
- Identify and score the most significant weaknesses using evidence from audits, simulations, surveys and incident records.
- Initiate a security awareness audit with measurable indicators such as reporting rate, click rate, knowledge test results and escalation time.
- Support the security specialist by giving the cybersecurity manager authority, resources and access to management decision-making.

10 CONCLUSION

Effective cybersecurity education is not a one-time activity but a long-term pedagogical process that must reflect the responsibilities, prior knowledge and risk exposure of different learner groups. The paper contributes a practice-orientated framework that links related work, SWOT-based self-assessment, learner roles, educational approaches and measurable outcomes.

The most successful organisations are those that manage to connect theory with practice and create an environment in which education becomes a natural part of corporate culture. It is crucial, especially for leadership, to understand that education is not an expense but an investment—an investment in the stability, reputation and credibility of the organisation. Every euro invested in employee development pays off in the form of lower incident risk, greater efficiency and better readiness to face increasingly complex challenges. Cyber security thus begins with corporate management. Leaders set the tone, shape the culture and, by their example, determine whether security measures will truly work. When management actively engages in education, supports security specialists and sends a clear message that security is a strategic priority, this attitude gradually permeates the entire organisation.

The creation of SWOT analyses for organisational self-assessment can provide companies with a clear and effective framework for identifying key areas requiring attention. Furthermore, it can serve as a starting point for the implementation of specific measures and for enhancing security awareness across the organisation.

Operational recommendations derived from the SWOT analyses:

- Introduce mandatory but role-specific cybersecurity training, with short modules for all staff and deeper exercises for high-risk roles.
- Use simulated attacks only with feedback, reflection and follow-up training, and measure both click rates and reporting behaviour.
- Establish internal cybersecurity ambassadors who connect local work practices with central security policies.
- Raise awareness of AI-related threats through scenarios covering deepfakes, voice cloning and social engineering.
- Implement BYOD and secure remote-access rules as part of training, not only as technical or legal documents.
- Foster a cybersecurity culture that rewards early reporting and treats errors as opportunities for organisational learning.

For all the reasons mentioned, it can be concluded that education in the field of cybersecurity is not merely a matter of legal compliance or the fulfilment of formal requirements, but above all a tool for long-term competitiveness. Companies that approach it strategically gain an advantage not only today but also in the future.

11 REFERENCES

[1] Redakcia, *Počet kybernetických útokov na Slovensku v prvom polroku prudko rástol*, NEXTECH 2025. [Online]. Available: https://www.nextech.sk/a/Pocet-kybernetickych-utokov-na-Slovensku-v-prvom-polroku-prudko-rastol

[2] I. Lella, M. Theocharidou, E. Magonara, A. Malatras, R. Svetozarov Naydenov, C. Ciobanu, and G. Chatzichristos, Eds., *ENISA Threat Landscape 2024*, 2024. [Online]. Available: https://www.enisa.europa.eu/sites/default/files/2024-11/ENISA%20Threat%20Landscape%202024_0.pdf

[3] ESET, *Školenie kybernetickej bezpečnosti*, 2026. [Online]. Available: https://www.eset.com/sk/firemna-it-bezpecnost/bezpecnostne-sluzby/services/riadenie-it-bezpecnosti/skolenie-kybernetickej-bezpecnosti/

[4] IBM, *Cost of a Data Breach Report 2025*, 2025 [Online]. Available: https://www.ibm.com/downloads/documents/us-en/131cf87b20b31c91

[5] Národný bezpečnostný úrad SR, *Upozornenie na AI model*, 2025. [Online]. Available: https://www.nbu.gov.sk/upozornenie-na-ai-model/

[6] IBM, *Cost of Data Breach Report 2023*, 2023. [Online]. Available: https://thehackernews.com/2023/12/cost-of-data-breach-report-2023.html

[7] ISACA, *ISACA Journal, Volume 5, 2022*. [Online]. Available: https://www.isaca.org/resources/isaca-journal/issues/2022/volume-5

[8] J. Prümmer, T. van Steen, and B. van den Berg, "A systematic review of current cybersecurity training methods," *Computers & Security*, vol. 136, p. 103585, 2024. https://doi.org/10.1016/j.cose.2023.103585
[9] D. Hillman, M. Hennessy, and C. B. Mayhorn, "Evaluating organizational phishing awareness training on an enterprise scale," *Computers & Security*, vol. 134, p. 103461, 2023. https://doi.org/10.1016/j.cose.2023.103461
[10] A. M. Alnajim, S. Habib, M. Islam, H. S. AlRawashdeh, and M. Wasim, "Exploring cybersecurity education and training techniques: A systematic review," *Symmetry*, vol. 15, no. 12, p. 2175, 2023. https://doi.org/10.3390/sym15122175
[11] R. Petersen, D. Santos, M. C. Smith, K. A. Wetzel, and G. Witte, "Workforce framework for cybersecurity (NICE framework)," NIST Special Publication 800-181 Revision 1, National Institute of Standards and Technology, 2020. https://doi.org/10.6028/NIST.SP.800-181r1
[12] G. Ho *et al.*, "Understanding the efficacy of phishing training in practice," in *Proceedings of the IEEE Symposium on Security and Privacy*, 2025. https://doi.org/10.1109/SP61157.2025.00076
[13] S. Deterding, D. Dixon, R. Khaled, and L. Nacke, "From game design elements to gamefulness: Defining gamification," in *Proceedings of the 15th International Academic MindTrek Conference*, 2011, pp. 9–15. https://doi.org/10.1145/2181037.2181040
[14] N. H. Weeratunge *et al.*, "Game-based cybersecurity awareness and education: A scoping review," *Information Systems Frontiers*, 2026. https://doi.org/10.1007/s10207-026-01239-9
[15] PwC, *2022 Global Risk Survey*, 2022. [Online]. Available: https://www.pwc.com/us/en/services/consulting/cybersecurity-risk-regulatory/assets/pwc-global-risk-survey-report-2022-main.pdf
[16] GDPR – General Data Protection Regulation.
[17] NIS2 – Directive (EU) 2022/2555.
[18] Denisa Šukolová, *Kontexty andragogického výskumu*. Bratislava: Národný inštitút vzdelávania a mládeže, 2019. [Online]. Available: https://www.researchgate.net/publication/338535965_KONTEXTY_ANDRAGOGICKEHO_VYSKUMU
[19] V. Tamášová, J. Péteriová, and S. Barnová, "Nové výzvy a trendy v andragogickej profesionalizácii študentov andragogiky na Slovensku," ResearchGate, 2018. [Online]. Available: https://www.researchgate.net/publication/327766191_Nove_vyzvy_a_trendy_v_andragogickej_profesionalizacii_studentov_andragogiky_na_Slovensku
[20] Y.-M. Lee, "Mobile microlearning: A systematic literature review and its implications," *Interactive Learning Environments*, vol. 31, no. 7, pp. 4636–4651, 2023. https://doi.org/10.1080/10494820.2021.1977964
[21] S. Balasundaram, J. Mathew, and S. Nair, "Microlearning and learning performance in higher education: A post-test control group study," *Journal of Learning for Development*, vol. 11, no. 1, pp. 1–14, 2024. [Online]. Available: https://files.eric.ed.gov/fulltext/EJ1423546.pdf
[22] J. Stebila, "Rozvoj inovatívnych foriem vzdelávania. Didaktika odborného výcviku," Banská Bystrica: Univerzita Mateja Bela, n.d. [Online]. Available: https://lms.umb.sk/mod/resource/view.php?id=38624
[23] E. Wenger, *Communities of Practice: Learning, Meaning, and Identity*. Cambridge: Cambridge University Press, 1998. https://doi.org/10.1017/CBO9780511803932
[24] SURF, "Blended education explained," n.d. [Online]. Available: https://www.surf.nl/en/themes/blended-education/blended-education-explained
[25] M. Púpavová, "Gamifikácia a eLearning vo vzdelávaní: Čo tieto pojmy znamenajú?" *Eduworld*. [Online]. Available: https://eduworld.sk/cd/martina-pupavova/2170/gamifikacia-a-elearning-vo-vzdelavani-co-tieto-pojmy-znamenaju
[26] S. Tesaříková, "Gamifikace výuky kybernetické bezpečnosti za využití CTF platforem," 2021. [Online]. Available: https://theses.cz/id/uwx32r/

[27] R. Machová, F. Lilla, Z. Godany, and E. Korcsmáros, "Gamifikácia a vzdelávanie manažérov – Inovatívne metódy vo vzdelávaní v teórii a praxi," ResearchGate, 2020. [Online]. Available: https://www.researchgate.net/publication/354294716_Gamifikacia_a_vzdelavanie_manazerov_-_Inovativne_metody_vo_vzdelavani_v_teorii_a_praxi
[28] V. Koutroubas and M. Galanakis, "Bandura's social learning theory and its importance in the organizational psychology context," *Psychology Research*, vol. 12, no. 6, pp. 315–322, 2022. https://doi.org/10.17265/2159-5542/2022.06.001
[29] S. McLeod, "Albert bandura's social learning theory," SimplyPsychology, 2025. [Online]. Available: https://www.simplypsychology.org/bandura.html (cit. 14.9.2025).
[30] B. Halúsková and E. Mošková, "Využívanie technológií v oblasti vzdelávania v bezpečnosti," Zlín: UTB, 2022. [Online]. Available: https://trilobit.fai.utb.cz/Data/Articles/PDF/f28a8f78-693b-439d-989e-a104780e8925.pdf (cit. 14.9.2025).
[31] L. Hofreiter, "Security culture and security management," *Krízový Manažment*, vol. 14, no. 2, pp. 63–68, 2015. https://doi.org/10.26552/krm.C.2015.2.63-68
[32] S. Heseková, "Problematika ESG na finančných trhoch," Zenodo, 2023. [Online]. Available: https://doi.org/10.33542/VSCD-0269-5-07
[33] Slov-lex. Zákon č. 69/2018 Z. z. [Online]. Available: https://www.slov-lex.sk/ezbierky/pravne-predpisy/SK/ZZ/2018/69/
[34] Slov-lex. Zákon č. 366/2024 Z. z. [Online]. Available: https://www.slov-lex.sk/ezbierky/pravne-predpisy/SK/ZZ/2024/366/
[35] Slov-lex. Zákon č. 226/2025 Z. z. [Online]. Available: https://www.slov-lex.sk/ezbierky/pravne-predpisy/SK/ZZ/2025/226/vyhlasene_znenie
[36] Slov-lex. Zákon č. 227/2025 Z. z. [Online]. Available: https://www.slov-lex.sk/ezbierky/pravne-predpisy/SK/ZZ/2025/227/vyhlasene_znenie
[37] EUR-Lex. Directive (EU) 2022/2555 of the European Parliament and of the Council. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32022L2555

12 AUTHORS

Pavel Beňo is currently working at Comenius University in Bratislava and at Trnava University in Trnava, has a Ph.D. from the Faculty of Applied Informatics at Tomas Bata University in Zlín, Czech Republic, in the fields of remote laboratories, security and cloud computing. He is a research assistant and creator of the cloud computing technology for university and REMLABNET purposes. He is also an expert in network security and penetration testing in computer crime prevention. He is the author of many publications in the field of informatics, security and education. For many years he has worked as a teacher with research in pedagogy and didactics of the sciences (E-mail: pavel.beno@uniba.sk).

Roman Hrmo is a Professor at the Department of Didactics of Vocational Subjects at DTI University, Slovakia. A leading expert in engineering pedagogy, he serves on the doctoral council for Didactics of Technical Subjects. He has contributed to internationally recognised research and led multiple scientific projects. He holds memberships in key bodies, including the Executive of IGIP and the EUR-ACE® Label Committee of ENAEE, and serves as President of the Slovak Monitoring Committee of IGIP (E-mail: hrmo@dti.sk).

Online-Journals.org

iJEP International Journal of Engineering Pedagogy

iJEP | eISSN: 2192-4880 | Vol. 16 No. 5 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijep.v16i5.61821

PAPER

AI-Based Learning Analytics and Real-Time Monitoring for IoT-Enabled Smart Laboratory of Engineering Education

Haider TH. Salim ALRikabi[1] (✉),
Farah Sabir Mohammed[2],
Huda Abbas Kanber[3],
Meithem Hashem Ali[4],
Hussain Ali Mutar[1],
Ibtihal R. Niama ALRubeei[1]

[1]Wasit University, Wasit, Iraq

[2]Al-Karkh University of Science, Baghdad, Iraq

[3]University of Baghdad, Baghdad, Iraq

[4]Iraqia University, Baghdad, Iraq

hdhiyab@uowasit.edu.iq

ABSTRACT

Engineering laboratories play a significant role in facilitating problem-based learning across electrical, environmental, computer, and interdisciplinary engineering programs; however, most lab sessions still rely on physical attendance, delayed grading, limited equipment references, and little visibility into student engagement. This lack of visibility compromises instructors' ability to identify learning barriers, unsafe conditions, uneven resource use, and at-risk students during lab sessions. An Internet of Things (IoT) smart lab framework is proposed that uses real-time sensor data, edge processing, and cloud storage to support learning analytics for improved operational and pedagogical decisions. The framework integrates data from environmental sensors, smart equipment, workstation logs, access control, and learning platforms to create a continuous data stream. An analytic layer processes this data using structured event learning and sequence modeling to estimate engagement, detect at-risk sessions, identify equipment bottlenecks, and enable timely intervention. A prototype simulated undergraduate engineering lab is developed to evaluate latency, reliability, predictive performance, and interpretability. Results show 93.4% engagement accuracy, 0.914 macro-F1, 0.887 AUROC for early risk detection, and 1.8 seconds median latency, outperforming temporal and non-temporal baselines. These findings demonstrate that multimodal sensing with explainable AI improves operational visibility and educational analytics. The framework defines the engineering lab as a cyber-physical learning environment rather than a collection of devices, supporting safer, more efficient, and data-driven learning across engineering disciplines.

KEYWORDS

Internet of Things (IoT), smart laboratory, engineering education, real-time monitoring, learning analytics, edge AI

ALRikabi, H. T. S., Mohammed, F. S., Kanber, H. A., Ali, M. H., Mutar, H. A., ALRubeei, I. R. N. (2026). AI-Based Learning Analytics and Real-Time Monitoring for IoT-Enabled Smart Laboratory of Engineering Education. *International Journal of Engineering Pedagogy (iJEP)*, 16(5), pp. 46–61. https://doi.org/10.3991/ijep.v16i5.61821

Article submitted 2026-02-06. Revision uploaded 2026-04-10. Final acceptance 2026-04-22.

1 INTRODUCTION

Laboratory work is essential to engineering education by connecting abstract concepts and applying principles to real experiments. Unfortunately, in many schools, the lab environment remains largely unobservable, such as manually taking attendance, inferring who or how many people are using a workstation informally, and instructors' need to use their intuition instead of having access to ongoing evidence of a team's engagement, confusion, waiting for equipment, or unsafe working conditions [1–3]. The gap created by these unobservable activities is widening due to an increase in class size, networked laboratory equipment, and a greater emphasis on linking the results of independent experimentation, through the use of data, to reflections in group settings [4, 5].

An intelligent learning space is possible due to a combination of Internet of Things (IoT) infrastructure and embedded sensing/AI learning analytics [6, 7]. Low-cost, IoT-sourced sensor data on environmental factors (environment, resource consumption, activity at bench) can be converted into engagement/progress/risk indicators through AI-based learning analytics that utilize disparate (heterogeneous) data signals. There has been a steady increase recently in historical scholarly literature on these areas, including smart ed systems, AI learning analytic dashboards, edge computing-enabled real-time ed analytics, showing that the actual underlying techs have developed through time as shown in Figure 1, but typically are looked at/interpreted individually and not in an integrated lab setting [8–11]. Smart lab.

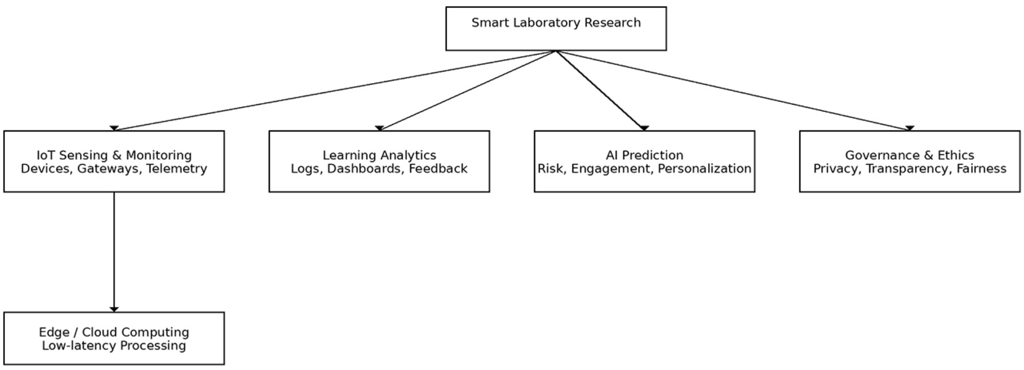

Fig. 1. Taxonomy of research themes converging on the smart laboratory problem, including IoT sensing, learning analytics, AI prediction, edge/cloud processing, and governance

This paper addresses that gap by proposing an IoT-enabled smart laboratory framework for engineering education with real-time monitoring and AI-based learning analytics. The paper contributes four elements. Firstly, it provides a layered architecture that integrates sensing, communication, edge processing, cloud services, AI inference, and dashboard delivery as shown in Figure 2. Secondly, it formulates smart laboratory analytics as a constrained multi-objective optimization problem balancing predictive quality, latency, privacy, and resource efficiency. Third, it defines a hybrid analytics pipeline that fuses structured event learning and temporal sequence modeling. Fourth, it demonstrates how figures, charts, and evaluation tables can be embedded into a journal-style paper to make the system design and results immediately interpretable.

Smart laboratories for Engineering require extra capabilities that can be differentiated from standard smart classrooms. The requirements for instrument contention, safety monitoring, environmental control, and phase-dependent task workflows will impact on the educational experience; therefore, these sources of variance should also be reflected in the analytical layer of data [12–15]. An inactive student due to disengagement is educationally different than an inactive student who is waiting for a shared oscilloscope or troubleshooting a sensor interface. Therefore, the smart laboratory must analyze both the operational context and the pedagogical signals collectively to provide efficient learning rather than analyzing them in isolation from one another [16–18].

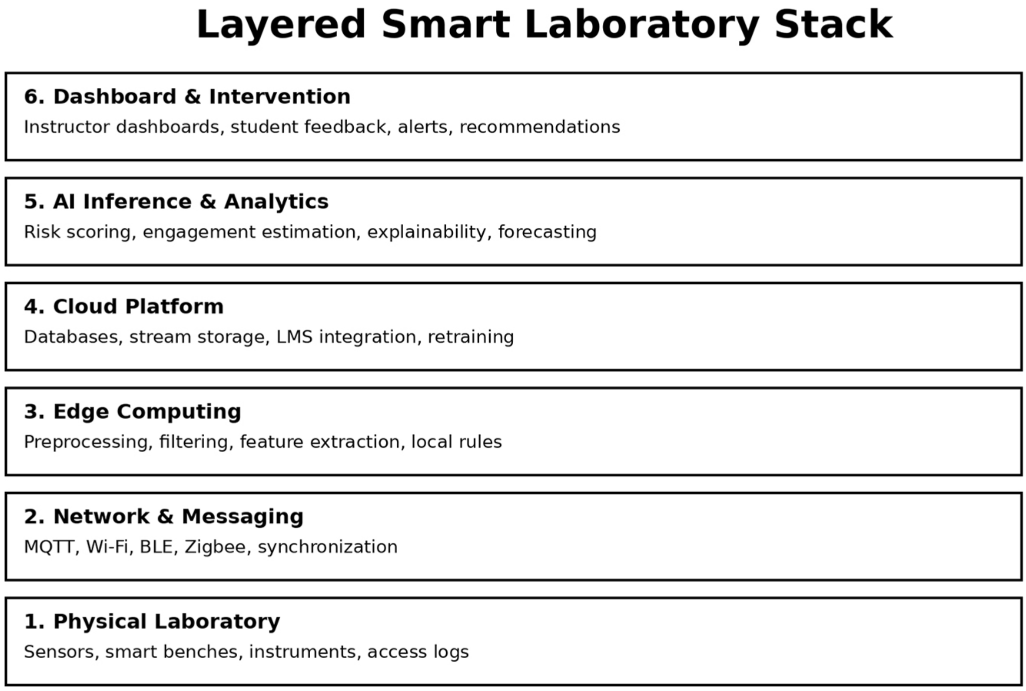

Fig. 2. Layered stack of the proposed smart laboratory, from physical sensing to dashboard-based intervention

2 RELATED WORK

This paper reviews literature from three areas that are interrelated: IoT-enabled educational environments, learning analytics for laboratories or hands-on practice-based scenarios, and AI systems at the edge with real-time support. Recent reviews of smart classrooms indicate that connected sensors, orchestrated devices, and adaptive digital infrastructure are being used in the growing number of classrooms and laboratory-like facilities. [19, 20]. Simultaneously, systematic reviews of AI-powered assisted learning dashboards and AI-assisted collaborative learning dashboards show an increased interest in prediction support, early warning systems, and visual analytics directed towards educators [21–23]. A third stream of research examines the implications of 'edge-enabled' educational processing and argues for the potential of 'low latency' analytics as timely and actionable for educational intervention [24, 25].

While there are some promising developments within these areas, literature continues to exhibit evidence of fragmentation [26–28]. Most of the IoT studies within education emphasize hardware or platform design as opposed to learning analytics; conversely, most of the learning analytics literature relies upon LRS traces or VLEs and does not consider the physical/sociocultural/safety complexities of engineering labs as illustrated in Table 1. Therefore, there is a disconnect between operational (i.e., smart) lab monitoring and pedagogically relevant analytics [26, 27, 29, 30].

Table 1. Comparative positioning of the proposed framework against major research directions in smart education and learning analytics

Study Focus	IoT Sensing	Real-Time Support	AI Analytics	Lab Specificity	Main Limitation
Smart education IoT reviews	High	Medium	Low	Medium	Broad scope, limited engineering-lab specificity
Learning analytics dashboards	Low	Medium	High	Low	Often weak on physical telemetry
Virtual laboratory analytics	Low	Medium	Medium	Medium	Physical bench context absent
Edge-enabled educational analytics	Medium	High	Medium	Low	Pedagogical interpretation limited
Proposed framework	High	High	High	High	Designed as integrated cyber-physical educational system

This study will take place at the convergence of three distinct streams of research [31]. The current proposal will integrate real-time data sensing into existing methods of extracting educationally relevant features, building explainable AI to support educational interventions, and using this integrated architecture to overlay instructor-oriented intervention logic. This combination of methodologies has been called for by the recent emphasis on using human-centered AI in education, as successful implementation of AI requires trust, explainability, and instructor input [32, 33].

2.1 Problem formulation

This smart lab is a cyber-physical learning environment that generates asynchronous data streams over time with respect to the students, their equipment, the workstations they are working from, and the environmental conditions they are experiencing. We will denote by t the time index, i the student or team index, and x_i,t the fused feature vector we observe at t for each student/team i through a sliding window of time. Fused feature vectors are based on measurements of the environmental conditions, attendance/access events, usage statistics for each piece of equipment, workstation activity logs, and learning platform traces.

$$x_{i,t} = \phi(s_{t-w:t}, a_{t-w:t}, u_{t-w:t}, l_{t-w:t})$$

$$\hat{y}_{i,t} = f_{\theta}(x_{i,1:t}) \rightarrow [\text{engagement, risk, operational state}]$$

There are three ways that an Engagement System can be inferred in Figure 3:

1. By inferring the engagement level of a learner (or team)
2. The chance that your ongoing session will provide either poor completion performance or low understanding.
3. The operational state of the laboratory includes equipment congestion (shared equipment), resource idleness, or environmental abnormality (e.g., temperature or humidity). Since the objectives above are dependent upon each other, the design will be to treat this as a constrained multi-objective optimization problem, rather than merely making a single classification decision.

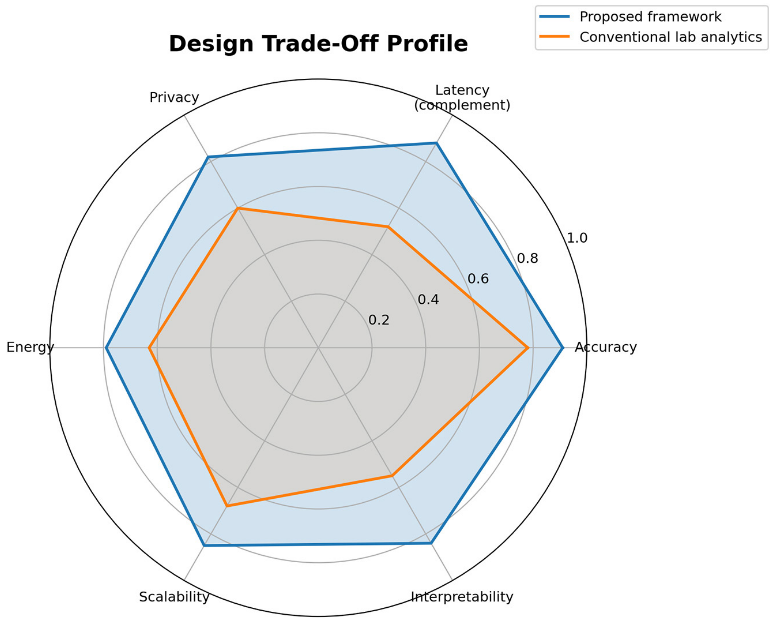

Fig. 3. Design trade-off profile showing the intended balance between prediction quality, latency, privacy, energy, scalability, and interpretability

$$L = \lambda_1 L_{\text{eng}} + \lambda_2 L_{\text{risk}} + \lambda_3 L_{\text{ops}}$$

$$\text{subject to } \tau_{\text{infer}} \leq \tau_{\max}, E_{\text{node}} \leq E_{\max}, P_{\text{leak}} \leq \varepsilon$$

Figure 4 represents the realities of deployment: An educational monitoring or assessment system should be as accurate as possible within its framework, have the capability to react in the same lab period, and maintain the privacy of students as required by institutional policy. If a system is accurate and does not operate in “real-time,” or provides useful information about learning but does not disclose it to learners, then it will not be very useful in an actual engineering education programmer.

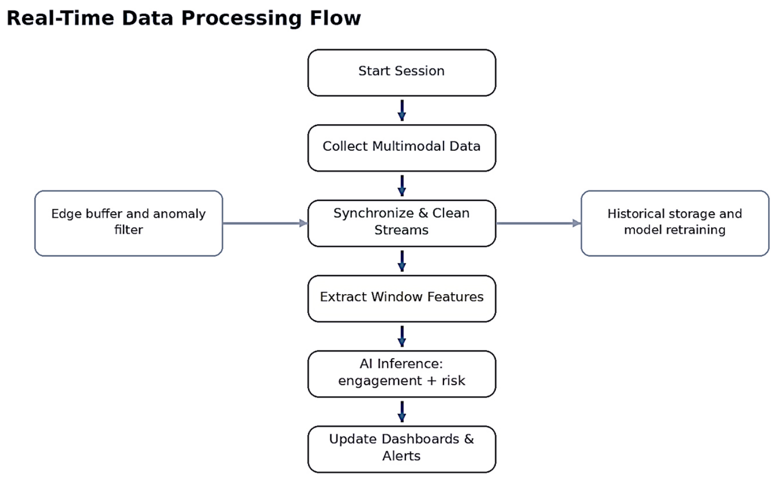

Fig. 4. Real-time data processing flow from session start to dashboard update

3 PROPOSED IOT-ENABLED SMART LABORATORY SYSTEM

This system is organized into six layers. The Sensory Layer contains all of the environmental sensors, power meter, smart plug, workstation agents, and any other access-control components we will use. The Communication Layer provides communication between the devices through lightweight protocols (e.g., Wi-Fi, BLE, ZigBee, and MQTT) to the gateway. The Edge Layer performs timestamp synchronization, noise reduction, missing data recovery, and executes first-stage rule processing. The Cloud Layer contains historical and real-time data and allows for the retraining of models and also has report generation and learning management system (LMS) integration. The AI Layer estimates a user's engagement, detects a user at-risk of failure in completing their session, predicts congestion, and also provides explanations. The dashboard serves as a means to deliver insight back to users and teachers.

3.1 System overview

The main design principle is to remember that raw telemetry data alone does not provide insight into education. You must consider the context of the sensor signals (for example, when devices are being used/but within a learning environment) in addition to the tasks or phases that the sensors are monitoring/recording in order to make sure the resulting analytics accurately reflect learning conditions, rather than stand-alone device events.

3.2 Multimodal data acquisition and fusion

Different types of signals are continuously created at various sampling rates and have different meanings in terms of semantics in the laboratory, as shown in Figure 5. Environmental streams provide context (e.g., temperature, humidity, noise, light, and CO_2 levels), operational streams capture the power state of the equipment, the length of time the equipment is at the bench and the queue for the workstation, and what errors occur with the equipment, presence streams record entry or exit to the lab or workstation, workstation assignments, or the length of time spent at a given workstation, interaction streams record the actions taken with the software, commands sent to the instruments, the number of cycles it takes to compile, and when a particular milestone occurs for the task, and learning streams provide data from quizzes, rubrics and LMS. These streams can be compared over a sliding window and transformed into structured descriptors (e.g. transition delay, occupancy ratio, idle-to-active ratio, and resource contention counts).

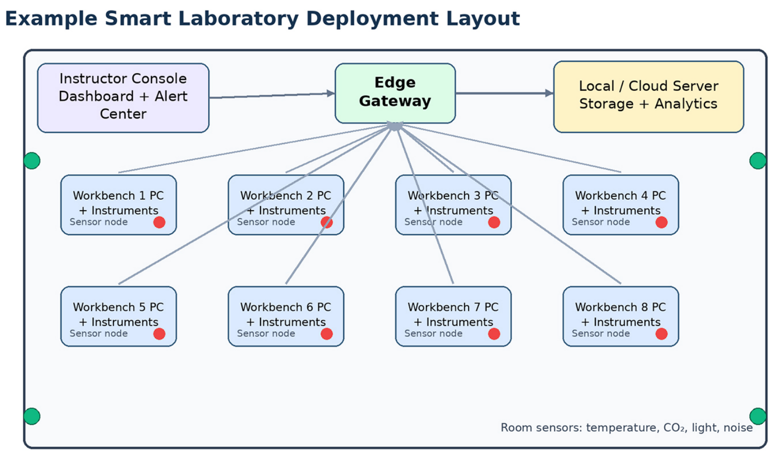

Fig. 5. Example deployment layout showing workbenches, room sensors, edge gateway, instructor console, and cloud/server connectivity

3.3 Artificial intelligence-based learning analytics module

The hybrid ensemble analytics module operates. Features are first processed using a structured event tree model with a non-linear decision boundary (XGBoost) to predict a non-linear relationship between regular attendance, queuing, workstations, and available space. Second, the temporal behavior of experimental sessions is modelled using an LSTM such as sequential encoder to represent the progression of behavior over time. The results of both models are then fused together to produce an overall prediction of the participant's engagement category and the risk rating. Finally, a feature attribution layer provides an explanatory layer to the instructor in order to explain both alerts and recommendations associated with them.

This hybrid design has benefits since the engineer's lab work is both event-based and time-based as shown in Figure 6. Examples include a sudden outpouring of error messages while compiling and how long it takes to process through the queue can both provide valuable insight on their own; however, when viewed together (in time), repetitive shifts between being Idle, Troubleshooting, and Active throughout a session, create a historical representation of a struggle and/or how long it takes to successfully complete a task(s) [34].

$$\hat{y} = \alpha f_{\text{tab}}(z) + (1-\alpha) f_{\text{seq}}(x_{1:t})$$

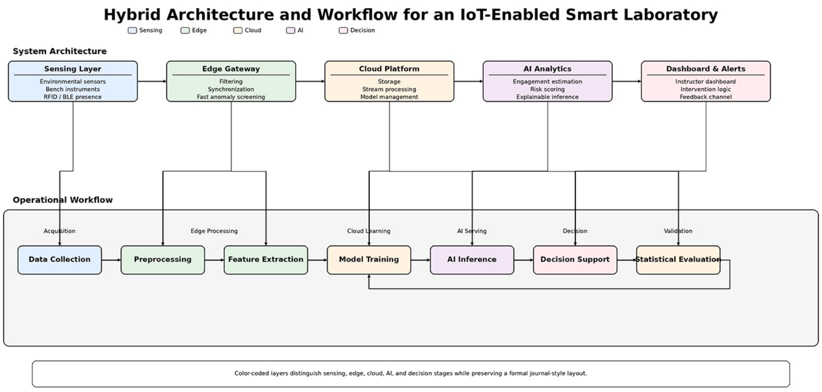

Fig. 6. Experimental workflow used to train, validate, and emulate the real-time analytics pipeline

3.4 Algorithmic procedure

Algorithm 1 summarizes the online procedure used by the system during a laboratory session.

Algorithm 1: Real-Time Smart Laboratory Analytics
Input: Multimodal stream D_t from sensors, devices, and LMS Output: Engagement score, risk alert, dashboard update **1.** Acquire streaming data from all active nodes. **2.** Perform timestamp alignment and remove invalid or noisy packets. **3.** Aggregate measurements over the current sliding window. **4.** Build fused feature vector x_i,t for each learner or team. **5.** Apply structured-event model and temporal-sequence model. **6.** Fuse outputs to estimate engagement and at-risk probabilities. **7.** Compute intervention priority using risk, congestion, and anomaly scores. **8.** Update instructor dashboard and student feedback channels. **9.** Store logs for historical analysis and subsequent retraining. **10.** Repeat for the next time window.

Although not explicitly written as equations, the algorithm implies:
Feature Construction:

$$\boldsymbol{x}_{i,t} = \text{Aggregate}(\boldsymbol{D}_t^{(i)})$$

Decision Score:

$$\text{Priority}_i = g(\text{risk}_i, \text{congestion}_i, \text{anomaly}_i)$$

Instructor judgment is not replaced by intervention logic. Instead, it allows an instructor to be able to rank the urgency of workstations/sessions/teams so that the instructor can concentrate on the areas of most need.

3.5 Complexity, privacy, and governance

The pre-processing step for edge computing typically increases at an approximate linear rate due primarily to the number of events and features in each time window, thereby making this type of system well-suited for resource-constrained/gateways. The same is true of resource-hungry operations/retraining, which have to remain in the Cloud or on Local Server infrastructure [35]. To address privacy issues, the framework uses data minimization, role-based access control, audit logging, and a preference for low-intrusive modalities when equivalent insight can be gained. This governance philosophy aligns with the general educational AI literature regarding the importance of human supervision and self-explanatory design for intervention [32, 33].

4 EXPERIMENTAL SETUP AND SIMULATION

To assess the framework in a repeatable manner, a realistic semester-long laboratory configuration has been established as Table 2. The simulated environment contains 10 benches with 40 students being placed over 16 weeks, with lab sessions occurring on an ongoing basis. Each lab session generates streams of events associated with student attendance, bench access, equipment power use, student physical state, as well as other environmental parameters, combined with how students interacted with their LMS. The simulation does not replace actual field data for evaluating the latency, practicality, and accuracy of the categorization method, but instead creates a replicable framework providing the means for evaluating these three characteristics prior to being placed into an actual operational field environment.

Table 2. Multimodal data schema used for the simulated smart laboratory evaluation

Data Source	Example Features	Frequency/Trigger	Educational Role
Environment	Temperature, humidity, CO_2, light, noise	10 s sampling	Context, safety, comfort
Equipment	Power draw, on/off state, overload flag	Event-based	Resource use, bottlenecks
Presence	RFID/BLE entry, login, dwell time	Event-based	Attendance and continuity
Interaction	Compile count, commands, task milestones	Event-based	Engagement and workflow
Learning platform	Quiz, rubric, LMS access	Session/daily	Outcome linkage

We have four different baseline benchmarks as shown in Table 3 (i.e. Logistic Regression, Random Forest, XGBoost without temporal features, and secondly, LSTM without pre-processing) that serve as a foundation for evaluating the value added through temporal features, fused census and image data, and edge deployment of both data types.

Table 3. Core simulation and evaluation parameters

Parameter	Value	Role
Weeks/sessions	16 weeks/160 sessions	Semester-scale emulation
Window length	30 s	Feature aggregation interval
Train/validation/test split	70/10/20	Model development
Random seed	42	Repeatable experiments
Metrics	Accuracy, F1, AUROC, MCC, latency	Predictive and operational evaluation

5 RESULTS AND ANALYSIS

The outcome is given as an example of a prototype developed, not as a statement about how good (or complete) an object's performance is when used in real-world conditions as illustrated in Table 4 and Figure 7. Regardless of that assumption, the numbers demonstrate that working together with multimodal sensors and edge-aware AI improves the ability to make predictions and respond quickly.

Table 4. Main predictive and latency results for the proposed framework and benchmark baselines

Model	Accuracy (%)	Macro-F1	AUROC	Median Latency (s)
Logistic Regression	82.1	0.781	0.756	3.9
Random Forest	86.7	0.842	0.811	3.4
XGBoost	89.5	0.874	0.846	3.0
LSTM	90.8	0.889	0.861	4.7
Proposed framework	93.4	0.914	0.887	1.8

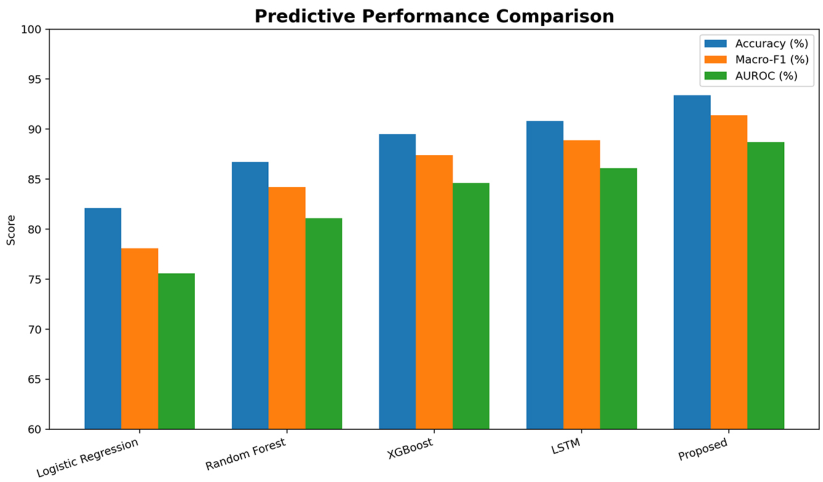

Fig. 7. Comparative predictive performance across baseline models and the proposed framework

The model that has been proposed produces the greatest accuracy for Engagement Classification and Macro-F1 with the least amount of time to respond compared to all other models evaluated. The improvement of this model versus the LSTM baseline demonstrates that temporal modeling alone does not explain all the advantages of edge preprocessing and structured event fusion. The improvement over XGBoost indicates that temporal context provides additive value beyond aggregate features, as shown in Figure 8.

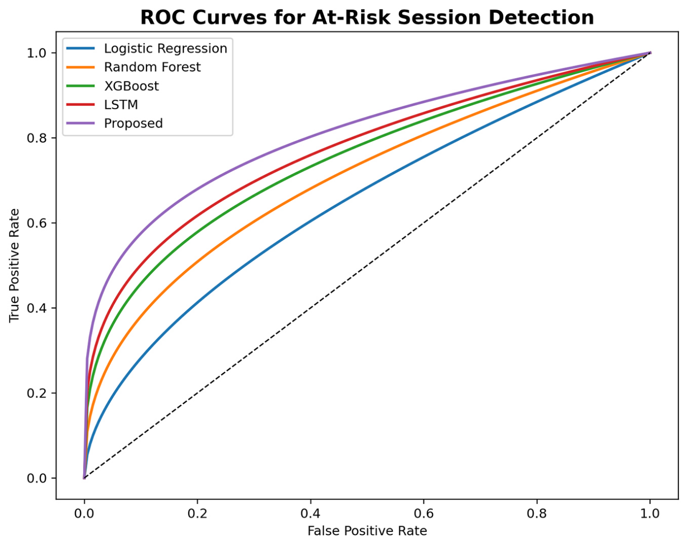

Fig. 8. ROC curves for early at-risk session detection

The results of the ROC analysis demonstrate that the proposed method has a greater ability to determine which teams are at high risk than current methods do. This confirmation is cancellous, as instructors will only be able to support a few teams during an already limited number of possible intervention sessions. The confidence-based reporting associated with the proposed model is summarized by the following statistics: macro-F1 = 0.914; AUROC = 0.887; 95% CI for macro-F1 = [0.901, 0.926], 95% CI for AUROC = [0.871, 0.902] as shown in Figure 9.

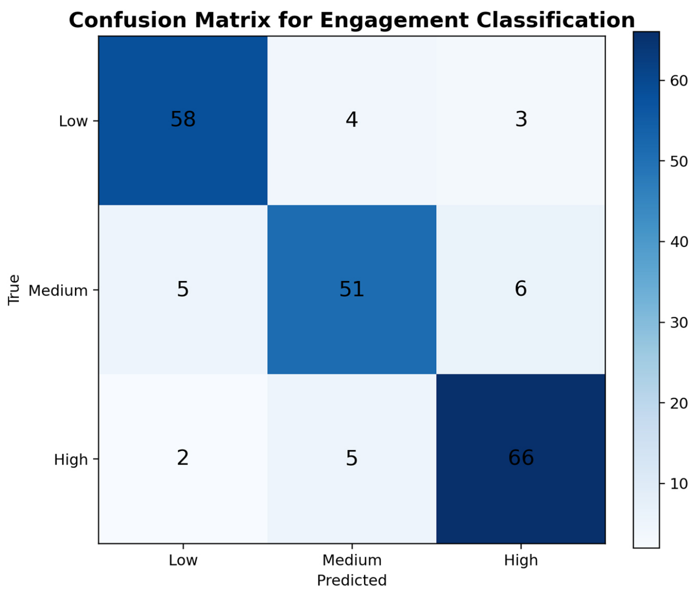

Fig. 9. Confusion matrix for three-level engagement-state classification

The confusion matrix indicates that the majority of mistakes occur between two closely related engagement categories as opposed to between two extremes. This makes sense given that moderate levels of engagement appear to exist in the intersection of either productive struggle or temporary inactivity, which both represent different ends of the spectrum of engagement as shown in Figure 10.

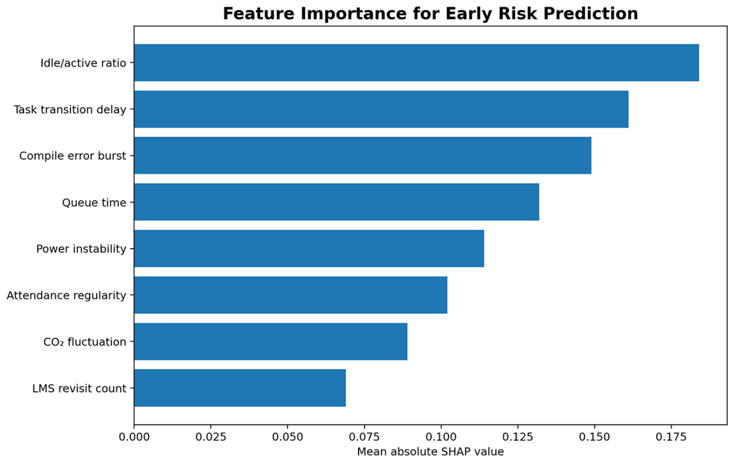

Fig. 10. Ablation analysis showing the contribution of environmental, operational, temporal, and edge-processing components

The results of the ablation experiments demonstrate that both operational features and temporal modelling have the largest mean decrease in performance when removed, indicating that laboratory-specific contextual information is essential as shown in Figure 11. Environmental features resulted in smaller improvements in performance, but still positive, which is likely due to comfort and air quality impacting sustained engagement, and due to the possibility that anomalies signal abnormal laboratory states.

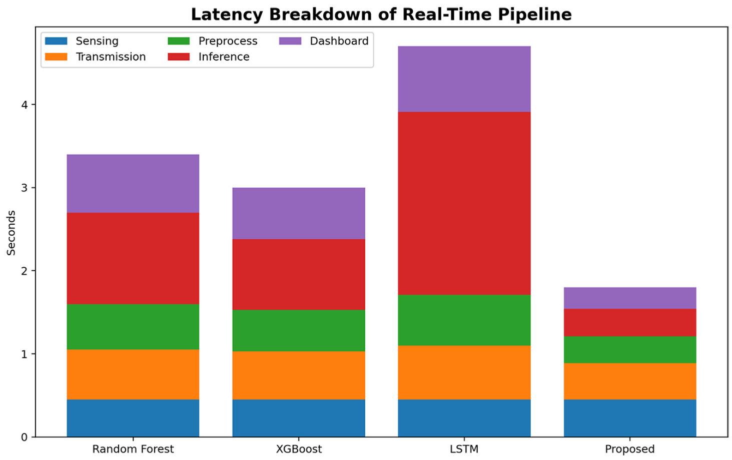

Fig. 11. End-to-end latency decomposition across sensing, transmission, preprocessing, inference, and dashboard rendering

The latency analysis shows that the suggested framework can not only reduce the time for modeling and predicting, but also the total cost of the pipeline, because it aggregates features and applies early filters close to the data source. This is particularly useful when there are multiple workbenches creating events at the same moment in time.

According to the feature importance rankings, the idle to active ratio, transition delay, error bursts, and queue time are more informative than any of the individual environmental variables as shown in Figure 12. This supports that the operational behaviors of learning analytics within engineering laboratories should be interpreted as a signal for learning.

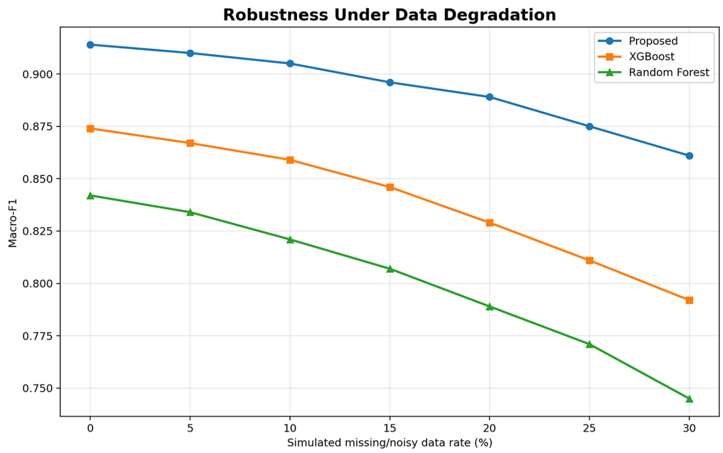

Fig. 12. Robustness of the proposed framework under increasing data degradation and missing/noisy inputs

The proposed framework shows better maintenance of performance degradation (five barrels beating only one barrel), which is due to the redundancy provided by the use of multiple modalities of information, which allows it to continue working even when there is sensor failure or data is partially missing due to a poor connection between sensors or a temporary malfunction of the sensor itself. This robustness is essential for real laboratories, in which all of the above can occur at any time.

6 DISCUSSION

The paper illustrates that the smart lab can be considered an example of a cyber-physical educational system where sensors, analytics and pedagogy are designed together. In addition to prediction accuracy, the real-time situational awareness data from the smart lab allows for enhancements to instructor coordination, reduction in unobserved bottlenecks, increased compliance with safety requirements, and a greater evidential base for reflection and formative feedback. One of the major design insights that the framework presents is that having raw visibility of sensor events does not equate to gaining any sort of useful educational insight. Instructors will be flooded with streams of sensor events unless domain-informed feature design and explainable intervention logic have been created. Summarization, ranking and interpretable feature attribution are all emphasized in the proposed architecture. The study has a few constraints. The first is that the current paper reflects a simulative model rather than a multi-site field test. Secondly, engagement labels will not be perfect and should be validated using multiple levels of observation including rubric basis, subjective accounts through self-reporting, and performance outcomes. Privacy regulations by institutions may also prohibit the deployment of certain devices such as cameras or wearables. Future applications of this work should focus on having an opt-in basis for use, data minimization, and placing humans into the process as an intermediary to enhance quality assurance via human evaluation.

7 CONCLUSION AND FUTURE WORK

The paper developed an IoT-based Smart Lab Framework which utilizes real time monitoring with AI Learning Analytics for the purpose of Engineering Education. The approach consists of a single architecture consisting of multimodal sensing devices, edge computing, cloud service and explainable AI to provide both operational monitoring as well as pedagogical intervention within the same system.

Diagrams, flowcharts, charts, and tables have been embedded directly into the paper to illustrate both the methodology and simulation pipeline as well as visually represent how to interpret results. In addition, the evaluated graphical representation achieved classifying results of high quality and less latency than traditional competitive systems, indicating that smart labs can provide real-time support that is actionable for instructors.

In future research, verifying the suggested structure in real-world electronics labs, embedded control systems, communication labs, and testing and validation labs will be priority one. There is very little information about applying causal-intervention methods and techniques to develop federated and/or privacy-preserving on-device learning. Another research direction would be the creation and usage of digital twins to represent the lab environment to facilitate the planning and execution of experiments.

8 REFERENCES

[1] A. Banagar and R. Khattar, "IoT based smart laboratory system," *International Journal of Engineering Research and Technology*, vol. 9, no. 1, 2020. https://doi.org/10.17577/IJERTV9IS010178

[2] A. Pfeiffer, B. Heinemann, D. Uckelmann, and U. Schroeder, "Learning analytics in engineering education: How to support laboratory-based learning with learning analytics," in *ICERI2020 Proceedings IATED*, 2020, pp. 2484–2492. https://doi.org/10.21125/iceri.2020.0589

[3] T. Zuhelmi *et al.*, "Smart lab energy – For real-time electricity consumption monitoring in the electronics engineering technology laboratory, polytechnic state of Lampung," *Electrician: Jurnal Rekayasa dan Teknologi Elektro*, vol. 20, no. 1, pp. 46–55, 2026. https://doi.org/10.23960/elc.v20n1.2970

[4] S. Matarneh, L. AlQaraleh, T. Alkhrissat, and M. Abdel-Jaber, "An analysis of E-learning system challenges in engineering education: An empirical study," *Cogent Education*, vol. 12, no. 1, p. 2445967, 2025. https://doi.org/10.1080/2331186X.2024.2445967

[5] C. U. Lei, H. N. Liang, and K. L. Man, "Building a smart laboratory environment at a university via a cyber-physical system," in *Proceedings of 2013 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)*, 2013, pp. 243–247. https://doi.org/10.1109/TALE.2013.6654439

[6] A. Dhouib, M. H. Fadi Hijab, K. Chemnad, D. Al-Thani, and A. Othman, "Advancing inclusive smart learning environments: A systematic review of technologies, challenges, and best practices for students with disabilities," *Smart Learning Environments*, vol. 12, no. 1, p. 70, 2025. https://doi.org/10.1186/s40561-025-00416-y

[7] M. Bargavi, H. Muhammed, P. Harish, and D. Dhanush, "Edge computing and AI for real-time analytics in smart devices," *Asian Journal of Basic Science & Research*, vol. 7, no. 2, pp. 1–9, 2025. https://doi.org/10.38177/AJBSR.2025.7201

[8] L. Cabral, R. Pinto, and G. Gonçalves, "AI-powered learning analytics dashboards: A systematic review of applications, techniques, and research gaps," *Discover Education*, vol. 4, no. 1, p. 525, 2025. https://doi.org/10.1007/s44217-025-00964-y

[9] M. M. Asad, A. Naz, A. Shaikh, M. Alrizq, M. Akram, and A. Alghamdi, "Investigating the impact of IoT-Based smart laboratories on students' academic performance in higher education," *Universal Access in the Information Society*, vol. 23, no. 3, pp. 1135–1149, 2024. https://doi.org/10.1007/s10209-022-00944-1

[10] K. M. Al-Aubidy, "AI and IoT technologies for remotely accessed laboratories," in *2025 18th International Conference on Development in eSystem Engineering (DeSE)*, 2025, pp. 302–307. https://doi.org/10.1109/DeSE68208.2025.11367863

[11] W. Zhang, W. Chen, Q. Wang, J. Ma, and F. Zhang, "Integrating artificial intelligence and the internet of things for smart laboratory engineering construction and management team optimisation," *International Journal of Information and Communication Technology*, vol. 26, no. 48, pp. 40–59, 2025. https://doi.org/10.1504/IJICT.2025.150949

[12] S. Amador Nelke *et al.,* "Enhancing lessons on the internet of things in science, technology, engineering, and medical education with a remote lab," *Sensors*, vol. 24, no. 19, p. 6424, 2024. https://doi.org/10.3390/s24196424

[13] Y. Youssef, J. Schneider, and D. Schiffner, "When and how do smart learning environments intervene? A classification framework for context-aware learning," in *2025 International Conference on Education Technology and Computers (ICETC)*, 2025, pp. 832–836. https://doi.org/10.1109/ICETC66579.2025.11387254

[14] M. R. R. Akash and K. Shikder, "IoT based real time health monitoring system," in *2020 Research, Innovation, Knowledge Management and Technology Application for Business Sustainability (INBUSH)*, 2020, pp. 167–171. https://doi.org/10.1109/INBUSH46973.2020.9392163

[15] H. A. Mutar, S. M. M. Najeeb, M. L. Aldabag, and H. T. Salim, "Hybrid neural network-genetic algorithm framework for EEG and ECG signal classification," *Journal of Machine Computing*, vol. 6, no. 1, pp. 280–295, 2026. https://doi.org/10.53759/7669/jmc202606021

[16] L. Yan *et al.,* "Evidence-based multimodal learning analytics for feedback and reflection in collaborative learning," *British Journal of Educational Technology*, vol. 55, no. 5, pp. 1900–1925, 2024. https://doi.org/10.1111/bjet.13498

[17] F. Chen and G. Chen, "Learning analytics in inquiry-based learning: A systematic review," *Educational Technology Research and Development*, vol. 73, no. 4, pp. 2131–2161, 2025. https://doi.org/10.1007/s11423-025-10507-9

[18] A. H. Hassan, E. M. Ahmed, J. M. Hussien, R. B. Sulaiman, M. Abdulhak, and H. Kahtan, "A cyber physical sustainable smart city framework toward society 5.0: Explainable AI for enhanced SDGs monitoring," *Research in Globalization*, vol. 10, p. 100275, 2025. https://doi.org/10.1016/j.resglo.2025.100275

[19] S. Jayousi, P. Lucattini, L. Petti, F. Bruni, and L. Mucchi, "Smart learning by design: A framework for IoT-driven adaptive classrooms and inclusive education," *Education Sciences*, vol. 15, no. 10, p. 1338, 2025. https://doi.org/10.3390/educsci15101338

[20] D. Hasan, "Iot-based smart education: A systematic review of the state of the art," *Journal of Intelligent Systems and Information Technology*, vol. 2, no. 1, pp. 1–16, 2025. https://doi.org/10.61971/jisit.v2i1.106

[21] L. Paulsen and E. Lindsay, "Learning analytics dashboards are increasingly becoming about learning and not just analytics – A systematic review," *Education and Information Technologies*, vol. 29, no. 11, pp. 14279–14308, 2024. https://doi.org/10.1007/s10639-023-12401-4

[22] Z. Li, "The early warning model of college students' learning situations based on machine learning," in *Proceedings of the 2024 International Conference on Intelligent Education and Computer Technology*, Guilin, China, 2024, pp. 540–546. [Online]. Available: https://doi.org/10.1145/3687311.3687408

[23] H. A. Mutar, I. R. N. ALRubeei, O. H. Yahya, N. A. Hussien, H. T. S. AlRikabi, and A. H. M. Alaidi, "Auto-PPA: An adaptive deep RL agent for VLSI Physical design optimization," *Journal of VLSI Circuits and Systems*, vol. 8, no. 1, pp. 9–19, 2026. https://doi.org/10.31838/JCVS/08.01.02

[24] V. Maanu, F. Boateng, and E. Larbi, "Comparison of AI-assisted learning in a collaborative environment with conventional teaching methods on pre-service teachers' mathematics performance," *SSRN Electronic Journal*, 2025. https://doi.org/10.2139/ssrn.5141696

[25] K. Kanagarla, "Edge computing and analytics for IoT devices: Enhancing real-time decision making in smart environments," *SSRN*, 2024. https://doi.org/10.2139/ssrn.5012466

[26] T. Nur Fitria, N. Simbolon, and Afdaleni, *Internet of Things (IoT) in Education: Opportunities and Challenges*, 2023.

[27] M. Chatti *et al.*, "Learning analytics: Challenges and future research directions," *eleed*, vol. 10, 2014.

[28] H. A. Mutar, A. K. Abdullah, O. A. Abdaumran, I. R. N. ALRubeei, and H. T. S. ALRikabi, "Hybrid AI model-driven dynamic spectrum sharing for 6G wireless IoT networks," *Studies in Informatics and Engineering*, vol. 8, no. 1, 2026. https://doi.org/10.37868/sei.v8i1.id722

[29] S. Javed, I. Fahad, E. Azhar, M. Syed, O. Ahmed, and F. Zafar, "Bridging learning and technology: How digital platforms impact academic performance," *Journal for Social Science Archives*, vol. 3, pp. 724–743, 2025. https://doi.org/10.59075/jssa.v3i1.154

[30] M. Kurni and K. G. Srinivasa, "Online laboratories using IoT," in *The Internet of Educational Things: Enhancing Students' Engagement and Learning Performance*, M. Kurni and K. G. Srinivasa, Eds., Cham: Springer Nature Switzerland, 2025, pp. 97–111. https://doi.org/10.1007/978-3-031-67387-0_7

[31] H. Mutar, A. Abdullah, O. Abdaumran, I. Alrubeei, and H. Alrikabi, "Hybrid AI model-driven dynamic spectrum sharing for 6G wireless IoT networks," *Sustainable Engineering and Innovation*, vol. 8, pp. 53–72, 2026. https://doi.org/10.37868/sei.v8i1.id722

[32] R. Alfredo *et al.*, "Human-centred learning analytics and AI in education: A systematic literature review," *Computers and Education: Artificial Intelligence*, vol. 6, p. 100215, 2024. https://doi.org/10.1016/j.caeai.2024.100215

[33] F. Ouyang and L. Zhang, "AI-driven learning analytics applications and tools in computer-supported collaborative learning: A systematic review," *Educational Research Review*, vol. 44, p. 100616, 2024. https://doi.org/10.1016/j.edurev.2024.100616

[34] A. Abdullah, H. Mutar, A. Hamad, I. Alrubeei, and H. Alrikabi, "Towards sustainable cropping: AI-driven precision agriculture for optimal water and pesticide use via drones and soil sensors," *Heritage and Sustainable Development*, vol. 8, pp. 161–176, 2026. https://doi.org/10.37868/hsd.v8i1.1887

[35] I. R. N. ALRubeei, H. A. Mutar, H. T. ALRikabi, I. L. H. Alsammak, H. A. Kanber, and B. H. Majeed, "Design of a hybrid AI-driven engineering model for energy-efficient and sustainable educational systems," *International Journal of Engineering Pedagogy*, vol. 16, no. 1, 2026. https://doi.org/10.3991/ijep.v16i1.60437

9 AUTHORS

Haider TH. Salim ALRikabi is with the Electrical Engineering Department, College of Engineering, Wasit University, Wasit, Iraq (E-mail: hdhiyab@uowasit.edu.iq).

Farah Sabir Mohammed is with the Al-Karkh University of Science/College of Remote Sensing and Geophysics, Baghdad, Iraq.

Huda Abbas Kanber is with the University of Baghdad/College of Islamic Sciences, Baghdad, Iraq.

Meithem Hashem Ali is with the Student Registration and Affairs Department, Iraqia University, Baghdad, Iraq.

Hussain Ali Mutar is with the Computer Department, College of Computer Science and Information Technology, Wasit University, Wasit, Iraq.

Ibtihal R. Niama ALRubeei is with the Electrical Engineering Department, College of Engineering, Wasit University, Wasit, Iraq.

Online-Journals.org

iJEP International Journal of Engineering Pedagogy

iJEP | eISSN: 2192-4880 | Vol. 16 No. 5 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijep.v16i5.60331

PAPER

Exploring the Ethical Boundaries of AI Use in Secondary Vocational Education

Peter Tokoš[1] (✉), Roman Hrmo[2], Juraj Miština[3], Lucia Krištofiaková[2], Lucie Smékalová[2]

[1]DTI University, Dubnica nad Váhom, Slovakia

[2]Czech University of Life Sciences Prague, Prague, Czech Republic

[3]University of Ss. Cyril and Methodius in Trnava, Trnava, Slovakia

peter.tokos@petertokos.com

ABSTRACT

The integration of artificial intelligence (AI) into vocational education presents both significant opportunities and complex ethical challenges. This study examines the use of AI among learners attending secondary technical and vocational schools, with a particular focus on the boundary between legitimate learning support and academic dishonesty. A quantitative questionnaire survey was conducted with 1,745 learners from Slovakia, the Czech Republic, Hungary and Poland. The collected data were analysed using descriptive statistics and a thematic analysis of open-ended responses. The results indicate widespread use of AI tools among the surveyed learners. Most respondents reported regular use of AI to understand learning materials, generate texts, complete assignments and support project work. Many respondents reported confidence in evaluating AI-generated content, suggesting a perceived level of digital literacy and critical awareness. Nevertheless, open-ended responses revealed several forms of academically dishonest AI use, particularly for generating code, writing essays, preparing presentations and completing tasks without meaningful cognitive engagement. Thematic analysis identified key motivations such as time efficiency and pragmatic task management, alongside a nuanced awareness of the ethical boundary between legitimate assistance and misconduct. The findings highlight the urgent need for pedagogical approaches that promote responsible and ethical use of AI. Moreover, the study reinforces the view that, in an increasingly technology-driven educational landscape, competencies in interacting with AI, such as formulating effective prompts, verifying outputs, and engaging in critical evaluation, are becoming essential skills for vocational school graduates.

KEYWORDS

artificial intelligence (AI), vocational education, ethics in education, academic dishonesty, digital competencies, secondary technical schools

1 INTRODUCTION

Artificial intelligence (AI) is increasingly shaping educational practice and transforming how learners access information, solve problems and complete

Tokoš, P., Hrmo, R., Miština, J., Krištofiaková, L., Smékalová, L. (2026). Exploring the Ethical Boundaries of AI Use in Secondary Vocational Education. *International Journal of Engineering Pedagogy (iJEP)*, 16(5), pp. 62–79. https://doi.org/10.3991/ijep.v16i5.60331

Article submitted 2025-12-22. Revision uploaded 2026-06-12. Final acceptance 2026-06-13.

academic tasks. The widespread availability of generative AI tools such as ChatGPT, Microsoft Copilot and Google Gemini has introduced new possibilities for personalised learning, immediate feedback and knowledge support. At the same time, these technologies raise important questions concerning academic integrity, learner autonomy, critical thinking and the ethical boundaries of AI-assisted learning. These issues are particularly relevant in vocational education, where the development of both technical competencies and professional responsibility represents a central educational objective.

At the European level, the growing role of AI in education is reflected in strategic policy initiatives. The Digital Education Action Plan 2021–2027 emphasises the need to strengthen digital readiness, promote high-quality digital education and equip learners with competencies required for participation in an increasingly technology-driven society [36]. Similarly, the DigComp 2.2 framework identifies critical and responsible use of digital technologies as a key component of digital competence, including the ability to evaluate information, understand technological limitations and act ethically in digital environments [37]. These priorities are particularly relevant for vocational education, where digital competence, technical expertise and professional responsibility are closely interconnected.

A broad spectrum of scholars has examined the integration of AI into education. Given the diversity of perspectives and research objectives, existing studies can be grouped into five thematic areas relevant to the present research:

1. Conceptual and strategic perspectives on AI in education [1–5];
2. Inclusion, accessibility and equity through AI [6, 7];
3. AI, academic integrity and ethical challenges [8–11];
4. Attitudes, adoption and use of AI by teachers and learners [12–14];
5. Applications of AI in specific educational contexts [15, 16].

Research consistently demonstrates that AI can enhance teaching and learning by supporting personalised instruction, adaptive learning environments, immediate feedback and greater accessibility of educational content [2, 4, 6]. AI technologies may help learners better understand subject matter, identify knowledge gaps and engage with educational resources tailored to their individual needs. In vocational education, AI also offers opportunities to simulate authentic professional situations, support technical problem-solving and strengthen competencies increasingly demanded by contemporary labour markets [17–20].

At the same time, the growing availability of AI introduces important pedagogical and ethical challenges. Tools capable of generating text, code, presentations, images and solutions to problems may support learning, but they may also reduce learners' cognitive engagement when used as substitutes for independent work. Consequently, questions concerning academic integrity, learner autonomy, critical thinking and the ethical boundaries of AI-supported learning have become increasingly prominent in educational research [8–11].

The ethical dimension of AI use in education extends beyond the question of whether AI is used and includes the purposes, conditions and consequences of its use. European approaches to trustworthy AI emphasise principles such as human agency and oversight, transparency, fairness, accountability, privacy protection and the prevention of harm [38]. In educational settings, these principles imply that AI should support, rather than replace, learning processes and be integrated in ways that preserve meaningful learner engagement and educational integrity. The Ethical

Guidelines on the use of AI and data in Teaching and Learning for Educators further stress the importance of responsible implementation, teacher preparedness and clear institutional policies governing AI use in schools [39].

These issues are particularly significant in secondary vocational education. Learners in technical and vocational programmes are among the most intensive users of digital technologies and are simultaneously preparing for professions in which AI-assisted work is becoming increasingly common. Understanding how these learners use AI, how they perceive its benefits and risks, and how they navigate the boundary between legitimate educational support and academic dishonesty, therefore, represents an important research challenge.

The present study addresses this challenge by examining the use of AI among learners attending secondary vocational schools in four Central European countries: Slovakia, the Czech Republic, Hungary and Poland. Particular attention is paid to the ethical boundaries of AI use, including the distinction between meaningful learning support and academic dishonesty. By analysing learners' experiences, attitudes and reported behaviours, the study aims to contribute to the ongoing discussion on responsible AI integration in vocational education and to provide evidence to support future pedagogical, institutional, and policy decisions.

2 ETHICAL BOUNDARIES IN THE USE OF ARTIFICIAL INTELLIGENCE IN EDUCATION

As noted by [4], although AI offers significant potential for personalised teaching and learning, its integration into education raises important ethical and pedagogical challenges. The ethical boundaries of AI use in education should not be understood solely as individual decisions made by learners or teachers. Rather, it is shaped by broader legal, institutional, and ethical frameworks. The European concept of trustworthy AI defines AI systems as lawful, ethical and robust, while emphasising principles such as human agency and oversight, transparency, fairness, accountability, privacy protection and the prevention of harm [38]. In educational settings, these principles imply that AI should support learning processes without replacing learners' cognitive engagement and should remain subject to meaningful human supervision. One of the central issues concerns the boundary between the legitimate use of AI as a learning aid and its misuse for academic dishonesty. While some learners use AI to better understand educational content, others may rely on it to replace their own cognitive engagement and original work. Studies indicate that teachers are increasingly aware of this risk and perceive a growing prevalence of AI-assisted misconduct, although most do not consider the use of AI itself inherently unethical [8]. These concerns reflect broader tensions regarding academic integrity in technology-enhanced learning environments.

The risks associated with AI misuse have been highlighted in several educational contexts. Research conducted during the COVID-19 pandemic showed that distance learning environments increased learners' reliance on digital technologies for cheating, often justified by low motivation or disengagement from school tasks [9]. More recent studies focusing on generative AI, particularly in programming education, demonstrate that AI systems can produce sophisticated solutions to assignments, thereby complicating objective assessment and creating opportunities for academic misconduct [10]. At the same time, these technologies may support learning, motivation and feedback when used appropriately. However, inaccurate or misleading AI-generated outputs, together with excessive dependence on automated solutions, may undermine the development of authentic skills and critical thinking. Consequently, several authors emphasise the importance of formative assessment strategies and pedagogically guided AI integration that promotes academic integrity [9, 10].

Research further suggests that learners' attitudes toward AI-assisted cheating are shaped by personal values, moral beliefs and the educational environment [11]. Studies show that learners are often reluctant to openly admit to dishonest AI use, particularly when directly questioned, whereas anonymous responses reveal substantially higher levels of self-reported misconduct [11, 24, 25]. These findings underline the need for supportive educational environments that strengthen intrinsic motivation, reduce excessive performance pressure and incorporate values-based education. Simultaneously, teachers face significant barriers in integrating AI into pedagogical practice, including concerns about academic dishonesty, limited confidence in their own AI competencies and restrictive institutional policies [12, 14]. This discrepancy is evident in learners adopting AI tools considerably faster than teachers [12, 13], creating tension between rapid technological development and the readiness of educational institutions to implement AI responsibly and effectively.

3 VOCATIONAL EDUCATION AND THE ROLE OF ARTIFICIAL INTELLIGENCE

Vocational education, whether delivered in face-to-face or distance learning formats, focuses on developing learners' technical reasoning, creativity and practical skills. In doing so, it supports the acquisition of essential technical literacy and competencies required for informed career decisions and further professional development. Vocational education encompasses a range of pedagogical and psychological dimensions that influence the quality, efficiency, and effectiveness of instruction [17–20].

In this context, AI is becoming an increasingly important component of modern vocational education. AI technologies can support personalised learning, identify knowledge gaps, propose individualised learning activities, and create adaptive educational environments. Furthermore, they enable the simulation of authentic technical scenarios, allowing learners to gain practical experience even in online or hybrid settings. In technical education, AI can also support data analysis, process modelling, automation and the design of technical solutions.

As Huľová et al. [17] emphasise, modern technical education should integrate practical skills, learner engagement, digital technologies, high-quality feedback, creativity, ethical standards and preparation for future professional practice. Within this framework, AI may support vocational education by enabling adaptive learning, feedback, simulation of technical scenarios, and the development of digital competencies required in technical professions.

At the same time, it is essential to acknowledge the risks associated with AI misuse. When completing assignments, projects, or practical tasks, learners may rely on AI in ways that reduce genuine cognitive engagement and hinder the development of professional competencies. Consequently, vocational education should incorporate not only technical instruction in AI use but also explicit guidance regarding its responsible and ethical application. Such an approach can help ensure that learners develop both the technical competencies and the ethical awareness necessary for effective participation in increasingly AI-supported professional environments.

4 RESEARCH METHODOLOGY

Given the growing significance of AI in vocational education, along with its potential benefits and risks, a survey was conducted among learners at secondary vocational schools. The primary objective of the research was to obtain an authentic perspective from learners regarding the use of AI in the educational process. The study focused on how learners perceive AI and the ways it is utilised for learning, preparing for classes, completing homework and working on projects. Particular attention was paid to the extent to which learners are aware of the boundaries between meaningful use of AI and its potential misuse.

4.1 Research questions

In alignment with the main objective of the study, the following research questions were formulated:

RQ$_1$ *How do learners in secondary vocational schools use artificial intelligence for learning, class preparation, and fulfilling academic responsibilities?*
RQ$_2$ *To what extent do learners use AI tools in ways that may be considered cheating or academic dishonesty?*

4.2 Study sample

The study sample comprised 1,745 learners enrolled in the first through fourth years of secondary vocational schools, with a focus on technical education, across four Central European countries: Slovakia, the Czech Republic, Hungary and Poland. The respondents were recruited through convenience sampling, primarily via existing professional contacts with secondary vocational schools focused on technical education, and learners voluntarily participated by completing the online questionnaire. This non-probabilistic sampling approach was chosen primarily for practical reasons, including accessibility and feasibility across multiple countries. No specific criteria were applied regarding gender, academic achievement, socio-economic status, or other personal characteristics; thus, the sample represents a diverse cross-section of learners in technical secondary education. Participation was entirely voluntary and anonymous, with respondents informed of the study's purpose and assured of confidentiality before completing the questionnaire. In terms of distribution, the largest proportion of respondents was from Slovakia (n = 612; 35.08%), followed by the Czech Republic (n = 537; 30.77%), Poland (n = 356; 20.39%), and Hungary (n = 240; 13.75%). This distribution reflects the varying levels of institutional participation across the participating countries. Although the sample cannot be considered statistically representative of the entire population of secondary vocational learners in these nations, it provides a substantial, contextually relevant dataset for examining trends and comparisons in technical education in Central Europe. Therefore, the findings should be interpreted as indicative of tendencies observed within the sample rather than as population-level conclusions.

4.3 Measurement and evaluation methods

In the study, the primary data collection method was a quantitative questionnaire administered electronically via Google Forms. The non-standardised questionnaire, developed by the researcher, comprised 17 items, predominantly closed-ended (dichotomous, multiple-choice and Likert-type), along with several semi-open-ended questions to gather information about learners' experiences, behaviours and opinions on the use of AI in education [21, 22].

The questionnaire was designed as an exploratory research instrument focused on several thematic areas related to the use of AI in the educational process. Example questionnaire items focused on learners' experiences with AI-supported learning, recognition of inaccurate AI-generated outputs and the use of AI to complete school assignments, generate text, or write code. The items primarily focused on the use of AI in learning, AI literacy and critical evaluation of AI-generated outputs, perceptions of AI in the school environment, and ethical aspects of AI use (refer to Table 1). The content validity of the questionnaire was verified through expert evaluation by five specialists in didactics, vocational education, educational technologies and the implementation of AI in educational practice.

The internal consistency of the selected closed-ended ordinally scalable questionnaire items was orientationally verified using Cronbach's alpha coefficient ($\alpha \approx 0.79$). However, due to the multidimensional nature of the research instrument, this coefficient cannot be interpreted as the reliability of a single homogeneous scale. Cronbach's alpha, therefore, represents a general orientational indicator of the internal consistency of the selected closed-ended items of the research instrument.

Table 1. Thematic areas of the questionnaire and relationship of items to Cronbach's alpha calculation

Thematic Area	Questionnaire Items	Focus of Items	Included in α Calculation
Use of AI in Education	2, 3, 4, 5, 6, 7	Use of AI in learning, homework, projects, and perceived usefulness of AI	yes: 2, 4, 5, 6, 7; no: 3
AI Literacy and Critical Evaluation of AI	9, 12, 13	Recognition of inaccurate AI responses, orientation in AI tools, and safe AI use	yes: 9, 13; no: 12
Perception of AI in the School Environment	10, 11, 14, 15	Integration of AI into teaching, AI-related risks, expected teacher support, experience with AI prohibition	yes: 10; no: 11, 14, 15
Ethical Aspects of AI Use	16, 17	Reflection on experiences, dishonest AI use, and the boundary between assistance and cheating	no–open ended responses

Notes: Item 1 represented a demographic variable (year of study) and was therefore not included in the thematic categorisation. Item 8 consisted of multiple-choice subject categories and was analysed descriptively but was not included in the Cronbach's alpha calculation. Only items with a closed-ended format that could be clearly ordinally coded were included in the Cronbach's alpha calculation. Multiple-choice items, nominal categories and open-ended responses were not included in the calculation.

As shown in Table 2, descriptive statistics were used to summarise the collected data, including measures of central tendency (arithmetic mean, median), variability (standard deviation, standard error of the mean), and distributional shape (skewness and kurtosis coefficients) [23].

Skewness and kurtosis were calculated using Fisher's moment coefficients, as implemented in IBM SPSS Statistics.

Table 2. Overview of statistical methods used in the analysis of questionnaire data

Area of Data Processing	Statistical Tool/ Method Used	Description of Use
Data Processing Software	IBM SPSS Statistics (Version 29)	Data entry, cleaning, and analysis of questionnaire data
Descriptive Statistics	Measures of Central Tendency	Calculation of mean and median
Descriptive Statistics	Measures of Variability and Distribution Shape	Calculation of standard deviation, standard error of the mean, skewness coefficient, and kurtosis coefficient
Qualitative Analysis of Responses	Thematic Analysis (manual theme classification)	Analysis of open-ended responses, identification of meaningful patterns and thematic areas
Final Data Interpretation	Tabular and Graphical Presentation	Outputs in the form of tables and graphs, accompanied by a verbal description

Open-ended responses were analysed using an inductive thematic analysis approach. The coding process involved repeated reading of the responses and identification of recurring ideas, expressions and behavioural patterns related to the use of AI in education. Conceptually similar codes were subsequently grouped into broader thematic categories. Theme development was guided by the frequency of occurrence, semantic similarity, and relevance to the research questions. Each response was assigned to the thematic category that best reflected its dominant meaning and intention.

Separate questionnaire versions were prepared for each participating country. Learners from Slovakia and the Czech Republic completed a Slovak-language version of the questionnaire, while learners from Poland and Hungary completed an English-language version. The content, structure and order of questionnaire items remained identical across all versions to ensure comparability of the collected data. The questionnaire was anonymous and did not collect personally identifiable information. Responses were analysed only in aggregated form and were not linked to individual respondents or schools.

4.4 Ethical considerations

The study was conducted in accordance with the ethical principles for educational research involving human respondents. Prior to data collection, the research design, questionnaire instrument and data management procedures were reviewed and approved by the Ethics Committee of the University of Ss. Cyril and Methodius in Trnava (Ref. No. 2025/ET/017), by the Ethics Committee of the Czech University of Life Sciences Prague (Ref. No. 2025/EK/CZU/022) and by the Ethics Committee of DTI University, Dubnica nad Váhom (Ref. No. DTI-EK-2025-03-14). The study was conducted in accordance with institutional ethical requirements and applicable GDPR regulations. Because the study involved learners attending secondary vocational schools, particular attention was paid to informed consent procedures. Participation was voluntary, and respondents were informed about the purpose of the study, the anonymous nature of data collection, and their right to discontinue participation at any stage without consequences. The study was conducted across four countries (Slovakia, the Czech Republic, Hungary and Poland). Data collection procedures were designed to comply with applicable national regulations and the principles of the General Data Protection Regulation (GDPR). To ensure consistency across participating countries, identical information regarding participation, confidentiality and data processing was provided to all respondents. No personally identifiable information was collected. Parental or legal guardian consent procedures were handled by participating schools in accordance with applicable national and institutional regulations. To minimise cross-country procedural differences, identical survey instruments, instructions and consent procedures were used across all participating countries. All responses were anonymised at the point of collection, and the dataset contained no names, addresses, contact details, IP addresses, or other information that could directly identify individual respondents or schools. The collected data were stored on password-protected institutional devices accessible only to the research team. Research data will be retained for a maximum of three years following publication of the study for verification and scientific purposes and will subsequently be securely deleted in accordance with institutional data management policies.

5 RESULTS AND INTERPRETATION

Of the 17 questionnaire items, the interpretative section focuses on a selection of representative questions identified as the most significant to the research objectives. These items were chosen because they exhibited apparent differences in responses or revealed prominent behavioural tendencies among the respondents. The selected items illustrate the key findings, while the remaining items contribute to a more comprehensive understanding and may warrant further analysis. The initial questionnaire item assessed the respondents' year of study (refer to Table 3). The largest group consisted of first-year learners [n = 503].

Table 3. Learners by year of study

Year of Study	Number (n)	Percentage (%)
First	503	28.83
Second	486	27.85
Third	414	23.72
Fourth	342	19.60

In the second item, respondents were asked whether they had ever used AI in preparing for lessons. The findings indicate that the majority of respondents utilise AI for lesson preparation. The average ordinal response value [AM = 2.49] and the median [MDN = 3.00] suggest that responses predominantly ranged between "yes, occasionally" and "yes, often", with the most frequent choice being regular use of AI. A significantly negative skewness coefficient [$g_1 = -1.48$] indicates that responses are concentrated toward the higher end of the scale, meaning that most respondents actively use AI tools. The kurtosis coefficient [$g_2 = 2.69$] further suggests a moderate variability in the intensity of AI usage (refer to Table 4).

Table 4. Use of AI by respondents in preparation for lessons

AM	MDN	SD	SE	g_1	g_2	n
2.49	3.00	.68	.016	–1.48	2.69	1745

Key: AM – arithmetic mean, MDN – median, SD – standard deviation, SE – standard error of the mean, Skewness (g_1) – skewness coefficient, Kurtosis (g_2) – kurtosis coefficient, n – number of responses. (Applied within Tables 5–10).

In the third questionnaire item, respondents were asked what they most frequently use AI for during learning or completing assignments. The data indicate that AI is most often used to explain subject matter and generate texts. The average ordinal response value [AM = 1.95] and the median [MDN = 2.00] suggest that responses predominantly fell between the first two options, namely "explaining subject matter" and "text creation." A positive skewness coefficient [g_1 = .97] indicates a concentration of responses toward the lower end of the scale, suggesting that the majority of respondents actively use AI. Conversely, only a small portion reported not using AI at all. The kurtosis coefficient [g_2 = .32] suggests a mild concentration of responses around the most common options, with relatively low variability in preferences (refer to Table 5).

Table 5. Use of AI in learning and completing assignments

AM	MDN	SD	SE	g_1	g_2	n
1.94	2.00	1.09	.026	.97	.32	1745

In the third questionnaire item, in addition to the preset options, respondents were also allowed to select an "Other" response, which [n = 165] respondents chose. Based on a qualitative analysis of their open-ended answers, AI usage within this group was described as multifunctional, personalised and often combined with other uses. Respondent statements revealed that AI was used for a broad range of tasks, from combining several preset options (e.g., explaining subject matter and programming) to more specific tasks such as note-taking, solution searching, error correction, text reformatting, idea generation and product searching based on descriptions. Multiple responses indicated practical, everyday use of AI across all learning areas, with an emphasis on efficiency, speed of information retrieval, and support in both creative and routine tasks.

In the fourth questionnaire item, respondents were presented with the statement "AI helps me learn more effectively" and responded on a five-point Likert scale.

The analysed data show that most respondents agreed or strongly agreed with this statement. The average ordinal response value [AM = 3.89] and median [MDN = 4.00] indicate that responses were primarily concentrated in the upper range of the scale. The negative skewness coefficient [g_1 = –.72] indicates a predominance of higher ratings, supporting the finding that most respondents perceive AI as a tool that aids more effective learning. The kurtosis coefficient [g_2 = –.05] suggests that the distribution of responses deviates only slightly from normality, with a balanced spread of preferences and no significant extremes (refer to Table 6).

Table 6. Effectiveness of learning with AI

AM	MDN	SD	SE	g_1	g_2	min	max	n
3.89	4.00	1.03	.025	–.72	–.05	1	5	1745

The visualisation of the response distribution (see Figure 1) indicates a predominance of higher Likert ratings. The median falls within the agreement area, indicating that most respondents expressed positive attitudes toward the statement. A slight extension toward lower values also indicates the presence of respondents with more reserved opinions.

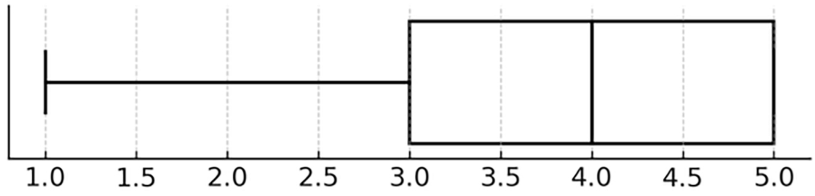

Fig. 1. Distribution of agreement levels with the statement "AI helps me learn more effectively"

One questionnaire item asked respondents whether they could recognise when an AI-generated response was incorrect. Responses were categorised into four options, with the majority selecting "Yes, mostly", indicated by [n = 1001] respondents. The mean response value [AM = 1.49] and the median [MDN = 1.00] suggest that most respondents report a high ability to identify inaccuracies in AI responses. A positive skewness coefficient [g_1 = 1.54] indicates that the distribution of responses is concentrated toward the lower end of the scale, i.e., agreement, with fewer responses falling into the "No" or "I do not know" categories. The kurtosis coefficient [g_2 = 3.20] suggests a sharp concentration of responses around the dominant category. These results indicate that most respondents reported confidence in their ability to critically assess the accuracy of AI-generated outputs (refer to Table 7).

Table 7. Ability to identify inaccurate AI responses

AM	MDN	SD	SE	g_1	g_2	n
1.49	1.00	.65	.016	1.54	3.20	1745

The questionnaire measured respondents' level of agreement with the statement that AI should be integrated into school teaching. Responses were recorded on a five-point Likert scale ranging from "Definitely yes" to "Definitely no." The most frequently chosen response was "Rather yes" [n = 581], followed by "Definitely yes" [n = 559], indicating a predominantly positive attitude among respondents toward the integration of AI in education. The mean response value [AM = 2.22] and median [MDN = 2.00] suggest that answers clustered around agreement. A positive skewness coefficient [g_1 = .68] indicates a slight predominance of lower (agreeing) values on the scale, while a negative kurtosis coefficient [g_2 = –.42] suggests a slightly flattened distribution, reflecting a more dispersed occurrence of opinions beyond the most common responses (refer to Table 8). It shows that respondents mainly hold a favourable view of incorporating AI into school education, with "Rather no" [n = 213] and "Definitely no" [n = 67] accounting for the remaining disagreement.

Table 8. AI as a part of school education

AM	MDN	SD	SE	g_1	g_2	min	max	n
2.22	2.00	1.13	.027	.68	–.42	1	5	1745

The distribution of responses is visualised in Figure 2, which confirms a concentration in the lower range of the Likert scale. The median is 2, corresponding to the response category 'Rather yes', while the distribution is concentrated in the categories 'Definitely yes' and 'Rather yes'. A slight elongation of the distribution toward higher values indicates a greater prevalence of reserved attitudes, though they were only marginally represented. Figure 2 visually supports the conclusion that there is a predominantly positive perception of integrating AI into education.

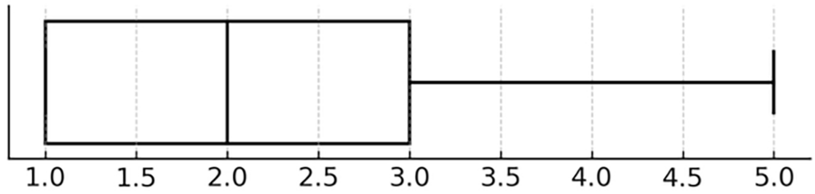

Fig. 2. Distribution of responses to the statement "The use of AI in learning should be part of school education"

Another questionnaire item focused on identifying the risks respondents perceive in using AI within the educational process. Respondents were presented with six categories of potential risks. The most frequently selected response was "reduced independent thinking" [n = 912], followed by "false or misleading information" [n = 324] and "dependence on AI" [n = 240]. Other options, such as "misuse for cheating" [n = 45], "none" [n = 129], and "all of the above" [n = 95], were chosen considerably less often. The average ordinal value of responses [AM = 2.54] and the median [MDN = 2.00] suggest that responses were concentrated at the lower end of the scale, indicating a predominance of cognitively oriented concerns about AI use. The skewness coefficient [g_1 = 1.33] indicates a prevalence of lower values in the distribution, suggesting that perceived risks are primarily associated with a decline in independent reasoning. The kurtosis coefficient [g_2 = 1.11] further indicates an increased concentration of responses around the most frequently selected category ("reduced independent thinking") and a lower incidence of extreme values, supporting the interpretation of low variability in risk assessment (refer to Table 9).

Table 9. Perceived risks of using AI in education

AM	MDN	SD	SE	g_1	g_2	n
2.54	2.00	1.29	.031	1.33	1.11	1745

The following item in the questionnaire examined respondents' experiences with teachers prohibiting the use of AI. The most frequently selected response was "Yes, multiple times" [n = 1001], followed by "No" [n = 296], "Yes, once" [n = 230], and "I do not know" [n = 218]. The average ordinal response value [AM = 1.85] and the median [MDN = 1.00] suggest that the experience of being prohibited from using AI is relatively widespread among respondents, with a significant portion reporting repeated occurrences. The skewness coefficient [g_1 = 1.08] indicates a concentration of responses toward the lower end of the scale (i.e., more frequent prohibitions). In contrast, the kurtosis coefficient [g_2 = .24] indicates a moderate increase in clustering of responses around the most common option ("Yes, multiple times"), with relatively low variability (refer to Table 10). These findings suggest that teacher-imposed restrictions on AI use are a common experience for a substantial number of respondents.

Table 10. Experience with AI prohibition by teacher

AM	MDN	SD	SE	g_1	g_2	n
1.85	1.00	1.10	.026	1.08	.24	1745

As part of the questionnaire, respondents were allowed to elaborate on their answers to a question concerning the potentially dishonest use of AI in learning or completing assignments. A total of [n = 1242; 71.15%] respondents provided responses, which were analysed using a qualitative thematic analysis. Drawing on recurring linguistic patterns and frequently used expressions, five dominant thematic areas were identified in the responses (t_{o1} to t_{o5}):

- **[t_{o1}]** The use of AI to generate solutions to tasks, including programming code, often without a deeper understanding of the resulting output;
- **[t_{o2}]** Assistance in producing written outputs, such as presentations, essays, or reports, with an emphasis on saving time or reducing the perceived difficulty of the assignment;
- **[t_{o3}]** Substitution of one's activity with AI-generated solutions, frequently in contexts of unpreparedness, lack of motivation, or a desire to circumvent teachers' expectations;
- **[t_{o4}]** Various forms of automated copying or delegation of the entire task to an AI tool, with only minimal subsequent editing;
- **[t_{o5}]** Reflections on the ethical dimension of AI use, where respondents acknowledged the boundary between acceptable assistance and rule violation, often accompanied by an awareness that the approach was non-standard.

The content analysis of these responses suggests that AI was primarily perceived as a tool for reducing cognitive load, bypassing creative effort and accelerating task completion, particularly in situations that respondents regarded as formal, repetitive, or excessively demanding, given the time available or their personal motivation. Such use was often framed pragmatically, as a coping strategy aimed at fulfilling school obligations while minimising the effort required. Furthermore, many responses revealed a relativized perception of the boundary between legitimate assistance and dishonest conduct, with respondents frequently rationalising their approach by citing efficiency, ease of access to the tool, or a low level of personal investment in the subject.

This trend may reflect a broader shift in how respondents perceive school assignments as formal performances that can be optimised through technology. However, some responses also pointed to reflective and constructive uses of AI, particularly when it was employed as a supportive tool for understanding the subject matter, structuring tasks, or serving as a "starting point" for individual creative work. In this regard, AI is not viewed solely as a means of circumventing effort, but in some instances, as a learning manager, highlighting its potential in educational contexts, provided its use is guided by pedagogical reflection and supervision. These findings underscore the need for a didactic framework that integrates AI use into teaching, alongside an emphasis on shaping a value-based orientation in which respondents are encouraged to distinguish between assistance and the substitution of their activity.

Based on content analysis of responses to the item "Which AI tools do you know or use?" a categorisation of reported AI tools was conducted. Responses were classified, and individual entries were assigned to relevant AI-based tools or applications. During processing, duplicates, linguistic variations, typographical errors and non-standard or unidentifiable mentions were eliminated.

The most frequently mentioned tool was ChatGPT, which appeared in most responses. Other tools cited with high frequency included Microsoft Copilot/Bing AI, Google Gemini and AI features integrated into applications such as Canva, Notion and Duolingo, representing commonly accessible solutions with embedded AI functionality. Tools such as Grammarly, DeepSeek, Claude, Grok and GitHub Copilot were reported with significantly lower frequency.

Less common, yet identifiable entries included locally operated large language models (LLMs) and tools such as Perplexity, Brave AI, Ollama, or those labelled as Qwen. A smaller number of responses contained irrelevant or unidentifiable entries, which were categorised as “unclassified”. The overall classification (refer to Table 11) contributed to greater accuracy and clarity in the analysis of AI tools used or known to the respondents. These findings indicate a high level of awareness and active use of a diverse range of AI tools within the target group.

Table 11. Frequency of reported AI tools in respondents’ answers

AI tool	Occurrence (n)
ChatGPT	n = 1745
Microsoft Copilot/Bing AI	n = 873
Google Gemini	n = 727
AI in applications (e.g., Canva, Duolingo …)	n = 543
Grammarly	n = 196
DeepSeek	n = 95
Claude	n = 34
Grok	n = 22
Github Copilot	n = 22
Perplexity	n = 17

6 DISCUSSION AND COMPARISON WITH RELATED RESEARCH

Learners reported regularly using AI tools for their studies. These findings indicate substantial use of AI tools among the surveyed respondents and are consistent with the conclusions of authors [12, 13, 24], who indicate that a significant portion of respondents actively use AI in their daily school practice. In the item investigating the purposes for which AI is utilised, the most frequently mentioned uses were text generation and subject-matter explanation.

The findings are also relevant in the context of ongoing educational reforms. In Slovakia, the recently introduced roadmap for AI in Education emphasises the development of AI literacy, responsible use of AI, teacher preparedness and the creation of methodological guidance for schools [40]. Similar priorities can be found in the Czech Strategy for the Education Policy 2030+, the Policy for the development of AI in Poland from 2020 and Hungary’s Artificial Intelligence Strategy 2020–2030, all of which stress digital competencies, AI literacy, and preparation for technological change [41–43]. Together, these strategic initiatives indicate a broader Central European trend towards integrating AI competencies into education systems while simultaneously addressing ethical, societal and workforce-related challenges associated with AI technologies.

The results correspond with the claims of [1, 2], who state that AI enables personalised learning, content generation and immediate feedback. They also support previous findings concerning AI’s potential to facilitate cognitive processes and adapt educational content to individual learner needs [6]. Respondents generally reported confidence in recognising inaccurate AI outputs, which aligns with the digital literacy requirements outlined in [3]. Moreover, it suggests that respondents perceive themselves as possessing a certain level of digital competence necessary for the responsible use of AI in education. Positive attitudes toward integrating AI into teaching further correspond with trends in inclusive and adaptive education identified in [2, 5, 6, 7].

At the same time, the findings reveal important ethical concerns. Respondents identified reduced independent thinking as the primary risk associated with AI use, which is consistent with concerns raised in studies examining the boundary between educational assistance and the replacement of respondents' cognitive activity [10, 11]. Teachers' restrictions on AI use, as reported by respondents, reflect broader concerns about academic dishonesty, uncertainty about AI integration and limited teacher preparedness [8, 14, 16, 24, 25].

Open-ended responses revealed several forms of academically dishonest AI use, including automated task completion, code generation without understanding, AI-produced essays and presentations, and complete delegation of assignments to AI tools. Similar concerns have been documented in previous studies on AI-assisted cheating and academic integrity [9–11, 35]. Nevertheless, some respondents also described constructive uses of AI for task analysis, problem decomposition, and learning support, reflecting the educational potential of AI-enhanced learning [10, 26].

The findings are consistent with recent studies examining AI in educational settings. Research involving university students and teachers highlights both the pedagogical benefits of AI and concerns regarding academic integrity, ethical responsibility, transparency and institutional preparedness [26–28]. Likewise, studies conducted in K–12 contexts emphasise the importance of curriculum integration, ethical frameworks, data governance, and systematic policy implementation to ensure responsible AI adoption [29–33]. The present findings support these conclusions by demonstrating that vocational secondary school learners actively use AI while simultaneously encountering ethical challenges related to its responsible application.

According to [34], AI is increasingly used by secondary school learners to support homework and other academic activities, while [35] demonstrates that generative AI has altered the strategies learners use to engage in academic dishonesty. Together with the present findings, these studies suggest that the challenge for schools is no longer whether learners will use AI, but how educational institutions can guide its ethical and pedagogically meaningful use.

Based on the synthesis of these findings, research question RQ1 was answered affirmatively within the surveyed sample: AI was reported to be widely used by vocational secondary school learners in the learning, preparation and completion of school tasks. Regarding research question RQ2, it was confirmed that AI is, to some extent, also used in ways that can be characterised as academically dishonest, with the boundary between legitimate use and misuse being perceived subjectively and variably. These findings further underscore the need for systematic pedagogical guidance toward responsible and ethical AI use in the educational process.

A limitation of the present study is that several findings regarding AI literacy, critical evaluation of AI-generated outputs and recognition of inaccurate responses are based on respondents' self-reported perceptions rather than direct assessments of their actual competencies. Consequently, the reported results should be interpreted with appropriate caution. Future research could complement self-report measures with performance-based and task-based assessments that directly evaluate respondents' ability to use AI tools critically, effectively and ethically in authentic educational situations.

7 CONCLUSION

The study analysed the use of AI in the educational process at secondary vocational schools. The findings revealed a broad application of AI tools by learners across various dimensions of learning, including knowledge acquisition, text generation, task completion and project implementation. The integration of generative AI platforms such as ChatGPT, Microsoft Copilot and Google Gemini into learners' everyday academic practice indicated widespread use of these technologies among the surveyed respondents.

The data further indicated that a considerable proportion of respondents reported being able to critically assess the accuracy and validity of AI-generated outputs, suggesting a degree of digital and critical literacy. At the same time, it was identified that a significant number of respondents employed AI in ways that circumvented active cognitive engagement, including the automated generation of programming code, written assignments and task solutions without adequate understanding of the outcomes. This instrumental use of AI reflected pragmatic strategies aimed at minimising time and cognitive load, with some respondents acknowledging an ethical boundary between legitimate assistance and academic dishonesty.

The findings confirm the need for a comprehensive, ethically grounded pedagogical framework that systematically fosters respondents' digital, cognitive and metacognitive competencies while equipping educators with the tools and skills to responsibly integrate AI into educational practice. As AI becomes increasingly embedded in vocational and professional environments, the ability to critically evaluate AI-generated outputs, formulate effective prompts and engage in responsible human-AI collaboration is likely to become an essential component of vocational competence.

8 REFERENCES

[1] J. Sardi *et al.*, "How generative AI influences students' self-regulated learning and critical thinking skills? A systematic review," *International Journal of Engineering Pedagogy (iJEP)*, vol. 15, no. 1, pp. 94–108, 2025. https://doi.org/10.3991/ijep.v15i1.53379

[2] J. Singh and J. S. Goyal, "The future of AI in education: A conceptual exploration," *International Journal of Indian Psychology*, vol. 13, no. 1, pp. 3022–3027, 2025. https://ijip.in/articles/future-of-ai-in-education/

[3] E. Kasneci *et al.*, "ChatGPT for good? On opportunities and challenges of large language models for education," *Learning and Individual Differences*, vol. 103, Article 102274, 2023. https://doi.org/10.1016/j.lindif.2023.102274

[4] B. K. Prahani, I. A. Rizki, B. Jatmiko, N. Suprapto, and A. Tan, "Artificial intelligence in education research during the last ten years: A review and bibliometric study," *International Journal of Emerging Technologies in Learning (iJET),* vol. 17, no. 8, pp. 169–188, 2022. https://doi.org/10.3991/ijet.v17i08.29833

[5] I. Pondelíková, *Enhancing University Education in Slovakia: Pioneering AI Tools for Achieving Excellence in the Educational Process of English Language and Anglophone Cultures*. Trnava, Slovakia: University of Ss. Cyril and Methodius in Trnava, 2025. [Online]. Available: https://www.ucm.sk/files/sk/ine-pracoviska/centrum-informacnych-zdrojov-ucm-trnave/referat-informacnych-sluzieb/e-zdroje/ucebne-texty-k-stiahnutiu/enhancing-university-education-slovakia.pdf

[6] N. Bi, "Inclusive and equitable education with AI: Addressing the needs of diverse learners through AI solutions, ensuring quality and accessibility," *International Journal of Humanities and Social Science Invention*, vol. 14, no. 4, pp. 69–74, 2025. https://doi.org/10.35629/7722-14046974

[7] I. Pondelíková and J. Luprichová, "AI-assisted enhancing of gender awareness through reading comprehension in history and literature courses of anglophone cultures," in *Proceedings of CELDA 2024*, 2024. [Online]. Available: https://eric.ed.gov/?id=ED665423

[8] R. Denkin, "On perception of prevalence of cheating and usage of generative AI," *arXiv preprint arXiv:2405.18889*, 2024. https://doi.org/10.48550/arXiv.2405.18889

[9] M. Černochová, H. Selcuk, and T. Podoljak, "Perspectives of Czech high school students on cheating in remote education," in *Proceedings of the European Conference on e-Learning*, 2024, vol. 23. https://doi.org/10.34190/ecel.23.1.2773

[10] N. M. Finnie-Ansley, P. Denny, J. Becker, J. Prather, A. Luxton-Reilly, and B. A. Becker, "The robots are coming: Exploring the implications of OpenAI codex on introductory programming," in *Proceedings of the Australasian Computing Education Conference (ACE 2022)*, 2022, pp. 10–19. https://doi.org/10.1145/3511861.3511863

[11] E. Pariyanti, M. Wibowo, Z. Sultan, and S. Patiro, "Navigating the ethical dilemma in digital learning: Balancing AI with spiritual integrity to address cheating," *Journal of Applied Research in Higher Education*, vol. 18, no. 4, pp. 1031–1043, 2025. https://doi.org/10.1108/JARHE-10-2024-0522

[12] UNESCO, "Guidance for generative AI in education and research," 2023. https://unesdoc.unesco.org/ark:/48223/pf0000386693

[13] D. Dobrovská, D. Vaněček, and Y. I. Yorulmaz, "Students' attitudes towards AI in teaching and learning," *International Journal of Engineering Pedagogy (iJEP),* vol. 14, no. 8, pp. 88–106, 2024. https://doi.org/10.3991/ijep.v14i8.52731

[14] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, "Systematic review of research on artificial intelligence applications in higher education – where are the educators?" *International Journal of Educational Technology in Higher Education*, vol. 16, no. 39, 2019. https://doi.org/10.1186/s41239-019-0171-0

[15] I. Pondelíková and J. Luprichová, "Exploring the efficacy of ChatGPT in enhancing specialized communication skills in english language learning," *Journal of Teaching English for Specific and Academic Purposes*, vol. 13, no. 1, pp. 25–40, 2025. https://doi.org/10.22190/JTESAP250125003P

[16] J. Luprichová, "Artificial intelligence as a teaching assistant in vocational education: Preliminary insights from AI tool evaluation," in *Proceedings of UMTEB 2025*, A. N. Özker and A. Ada, Eds., *Liberty Publishing House*, 2025, pp. 1–9.

[17] Z. Huľová and E. Bolčová, "Implementation of the STEAM concept in project learning," in *Technical Creativity in School's Curricula with the Form of Project Learning: From Idea to Product – From the Kindergarten to the Technical Faculty: 27th International Science Symposium*, J. Bezjak, Ed., Somaru, Slovenia, 2024, pp. 34–38.

[18] M. Hrobková and Z. Huľová, "Project-based learning as a strategy of teaching english language," in *QUAERE 2024: Reviewed Proceedings of the Interdisciplinary Scientific International Conference for PhD Students and Assistants*, vol. 14, 2024, pp. 490–498.

[19] R. Hrmo, J. Miština, and L. Krištofiaková, "Improving the quality of technical and vocational education in Slovakia for European labour market needs," *International Journal of Engineering Pedagogy (iJEP)*, vol. 6, no. 2, pp. 14–22, 2016. https://doi.org/10.3991/ijep.v6i2.5369

[20] P. Andres, D. Dobrovská, D. Vaněček, and J. Miština, "The impact of the pandemic crisis on technology standard of traditional university education," in *Mobility for Smart Cities and Regional Development – Challenges for Higher Education*, M. E. Auer, H. Hortsch, and O. Michler, Eds., vol. 2, Springer, Charm, pp. 187–198, 2022. https://doi.org/10.1007/978-3-030-93907-6_20

[21] P. Gavora, *Úvod do pedagogického výskumu*. Brno, Czech Republic: Paido, 2000.
[22] P. Gavora, "Elektronická učebnica pedagogického výskumu," *Bratislava, Slovakia: Univerzita Komenského,* 2010. http://www.e-metodologia.fedu.uniba.sk/
[23] A. Kaščáková and G. Nedelová, *Štatistické metódy pre spoločenské a humanitné vedy*. Banská Bystrica, Slovakia: UMB, 2011.
[24] Y. Çetin, H. Alakuş, and H. Kaplan, "Examining school principals' and teachers' perceptions of using ChatGPT in education," *Educational Process: International Journal*, vol. 13, no. 3, pp. 85–96, 2024. https://doi.org/10.22521/edupij.2024.133.5
[25] F. Gjermeni, F. Prodani, and E. Zeqo, "Role of AI in education: A review," *International Journal of Engineering Pedagogy (iJEP),* vol. 15, no. 4, pp. 127–142, 2025. https://doi.org/10.3991/ijep.v15i4.54055
[26] J. Sevilla-Bernardo, L. Cervera, and J. Martin-Robles, "Impact and opportunities of generative artificial intelligence in education: A study of academic perceptions," *International Journal of Emerging Technologies in Learning (iJET),* vol. 20, no. 3, pp. 55–71, 2025. https://doi.org/10.3991/ijet.v20i03.55809
[27] D. Stoyanova, S. Stoyanova-Petrova, and N. Mileva, "Exploring students' and teachers' perceptions about using ChatGPT in programming education," *International Journal of Engineering Pedagogy (iJEP)*, vol. 15, no. 2, pp. 15–41, 2025. https://doi.org/10.3991/ijep.v15i2.50607
[28] G. Asiksoy, "An investigation of university students' attitudes towards artificial intelligence ethics," *International Journal of Engineering Pedagogy (iJEP)*, vol. 14, no. 8, pp. 153–169, 2024. https://doi.org/10.3991/ijep.v14i8.50769
[29] I. Irwanto, "Research trends on artificial intelligence in K–12 education in Asia: A bibliometric analysis using the scopus database (1996–2025)," *Discover Artificial Intelligence*, vol. 5, 2025. https://doi.org/10.1007/s44163-025-00389-4
[30] T. K. F. Chiu, H. Meng, C. -S. Chai, I. King, S. Wong and Y. Yam, "Creation and evaluation of a pretertiary artificial intelligence (AI) curriculum," *IEEE Transactions on Education*, vol. 65, no. 1, pp. 30–39, 2022. https://doi.org/10.1109/TE.2021.3085878
[31] J. Y. Chung and S. Lee, "Dropout early warning systems using machine learning in school education," *Children and Youth Services Review*, vol. 96, pp. 346–353, 2019. https://doi.org/10.1016/j.childyouth.2018.11.030
[32] C. S. Chai, P.-Y. Lin, M. S. Y. Jong, Y. Dai, T. K. F. Chiu, and J. Qin, "Perceptions of and behavioral intentions towards learning artificial intelligence in primary school students," *Educational Technology & Society*, vol. 24, no. 3, pp. 89–101, 2021. [Online]. Available: https://www.jstor.org/stable/27032858
[33] H. Crompton, M. V. Jones, and D. Burke, "Affordances and challenges of artificial intelligence in K–12 education: A systematic review," *Journal of Research on Technology in Education*, vol. 56, no. 3, pp. 248–268, 2024. https://doi.org/10.1080/15391523.2022.2121344
[34] M. Turós, R. Nagy, and Z. Szűcs, "What percentage of secondary school students do their homework with the help of artificial intelligence? – A survey of attitudes towards artificial intelligence," *Computers and Education: Artificial Intelligence*, vol. 8, 2025. https://doi.org/10.1016/j.caeai.2025.100394
[35] V. R. Lee, D. Pope, S. Miles, and R. C. Zárate, "Cheating in the age of generative AI: A high school survey study of cheating behaviors before and after the release of ChatGPT," *Computers & Education: Artificial Intelligence*, vol. 7, 2024. https://doi.org/10.1016/j.caeai.2024.100253
[36] European Commission, *Digital Education Action Plan 2021–2027: Resetting Education and Training for the Digital Age*. Brussels, Belgium: European Commission, 2020. [Online]. Available: https://education.ec.europa.eu/sites/default/files/document-library-docs/deap-communication-sept2020_en.pdf

[37] R. Vuorikari, S. Kluzer, and Y. Punie, *DigComp 2.2: The Digital Competence Framework for Citizens – With New Examples of Knowledge, Skills and Attitudes*, Luxembourg: Publications Office of the European Union, 2022. https://dx.doi.org/10.2760/115376

[38] European Commission, *Ethics Guidelines for Trustworthy AI*. 2019. [Online]. Available: https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

[39] European Commission, Directorate-General for Education, Youth, Sport and Culture, *Ethical Guidelines on the Use of Artificial Intelligence and Data in Teaching and Learning for Educators*. Luxembourg: Publications Office of the European Union, 2022. https://doi.org/10.2766/153756

[40] Ministry of Education, Research, Development and Youth of the Slovak Republic, *AI in Education in Slovakia: Roadmap for AI in Education*. Bratislava, Slovakia: MŠVVaM SR, 2025. [Online]. Available: https://ai.iedu.sk/en/

[41] Ministry of Education, Youth and Sports of the Czech Republic, *Strategy for the Education Policy of the Czech Republic up to 2030+*. Prague. Czech Republic: MEYS, 2020. [Online]. Available: https://msmt.gov.cz/vzdelavani/skolstvi-v-cr/strategie-2030

[42] Government of Hungary, "Hungary's artificial intelligence strategy 2020–2030," Budapest, Hungary: Government of Hungary, 2020. [Online]. Available: https://ai-hungary.com

[43] Council of Ministers of the Republic of Poland, *Policy for the Development of Artificial Intelligence in Poland from 2020*, Warsaw, Poland: Council of Ministers of the Republic of Poland, 2020. [Online]. Available: https://www.gov.pl/attachment/928200fa-b1a6-4c0c-b3a8-d1fbf1e1175a

9 AUTHORS

Peter Tokoš is a researcher at the Department of Didactics of Vocational Subjects at DTI University in Dubnica nad Váhom, Slovakia. His research focuses on technical and vocational education, distance and hybrid learning, and the integration of artificial intelligence into vocational teaching (E-mail: peter.tokos@petertokos.com).

Roman Hrmo is a Professor at the Czech University of Life Sciences in Prague, Czechia. His research interests include engineering pedagogy and the didactics of technical subjects (E-mail: hrmo@ivp.czu.cz).

Juraj Miština is an Associate Professor at the Faculty of Arts, University of Ss. Cyril and Methodius in Trnava, Slovakia. His research focuses on field didactics, internet linguistics, digital communication, and technology-enhanced learning (E-mail: juraj.mistina@ucm.sk).

Lucia Krištofiaková is an Associate Professor at the Department of Pedagogy at the Czech University of Life Sciences in Prague, Czechia. Her research focuses on engineering pedagogy, educational quality, and quality assurance in education (E-mail: kristofiakova@ivp.czu.cz).

Lucie Smékalová is an Assistant Professor at the Institute of Education and Counselling at the Czech University of Life Sciences in Prague, Czechia. Her research interests include teacher competencies, transferable skills, adult education, and innovative teaching methods (E-mail: smekaloval@ivp.czu.cz).

Online-Journals.org

iJEP International Journal of Engineering Pedagogy

iJEP | eISSN: 2192-4880 | Vol. 16 No. 5 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijep.v16i5.60647

PAPER

Undergraduate Research Training and Generic Competencies in Engineering Graduates

Katerina Galantini Velarde (✉), Karen Urquizo Baldárrago, Lisette Abrahamzon Garcia

Universidad de Lima, Lima, Peru

kgalanti@ulima.edu.pe

ABSTRACT

Higher education programs are embracing curricular models that incorporate active teaching-learning methodologies to foster students' active participation in knowledge building, based on competency-based training. Research-based learning (RBL) stands out as an active methodology that can be used at various academic levels, including undergraduate. In this context, the present research explores the contribution of undergraduate research training to the process of developing generic competencies in engineering students. The study focuses on the perceptions of a group of employers and graduates from a Peruvian higher education institution. A mixed-methods approach was adopted, as interviews and surveys were applied. The study had a descriptive purpose with a concurrent design. The findings suggest that undergraduate research training is perceived as supporting the development of generic competencies such as research, teamwork, effective communication, analytical and critical thinking, adaptability, digital literacy, intellectual curiosity, and lifelong learning (LL). Overall, the results highlight undergraduate research training, implemented through RBL, as an effective strategy associated with the development and strengthening of generic competencies and the alignment of Science, Technology, Engineering, and Mathematics (STEM) education with labor market demands, while underscoring the importance of consolidating an institutional research culture within competency-based curricula.

KEYWORDS

undergraduate research training, generic competencies, research-based learning (RLB), engineering education, science, technology, engineering, and mathematics (STEM)

1 INTRODUCTION

Over the last 100 years, educational trends have been leaning towards the use of active methodologies for the teaching-learning process [1, 2]. These are based on students having a leading role within the training process [3, 4, 5], as they encourage their participation towards the construction of knowledge [6]. In doing so, they promote the development and reinforcement of meta-learning, a necessary competency for

Galantini Velarde, K., Urquizo Baldárrago, K., Abrahamzon García, L. (2026). Undergraduate Research Training and Generic Competencies in Engineering Graduates. *International Journal of Engineering Pedagogy (iJEP)*, 16(5), pp. 80–111. https://doi.org/10.3991/ijep.v16i5.60647

Article submitted 2026-01-19. Revision uploaded 2026-06-02. Final acceptance 2026-06-25.

self-regulation [7], which is also needed to guarantee lifelong learning (LL) [8]. Active methodologies include project-based learning (PrBL) [9], problem-based learning (PBL) [10], team-based learning (TBL) [11], and research-based learning (RBL) [12].

Among the above, RBL, also identified as inquiry-based learning, stands out for its relationship with the development of generic competencies [13]. In fact, it is grounded in the "knowing how to know" and "knowing how to do," which represent two of the four (4) foundational attributes of competencies [8]. RBL has two fundamental properties: (1) it is research-directed and guided by a professor as part of the teaching role, and (2) the research agents are not research professionals but rather subjects in training [14]. RBL requires students to carry out activities such as conducting observations, proposing questions, examining literature, planning research, developing and applying tools to collect data, analyzing and interpreting information, suggesting solutions, and communicating results [8, 15, 16, 17].

In this context, RBL has been reported to bring several benefits for students, as it improves their knowledge, interest in learning, self-engagement [18], and creativity [19]. At the same time, it fosters the learning of all the stages of the research while developing critical thinking, promoting questioning styles of thinking, and making LL a core value [20]. As RBL focuses on engaging students in practical activities to investigate scientific phenomena [21], it is a methodology that indeed allows them to construct their own knowledge [22, 23]. Consequently, RBL can be used for research at various academic levels, including undergraduate.

Within the higher education context, RBL is used for undergraduate research training. Undergraduate research may be defined as research carried out by an undergraduate student, who aims to make an original intellectual or creative contribution to his or her discipline [13]. It is a collaborative activity in which the student, with the guidance of a teacher, develops all the phases of an investigation. Consequently, skills such as creative and critical thinking, effective communication, and the asking "what if" and "why not" questions are put into practice [24]. Within the Science, Technology, Engineering, and Mathematics (STEM) field, this last skill is particularly important, as students are required to test their ideas in a systematic and interactive way [25]. Thus, undergraduate research training has been integrated through diverse research experiences across engineering curricula [5, 8, 26, 27, 28].

In a parallel scenario, higher education programs are committed to competency-based curricular models. In fact, at the "World Conference on Higher Education 2022" (CMES), integral training based on competencies was reaffirmed as an axis for higher education [29]. Competencies may be understood as a set of skills, attitudes, and values that are required for the holistic development of the learners [30]. Competency-based curricular models, grounded in the development of competencies, equip students to adapt effectively to ongoing environmental changes, while constructing knowledge across diverse contexts. In fact, a competency-based curriculum emphasizes the development of both specific competencies, that are particular to each discipline, and generic or transversal competencies, that are shared across professional fields [31]. Across the literature, specific competencies may also be identified as hard skills, while generic competencies are acknowledged as soft skills [32]. Generic competencies are also referred to by a variety of terms, such as key competencies [33], transferable skills [34], professional skills [35], non-technical skills [36], employability skills [37], and twenty-first-century skills [16].

Generic competencies are nourished by knowledge from all academic areas and use the contributions of daily experiences and the challenges of the environment, allowing a knowledge-based societal perspective [38]. Furthermore, they actively contribute to the achievement of the 17 Sustainable Development Goals (SDGs), since they imply adapting to technological advances and collaborating internationally [39]. Certainly, they support students in keeping their knowledge current by fostering LL [8] while contributing to the effective acquisition, development, and consolidation of hard skills [40]. Effective communication, teamwork, leadership, adaptability, critical thinking, or emotional intelligence may be considered as examples of generic competencies [41, 32, 42, 43]. Along these lines, educational stakeholders and accreditation boards worldwide emphasize the importance of addressing these competencies throughout the curriculum, as they provide better employment opportunities and mobility possibilities between different job positions [30].

To date, the literature highlights the benefits of undergraduate research training for developing specific competencies [44, 45], shaping professional aspirations [46, 47], strengthening an institutional research culture [48], fostering employability outcomes [48, 28], and promoting the acquisition of disciplinary research skills [26, 27]. However, there is a lack of specific evidence specifically linking how undergraduate research training contributes to the development of generic competencies in STEM education.

To address this gap, the present case study examines the relationship between undergraduate research training and the development of generic competencies within three undergraduate engineering programs at a private Peruvian university: Industrial, Civil, and Systems. In doing so, it explores employers' and graduates' perceptions regarding how such undergraduate research training contributes to the acquisition and reinforcement of generic competencies. For the purposes of this study, the research question was formulated as follows: how is the contribution of undergraduate research training to the process of developing generic competencies in engineering graduates in Lima, Peru? Additionally, to ensure a narrower scope of this study, two specific objectives of this study were defined: (1) identify the generic competencies most valued by employers of engineering graduates and those missing from the graduate profile, and (2) describe the perception of levels of knowledge in research among engineering graduates.

2 LITERATURE REVIEW

2.1 Research culture

Regularly, undergraduate research training is exercised within a research culture, or culture of research framework, as undergraduate research training is a fundamental pillar for reducing the gap between scientific productivity and the challenges of the industry [49]. To date, "research culture" is a term that does not have a single definition throughout the literature [50], even though most authors suggest the idea of having a particular research environment. In fact, they hold different perspectives.

An often-accepted meaning is the one provided by [51], who stated that research culture refers to an environment characterized by interpersonal support and collaboration, in which colleagues share an affinity for the value of research [51] and uphold behaviors, values, expectations, attitudes, and norms associated with scholarly activity [52]. In addition, [53] proposes that research culture shapes and regulates aspects of the scientific process. These aspects go from how research is conducted in the laboratory to how discoveries are communicated to the public. Other authors such as [54], [55], [56], [57], [58], and [59] support this definition too.

Furthermore, [60], [61], and [62] state that research culture is an enabling environment that encourages better research outputs. [63] and [64] indicate that research culture requires a constant interaction between humans, curricula, and the normative within the university environment. When characterizing research culture, [65] argues that it includes each individual's capacity to exercise research activities, which can be built, enhanced, and refined through proper training. As for this study, research culture may be understood as a dynamic academic environment, where shared values, norms and institutional practices (1) support undergraduate research training; (2) strengthen individual and collective research capacities; and (3) facilitate the integration of research into curricula, professional practice and societal and industry-related challenges.

2.2 Undergraduate research training

Undergraduate research training encompasses both the production of research outcomes and a student-centered approach. This approach fosters the development of skills such as a deeper understanding of discipline-specific concepts and the construction of new knowledge based on existing information [13, 14]. According to [66], it may be defined as: "an inquiry or investigation conducted by an undergraduate student that makes an original intellectual or creative contribution to the discipline." Undergraduate research training requires the support of a professor as a guide to develop all the phases of the research process, according to the student's discipline [24].

Undergraduate research training uses research as an active method in the teaching-learning process. It is supported by RBL, an active methodology where students take the leading role in the research process. In RBL, the instructor assumes a facilitator role, while students autonomously carry out research tasks [67, cited by 68]. Through a series of activities that they must carry out, such as asking questions, examining sources of information, and proposing solutions, students become active participants in their own learning [69]. While conducting these activities, competencies such as critical and creative thinking, oral and written communication, and the habit of asking "what if" and "why not" questions are put into practice [24]. Thus, undergraduate research training may benefit students on personal, professional, and intellectual levels [70].

For this reason, undergraduate research training has been integrated through diverse research experiences embedded across STEM education [5, 8, 13, 26, 27]. There are various strategies to integrate these experiences throughout the curricula: workshops, honor programs, faculty research projects, tutoring by professors in independent studies [71], and student organizations [72]. Another strategy is course-based undergraduate research experiences, which are curriculum-based research opportunities [43].

Undergraduate research training in STEM education not only promotes the development of discipline-specific and research-related competencies but also contributes to the strengthening of generic and employability-related competencies, including effective communication, teamwork, and leadership [8, 44, 45]. It also provides a structured framework through which students address real-world problems related to professional practice, thereby strengthening analytical thinking and intellectual curiosity, which are considered fundamental pillars within STEM fields. Additionally, it promotes autonomy and self-discipline, enhancing students' ability to acquire new knowledge. Consequently, it fosters LL, which is essential for keeping professionals up to date throughout their careers [13].

2.3 Generic competencies

Generic competencies constitute a core component of competency-based STEM education, as they integrate knowledge, skills, and values that are transferable across disciplines and professional contexts [73]. Unlike specific competencies, which are directly related to discipline-specific and technical expertise, generic competencies address transversal aspects of professional performance, enabling professionals to adapt to diverse and changing environments [8, 74].

Effective communication, teamwork, leadership, ethical and professional responsibility, structured work planning, meta-learning, and LL are among the generic competencies commonly fostered in STEM education [41]. Because these competencies are applicable across different stages of professional life, they are considered to be more enduring than specific competencies and serve to complement disciplinary knowledge [74]. Given the need to enhance graduates' employability and align academic training with labor market expectations, the development of generic competencies has become especially pertinent [30].

As highlighted by [13], generic competencies are among the most valued by organizations, as they facilitate professional integration, adaptability to change, and LL. Employers increasingly demand engineers who can communicate effectively, collaborate in multidisciplinary teams, and apply knowledge ethically and responsibly in real-world contexts. Consequently, STEM programs are required to implement active and student-centered methodologies that promote the systematic development of these competencies throughout the curriculum.

However, despite their relevance, the development of generic competencies in higher education continues to face unresolved challenges associated with institutional and curricular support. These challenges include pedagogical approaches, assessment practices, and the perceptions of both teachers and students [75]. In this context, [76] identified conditions that may enhance their development: interactive teaching focused on conceptual understanding, collaborative learning processes, ongoing feedback and tutoring, and flexible assessment methods. Accordingly, the development of generic competencies is fostered through the integration of active learning methodologies [75], such as PrBL, PBL, TBL, and RBL [77].

Thus, undergraduate research training has been identified as a key pedagogical strategy for fostering generic competencies in STEM education. Previous studies in STEM education have emphasized the contribution of undergraduate research to disciplinary research skills and employability outcomes [26, 27]. Furthermore, [13] explicitly demonstrated how undergraduate research training contributes to the development and reinforcement of generic competencies specifically within a civil engineering program. The findings show that RBL, applied through undergraduate research training, functions as a formative bridge between academic training and professional practice, promoting effective communication, teamwork, ethical awareness, and meta-learning. Moreover, this approach not only strengthens students' research skills but also enhances their employability, adaptability, and LL disposition, responding effectively to the demands of the STEM field.

In conclusion, within competency-based education, active learning methodologies play a central role in fostering the development of generic competencies. In this context, RBL provides students with opportunities to engage in undergraduate research experiences that promote research skills, communication, analytical thinking, and problem-solving. These experiences are supported by an institutional research culture that encourages active participation in knowledge construction. Consequently, undergraduate research training implemented through RBL can be conceptually associated with the perceived development of generic competencies relevant to engineering education and professional practice. The theoretical model linking these concepts is shown in Figure 1.

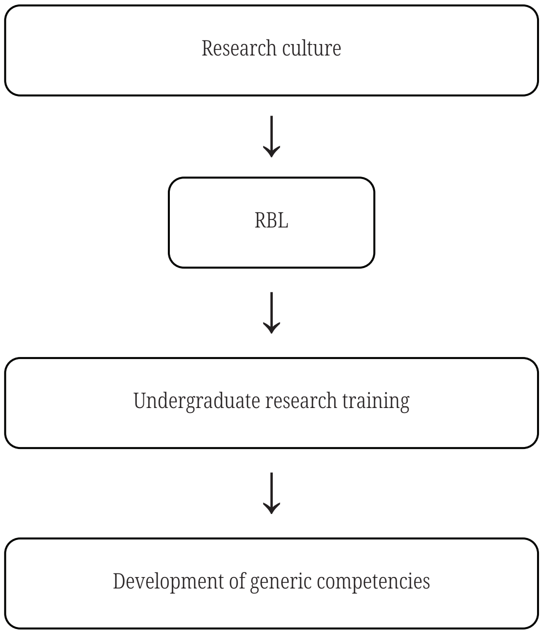

Fig. 1. Theoretical model: RBL, undergraduate research training, research culture, and generic competencies

3 MATERIALS AND METHODS

3.1 Design and participants

The research followed a mixed approach [49]. The study adopted a concurrent design in which qualitative and quantitative data were collected during the same stage of the research process and analyzed in parallel. Integration between both strands occurred during the interpretation and discussion phases through methodological triangulation, allowing the comparison and complementarity of employers' perceptions and graduates' self-perceptions regarding the contribution of undergraduate research training to the development of generic competencies [78].

In this sense, qualitative findings provided contextual and interpretative insights into the competencies valued within professional practice, while quantitative findings contributed descriptive evidence regarding graduates' self-perceived research knowledge across cognitive, investigative, methodological, and collaborative dimensions. The integration of both datasets enabled a broader understanding of the research phenomenon and strengthened the interpretation of the findings.

The study had a descriptive purpose, since the objective was to characterize the contribution of undergraduate research training to the process of developing generic competencies in engineering graduates in Lima, Peru [49].

The participants of this study included two different educational stakeholders from Civil, Industrial and System engineering programs at a Peruvian higher education institution: employers and graduates. In the case of employers, senior professionals representing national companies in the engineering field were considered. As for graduates, professionals with a maximum of two years of graduation, who are currently employed, were included.

Thus, the resultant sample included ten (10) informants for the interviews, according to what is suggested by the literature, as recommendations for qualitative research emphasize the depth of the data collected rather than statistical representativeness. Consequently, nonprobability sampling was applied, specifically judgment sampling, since the researchers deliberately selected the participants based on the characteristics of the target population and the technical criteria previously described [79]. Table 1 presents a detailed overview of the sample's characteristics.

Table 1. Employers' sample characteristics by industry

Industry	Sample
Architecture	1
Industrial Engineering	5
Civil Engineering	4
Total	**10**

However, regarding the survey, the sample size was calculated to ensure the representativeness of the target population, which is predominantly composed of Industrial Engineering graduates. Consequently, the higher proportion of participants from this discipline reflects the actual distribution of graduates within the institution rather than a sampling imbalance. Stratified probabilistic sampling was used, according to the professional careers included in the study, ensuring a 95% confidence level [78]. A total of 140 surveys were obtained. From the total sample, 57.14% of surveyed graduates belong to the 2021–2025 cohorts, whereas 42.86% graduated in 2020 or earlier. Table 2 presents a detailed overview of the sample characteristics.

Table 2. Graduates' sample characteristics by industry

Industry	Sample
Industrial Engineering	113
Systems Engineering	19
Civil Engineering	8
Total	**140**

3.2 Data collection

Data were collected through two different techniques, according to the mixed approach: interviews and a survey.

Exhaustive interviews were applied to employers, with the purpose of identifying the generic competencies most valued in engineering graduates. Those competencies that still needed to be developed and/or reinforced were also identified. A semi-structured guide was developed, with the aim of having the freedom to introduce additional questions to delve into issues that arose throughout the interview. The guide included four sections: (I) introduction, (II) demographic information, (III) applied questions, and (IV) closure. Table 3 presents the eight questions that addressed the requirements of the industry, which correspond to section III.

Table 3. Questions for the interview guide for employers

No	Questions Asked
1	According to your experience, what are the requirements of your sector? And what are the training requirements that you would demand from professionals at the university level?
2	What is your opinion about the preparation of educational institutions at university level to respond to the requirements of their sector?
3	What gaps do you see in university education according to the requirements of your sector?
4	What are the generic competencies (soft skills) most valued by your sector for graduates? And the specific ones (hard skills)? Why?
5	Of the following generic competencies: leadership, collaborative work, proactivity and autonomy, positive attitude towards innovation and entrepreneurship, analytical skills, oral communication, writing, ethical behavior and commitment to sustainable development, which do you think are, in ascending order, the most valued by the market?
6	What generic competencies (soft skills) do you think graduates still need to develop? And which ones to strengthen?
7	Have you heard about "undergraduate research training"? What notions do you have about it? What is your opinion on this? Is it relevant to professional performance?
8	During your academic training, did you receive training in research? What was its scope? What impact did it have on your professional performance?

A survey was also conducted among the graduates. This allowed for describing the self-perceived levels of research knowledge among engineering graduates. For the construction of the survey, the Scopus database was revised to identify existing validated questionnaires measuring self-perceived levels of research knowledge [80, 81, 82, 83].

Survey questions from the selected instruments were organized into dimensions following the framework proposed by [84]: cognitive, investigative, methodological, and collaborative. Following common practice in research, the items were reviewed, selected, and adapted to measure the study variables within the specific context of the present research [78]. The questionnaire subsequently underwent expert validation procedures to ensure both methodological rigor and content validity.

As a result, a questionnaire of 29 closed questions was obtained, using a 5-point Likert scale whose values went from 1, 'strongly disagree,' to 5, 'strongly agree.' The questionnaire was organized into four sections, corresponding to the dimensions: (I) cognitive, (II) investigative, (III) methodological, and (IV) collaborative. Section (I) contained six items; section (II), five; section (III), 12; and section (IV), six, as shown in Table 4.

Table 4. Questionnaire on undergraduate research training for graduates

Dimension	Statements
Cognitive skills	I identify the relevant problems in my environment for the development of research.
	I value the textual and non-textual information that I find in databases such as Scopus, Scielo, among others.
	I organize the information found by topics, levels, or categories based on the identification of differences and similarities of a research topic.
	I verify that the writing of my research is clear and precise in order to communicate it.
	I support my arguments with quotes from relevant authors, data, and facts to ensure their validity.
	I relate the different components of the research (title, problem, question, objectives, methodology, results, and conclusion) so that there is coherence between them.
Investigative skills	I use concepts and keywords to search for information in reliable sources.
	I look for information in databases to build research (Scopus, Redalyc, Latindex, Scielo, and Google Scholar).
	I use bibliographic managers to organize information (Mendeley, Zotero, Endnote, and Refworks).
	I use ICT and AI to organize information (Dropbox, Pocket, OneDrive, ICloud, and ChatGPT).
	I use social networks to communicate research results (Linkedin, Google and Scholar).
Methodological skills	I categorize bibliographic sources relevant to the topic to identify possible research challenges.
	I identify a research challenge with the guidance of the professor to autonomously increase my specific knowledge about the profession.
	I formulate the problem statement and the research question, relating them to the context to demonstrate a critical position on the topic.
	I define the scope of the research according to the level required for the topic to establish a detailed work plan.
	I formulate research objectives in a precise, clear, and achievable way to answer the research question.
	I consolidate a review of the state of the art on the subject of study to contextualize the key points of the research.
	I select the relevant theories and theoretical foundations to build a theoretical framework that supports the hypothesis of my research.
	I formulate the hypothesis about the research topic to contrast the statement of the problem and the results obtained.
	I interpret the results objectively to establish relationships between new knowledge and pre-existing knowledge.
	I develop conclusions to evaluate the processes developed and the results obtained from the bibliographic review.
	I suggest recommendations based on the results obtained to support the implementation of improvement.
	I write documents with scientific-technical rigor to disseminate the results of the research following a citation style (APA, Harvard, Chicago).
Collaborative skills	I use digital tools to communicate and coordinate with the members of the research team (WhatsApp, forums, Facebook, Skype, Hangouts, and email).
	I use virtual platforms to share, analyze, discuss, and build knowledge (Google Drive, Dropbox, and OneDrive).
	I participate in the planning of the work, the distribution of tasks, and the setting of deadlines to ensure the efficient fulfillment of the objectives of the research.
	I assume the fulfillment of the assigned tasks and collaborate with the members of the research team when they have difficulties to allow for the correct progress of the research.
	I recognize the potential of all team members for task assignment.
	I consider the points of view of others and make constructive criticism to ensure optimal fulfillment of research objectives.

Both research instruments were reviewed and approved by the *Comité de Integridad y Ética en la Investigación de la Facultad de Ingeniería* from Universidad de Lima. Participants' prior informed consent was also obtained before application. All results were securely stored in files accessible only to the research team.

3.3 Data analysis

In a first instance, data analysis employed a thematic analysis approach [85]. The qualitative data from the interviews was transcribed verbatim and coded line by line to include relevant quotes from every participant. This process yielded an initial set of codes that were subsequently reviewed and refined using ATLAS.ti software [86].

These obtained codes were reviewed manually and grouped into categories: families that share common characteristics. Finally, categories were associated with themes [87]. Since the approach of this study prioritizes interpretation and contextual understanding of competencies, codes were organized according to eight of them: (1) teamwork, (2) effective communication, (3) research, (4) LL, (5) intellectual curiosity, (6) adaptability, (7) analytical and critical thinking, and (8) digital literacy. Figures 2 to 5 illustrate this process, which includes the coding structure, emerging codes, categories, and themes.

In a second instance, for the quantitative data, information coding was used. Data was manually entered and coded for processing using Microsoft Excel, as suggested by the literature [78]. The Likert-scale items were analyzed through descriptive statistics to identify patterns and central tendencies. Values of 5 and 4 were interpreted as levels of agreement, whereas values of 1 and 2 indicated levels of disagreement.

4 RESULTS

The following section presents the findings from the applied data collection techniques: interview and survey. Thus, it is organized into two (2) subsections to address each method in turn.

4.1 Interview

In the first phase of data collection, employers were interviewed to identify the generic competencies most valued in engineering graduates, as well as perceived gaps in their development during professional training. Since the focus was competencies, this subsection is organized according to the categories and themes around them. The identified competencies were research, LL, critical and analytical thinking, effective communication, teamwork, intellectual curiosity, adaptability, and digital literacy. As employers represent a principal stakeholder within the educational context, this perspective enabled the identification of the need to strengthen coordination between university and industry.

Research competency was addressed by employers who considered that undergraduate research experiences are fundamental for its development. They identified several related categories for this theme, as shown in Figure 2: impact of professional research, research-oriented thinking, and research capacity.

Regarding the first category, impact of professional research, employers acknowledged that research training may have a positive impact on the professional field, as research promotes an analytical way of thinking. They recognized this is the reason why research is needed, not only at a doctoral or master level, but also on companies. As for the second category, research-oriented thinking, employers stated that research experiences promote students asking questions about their surroundings. Moreover, they support learning about different topics, fostering creativity. Finally, about the third category, research capacity, employers highlighted the methodological approach to thinking that it promotes, encouraging individuals to explore multiple solutions to the same problem:

> *"[Research training impacted my professional performance because I always perform] product analysis in marketing."*

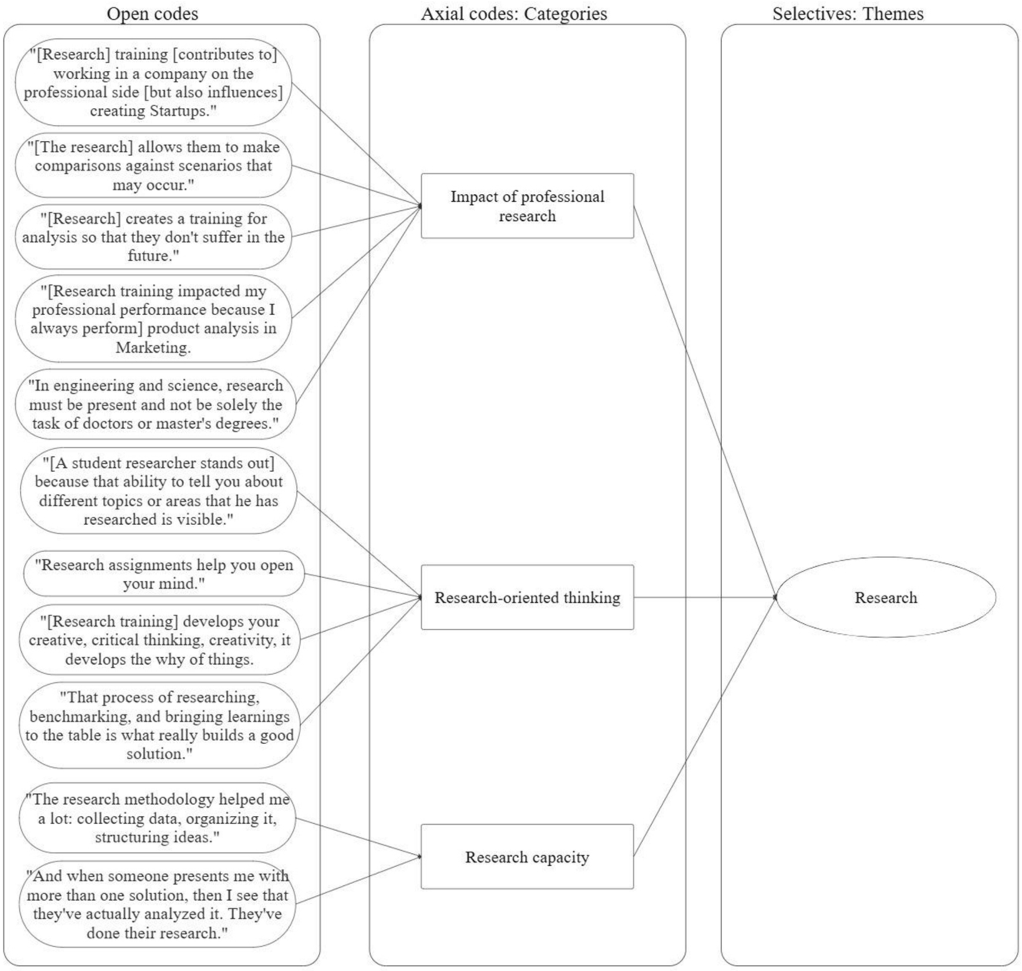

Fig. 2. Codes, categories, and themes identified for the research competency

Lifelong learning was also discussed. Employers considered that implementing undergraduate research experiences has significant relevance for the development of this competency. Commitment, continuous improvement, and ongoing training were some of the identified categories for this theme, as presented in Figure 3. While commitment associates LL with the idea of generating value to organizations, continuous improvement is associated with quality, as stated:

> *"…it's not enough to have your position, it's your ability to generate value…"*
> *"I always tell my team we're about quality, and quality is continuous improvement."*

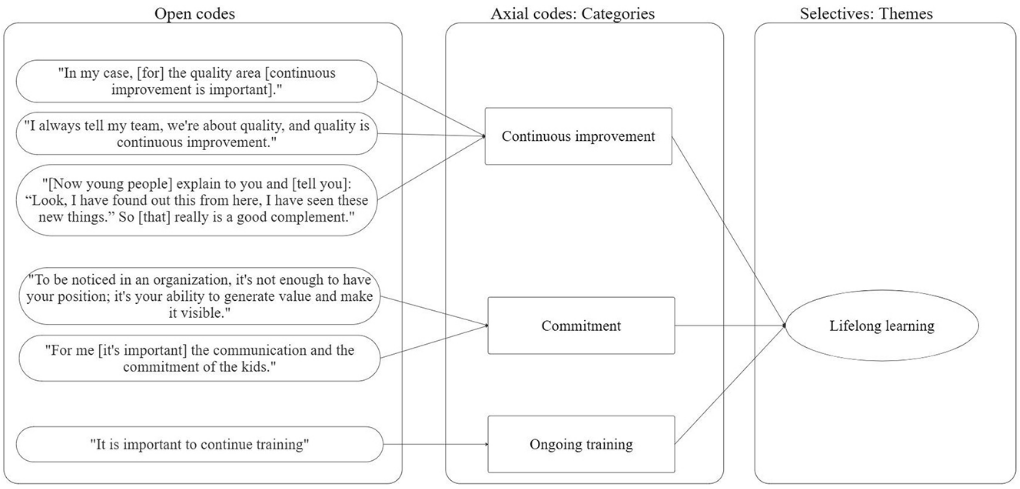

Fig. 3. Codes, categories, and themes identified for the LL competency

Analytical and critical thinking was also addressed by employers who considered that implementing undergraduate research experiences may also positively impact the development of this competency. Categories identified for this theme included strategic, analytical, critical, structured, and cross-cutting analytical thinking. These are shown in Figure 4.

Regarding strategic thinking, employers recognized that this competency is closely related to research practices as they lead the student to formulate questions and hypotheses about a determined subject. In the case of analytical thinking, employers highlighted its importance in the decision-making process, particularly for both deductive and inductive analysis. They believed that young people possess a strong capacity for analysis when using new technologies; however, they require a better understanding of the scientific method to produce accurate reports and reliable indicators. This is stated as follows:

> *"This sector's requirement is to include a strong critical and analytical approach to producing reports and indicators to be implemented."*

In relation to critical thinking, employers recognized the relevance to formulate individual conceptions of what is learned to really understand a subject. It was stated that this competency would be valuable to produce reports and indicators to differentiate correlation from causality.

> *"Many people only describe without truly understanding what they're analyzing. A critical skill is knowing how to differentiate correlation from causation."*

For structured thinking, employers argued that while being asked to solve a problem as a manager, it is key to correctly structure thoughts and generate a coherent line of ideas. This is also important when evaluating somebody else's answer to a problem. Finally, in respect to cross-cutting analytical thinking, the professionals highlighted its relationship with analytical skills, which allows candidates to reason instead of just applying the theory they were taught. It is believed this training allows active learning where individuals are able to construct answers that are rarely given in real-world scenarios.

"That kind of training [through analytical thinking] – where you're taught to reason instead of just applying it – is what really translates into the real world, where answers are rarely given, and you almost always have to construct them."

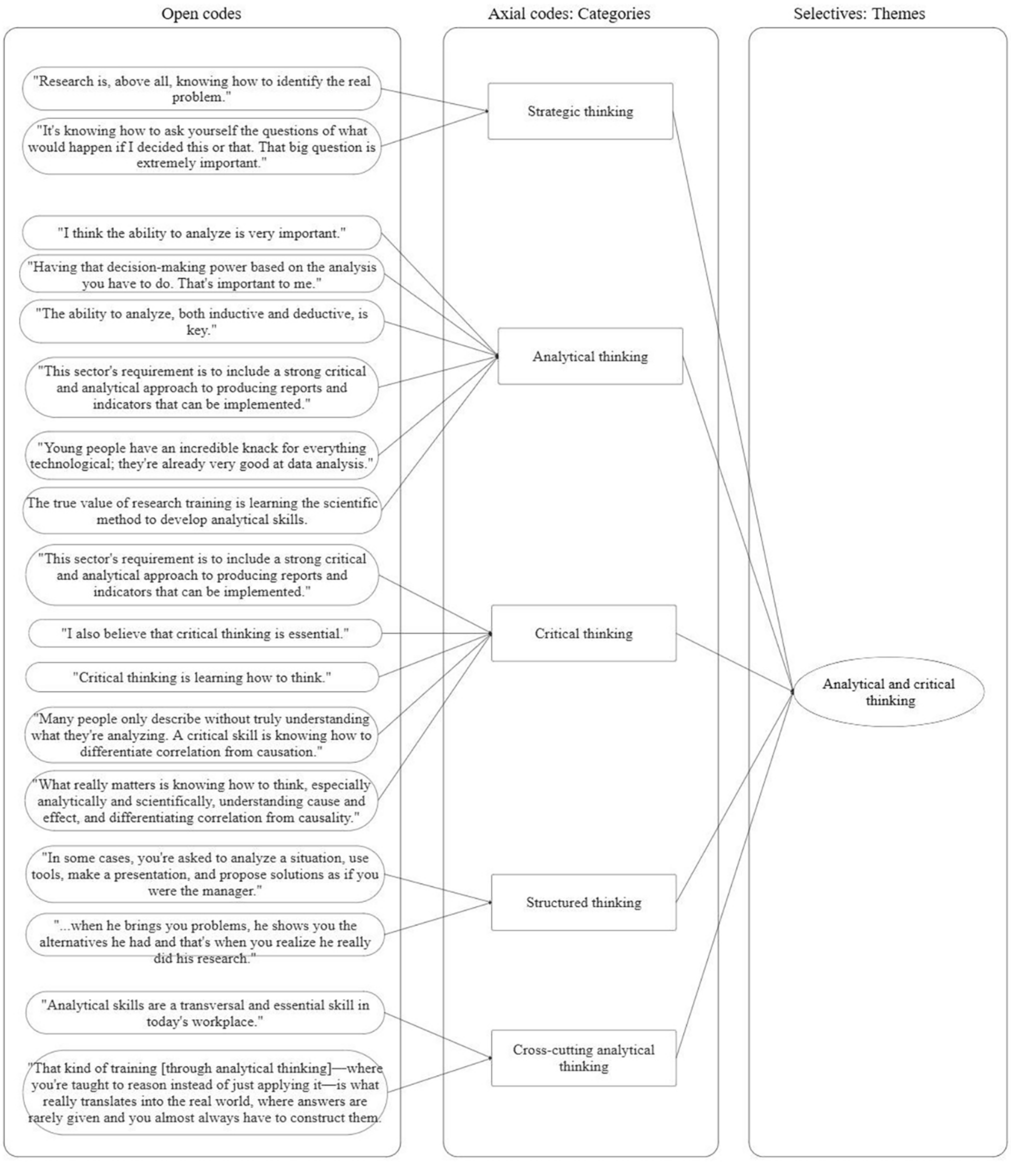

Fig. 4. Codes, categories, and themes identified for the analytical and critical thinking competency

Effective communication was discussed by employers. They considered that implementing undergraduate research experiences has a significant relevance for the development of this competency. They identified several related categories for this theme, such as effective communication, communication for professional performance, active listening, and communicative skills, as shown in Figure 5.

With respect to effective communication, employers stated this competency is essential at all levels. Professionals should be capable of expressing their ideas to stakeholders at all organizational levels, from entry-level to executive positions. Proficiency in adapting the speech to audiences is needed, as stated:

"Knowing how to communicate is also essential. Good ideas are useless if you don't know how to express them."

As for communication for professional performance, it is necessary for a variety of activities such as supporting projects and carrying out good interviews or even an argument. Effective communication is associated with convincing an audience. At the same time, it includes listening. In fact, employers identified active listening as an essential component of effective communication, highlighting its relevance for conflict resolution, especially at the management level. Finally, about communicative skills, employers identified communication as a requirement for professional development at all levels:

"At every level, the ability to communicate is vital."

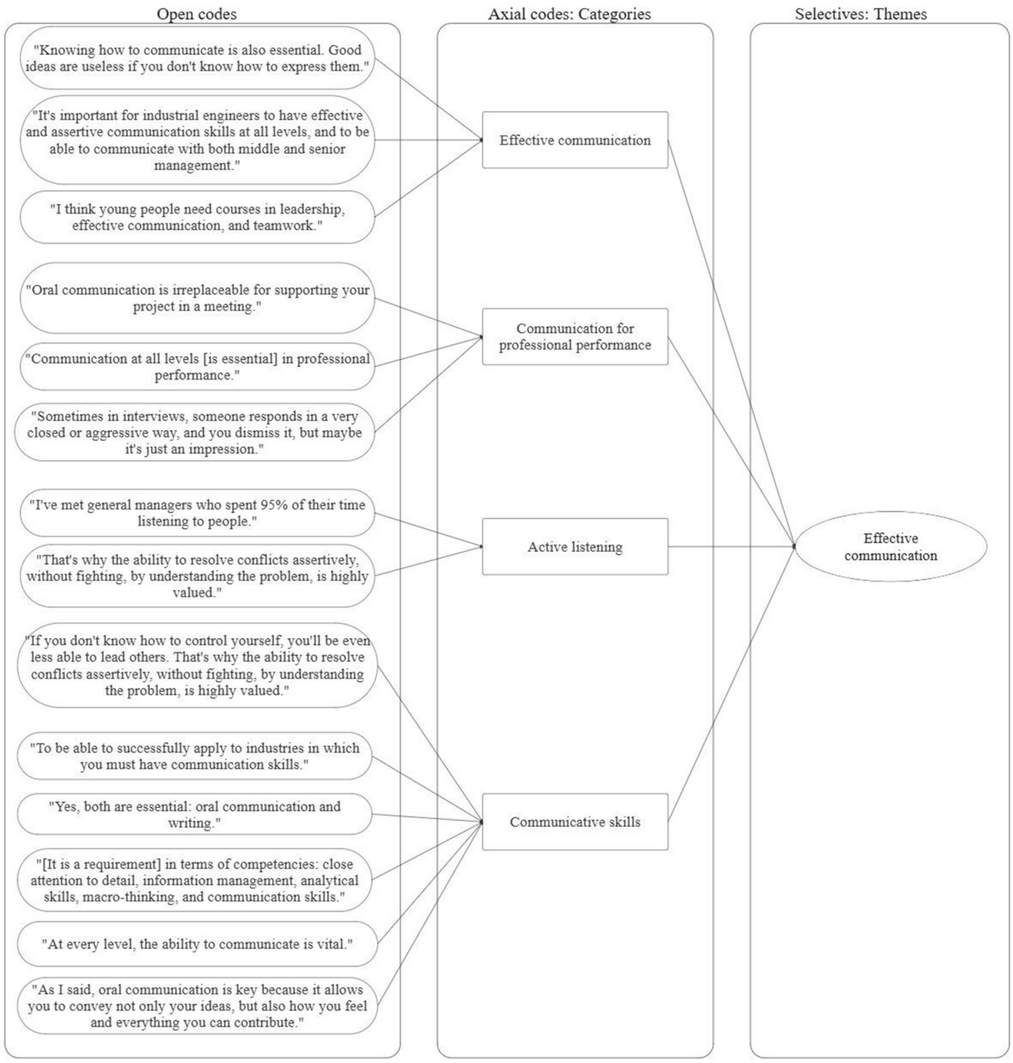

Fig. 5. Codes, categories, and themes identified for the effective communication competency

About teamwork, employers considered that implementing undergraduate research experiences has a significant relevance for the development of this competency. The most relevant categories identified for this theme were complementary competencies and multidisciplinary teams. Regarding multidisciplinary teams, employers stated that projects nowadays are developed by a variety of professionals who are expected to collaborate with each other, reason why teamwork has become more complex. As for complementary competencies, they recognized that teamwork is closely related to other competencies, such as effective communication, leadership, and organizational and management skills. They also identified teamwork as a generic competency necessary for the engineering professional field. However, they also acknowledged further training is needed for its development, as stated below:

> *"I think young people need courses in leadership, effective communication, and teamwork."*

Intellectual curiosity was also discussed by employers. They considered that undergraduate research experiences may also promote the development of this competency. Categories identified for this theme were: academic curiosity, technological support, and professional curiosity. As for technological support, employers stated that this curiosity is fostered by technology, as this can be a source to obtain information. Regarding academic curiosity, it is associated with creativity and a desire to continue learning, while professional curiosity may be transferred to students' academic path, as stated:

> *"[Research training] promotes intellectual curiosity."*
> *"Then, with that attitude, they began to better approach their profession."*

As for adaptability, employers stated that this competency may also be fostered by undergraduate research experiences. Categories identified for this theme included resilience, flexibility, and adaptability. Regarding resilience, employers recognized that adaptability is closely related to other competencies, such as emotional management, pressure management, and people management. They also identified adaptability as a generic competency necessary for the professional field. With respect to flexibility, employers considered that it leads to a stronger capacity to adapt to changing circumstances and unexpected challenges. This capacity allows individuals and teams to remain effective even in dynamic environments, ensuring that goals can still be met despite shifting priorities or unforeseen obstacles. Finally, when referring to adaptability, they acknowledged it is important that professionals are able to transform themselves according to the permanent cycle of constant changes of the environment:

> *"Adapting to generational changes is key."*

Finally, employers stated that developing digital literacy is highly relevant for enhancing professional performance across various sectors. In this regard, categories identified within this theme included: training in AI, the use of technological tools, and technology specific to each sector. With respect to the application of technological tools, professionals considered that automating is key now that artificial intelligence is used more. BIM methodology was pointed out as an example. In this line, with relation to the sector-specific technology, employers found it important for students to master it. For example, in construction, young engineers are expected to use tablets to transform virtual construction into a real one. Lastly, regarding training in AI, they stated that this is an emerging field that should be explored.

4.2 Survey

In the second stage of data collection, surveys were applied to graduates to determine their perceptions about their own research knowledge. To measure the variables, the survey was organized into four sections: (I) cognitive, (II) investigative, (III) methodological, and (IV) collaborative. Consequently, this subsection is organized according to these sections, that might as well be identified as dimensions.

Cognitive skills. Figure 6 presents the results obtained for the cognitive dimension, composed of six items: (1) identification of relevant problems in the environment for research development; (2) assessment of textual and non-textual information found in databases; (3) organization of information by topic, level, or category; (4) verification of the clarity and accuracy of the research writing; (5) ability to support arguments through citations, data, and relevant evidence; and (6) ability to coherently relate the components of the research.

Overall, graduates reported high levels of agreement across the dimension, particularly regarding the verification of clarity and accuracy in research writing (61.4% strongly agreed and 34.3% agreed), the support of arguments through citations, data, and relevant evidence (58.6% strongly and 31.4% agreed), and the coherent articulation of research components (53.6% strongly agreed and 37.9% agreed). Similarly, most participants perceived themselves as capable of identifying relevant research problems (44.3% strongly agreed and 44.3% agreed).

These findings suggest that graduates perceive themselves as possessing strong cognitive skills associated with questioning, critical analysis, and academic writing within research contexts. Nevertheless, a smaller proportion of neutral and negative responses was identified in the item related to the evaluation and organization of information from scientific databases (8.6% neither agreed nor disagreed, 5.7% disagreed, and 1.4% strongly disagreed) and the organization of information according to topics, levels, or categories (10.0% neither agreed nor disagreed, 5.7% disagreed, and 1.4% strongly disagreed), indicating opportunities to further strengthen these processes during undergraduate research training.

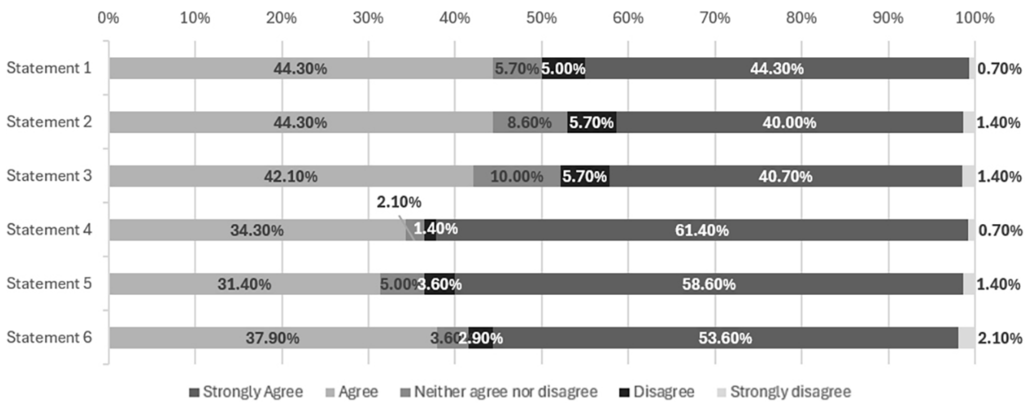

Fig. 6. Values obtained for engineering graduates' self-perceptions of cognitive skills

Note: The numbering on the vertical axis of the figure corresponds to the numbering of the questionnaire found in Table 4.

Investigative skills. Figure 7 presents the values obtained for the investigative dimension, composed of five items: (1) use of concepts and keywords for searching information in reliable sources; (2) search for information in reliable databases;

(3) use of reference managers to classify information; (4) use of ICT and AI to organize information; and (5) use of social networks to communicate research results.

Overall, graduates reported positive perceptions regarding the use of keywords (62.1% strongly agreed and 31.4% agreed) and reliable databases for information retrieval (47.9% strongly agreed and 34.3% agreed), as well as the use of ICT and AI tools to organize information (42.9% strongly agreed and 38.6% agreed). However, lower levels of agreement were identified in relation to the use of reference managers, such as Mendeley and Zotero, for classifying information (27.9% neither agreed nor disagreed, 19.3% disagreed, and 4.3% strongly disagreed) and the use of social networks, such as LinkedIn or Google Scholar, for disseminating research results (32.1% neither agreed nor disagreed, 19.3% disagreed, and 7.9% strongly disagreed). These findings suggest that, while graduates perceive strengths in information searching and organization, additional support may be needed to strengthen skills associated with the management of specialized research scientific tools and the communication of results.

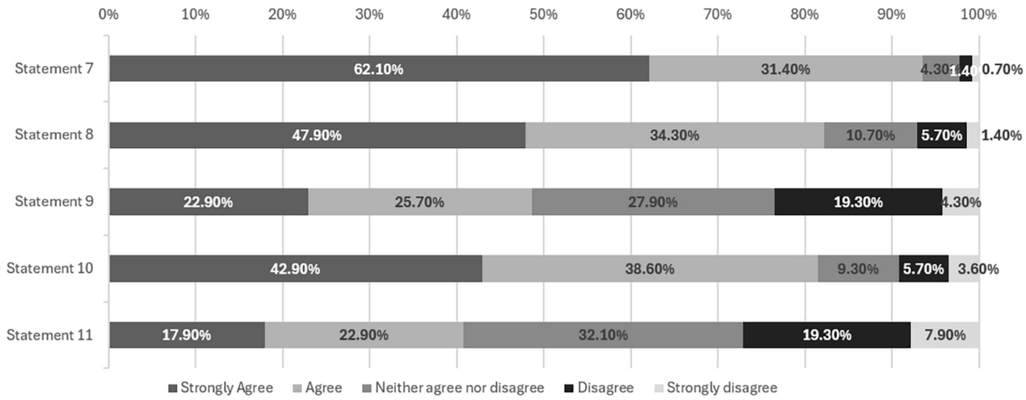

Fig. 7. Values obtained for engineering graduates' self-perceptions of investigative skills

Note: The numbering on the vertical axis of the figure corresponds to the numbering of the questionnaire found in Table 4.

Methodological skills. Figure 8 shows the values obtained for the methodological dimension, composed of twelve (12) items regarding the following abilities: (1) categorizing bibliographic sources relevant to the topic and identifying potential research challenges; (2) identifying a research challenge; (3) formulating a research problem and question; (4) defining the scope of research; (5) formulating research objectives; (6) consolidating a review of the state of the art on the study topic; (7) selecting relevant theories and theoretical foundations; (8) formulating hypotheses; (9) interpreting results; (10) developing conclusions; (11) suggesting recommendations; and (12) drafting documents with scientific-technical rigor.

Overall, graduates reported high levels of agreement across most methodological skills, particularly regarding the formulation of objectives (50.7% strongly agreed and 40% agreed) and hypotheses (42.9% strongly agreed and 47.1% agreed); the interpretation of results (47.9% strongly agreed and 45% agreed); the development of conclusions (45.7% strongly agreed and 45% agreed) and recommendations (51.4% strongly agreed and 37.1% agreed); and the definition of research scope (45.7% strongly agreed and 42.1% agreed).

Positive perceptions were also observed in relation to the construction of theoretical frameworks (46.4% strongly agreed and 40.7% agreed), the consolidation of a state of the art (41.4% strongly agreed and 41.4% agreed), and the formulation of a research problem (45% agreed and 43.6% agreed). Nevertheless, comparatively lower levels of agreement were identified in tasks associated with categorizing bibliographic sources (35% strongly agreed and 38.6%), identifying a research challenge (36.4% strongly agreed and 41.4% agreed) and drafting scientific documents with technical rigor (45% strongly agreed and 34.3% agreed), suggesting the need to further strengthen competencies related to scientific writing, questioning style of thinking, and literature management within undergraduate research training.

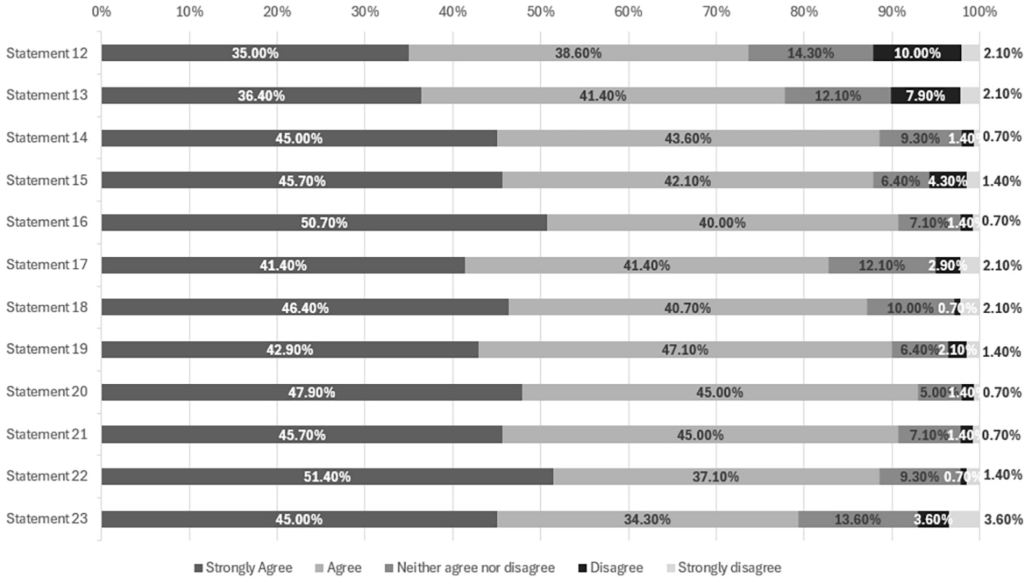

Fig. 8. Values obtained for engineering graduates' self-perceptions of methodological skills

Note: The numbering on the vertical axis of the figure corresponds to the numbering of the questionnaire found in Table 4.

Collaborative skills. Figure 9 shows the values obtained for the collaborative dimension, composed of six (6) items: (1) use of digital tools for communication and coordination with members of the research team; (2) use of virtual platforms to share, analyze, discuss, and build knowledge; (3) participation in every stage of research; (4) assumption of responsibility for fulfilling assigned tasks and collaborating with research team members; (5) recognition of team members' strengths for task allocation; and (6) consideration of others' points of view and constructive criticism.

Overall, graduates reported highly positive perceptions across all items, particularly regarding the use of virtual platforms for collaborative knowledge construction (57.9% strongly agreed and 31.4% agreed), the use of digital tools for communication and coordination (55.7% strongly agreed and 32.9% agreed), responsibility fulfillment (55% strongly agreed and 37.9% agreed) and the consideration of diverse perspectives during research processes (58.6% strongly agreed and 36.4% agreed). They also reported positive perceptions concerning participation (55.7% strongly agreed and 35.7% agreed) and recognition of others' strengths (50.7% strongly agreed and 40.7% agreed).

These findings suggest that graduates perceive themselves as possessing strong collaborative skills within research environments, especially in relation to teamwork, digital interaction, and effective communication. The consistently high levels of agreement across this dimension reinforce the relevance of undergraduate research experiences as spaces that may foster generic competencies.

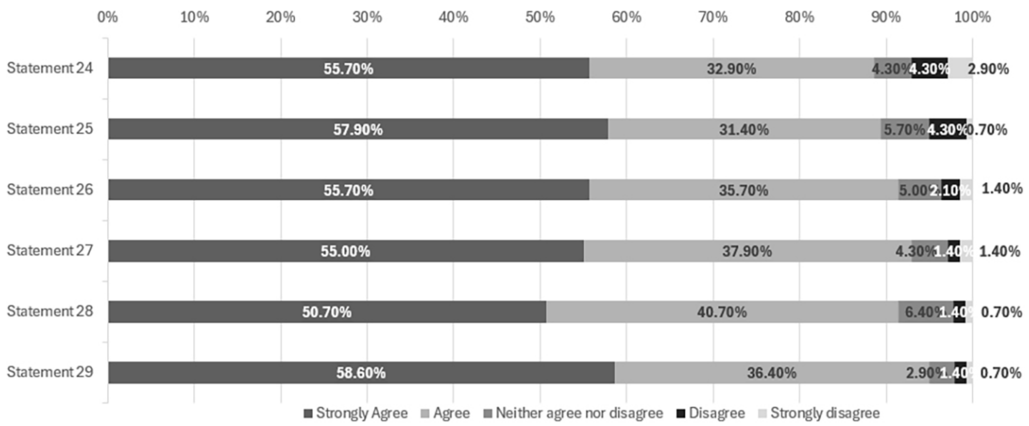

Fig. 9. Values obtained for engineering graduates' self-perceptions of collaborative skills

Note: The numbering on the vertical axis of the figure corresponds to the numbering of the questionnaire found in Table 4.

5 DISCUSSION

This section reports the findings derived from the two data collection techniques, interview and survey, which are presented in separate subsections, each corresponding to one method. Within each subsection, the results are discussed in relation to the specific objective it addresses.

5.1 Identification of the generic competencies most valued by employers and the gaps that need to be developed in engineering graduates

First, research competency emerged as the most prominent competency identified by employers, appearing 35 times as an emerging code during the interviews. Employers emphasized that undergraduate research experiences provide students with structured approaches to problem-solving that may later be transferred to professional practice. In this sense, research experiences integrated into the teaching–learning process allow students to engage with state-of-the-art disciplinary knowledge in a transversal manner [92].

Employers also highlighted the importance of fostering a research-oriented institutional culture to support the incorporation of undergraduate research experiences, strengthen academic productivity, and encourage the industry–academia synergy [48]. Previous studies have similarly suggested that RBL may enhance research skills while simultaneously supporting the perceived development of generic competencies [93]. Consequently, employers stressed the importance of strengthening research competency among undergraduate engineering students.

Furthermore, they also associated research competency with innovation capacity, reinforcing its relevance within contemporary engineering education and professional practice [94]. The findings also suggest that research competency may support the development of other generic competencies, particularly analytical and critical thinking, as well as LL [95].

Second, LL was also emphasized by employers, emerging twelve (12) times as a code during the interviews. They highlighted the role of this competency in bridging the gap between graduates' competencies and the continuous evolution of the labor market demands [96]. As reported by [41], LL equips professionals to cope with the challenges of economic globalization and to remain competitive. Similarly, [97] indicated that the ability to learn continuously and independently is valuable for multidisciplinary work, innovation, and expanding knowledge domains for career transitions. Employers shared this perspective, emphasizing that LL not only enhances employability [98] but also supports the development and application of meaningful knowledge and complementary competencies throughout professional practice.

Third, analytical and critical thinking emerged 13 times during the interviews, highlighting its relevance for engineering graduates. As previously discussed, employers emphasized that this competency is closely associated with undergraduate research experiences, since research processes encourage students to question their surroundings, evaluate information critically, and explore multiple approaches to problem-solving [105]. In this sense, employers perceived this competency as strongly interconnected with research competency and LL, as all three involve inquiry, continuous knowledge acquisition, reflection, and adaptability to changing professional environments. This perspective reinforces previous findings suggesting that analytical and critical thinking may be strengthened through research experiences at different educational levels [99].

Employers also acknowledged that higher education institutions generally provide solid preparation in analytical and critical thinking across engineering specialties. Nevertheless, they stressed the importance of continuing to reinforce it among engineering students due to their relevance for collaboration, idea exchange, and the generation of innovative solutions within professional contexts [95]. Furthermore, analytical and critical thinking has been associated with processes of information searching, selection, and critical evaluation, which are particularly relevant undergraduate research environments [106].

Fourth, employers particularly valued interpersonal competencies, especially effective communication, which emerged 21 times during the interviews, and teamwork, which emerged 18 times. Rather than functioning independently, employers emphasized that these competencies complement one another, contributing to a more comprehensive professional profile in engineering education, as stated by [90]. Their relevance to organizations is associated with employability [88] and professional performance [41] within increasingly collaborative work environments.

Certainly, [41] and [89] corroborated the importance of developing teamwork in engineering professionals, while [8] and [88] revealed that effective communication is needed to allow proper interaction, providing professionals with tools for argumentation and preparing them to exchange ideas within multidisciplinary contexts.

In this regard, employers highlighted the need to strengthen curricular opportunities that foster teamwork and effective communication among future engineers, demonstrating the importance of strengthening these competencies in engineering students. This concern reflects broader discussions regarding undergraduate training quality and the persistent challenges associated with the development of generic competencies [91].

Finally, employers also emphasized complementary competencies associated with professional adaptability and continuous development: intellectual curiosity, adaptability, and digital literacy. Intellectual curiosity emerged 15 times during the interviews and was associated with motivation for knowledge acquisition and proactive engagement with professional challenges. Employers perceived this competency as closely related to research competency, LL, and analytical and critical thinking, since curiosity encourages inquiry, stimulates reflective thinking, and supports professional growth [99]. Previous studies have similarly linked intellectual curiosity to confidence development, creative thinking, perseverance, and problem-solving [24, 100, 101]. In this regard, employers stressed the importance of further strengthening this competency among engineering students due to its relevance for addressing workplace challenges and fostering innovation-oriented attitudes.

Adaptability, which emerged five times during the interviews, was also considered essential within dynamic and constantly evolving professional environments. Employers emphasized that adaptability enables professionals to respond effectively to shifting priorities and organizational challenges through flexibility and resilience [102]. Furthermore, this competency was perceived as strongly connected to LL and the development of other generic competencies, particularly creativity, innovation, and problem-solving [102, 103]. Employers also highlighted that strengthening adaptability may expand graduates' employment opportunities across different organizational contexts [104].

Likewise, digital literacy emerged as a relevant competency for contemporary engineering practice, appearing 10 times during the interviews. Employers associated digital literacy with the effective management of digital tools, adaptation to technological innovations, and the optimization of organizational processes that support productivity and innovation [103, 104, 107]. Previous studies have similarly suggested that this competency facilitates information management and continuous professional training in response to evolving societal and labor market demands [107, 108, 109]. In this sense, employers perceived digital literacy as increasingly interconnected with research competency, LL, and adaptability within technology-driven professional environments.

5.2 Perception of research knowledge levels among engineering graduates

Cognitive skills. Cognitive skills may be defined as the abilities that allow acquiring, processing, storing, and transforming information. According to literature, these skills are essential for research because they involve logical reasoning and flexible thinking, facilitating decision-making and problem-solving processes [110].

The findings revealed high self-perceived levels of cognitive skills among engineering graduates. Graduates particularly reported strong self-perceptions regarding the verification of clarity and accuracy in research writing, the support of arguments through evidence and citations, and the coherent articulation of research components. Positive self-perceptions were also identified in relation to problem identification, information evaluation, and information organization.

These findings suggest that undergraduate research training may support the perceived development of critical and analytical thinking by exposing students to research-oriented tasks involving information management, argumentation, and problem-solving processes. In this sense, the quantitative findings complement the employers' perceptions obtained during the qualitative stage, where analytical and critical thinking was identified as a highly valuable competency for engineering graduates.

Previous studies have similarly suggested that RBL facilitates the understanding of complex theoretical concepts while fostering analytical and critical thinking [90].

Likewise, undergraduate research experiences have been associated with students' ability to critically evaluate information and apply knowledge in authentic academic and professional contexts [69]. Collectively, these findings reinforce the relevance of implementing undergraduate research experiences for supporting cognitive skills development, and thereby generic competencies, in engineering education.

Investigative skills. Investigative skills refer to the abilities that enable the understanding and explanation of phenomena through inquiry, experimentation, and hypothesis testing. According to the literature, these skills are essential for research because they strengthen critical, analytical, and reflective thinking [111].

Overall, graduates reported positive self-perceptions regarding investigative skills, particularly in relation to information retrieval through keywords and reliable databases, as well as the use of ICT and AI tools to organize information. Nevertheless, comparatively lower levels of agreement were identified regarding the use of reference management software and social media for communicating research results.

These findings suggest that undergraduate research training may provide solid foundations for information searching and organization, while simultaneously revealing opportunities to strengthen abilities associated with scientific dissemination and specialized research tools. This pattern is consistent with the qualitative findings, in which employers highlighted the importance of reinforcing effective communication to properly disseminate research outcomes.

Previous studies have similarly indicated that undergraduate research experiences may strengthen both research competency and other generic competencies essential for professional performance, such as LL [93]. In particular, research-oriented learning environments have been associated with improvements in information-searching processes and the management of academic sources [105]. These findings reinforce the importance of consolidating research training strategies that support not only information management but also scientific communication within engineering education.

Methodological skills. Methodological skills may be defined as the ability to approach research questions in a systematic, controlled, and organized manner, while translating theoretical aspects into practical applications and critically examining the information obtained. According to literature, these skills are fundamental for conducting structured and rigorous research processes [112].

The findings revealed consistently high self-perceived levels of methodological skills among engineering graduates. Stronger perceptions were identified in competencies related to formulating objectives and hypotheses, interpreting results, developing conclusions and recommendations, and defining research scope. Positive perceptions were also observed regarding the consolidation of a review of the state of the art, construction of theoretical frameworks, and the contextualization of a research problem.

Nevertheless, comparatively lower levels of agreement emerged in abilities associated with categorizing bibliographic sources, identifying research challenges, and drafting scientific documents with technical rigor. These findings suggest that, while undergraduate research experiences may contribute to the perceived development of methodological skills, additional reinforcement may still be needed in scientific writing, questioning style of thinking, and literature management processes.

Previous studies have similarly emphasized that undergraduate research experiences involve activities such as problem formulation, literature review, data collection, analysis, interpretation, and communication of findings [8]. Likewise, formative research has been associated with the strengthening of methodological skills among university students [113]. In this sense, the findings suggest that research-oriented learning environments may facilitate the integration of theoretical knowledge with practical inquiry processes, supporting the perceived development of methodological skills in engineering education.

Collaborative skills. Collaborative skills can be defined as the ability to coordinate actions with others in pursuit of shared goals through cooperation, communication, trust, and a focus on mutual benefit [93, 110]. According to literature, collaborative skills are essential for research because they facilitate effective communication, openness, trust, and creative thinking [24, 110].

The findings revealed highly positive self-perceptions regarding collaborative skills across all items within the dimension. Graduates particularly reported strong self-perceptions concerning the consideration of diverse perspectives during research processes, responsibility fulfillment, the recognition of others' potential; teamwork coordination; and the use of digital tools and virtual platforms to communicate and build knowledge.

These findings suggest that undergraduate research experiences may foster collaborative learning environments where competencies like effective communication, digital literacy, and teamwork are actively promoted. This result is consistent with the qualitative findings, in which employers emphasized teamwork and effective communication as essential competencies for professional engineering practice.

Previous studies have similarly suggested that collaborative practices contribute to the development of teamwork and effective communication competencies and facilitate effective interaction within multidisciplinary professional environments [95, 114, 115, 116, 117]. In this regard, research-oriented learning environments may support the perceived development of collaborative skills by engaging students in shared inquiry processes that resemble professional and organizational dynamics.

6 CONCLUSIONS

The findings of this study suggest a perceived association between undergraduate research training and the development of generic competencies among engineering graduates in Lima, Peru, particularly regarding cognitive, investigative, methodological, and collaborative skills, which are considered essential for professional integration and performance.

Regarding the first specific objective, employers identified research competency, LL, analytical and critical thinking, teamwork, effective communication, intellectual curiosity, adaptability, and digital literacy as highly valuable for engineering graduates. Rather than functioning independently, these competencies were perceived as strongly interconnected, collectively supporting graduates' capacity to respond to changing and highly technological professional environments. Nevertheless, perceived gaps were also identified, especially regarding effective communication, adaptability, and intellectual curiosity, suggesting the need to further strengthen curricular and institutional strategies aimed at supporting the development of generic competencies in engineering education.

With respect to the second specific objective, the findings revealed that graduates reported high self-perceived levels of research knowledge, particularly regarding cognitive, investigative, methodological, and collaborative skills. These perceptions suggest that undergraduate research training may support the development of competencies associated with critical analysis, information management, the application of scientific methodologies, and collaboration. Furthermore, the quantitative findings complemented the qualitative results, as both graduates and employers highlighted the relevance of competencies linked to research within engineering education and professional practice: effective communication, analytical and critical thinking, and teamwork. Nevertheless, the comparatively lower perceptions identified in the use of reference management tools and scientific communication strategies suggest the need to further strengthen technical training associated with applied research and research dissemination processes.

Taken together, the findings suggest that undergraduate research training is perceived as contributing to the development of generic competencies associated not only with academic performance but also employability, innovation, and professional adaptability in engineering contexts. In particular, competencies such as effective communication, teamwork, analytical and critical thinking, LL, and research competency emerged as strongly interconnected within both the qualitative and quantitative findings. Consequently, universities are encouraged to strengthen institutional research cultures oriented toward active learning and competency-based education, thereby enhancing the relevance of academic training in response to labor market demands and the challenges of the knowledge society.

However, the findings should be interpreted considering the limitations of the study: first, the qualitative component included only 10 employers. Thus, the findings cannot be generalized to all engineering employers or industries. Second, the quantitative sample of graduates was unevenly distributed across engineering programs, with a predominance of Industrial Engineering graduates. Consequently, the perceptions reported in the survey may reflect, to a greater extent, the experiences and training characteristics associated with that discipline. Finally, because the study was conducted within a single private university in Lima, Peru, the findings should be interpreted within this specific institutional context and should not be generalized broadly to other STEM higher education programs.

In this regard, future research could involve larger and more balanced samples from engineering programs at other STEM-oriented higher education institutions. Studies involving a more proportional representation of disciplines would allow for a more comprehensive understanding of how undergraduate research training is perceived. Expanding the number and diversity of employers participating could also provide broader insights into labor market expectations regarding generic competencies.

Explanatory research may also facilitate further analysis of potential associations, differences, and contextual factors related to the perceived development of generic competencies through undergraduate research training. Finally, future studies may also benefit from longitudinal or comparative designs, as well as from the inclusion of direct assessments of research knowledge, including performance-based evaluations, portfolio analysis, or external assessments, to complement self-perception data with objective measurements. This may provide a deeper understanding of the relationship between undergraduate research training and generic competencies.

7 ACKNOWLEDGMENT

The authors express their gratitude to the *Instituto de Investigación Científica* (IDIC) from *Universidad de Lima* for providing funding, as this paper was developed as part of the research project entitled Undergraduate Research Training and the

Development of Generic Competencies among Engineering Graduates. Also, thanks to the volunteers who participated in the interviews.

8 REFERENCES

[1] F. González-Ferriz, "Integrating challenge-based learning and agile methodologies to transform vocational training," *RAN – Revista Academia & Negocios*, vol. 11, no. 1, pp. 1–14, 2025. https://doi.org/10.29393/RAN11-9IBGF10009

[2] C. N. G. Curipoma, M. E. N. Ocampo, D. P. C. Cajilima, and S. R. T. Peralta, "Metodologías activas en el proceso de enseñanza-aprendizaje: Implicaciones y beneficios," *Ciencia Latina Revista Científica Multidisciplinar*, vol. 7, no. 3, pp. 3311–3327, 2023. https://doi.org/10.37811/cl_rcm.v7i3.6409

[3] A. Ortiz. *Modelos pedagógicos y teorías del aprendizaje*. Bogotá: Ediciones de la U. 2013.

[4] K. Samuelowicz and J. Bain, "Revisiting academics' beliefs about teaching and learning," *Higher Education*, vol. 41, no. 3, pp. 299–325, 2001. https://doi.org/10.1023/A:1004130031247

[5] L. Abrahamzon Garcia, K. Galantini Velarde, and A. F. Luna Torres, "Augmented reality for the development and reinforcement of spatial skills: A case applied to civil engineering students," *International Journal of Engineering Pedagogy*, vol. 14, no. 5, pp. 88–108, 2024. https://doi.org/10.3991/ijep.v14i5.47473

[6] M. Labrador and M. Andreu, "Metodologías activas," Ediciones Universidad Politécnica de Valencia, 2008.

[7] T. Van Woezik, J. Koksma, R. Reuzel, D. Jaarsma, and G. Van der Wilt, "How to encourage a lifelong learner? The complex relation between learning strategies and assessment in a medical curriculum," *Assessment & Evaluation in Higher Education*, vol. 45, no. 4, pp. 513–526, 2020. https://doi.org/10.1080/02602938.2019.1667954

[8] A. A. Del Savio, L. Cáceres, and K. Galantini, "A methodology for embedding research competencies in an undergraduate civil engineering program," *International Journal of Engineering Education*, vol. 37, no. 5, pp. 1201–1214, 2021. https://hdl.handle.net/20.500.12724/14105

[9] I. Made Sudana, D. Apriyani, and S. Nurmasitah, "Revitalization of vocational high school roadmap to encounter the 4.0 industrial revolution," *Journal of Social Sciences Research*, vol. 5, no. 2, pp. 338–342, 2019. https://doi.org/10.32861/jssr.52.338.342

[10] D. Das, "Problem-based learning for undergraduate civil engineering education in South Africa—A methodological approach," in *Lecture Notes in Civil Engineering*, Singapore: Springer, 2023, pp. 85–95. https://doi.org/10.1007/978-981-19-0503-2_8

[11] M. Imran, T. F. Halawa, M. Baig, A. M. Almanjoumi, M. M. Badri, and W. A. Alghamdi, "Team-based learning versus interactive lecture in achieving learning outcomes and improving clinical reasoning skills: A randomized crossover study," *BMC Medical Education*, vol. 22, no. 1, pp. 1–9, 2022. https://doi.org/10.1186/s12909-022-03411-w

[12] J. Noguez and L. Neri, "Research-based learning: A case study for engineering students," *International Journal on Interactive Design and Manufacturing*, vol. 13, pp. 1283–1295, 2019. https://doi.org/10.1007/s12008-019-00570-x

[13] K. Galantini Velarde, V. Briceño Weiss, M. Aguinaga Villegas, L. Abrahamzon Garcia, and A. A. Del Savio, "Undergraduate research for the development of generic competencies: A study of a civil engineering program," *Journal of Civil Engineering Education*, vol. 152, no. 3, p. 04026002, 2026. https://doi.org/10.1061/JCEECD.EIENG-2294

[14] C. Mugruza-Vassallo, "Integral and transformative engineering coursework in formative research for undergraduate curricula," in *IEEE Frontiers in Education Conference (FIE)*, Erie, PA, USA, 2016, pp. 1–8. https://doi.org/10.1109/FIE.2016.7757633

[15] S. Halawa, Y.-S. Hsu, and W.-X. Zhang, "Analysis of physics textbooks through the lens of inquiry practices," *The Asia-Pacific Education Researcher*, vol. 32, no. 4, pp. 497–506, 2023. https://doi.org/10.1007/s40299-022-00671-4

[16] National Research Council. *A Framework for K-12 Science Education: Practices, Crosscutting Concepts, and Core Ideas*. The National Academies Press, 2012.

[17] National Research Council. *Monitoring Progress Toward Successful K-12 STEM Education: A Nation Advancing?* National Academies Press, 2013. https://doi.org/10.17226/13509

[18] G. M. Sinatra, A. Mukhopadhyay, T. N. Allbright, J. A. Marsh, and M. S. Polikoff, "Speedometry: A vehicle for promoting interest and engagement through integrated STEM instruction," *Journal of Educational Research*, vol. 110, no. 3, pp. 308–316, 2017. https://doi.org/10.1080/00220671.2016.1273178

[19] Z. Smyrnaiou, E. Georgakopoulou, and S. Sotiriou, "Promoting a mixed-design model of scientific creativity through digital storytelling—the CCQ model for creativity," *International Journal of STEM Education*, vol. 7, no. 1, p. 25, 2020. https://doi.org/10.1186/s40594-020-00223-6

[20] Z. Öcek *et al.*, "A research training program in a Turkish medical school: Challenges, barriers and opportunities from the perspectives of the students and faculty members," *BMC Medical Education*, vol. 21, no. 1, p. 2, 2021. https://doi.org/10.1186/s12909-020-02454-1

[21] N. G. Lederman and L. S. Lederman, "Nature of scientific knowledge and scientific inquiry: Instructional capacity through professional development," in *Second International Handbook of Science Education*, B. J. Fraser, K. Tobin, and C. J. McRobbie, Eds., The Netherlands: Springer, Dordrecht, 2012, pp. 335–359. https://doi.org/10.1007/978-1-4020-9041-7_24

[22] R. W. Bybee, "Advancing STEM education: A 2020 vision," *Technology and Engineering Teacher*, vol. 70, no. 1, pp. 30–35, 2010.

[23] S. Halawa, Y.-S. Hsu, W.-X. Zhang, Y.-R. Kuo, and J.-Y. Wu, "Features and trends of teaching strategies for scientific practices from a review of 2008–2017 articles," *International Journal of Science Education*, vol. 42, no. 7, pp. 1183–1206, 2020. https://doi.org/10.1080/09500693.2020.1752415

[24] M. Y. Beckman and N. Y. Hensel, "Making explicit the implicit: Defining undergraduate research," *CUR Quarterly*, vol. 29, pp. 40–44, 2009.

[25] M. Grangeat, C. Harrison, and J. Dolin, "Exploring assessment in STEM inquiry learning classrooms," *International Journal of Science Education*, vol. 43, no. 3, pp. 345–361, 2021. https://doi.org/10.1080/09500693.2021.1903617

[26] M. K. Eagan, S. Hurtado, M. J. Chang, G. A. Garcia, F. A. Herrera, and J. C. Garibay, "Making a difference in science education: The impact of undergraduate research programs," *American Educational Research Journal*, vol. 50, no. 4, pp. 683–713, 2013. https://doi.org/10.3102/0002831213482038

[27] H. Khazragui and J. Hudson, "Measuring the benefits of university research: Impact and the REF in the UK," *Research Evaluation*, vol. 24, no. 1, pp. 51–62, 2015. https://doi.org/10.1093/reseval/rvu028

[28] G. Crebert, M. Bates, B. Bell, C. P. Patrick, and V. Cragnolini, "Developing generic skills at university, during work placement and in employment: Graduates' perception," *Higher Education Research & Development*, vol. 23, no. 2, pp. 147–165, 2004. https://doi.org/10.1080/0729436042000206636

[29] UNESCO, "El futuro de la Educación Superior. Propuestas globales para la III Conferencia Mundial de Educación Superior de la UNESCO 2022," 2022.

[30] M. Leandro Cruz, G. Saunders-Smits, and P. Groen, "Evaluation of competency methods in engineering education: A systematic review," *European Journal of Engineering Education*, vol. 45, no. 5, pp. 729–757, 2020. https://doi.org/10.1080/03043797.2019.1671810

[31] J. H. Flores, “Proyecto Tuning América Latina. Reflexiones y perspectivas de la Educación Superior en América Latina: Informe Final 2004–2007, Universidad Deusto-Universidad de Groningen, Bilbao, 2007, 427 páginas,” *Diálogos*, vol. 2008, no. 2, pp. 68–70, 2023. https://doi.org/10.5377/dialogos.v1i2.16201

[32] H. Karimi and A. Pina, “Strategically addressing the soft skills gap among STEM undergraduates,” *Journal of Research in STEM Education*, vol. 7, no. 1, pp. 21–46, 2021. https://doi.org/10.51355/jstem.2021.99

[33] Organization for Economic Co-Operation and Development (OCDE), “La definición y selección de competencias clave,” *Resumen ejecutivo*, 2005.

[34] J. J. Kemp and L. Seagraves, “Transferable skills—can higher education deliver?” *Studies in Higher Education*, vol. 20, no. 3, pp. 315–328, 1995. https://doi.org/10.1080/03075079512331381585

[35] L. J. M. Shuman Besterfield-Sacre and J. McGourty, “The ABET ‘professional skills’—can they be taught? Can they be assessed?” *Journal of Engineering Education*, vol. 94, no. 1, pp. 41–55, 2005. https://doi.org/10.1002/j.2168-9830.2005.tb00828.x

[36] C. G. Knobbs and D. J. Grayson, “An approach to developing independent learning and non-technical skills amongst final year mining engineering students,” *European Journal of Engineering Education*, vol. 37, no. 3, pp. 307–320, 2012. https://doi.org/10.1080/03043797.2012.684673

[37] I. Markes, “A review of literature on employability skill needs in engineering,” *Eur. J. Eng. Educ.*, vol. 31, no. 6, pp. 637–650, 2006. https://doi.org/10.1080/03043790600911704

[38] L. Villardón-Gallego, *Competencias genéricas en educación superior: Metodologías específicas para su desarrollo*. Narcea Ediciones, 2015.

[39] T. Yu, W. Shang, S. Liu, and J. Zhu, “How to assess generic competencies: From sustainable development needs among engineering graduates in industry,” *Sustainability*, vol. 14, no. 15, p. 9270, 2022. https://doi.org/10.3390/su14159270

[40] UNESCO. *La nueva dinámica de la educación superior y la investigación para el cambio social y el desarrollo*. París: UNESCO. 2009.

[41] C. J. Bucarey, S. M. Pérez, M. G. Marín, and L. A. Castillo, “Brechas en percepción de contribución de competencias genéricas entre estudiantes en Chile,” *Revista de Ciencias Sociales*, vol. 29, no. 1, pp. 386–403, 2023. https://doi.org/10.31876/rcs.v29i1.39758

[42] I. Kostikova, L. Holubnycha, Z. Girich, and N. Movmyga, “Desarrollo de habilidades blandas con estudiantes universitarios en clases de inglés,” *Revista Romaneasca pentru Educatie Multidimensionala*, vol. 13, no. 1, pp. 398–416, 2021. https://doi.org/10.18662/rrem/13.1/378

[43] C. Succi and M. Canovi, “Soft skills to enhance graduate employability: Comparing students and employers’ perceptions,” *Studies in Higher Education*, vol. 45, no. 9, pp. 1834–1847, 2020. https://doi.org/10.1080/03075079.2019.1585420

[44] A. R. Butz and J. L. Branchaw, “Entering research learning assessment (ERLA): Validity evidence for an instrument to measure undergraduate and graduate research trainee development,” *CBE Life Sciences Education*, vol. 19, no. 2, 2020. https://doi.org/10.1187/cbe.19-07-0146

[45] C. J. Faber *et al.*, “Undergraduate engineering students’ perceptions of research and researchers,” *J. Eng. Educ.*, vol. 109, pp. 780–800, 2020. https://doi.org/10.1002/jee.20359

[46] O. A. Adedokun, D. Zhang, L. C. Parker, A. Bessenbacher, A. Childress, and W. D. Burgess, “Understanding how undergraduate research experiences influence student aspirations for research careers and graduate education,” *J. Coll. Sci. Teach.*, vol. 42, pp. 82–90, 2012.

[47] A. Hunter, S. L. Laursen, and E. Seymour, “Becoming a scientist: The role of undergraduate research in students’ cognitive, personal, and professional development,” *Science Education*, vol. 91, no. 1, pp. 36–74, 2026. https://doi.org/10.1002/sce.20173

[48] Y. Ahmed, M. H. Taha, and S. Khayal, "Integrating research and teaching in medical education: Challenges, strategies, and implications for healthcare," *Journal of Advances in Medical Education & Professionalism*, vol. 12, no. 1, pp. 1–7, 2024. https://doi.org/10.30476/jamp.2023.99751.1854

[49] A. A. Del Savio, K. Galantini Velarde, L. Cáceres Montero, and M. A. Vergara Olivera, "A research training: Unraveling the research methodological design challenge in engineering programs," *International Journal of Engineering Pedagogy*, vol. 14, no. 7, pp. 30–53, 2024. https://doi.org/10.3991/ijep.v14i7.48987

[50] T. Casci and E. Adams, "Research culture: Setting the right tone," *eLife*, vol. 9, p. e55543, 2020. https://doi.org/10.7554/eLife.55543

[51] L. Hesli and J. M. Lee, "Faculty research productivity: Why do some of our colleagues publish more than others?" *PS Polit. Sci. Polit.*, vol. 44, no. 2, pp. 393–408, 2011. https://doi.org/10.1017/S1049096511000242

[52] I. D. Rojas Arenas, J. A. Durango Marín, and J. A. Rentería Vera, "Investigación formativa como estrategia pedagógica: caso de studio: ingeniería industrial de la I.U Pascual Bravo," Estudios Pedagógicos, vol. 46, no. 1, pp. 319–338, 2020. https://doi.org/10.4067/S0718-07052020000100319

[53] The Royal Society of London, "Research Culture," 2020. Available at https://royalsociety.org/topics-policy/projects/research-culture/

[54] E. Tikhonova and L. Raitskaya, "The culture of research: A systematic scoping review," *Journal of Language and Education*, vol. 10, no. 1, pp. 5–24, 2024. https://doi.org/10.17323/jle.2024.21526

[55] Z. A. Mamytbayeva, E. A. Orynbetova, U. K. Kyyakbayeva, K. Y. Yeralin, and A. K. Yeralina, "Bases para conformar la cultura investigativa de los futuros docentes-educadores en las instituciones de educación superior," *Bordón. Revista De Pedagogía*, vol. 76, no. 1, pp. 99–117, 2024. https://doi.org/10.13042/Bordon.2024.97666

[56] F. Callard, "Towards a critical-conceptual analysis of 'research culture'," *Area*, 2023. https://doi.org/10.1111/area.12905

[57] R. Meregildo-Gómez, R. Mas-Sandoval, R. Cruz-Aguilar, and L. Yglesias, "Construcción y análisis estructural de una escala para medir la cultura investigativa en universitarios peruanos," *Revista Internacional de Humanidades*, vol. 21, no. 2, pp. 477–492, 2023. https://doi.org/10.37467/revhuman.v21.5083

[58] R. González-Díaz, A. Acevedo-Duque, V. Martin-Fiorino, and E. Cachicatari-Vargas, "Latin American professors' research culture in the digital age," *Comunicar*, vol. 70, pp. 71–83, 2022. https://doi.org/10.3916/C70-2022-06

[59] L. Díez, J. Valencia, and E. Villa, "Promoción de la cultura investigativa como motor de desarrollo económico y social: una visión sistémica," *Espacios*, vol. 36, no. 1, 2015.

[60] B. Tucker and C. Tilt, "'You know it when you see it': In search of 'the ideal' research culture in university accounting faculties," *Critical Perspectives on Accounting*, vol. 64, 2019. https://doi.org/10.1016/j.cpa.2019.01.001

[61] H. T. L. Nguyen and T. Marjori-Banks, "Developing a university research culture in Vietnam: A leadership conceptual frame-work," in *Asia in Transition*, vol. 15, 2021, pp. 209–233. https://doi.org/10.1007/978-981-16-5055-0_12

[62] E. Iweka and R. Hyde, "Promotion of research culture among radiographers in one UK NHS trust through journal club activities – An autoethnographic study," *Radiography*, vol. 29, pp. 800–806, 2023. https://doi.org/10.1016/j.radi.2023.05.014

[63] S. M. Berrocal Villegas, W. Montalvo Fritas, C. R. Berrocal Villegas, V. R. Flores Rosas, and F. A. Jaimes Yabar, "Caracterización y desafíos de la cultura investigativa en dos universidades estatales de Lima, Perú," *Revista Universidad y Sociedad*, vol. 14, no. 1, pp. 375–383, 2022.

[64] G. Valkenburg, G. Dix, J. Tijdink, and S. de Rijcke, "Expanding research integrity: A cultural-practice perspective," *Science and Engineering Ethics*, vol. 27, no. 1, 2021. https://doi.org/10.1007/s11948-021-00291-z

[65] A. S. Lodhi, "A pilot study of researching the research culture in Pakistani public universities: The academics' perspective," *Procedia – Social and Behavioral Sciences*, vol. 31, pp. 473–479, 2012. https://doi.org/10.1016/j.sbspro.2011.12.089

[66] J. A. Halstead, "Council on undergraduate research: A resource (and a community) for science educators," *Journal of Chemical Education*, vol. 74, no. 2, p. 148, 1997. https://doi.org/10.1021/ed074p148

[67] L. Huber, "Forschungsbasiertes, Forschungsorientiertes, Forschendes Lernen: Alles dasselbe? Ein Pl ädoyer für eine Verst ändigung über Begriffe und Unterscheidungen im Feld forschungsnahen Lehrens und Lernens," *Das Hochschulwesen*, vol. 62, no. 1, pp. 22–29, 2014. Retrieved from https://www.fh-potsdam.de/fileadmin/user_upload/forschen/material-publikation/HSW1_2_2014_Huber.pdf

[68] I. Wessels, J. Rueß, C. Gess, W. Deicke, and M. Ziegler, "Is research-based learning effective? Evidence from a pre–post analysis in the social sciences," *Studies in Higher Education*, vol. 12, pp. 2595–2609, 2021. https://doi.org/10.1080/03075079.2020.1739014

[69] F. Espinoza-Figueroa, D. Vanneste, B. Alvarado-Vanegas, K. Farfán-Pacheco, and S. Rodriguez-Giron, "Research-based learning (RBL): Added-value in tourism education," *Journal of Hospitality, Leisure, Sport and Tourism Education*, vol. 28, p. 100312, 2021. https://doi.org/10.1016/j.jhlste.2021.100312

[70] S. Laursen, A.-B. Hunter, E. Seymour, H. Thiry, and G. Melton, *Undergraduate Research in the Sciences: Engaging Students in Real Science*. Hoboken, NJ: Wiley: 2010.

[71] A. Peachey and S. L. Baller, "Ideas and approaches for teaching undergraduate research methods in the health sciences," *Int. J. Learn. High. Educ.*, vol. 27, no. 3, pp. 434–442, 2015.

[72] K. Galantini Velarde, L. Cáceres Montero, and A. Pachas, "Peer learning and research culture within student organizations in engineering: Students' perceptions," *J. Eng. Educ. Transform.*, vol. 38, no. 1, pp. 109–121, 2024. https://doi.org/10.16920/jeet/2024/v38i1/24179

[73] R. V. Miche and R. De Armas Urquiza, "Tuning-América Latina y su compatibilidad con el modelo curricular Cubano," *Reencuentro—Universidad Autónoma Metropolitana*, vol. 54, pp. 73–82, 2009.

[74] M. Kupryaeva, O. Mamai, L. Panofenova, S. Syreskina, and N. Chigina, "Soft skills development in personnel training," in *Proc., E3S Web Conf.*, vol. 273, 2021, p. 12017. https://doi.org/10.1051/e3sconf/202127312017

[75] C. K. Y. Chan, E. T. Y. Fong, L. Y. Y. Luk, and R. Ho, "A review of literature on challenges in the development and implementation of generic competencies in higher education curriculum," *Int. J. Educ. Dev.*, vol. 57, pp. 1–10, 2017. https://doi.org/10.1016/j.ijedudev.2017.08.010

[76] D. Kember, D. Y. P. Leung, and R. S. F. Ma, "Characterizing learning environments capable of nurturing generic capabilities in higher education," *Res. High. Educ.*, vol. 48, no. 5, pp. 609–632, 2007. https://doi.org/10.1007/s11162-006-9037-0

[77] L. C. Montero, K. Galantini Velarde, A. Reátegui Arrué, and A. A. Del Savio, "Online learning environments for the promotion of undergraduate research in pandemic times: A case study in an engineering program," *J. Eng. Educ. Transform.*, vol. 36, no. 4, pp. 161–171, 2023. https://doi.org/10.16920/jeet/2023/v36i4/23126

[78] R. Hernández-Sampieri, C. Fernández-Collado, and P. Baptista-Lucio, *Metodología de la investigación*. México D.F.: McGraw-Hill, 2014.

[79] C. Wainerman, "En estado de tesis: cómo elaborar el proyecto de tesis en ciencias sociales," Manantial, Buenos Aires, 2020.

[80] E. O. Rocha and A. J. Dipp, "Escala de evaluación de competencias investigativas," *Praxis Investigativa ReDIE: Revista Electrónica De La Red Durango De Investigadores Educativos*, vol. 2, no. 3, pp. 72–75, 2010. Available: https://dialnet.unirioja.es/descarga/articulo/6534523.pdf

[81] M. Gonzales-Macavilca and M. Aguinaga-Villegas, "Panorama of Peruvian primary education teachers trained in ICT use before COVID-19 pandemic," in *2023 IEEE 3rd International Conference on Advanced Learning Technologies on Education & Research (ICALTER)*, Chiclayo, Peru, 2023, pp. 1–4. https://doi.org/10.1109/ICALTER61411.2023.10372904

[82] Ugaz, "Nivel percibido de competencias investigativas en estudiantes de la Escuela de Estomatología de la Universidad Señor de Sipán 2017," Universidad Señor de Sipán, 2017. https://hdl.handle.net/20.500.12802/4519

[83] F. Böttcher and F. Thiel, "Evaluating research-oriented teaching: A new instrument to assess university students' research competences," *Higher Education*, vol. 75, no. 1, pp. 91–110, 2017. https://doi.org/10.1007/s10734-017-0128-y

[84] J. C. Céspedes, L. M. Bermúdez, O. L. B. Matarrita, Y. R. Sánchez, and M. V. Sossa, "Competencias investigativas en el personal académico de la Escuela de Ciencias de la Educación de la UNED, Costa Rica," *UNED Research Journal*, vol. 4, no. 2, pp. 273–282, 2012. https://doi.org/10.22458/urj.v4i2.16

[85] L. S. Nowell, J. M. Norris, D. E. White, and N. J. Moules, "Thematic analysis: Striving to meet the trustworthiness criteria," *International Journal of Qualitative Methods*, vol. 16, no. 1, pp. 1–13, 2017. https://doi.org/10.1177/1609406917733847

[86] R. Quivy and L. y Van Carnpenhoudt, *Manual de investigación en ciencias sociales*. México D.F.: Limusa, 2005.

[87] J. Saldaña, *The Coding Manual for Qualitative Researchers*. Los Angeles, CA: Sage, 2009.

[88] D. B. de Campos, L. M. M. de Resende, and A. B. Fagundes, "The importance of soft skills for the engineering," *Creative Education*, vol. 11, pp. 1504–1520, 2020. https://doi.org/10.4236/ce.2020.118109

[89] M. Colburn, "An alternative to categorizing skills as soft or hard," *OD Practitioner*, vol. 50, no. 4, pp. 65–66, 2018. https://www.odnetwork.org/page/Publications

[90] J. L. Díaz and Y. Ordónez, "A classroom experience about the application of research-based learning for the teaching of probability in engineering," *STEM Education*, vol. 4, no. 2, pp. 127–141, 2024. https://doi.org/10.3934/steme.2024008

[91] C. Succi, "Are you ready to find a job? Ranking of a list of soft skills to enhance graduates' employability," *International Journal of Human Resource Development & Management*, vol. 19, pp. 281–297, 2019. https://doi.org/10.1504/IJHRDM.2019.100638

[92] J. Miyahira Arakaki, "La investigación formativa y la formación para la investigación en el pregrado," *Revista Médica Herediana*, vol. 20, no. 3, pp. 119–122, 2009. https://doi.org/10.20453/rmh.v20i3.1010

[93] D. Bowyer and M. Akpinar, "Experiences of academics and undergraduate students on research-based learning: A tale of two institutions," *Innovations in Education and Teaching International*, vol. 61, no. 1, pp. 45–56, 2022. https://doi.org/10.1080/14703297.2022.2149606

[94] A. R. Briones, E. G. Meza, S. A. D. Fritz, and D. A. Macias, "Innovación y competencias investigativas en universidades públicas," *Revista Venezolana De Gerencia*, vol. 29, no. 106, pp. 776–792, 2024. https://doi.org/10.52080/rvgluz.29.106.20

[95] J. I. Prado Juscamita, "Investigación formativa como estrategias de enseñanza-aprendizaje," *Human Review. International Humanities Review/Revista Internacional De Humanidades*, vol. 16, no. 3, pp. 1–9, 2023. https://dialnet.unirioja.es/servlet/articulo?codigo=8840075

[96] A. Mamdouh, M. Abdelkader, and T. Samir, “Analysis of the gap in architects’ skills of lifelong learning,” *Ain Shams Engineering Journal*, vol. 13, no. 6, p. 101805, 2022. https://doi.org/10.1016/j.asej.2022.101805
[97] N. Dawe, L. Romkey, A. Bilton, and K. Moozeh, “Identifying curriculum factors that facilitate lifelong learning in alumni career trajectories: Stage 1 of a sequential mixed-methods study,” in *2022 ASEE Annual Conference & Exposition*, Minneapolis, MN, 2024. https://doi.org/10.18260/1-2--41117
[98] E. Eppler-Hattab, “From lifelong learning to later life self-employment: A conceptual framework and an Israeli enterprise perspective,” *Journal of Enterprising Communities People and Places in the Global Economy*, vol. 16, no. 6, pp. 948–966, 2021. https://doi.org/10.1108/JEC-01-2021-0014
[99] O. Campos-Ugaz *et al.*, “Formative research to strengthen enquiry competence in university students,” *International Journal of Learning Teaching and Educational Research*, vol. 21, no. 11, pp. 443–464, 2022. https://doi.org/10.26803/ijlter.21.11.25
[100] A. L. Raine and M. Pandya, “Three keys to entrepreneurial success: Curiosity, creativity, and commitment,” *Entrepreneurship Education*, vol. 2, nos. 3–4, pp. 189–198, 2019. https://doi.org/10.1007/s41959-019-00019-y
[101] M. Jeraj, M. Marič, I. Todorović, M. Čudanov, and S. Komazec, “The role of openness and entrepreneurial curiosity in company’s growth,” *Amfiteatru Economic*, vol. 17, no. 38, pp. 371–389, 2015.
[102] I. F. Yarullin, N. A. Bushmeleva, and I. I. Tsyrkun, “The research competence development of students trained in mathematical direction,” *International Electronic Journal of Mathematics Education*, vol. 10, no. 3, pp. 137–146, 2015. https://doi.org/10.29333/iejme/296
[103] A. A. Del Savio, K. Galantini Velarde, B. Díaz-Garay, and E. Valcárcel Pollard, “A methodology for Embedding Building Information Modelling (BIM) in an undergraduate civil engineering program,” *Applied Sciences*, vol. 12, no. 23, p. 12203, 2022. https://doi.org/10.3390/app122312203
[104] D. B. Knight and B. J. Novoselich, “Curricular and cocurricular influences on undergraduate engineering student leadership,” *Journal of Engineering Education*, vol. 106, pp. 44–70, 2017. https://doi.org/10.1002/jee.20153
[105] J. Esquivel-Grados, V. Venegas-Mejía, C. P. Venegas-Mejía, M. T. Gonzáles-Benites, H. A. Valdivia-Huaranga, and N. B. Salazar, “Formative research: Perceptions of communication science students at a Peruvian university,” *Journal of Technology and Science Education*, vol. 13, no. 2, p. 565, 2023. https://doi.org/10.3926/jotse.1758
[106] M. Valderrama, C. Perez, G. Llaque, and J. Matute, “Investigative skills in university students. A systematic review,” in *Proceedings of the 20th LACCEI International Multi-Conference for Engineering, Education and Technology*, 2022. https://doi.org/10.18687/LACCEI2022.1.1.127
[107] J. I. Kino-Saravia, W. E. Vidaurre-García, J. M. Silva-Ravines, and H. L. Gonzales, “Herramientas tecnológicas y competencias investigativas en estudiantes universitarios,” *Revista Venezolana de Gerencia*, vol. 28, no. Especial 10, pp. 1610–1630, 2023. https://doi.org/10.52080/rvgluz.28.e10.45
[108] L. Briseño, “Los retos de la historia académica en la era digital,” *Historia y Memoria*, vol. 22, pp. 161–195, 2021. https://doi.org/10.19053/20275137.n22.2021.10907
[109] S. Tobón, *Metodología de gestión curricular. Una perspectiva socioformativa*. México D.F.: Trillas, 2013.
[110] F. Almeida and J. Morais, “Strategies for developing soft skills among higher engineering courses,” *Journal of Education*, vol. 203, no. 1, pp. 103–112, 2021. https://doi.org/10.1177/00220574211016417

[111] C. Corrales and L. Chumpitaz, "Investigative competencies of Industrial Engineering students. Exploratory study," in *Proceedings of the 21st LACCEI International Multi-Conference for Engineering, Education, and Technology*, 2023. https://doi.org/10.18687/LACCEI2023.1.1.1456

[112] J. Thiem, R. Preetz, and S. Haberstroh, "How research-based learning affects students' self-rated research competences: Evidence from a longitudinal study across disciplines," *Studies in Higher Education*, vol. 48, no. 7, pp. 1039–1051, 2023. https://doi.org/10.1080/03075079.2023.2181326

[113] M. Epiquién, O. J. O. Carrasco, J. D. F. Escobedo, and Y. A. S. Díaz, "Investigación formativa en el desarrollo de competencias investigativas en estudiantes universitarios," *Revista de Ciencias Sociales*, 2023. https://doi.org/10.31876/rcs.v29i4.41264

[114] A. M. Boelt, J. E. Holgaard, and A. Kolmos, "A thematic analysis of engineering students' experiences of teamwork in problem-based learning," Research Portal (King's College London), 2023. [Online]. Available: https://vbn.aau.dk/da/publications/37ffcdb4-2b8a-498e-8ab6-0f6b4b5170f9

[115] D. Zuo, M. Samuel, and S. Y. Tan, "Emerging engineering education in China: A systematic literature review," *Int. J. Eng. Ped.*, vol. 15, no. 2, pp. 153–164, 2025. https://doi.org/10.3991/ijep.v15i2.53627

[116] D. Khodadad, "Creating a supportive and effective learning environment for engineering students: Pedagogical strategies, engagement, and enhanced outcomes," *Int. J. Eng. Ped.*, vol. 13, no. 8, pp. 33–50, 2023. https://doi.org/10.3991/ijep.v13i8.41755

[117] C. De Pablos Heredero, S. Haider, and A. García Martinez, "Relational coordination as an indicator of teamwork quality: Potential application to the success of e-learning at universities," *Int. J. Emerg. Technol. Learn.*, vol. 10, no. 2, pp. 4–8, 2015. https://doi.org/10.3991/ijet.v10i2.4102

9 AUTHORS

Katerina Galantini Velarde is with the Architecture Program, Universidad de Lima, Lima, Peru. She is a Doctoral Candidate in Higher Education at *Universidad de Palermo*. She is a Master in Education by *Universidad Femenina del Sagrado Corazón* and an architect by *Universidad de Lima*. She is a professor and a researcher for the *Instituto de Investigación Científica* at the *Universidad de* Lima. Her research interests include undergraduate research training, undergraduate curriculum design and management, engineering and design pedagogy, generic competencies, and formative assessment (E-mail: kgalanti@ulima.edu.pe).

Karen Urquizo Baldárrago is with the Industrial Engineering Program, Universidad de Lima, Lima, Peru. She is an Industrial Engineer who graduated from *Universidad de Lima*. She has earned a Master's degree in Business Administration and Management from the same university and is currently working towards a doctorate in Education. In her role as Academic Secretary and teacher in the Industrial Engineering Program at *Universidad de Lima*, she is involved in academic coordination, curriculum development, and teaching undergraduate courses.

Lisette Abrahamzon Garcia is with the Civil Engineering Program, Universidad de Lima, Lima, Peru. She is a Civil Engineering specialized in Virtual Design and Construction, and is partially certified in 3D, 4D, and 5D BIM from the Universidad de Lima. She has been a teaching assistant for the VDC I and II and different construction subjects at the Faculty of Engineering at Universidad de Lima, Peru.

Online-Journals.org

iJEP International Journal of Engineering Pedagogy

iJEP | eISSN: 2192-4880 | Vol. 16 No. 5 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijep.v16i5.62187

PAPER

Improving Problem-Solving Skills and Learning Retention in a Thai Electrical Circuit Laboratory Using Flipped Classroom, Augmented Reality, and Microlearning

Cherisa Nantha[1], Aekkarat Lorphichian[1], Kanitphan Boonsomchuae[1], Winai Jaikla[2], Sumeth Theskul[1] (✉)

[1]Rajamangala University of Technology Thanyaburi, Pathum Thani, Thailand

[2]King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand

sumeth_t@rmutt.ac.th

ABSTRACT

This study aimed to develop and evaluate a flipped, microlearning, and augmented reality model to enhance undergraduate engineering students' conceptual understanding and problem-solving skills in an electrical circuit laboratory course. The participants consisted of 43 first-year engineering students, divided into an experimental group (n = 21) and a control group (n = 22). The experimental group was instructed using the integrated model, while the control group received traditional instruction. Research instruments included a learning achievement test, a problem-solving skills rubric, and a satisfaction questionnaire, all of which demonstrated acceptable validity and reliability. Data were analyzed using multivariate analysis of variance (MANOVA) and mixed ANOVA. The findings indicated that students in the experimental group significantly outperformed those in the control group in both learning achievement ($p < .05$) and problem-solving skills ($p < .01$). In addition, the experimental group demonstrated greater learning retention at two weeks after instruction. These results suggest that integrating augmented reality and microlearning within a flipped classroom framework effectively supports conceptual understanding and enhances problem-solving skills in engineering education. The integrated model provides a practical instructional approach for improving laboratory-based learning in science and engineering contexts. This study extends existing research by providing an instructional framework that supports both cognitive and experiential learning in higher education.

KEYWORDS

augmented reality, electrical circuit laboratory, flipped classroom, learning achievement, microlearning, problem-solving skills

1 INTRODUCTION

Thailand's higher education system has long emphasized student-centered approaches to promote natural learning and holistic student development [1].

Nantha, C., Lorphichian, A., Boonsomchuae, K., Jaikla, W., Theskul, S. (2026). Improving Problem-Solving Skills and Learning Retention in a Thai Electrical Circuit Laboratory Using Flipped Classroom, Augmented Reality, and Microlearning. *International Journal of Engineering Pedagogy (iJEP)*, 16(5), pp. 112–124. https://doi.org/10.3991/ijep.v16i5.62187

Article submitted 2026-03-29. Revision uploaded 2026-05-01. Final acceptance 2026-05-23.

However, as society evolves into the digital age, the characteristics of Gen Z students have changed significantly. Today's students are proficient with digital technology, think independently, and are highly self-reliant. These changes demand corresponding updates to instructional methods.

This study focused on first-year engineering students enrolled in the Electrical Circuit Laboratory (ECL) course at Rajamangala University of Technology Thanyaburi (RMUTT). Teaching practical fundamental electrical circuits to novice engineering students presents persistent challenges [2]. The ECL course integrates theory and practice in large classes of 20–40 students with diverse educational backgrounds, including high school graduates and students from vocational certificate programs. The ECL course also serves as a foundation for advanced studies in electrical circuits. Traditional teaching methods such as demonstrations and lectures may no longer adequately meet the expectations of either lecturers or students.

Blended learning (BL), which integrates online technology to enhance traditional learning, has been proposed as a solution [3]–[4]. BL creates a student-centered environment that allows students to develop and learn at their own pace. In 2007, Bergmann and Sams pioneered the flipped classroom (FC) concept, which reverses traditional instructor-student roles across in-class and out-of-class activities [5]. The four pillars of FC are a flexible environment, a learning culture, intentional content, and a professional instructor [6]. Research across higher education disciplines has consistently reported that FC significantly enhances students' knowledge and skills [7].

Another promising educational innovation is augmented reality (AR), which combines real and virtual worlds through devices such as webcams, computers, and software [8]. AR creates immersive, technology-assisted learning experiences that allow students to interact with 2D and 3D images alongside the physical world [9]. Studies have reported that AR effectively attracts attention, fosters positive attitudes, increases motivation, and enhances learning through hands-on visualization of abstract theoretical concepts [10], [11].

Also making its way is microlearning, which consists of short learning exercises delivered via technologies such as videos, tests, infographics, and other interactive learning modules [12]. Microlearning entails breaking down information into smaller pieces that students can learn within 5 to 15 minutes [13].

Although FC, AR, and microlearning have been studied extensively in higher education [14], [15], most research lacks an integrated teaching model that combines all three approaches to enhance learning achievement and problem-solving skills in engineering practical courses. The Thai RMUTT ECL course requires both skills and cognitive knowledge for long-term retention, applying theoretical knowledge to solve real-world electrical circuit problems, and success in future advanced courses.

The current investigation is based on three theories that complement each other. According to constructivist theory, the flipped learning concept is appropriate because students are able to gain knowledge and use it while working within small groups in class. The principle of cognitive load theory explains the use of microlearning because it allows splitting large topics into small chunks and thus reducing unnecessary load. The last theory—experiential learning—provides the basis for the process of problem-solving through the CIRER cycle.

Therefore, this study integrates three complementary theoretical perspectives: constructivist theory, cognitive load theory, and experiential learning [16]. Constructivism emphasizes that students actively construct knowledge through FC, engaging with outside-classroom content before class and applying it during in-class activities. AR with microlearning can motivate students and reduce extraneous cognitive load [17]. The proposed FLIP-MAR model focuses the learning process on hands-on experience [18], allowing students to transform existing knowledge by engaging in new activities, thereby acquiring new knowledge, problem-solving skills, and attitudes toward electrical circuits.

2 METHODS

The research framework (see Figure 1) integrates blended learning, flipped classroom, AR, and microlearning to enhance learning achievement (LA) and problem-solving skills (PSS) in the ECL course.

Fig. 1. The research framework

2.1 Research scope

The content scope covered the ECL course (0-3-1 credits, 3 practical hours/week) for undergraduate students in the Faculty of Industrial Education and the Faculty of Engineering at RMUTT. The focus was on five learning units: (1) reading 4-band and 5-band resistor color codes, (2) using a multimeter, (3) series circuits, (4) parallel circuits, and (5) combination circuits [19]. Data were collected from December 2025 to January 2026 (academic year 2025, semester 2).

2.2 Population

The population consisted of 238 first-year undergraduate students across five engineering majors (Electrical, Mechanical, Industrial, Computer, and Electronic Engineering) at RMUTT's Faculty of Industrial Education. The sample consisted of 43 first-year electrical engineering students enrolled in the ECL course. Cluster random sampling was used to select Electrical Engineering as the representative major, followed by simple random sampling to assign Section 1 (n = 21) to the experimental group (FLIP-MAR model) and Section 2 (n = 22) to the control group (traditional teaching) [20].

2.3 Variables

Independent variable: teaching method (traditional vs. FLIP-MAR). Dependent variables: LA (learning achievement) measured by a 45-item multiple-choice test, and PSS (problem-solving skills) assessed using a 5-item analytic rubric.

2.4 Research instruments

FLIP-MAR learning model. Developed using the ADDIE framework (Analysis, Design, Development, Implementation, Evaluation) [21]. The model integrates a flipped classroom (pre-class online content and in-class active learning), augmented reality (marker-based AR e-book), and microlearning (short, focused modules of 5–15 minutes) (see Figure 2). Five experts in instructional design, measurement and evaluation, and information technology assessed the model's quality and appropriateness using a 5-point Likert scale (1 = very low, 5 = excellent). The overall mean was 4.53 (SD = 0.50), indicating excellent performance.

Fig. 2. The experiment plan

AR ECL e-book. Developed following the ADDIE model. The e-book contains five learning units across nine class sessions. It uses marker-based AR: students scan images in the book with their Android smartphones to trigger 2D/3D animations, circuit visualizations, and explanatory videos. Five experts in instructional design and educational technology evaluated the e-book's quality using the same 5-point scale. The overall mean was 4.53 (SD = 0.50), excellent.

Learning achievement test. A 45-item multiple-choice test with five options per item, aligned with the learning objectives of the five units. Content validity was assessed by five experts in measurement and evaluation using the Index of Congruence (IOC). Items with IOC ≥ 0.5 were retained. The test was then piloted with 30 senior engineering students who had completed the course. Reliability was calculated using the Kuder-Richardson 20 (KR-20) formula, requiring a coefficient ≥ 0.8. Item difficulty (p) was set between 0.2 and 0.8; discrimination index (r) was set ≥ 0.2. The final test had a reliability of 0.887, difficulty ranging from 0.33 to 0.80, and discrimination ranging from 0.23 to 0.56, all meeting the required standards.

Problem-solving skills (PSS) rubric. A 5-item analytic rubric based on the CIRER cycle (Clarify, Investigate, Research, Evaluate, Reflect) [22]. Each item was scored on a 0–4 scale (0 = no demonstration, 4 = excellent). Two instructors and electrical circuit laboratory experts assessed inter-rater reliability (IRR) using Cronbach's alpha of the intra-class correlation coefficient (ICC) on 20 practical assignments from the previous academic year. The IRR values ranged from 0.943 to 0.991, well above the minimum threshold of 0.7 [23].

Satisfaction questionnaire. A 34-item questionnaire across seven components: content and learning activities, problem-solving skills development, AR e-book design, preparation activities, inside-classroom activities, outside-classroom activities, and overall model satisfaction. Items were rated on a 5-point Likert scale. Five experts in instructional design assessed content validity using IOC; all items had IOC between 0.94 and 1.00.

2.5 Procedures

The study was conducted in three phases.

Phase 1 (Design and Development). The research team reviewed literature on blended learning, flipped classrooms, AR, and microlearning [24]. The FLIP-MAR model was drafted and reviewed by experts. The AR e-book was developed using ADDIE, with microlearning design principles (each module ≤ 15 minutes). The LA test, PSS rubric, and satisfaction questionnaire were developed and validated as described above.

Phase 2 (Experiment). After obtaining ethics approval and informed consent, all participants completed a pre-test (LA test) via Google Forms. The control group received traditional instruction: in-class lectures, demonstrations, and individual lab work with a printed manual. The experimental group used the FLIP-MAR model: before each class, students studied AR e-book modules and short videos (microlearning). During class, they engaged in collaborative problem-solving using the CIRER cycle, hands-on lab activities, and peer discussions. Both groups had nine class sessions (3 hours each) over six weeks (January–February 2026). Immediately after the final session, both groups completed the same LA post-test and a practical circuit problem (assessed with the PSS rubric). Two weeks later, a retention test (same LA test) was administered.

Phase 3 (Data Analysis). Descriptive statistics (means, standard deviations, frequencies) were computed. MANOVA was used to compare LA and PSS between groups. A mixed ANOVA (repeated measures) examined LA changes across three time points (pre-, post-, and retention). One-sample t-tests compared satisfaction scores against the benchmark (3.50 = high). All assumptions (normality, homogeneity of variance, and covariance) were checked and met.

2.6 AI tools

During manuscript preparation, the authors used Google Translate to assist in translation from Thai to English. No generative AI was used for data analysis or interpretation.

3 RESULTS

3.1 The FLIP-MAR model components

The model includes the **CIRER problem-solving cycle** (see Figure 3):

- **C (Clarify)** – Understand the problem, identify components, and scope [25].
- **I (Investigate)** – Analyze circuit structure and relationships [26].
- **R (Research)** – Seek additional knowledge from AR e-books, videos, or online resources [27].
- **E (Evaluate)** – Verify solution practicality and accuracy [28]. *Problem-Based Learning for Engineering Education: Developing the Engineers of the Future*. Routledge.
- **R (Reflect)** – Reflect on the process and apply it to new problems [29].

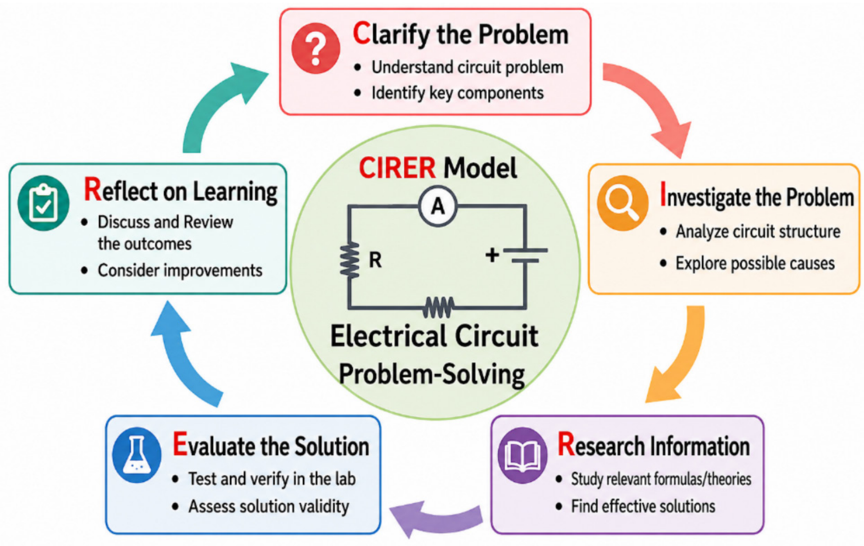

Fig. 3. CIRER cycle used in the FLIP-MAR learning model

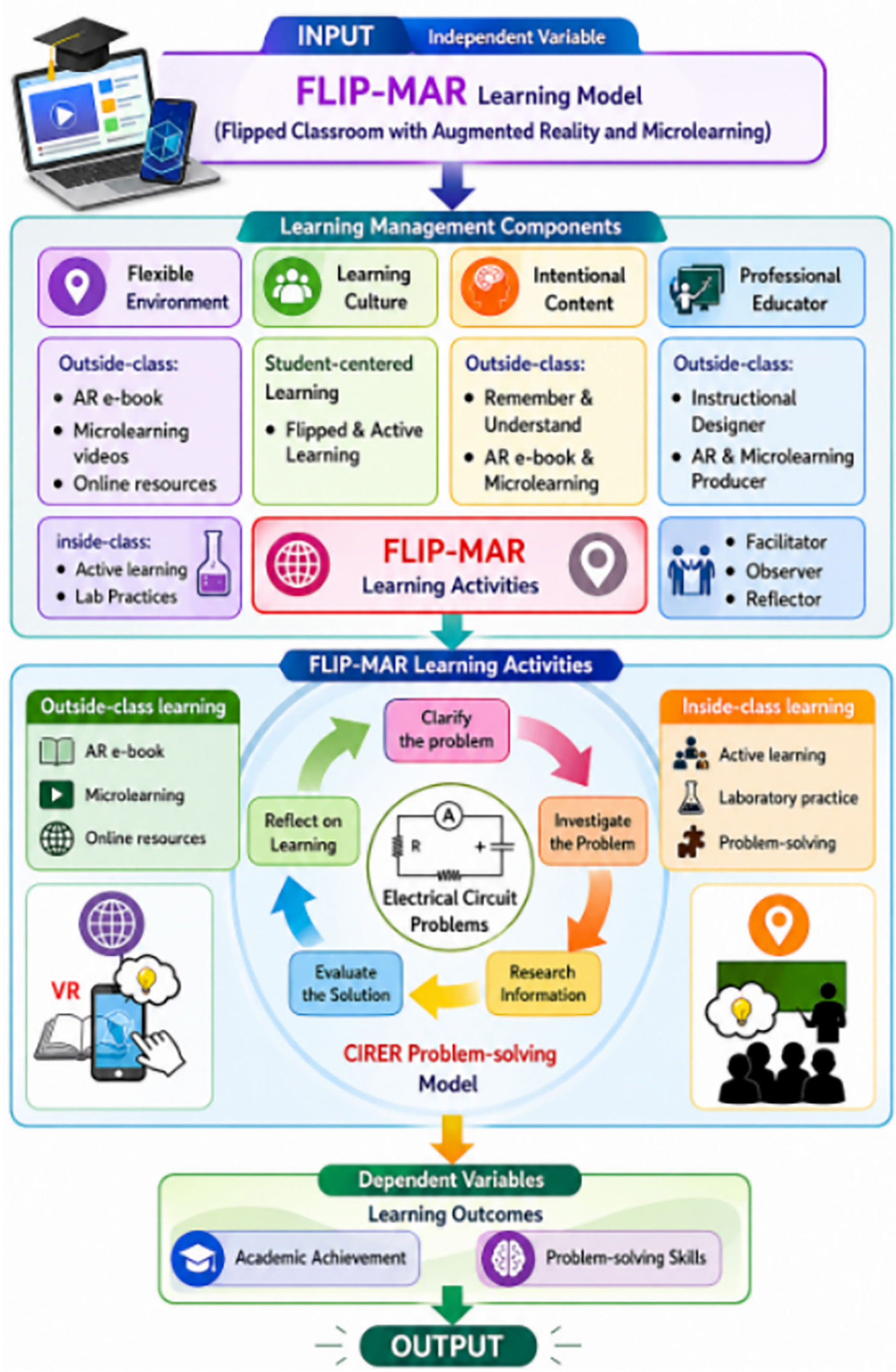

Fig. 4. The FLIP-MAR learning model

The full FLIP-MAR model (see Figure 4) integrates FC pillars (flexible environment, learning culture, intentional content, and professional educator) with microlearning components (microcontent, flexible learning, knowledge retention, outcome-oriented learning, and performance & skills development).

Expert evaluation yielded a total mean of 4.79 (SD = 0.41), indicating excellent performance based on the meta-evaluation standards for utility, feasibility, propriety, and accuracy [30]. Table 1 summarizes the results.

Table 1. Expert quality assessment of the FLIP-MAR learning model (n = 5)

Standard	Mean (M)	SD	Level
Propriety (Ethics & Standards)	4.82	0.39	Excellent
Utility (Practical Value)	4.68	0.48	Excellent
Feasibility (Practicality)	4.80	0.41	Excellent
Accuracy (Technical Soundness)	4.85	0.37	Excellent
Total	4.79	0.41	Excellent

The model achieved an overall mean of 4.79 (SD = 0.41), interpreted as excellent, confirming its high quality and appropriateness for implementation.

3.2 Learning achievement and problem-solving skills (MANOVA)

A multivariate analysis of variance revealed a statistically significant effect of teaching method (Wilks' $\lambda = 0.128$, $F(2, 40) = 136.3$, $p < .001$, $\eta^2 = 0.872$). Univariate follow-up tests showed that FLIP-MAR students scored significantly higher on both LA (M = 34.10, SE = 0.99 vs. 30.82, SE = 0.97; $p < .05$) and PSS (M = 48.99, SE = 0.34 vs. 40.28, SE = 0.41; $p < .01$) compared to the control group. Table 2 summarizes the MANOVA results.

Table 2. MANOVA for teaching method on LA and PSS (n = 43)

Dependent Variable	F(1, 41)	p	η^2
Learning achievement	5.558	.023	.119
Problem-solving skills	270.931	.000	.869

3.3 Learning retention (Mixed ANOVA)

Repeated measures analysis (Greenhouse-Geisser) showed a significant interaction between time and teaching method ($F(1.594, 65.372) = 20.790$, $p < .001$, $\eta^2 = 0.336$). The FLIP-MAR group maintained higher scores across the pre-test (M=19.57, SD = 1.28), post-test (M = 34.10, SD = 0.99), and two-week retention test (M = 38.88, SD = 1.14). The control group improved from pre-test (M = 19.27) to post-test (M = 30.82) but did not fully retain those gains at the two-week retention test (M = 27.18), whereas the FLIP-MAR group continued to improve from post-test (M = 34.10) to retention (M = 38.88).

3.4 Student satisfaction

Students in the experimental group (n = 18) reported overall satisfaction at the highest level (M = 4.26, SD = 0.71 on a 5-point scale). The highest-rated individual item was "Flipped classroom preparation" (M = 4.44, SD = 0.71). All components exceeded the "high" benchmark (≥3.50). Table 3 presents the mean scores for each of the seven main components.

Table 3. Student satisfaction with the FLIP-MAR model (n = 18)

Component	M	SD	Level
1. Content & learning activities	4.32	0.69	Highest
2. Problem-solving skills development	4.26	0.64	Highest
3. AR e-book design & quality	4.24	0.71	Highest
4. Preparation activities (FLIP-MAR)	4.24	0.69	Highest
5. Inside-classroom activities	4.32	0.69	Highest
6. Outside-classroom activities	4.27	0.68	Highest
7. Overall FLIP-MAR model	4.24	0.79	Highest

4 DISCUSSION

The FLIP-MAR approach had a profound positive impact on students' LA, PSS, and learning retention when compared with conventional pedagogy. This effect is based on the synergetic interplay of the components of this innovative learning approach.

Firstly, the flipped classroom learning model fosters cognitive engagement, active learning, and constructivist principles. In particular, through transferring direct instruction to preparatory classwork, in-class activities become problem-centered and experimental. This point was previously mentioned in several scientific works, including [7] and [31].

Secondly, AR technology is seen as situated scaffolding, which facilitates learning by providing a visualization of complex circuit concepts in 2D and 3D. This is supported by multiple studies reporting the efficacy of AR technology for deepening comprehension and motivation among students [10], [11]. For instance, according to the recent work of Hui et al. [32], marker-based AR contributes to problem-based learning in technical disciplines.

Thirdly, microlearning decreases cognitive load on students and promotes effective knowledge retention. In agreement with other research, the FLIP-MAR participants showed higher retention levels after two weeks [17], [33]. Additionally, this learning technique appeals to Gen Z students due to efficiency in using digital content [34].

Fourth, the CIRER cycle directly strengthens problem-solving skills. The structured inquiry steps (clarify, investigate, research, evaluate, reflect) gave students a clear framework for tackling circuit problems. This supports recent work on mobile-facilitated problem-solving [26] and scaffolding in STEM. The CIRER cycle extends traditional problem-based learning by embedding reflection as a distinct, final step, which likely contributed to the observed retention gains.

Fifth, the large effect size (partial $\eta^2 = 0.872$) indicates that about 87% of the variance in LA and PSS outcomes is attributable to the FLIP-MAR intervention—a highly practical significance. This exceeds effect sizes reported in studies examining FC alone (typically $\eta^2 = 0.20$–0.40) or AR alone ($\eta^2 = 0.15$–0.35), suggesting that the integration produces a multiplier effect.

Compared to other recent integrated models—such as AR with problem-based learning (Hui et al., 2024) [32] or flipped classroom with microlearning [35]—the FLIP-MAR model is unique in combining all three components within a single, theory-driven framework. The inclusion of the CIRER cycle provides a cognitive scaffold that may explain the sustained retention beyond immediate post-test gains.

Unlike other research studies that focused on FC, AR, or microlearning separately, this study proves that when FC, AR, and microlearning are applied as a whole, their results are more successful.

5 CONCLUSION

The proposed FLIP-MAR approach represents an effective theoretical model for improving learning effectiveness, solving problems, and retaining knowledge. This approach is based on the CIRER problem-solving cycle and focuses on the needs of digital-age students. This innovative educational approach is based on a learner-centered educational paradigm.

5.1 Practical implications

The Thai engineering education system can employ the FLIP-MAR approach without incurring huge costs on infrastructure since the AR e-book operates on common Android mobile phones. Teachers should spend one-third of classroom teaching time on microlearning lessons prior to class and two-thirds on in-class activities in the form of the CIRER cycle. It is advised that faculty members take faculty development workshops before the implementation of the approach regarding the creation of AR markers and brief videos. Where learning resources are scarce, microlearning elements should be provided using free applications such as YouTube and Google Forms, while AR should be integrated progressively.

5.2 Limitations and future research

Several limitations are worth noting. Firstly, the research took place in one particular institution, which makes it difficult to generalize about different settings. Secondly, while the number of participants ($n = 43$) was quite small, it was enough to perform MANOVA. Thirdly, the impact of students' digital literacy skills and socioeconomic status on the ability to use AR applications was not taken into account. Finally, the period during which participants were able to retain knowledge was only two weeks long.

Future research should be focused on: (1) generalizing the model of FLIP-MAR in different universities and in various engineering specializations (mechanical engineering, civil engineering, computer engineering); (2) using bigger samples with stratified randomization; (3) analyzing the impact of prior knowledge and Internet connection; (4) measuring retention within 3–6 months after the end of the course; (5) applying the model to non-laboratory lessons, for example, theoretical engineering or math lessons; and (6) determining the minimum amount of microlearning needed in a flipped classroom model.

6 REFERENCES

[1] W. Chansanam, L. T. Nguyen, and P. Kwangmuang, "Developing a lifelong learning ecosystem for students at Thai higher education institutions," *Higher Education, Skills and Work-Based Learning*, vol. 16, no. 2, pp. 1–19, 2026. https://doi.org/10.1108/HESWBL-09-2025-0435

[2] F. Awwad, "Enhancing electronics courses education: Active learning strategies for undergraduate engineering students," *International Journal of Engineering Pedagogy*, vol. 15, no. 2, pp. 42–73, 2025. https://doi.org/10.3991/ijep.v15i2.51739

[3] K. Siripongdee, P. Pimdee, and S. Tuntiwongwanich, "A blended learning model with IoT-based technology: Effectively used when the COVID-19 pandemic?" *Journal for the Education of Gifted Young Scientists*, vol. 8, no. 2, pp. 905–917, 2020. https://doi.org/10.17478/jegys.698869

[4] K. Siripongdee, S. Tuntiwongwanich, and P. Pimdee, "Blended learning model with IoT-based by smartphone," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 15, no. 11, pp. 166–182, 2021. https://doi.org/10.3991/ijim.v15i11.22441

[5] L. H. Lee, W. C. Li, and C. H. Yeung, "7 flipped classroom in K-12 science education," in *Innovative Teaching and Classroom Processes: Research Perspectives from Germany and China*, T. Ehmke and J. C.-K. Lee, Eds., Routledge, 2025, ch. 7. https://doi.org/10.4324/9781003436065-9

[6] R. Talbert and J. Bergmann, *Flipped Learning: A Guide for Higher Education Faculty*. Routledge, 2023. https://doi.org/10.4324/9781003444848

[7] M. I. Baig and E. Yadegaridehkordi, "Flipped classroom in higher education: A systematic literature review," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, pp. 1–26, 2023. https://doi.org/10.1186/s41239-023-00430-5

[8] S. Thangavel, "Revolutionizing education through augmented reality (AR) and virtual reality (VR): Innovations, challenges and future prospects," *Challenges and Future Prospects*, 2025. https://doi.org/10.2139/ssrn.5195697

[9] Y. Tan, W. Xu, S. Li, and K. Chen, "Augmented and virtual reality for education and training in the AEC industry," *Buildings*, vol. 12, no. 10, p. 1529, 2022. https://doi.org/10.3390/buildings12101529

[10] R. G. Boboc, R. Chiriac, and C. Antonya, "How augmented reality could improve the student's attraction to learn mechanisms," *Electronics*, vol. 10, no. 2, pp. 1–24, 2021. https://doi.org/10.3390/electronics10020175

[11] C. Chen, "AR videos as scaffolding to foster students' learning achievements and motivation in EFL learning," *British Journal of Educational Technology*, vol. 51, no. 3, pp. 657–672, 2020. https://doi.org/10.1111/bjet.12902

[12] N. F. Alias and R. A. Razak, "Revolutionizing learning in the digital age: A systematic literature review of microlearning strategies," *Interactive Learning Environments*, vol. 33, no. 1, pp. 1–21, 2025. https://doi.org/10.1080/10494820.2024.2331638

[13] B. Garner, A. Els, and T. Snyder, "Microlearning strategies: Engaging online adult learners," *Advances in Online Education: A Peer-Reviewed Journal*, vol. 4, no. 2, pp. 115–132, 2025. https://doi.org/10.69554/MRWW4300

[14] N. F. Alias and R. A. Razak, "Exploring the pedagogical aspects of microlearning in educational settings: A systematic literature review," *Malaysian Journal of Learning and Instruction*, vol. 20, no. 2, pp. 267–294, 2023. https://doi.org/10.32890/mjli2023.20.2.3

[15] W. K. Monib, A. Qazi, and R. A. Apong, "Microlearning beyond boundaries: A systematic review and a novel framework for improving learning outcomes," *Heliyon*, vol. 11, no. 2, Art no. e41413, 2025. https://doi.org/10.1016/j.heliyon.2024.e41413

[16] L. Gavrilas and K. T. Kotsis, "Integrating learning theories and innovative pedagogies in STEM education: A comprehensive review," *Eurasian Journal of Science and Environmental Education*, vol. 5, no. 1, pp. 11–17, 2025. https://doi.org/10.30935/ejsee/16538

[17] S. Lopez, "Impact of cognitive load theory on the effectiveness of microlearning modules," *European Journal of Education and Pedagogy*, vol. 5, no. 2, pp. 29–35, 2024. https://doi.org/10.24018/ejedu.2024.5.2.799

[18] M. N. A. Wahyudi, C. W. Budiyanto, I. Widiastuti, P. Hatta, and M. S. B. Bakar, "Understanding virtual laboratories in engineering education: A systematic literature review," *International Journal of Pedagogy and Teacher Education*, vol. 7, no. 2, pp. 102–118, 2024. https://doi.org/10.20961/ijpte.v7i2.85271

[19] K. Jayakumar and P. Balakrishnan, *Electronics Components and Testing: Concepts, Methods, and Applications*. Academic Guru Publishing House, 2025

[20] P. Pimdee, A. Sukkamart, C. Nantha, T. Kantathanawat, and P. Leekitchwatana, "Enhancing Thai student-teacher problem-solving skills and academic achievement through a blended problem-based learning approach in online flipped classrooms," *Heliyon*, vol. 10, no. 7, p. e29172, 2024. https://doi.org/10.1016/j.heliyon.2024.e29172

[21] F. Ebrahimi, T. Masoudian, and M. M. Khiabani, "Integrating ADDIE needs assessment with Kirkpatrick evaluation: A systematic review," *Asian Journal of Education and Social Studies*, vol. 51, no. 3, pp. 350–376, 2025. https://doi.org/10.9734/ajess/2025/v51i31832

[22] L. Mrangu, "Rubric as assessment tool for lecturers and students in higher education institution," *Acta Pedagogia Asiana*, vol. 1, no. 1, pp. 26–33, 2022. https://doi.org/10.53623/apga.v1i1.98

[23] P. Jakkaew, P. Putjorn, and N. Chondamrongkul, "Reliability in industry-academia assessment: A framework for validating competencies in IT education," in *2026 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunication Engineering (ECTI DAMT & NCON)*, 2026, pp. 1–6. https://doi.org/10.1109/ECTIDAMTNCON67592.2026.11460083

[24] D. Varsos, N. Zygouris, K. Kolomvatsos, A. Dadaliaris, and G. Dimitriou, "Prediction of secondary-school student cognitive performance in informatics," *International Journal of Engineering Pedagogy (iJEP)*, vol. 16, no. 1, pp. 66–86, 2026. https://doi.org/10.3991/ijep.v16i1.56637

[25] L. Lu, S. S. Mustakim, and M. M. Muhamad, "A meta-analysis of the effectiveness of problem-based learning on critical thinking," *European Journal of Educational Research*, vol. 14, no. 3, pp. 789–804, 2025. https://doi.org/10.12973/eu-jer.14.3.789

[26] L. Cong and C. S. Ironsi, "Integrating mobile learning and problem-based learning in improving students action competence in problem-solving and critical thinking skills," *Humanities and Social Sciences Communications*, vol. 12, no. 1, pp. 1–11, 2025. https://doi.org/10.1057/s41599-025-05397-4

[27] B. R. Belland, D. M. Weiss, and N. J. Kim, "High school students' agentic responses to modeling during problem-based learning," *The Journal of Educational Research*, vol. 113, no. 5, pp. 374–383, 2020. https://doi.org/10.1080/00220671.2020.1838407

[28] D. K. Das, *Problem-Based Learning for Engineering Education: Developing the Engineers of the Future*. Routledge, 2025. https://doi.org/10.1201/9781003529743

[29] T. Little, P. Dawson, D. Boud, and J. Tai, "Can students' feedback literacy be improved? A scoping review of interventions," *Assessment & Evaluation in Higher Education*, vol. 49, no. 1, pp. 39–52, 2024. https://doi.org/10.1080/02602938.2023.2177613

[30] D. L. Stufflebeam, "The metaevaluation imperative," *American Journal of Evaluation*, vol. 22, no. 2, pp. 183–209, 2001. https://doi.org/10.1177/109821400102200204

[31] I. Blau and T. Shamir-Inbal, "Re-designed flipped learning model in an academic course: The role of co-creation and co-regulation," *Computers & Education*, vol. 115, pp. 69–81, 2017. https://doi.org/10.1016/j.compedu.2017.07.014

[32] Y. K. Hui, M. F. A. Hanid, M. a. Z. M. Zakaria, M. N. H. M. Said, and M. I. Zakaria, "A systematic literature review on types of augmented reality (AR) technologies and learning strategies for problem-solving," *International Journal of Learning, Teaching and Educational Research*, vol. 23, no. 5, pp. 68–86, 2024. https://doi.org/10.26803/ijlter.23.5.4

[33] L. Yu, T. C. Ho, P. C. Teo, and S. Baskaran, "Microlearning implementation strategies and their impact on talent retention," *International Journal of Academic Research in Business and Social Sciences*, vol. 14, no. 10, pp. 1858–1866, 2024. https://doi.org/10.6007/IJARBSS/v14-i10/23302

[34] H. Choudhary and D. Pandita, "Maximizing learning outcomes in the digital age: The role of microlearning for Gen Z," *Development and Learning in Organizations: An International Journal*, vol. 38, no. 3, pp. 15–18, 2024. https://doi.org/10.1108/DLO-02-2023-0038

[35] N. P. W. Yunianti and D. Kusumawardani, "Microlearning as a digital learning strategy in higher health education: Literature review," *Jurnal Pendidikan Teknologi dan Kejuruan*, vol. 22, no. 1, pp. 1–11, 2025. https://doi.org/10.23887/jptkundiksha.v22i1.90686

7 AUTHORS

Cherisa Nantha is an Assistant Professor in the Department of Educational Technology and Communications, Faculty of Technical Education, RMUTT, Pathum Thani, Thailand. Her research focuses on flipped classrooms, active learning, educational technology, adaptive learning, and problem-based learning (E-mail: cherisa_n@rmutt.ac.th).

Aekkarat Lorphichian is a Ph.D. in the Information Technology Program, King Mongkut's Institute of Technology North Bangkok (KMITNB), Bangkok, Thailand. His research focuses on robotic programming, IoT, embedded systems, educational technology, AI learning, cloud computing, data mining, and computer education (E-mail: aekkarat@rmutt.ac.th).

Kanitphan Boonsomchuae is a Lecturer in the Department of Technical Education, Faculty of Technical Education, RMUTT, Pathum Thani, Thailand. He graduated with a D.Eng. in electrical engineering. He specializes in educational technology, power electronics, IoT, and artificial intelligence (E-mail: kanitphan_b@rmutt.ac.th).

Winai Jaikla is an Associate Professor in the Department of Engineering Education, School of Industrial Education and Technology, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand. His research interests include electronic communications, analog signal processing, and analog integrated circuits. He is a member of IEEE (USA) and ECTI (Thailand) (E-mail: winai.ja@kmitl.ac.th).

Sumeth Theskul is an Assistant Professor specializing in the integration of electrical engineering and educational research. His research expertise encompasses electrical power systems, energy management, and modern learning process management in engineering education. His work focuses on developing innovative instructional strategies to enhance technical competencies in electrical engineering (E-mail: sumeth_t@rmutt.ac.th).

Online-Journals.org

iJEP International Journal of Engineering Pedagogy

iJEP | eISSN: 2192-4880 | Vol. 16 No. 5 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijep.v16i5.62296

PAPER

Achievement Goal Motivation Influences Self-Efficacy in AI-Supported Collaborative Programming: Mediating Roles of Growth Mindset and Mastery Experience

Wen-Shyong Tzou[1], **Chia-Hsiang Ma**[2], **Yu-chu Yeh**[2] (✉), **Melissa T. A. Simarmata**[2]

[1]National Taiwan Ocean University, Keelung, Taiwan

[2]National Chengchi University, Taipei City, Taiwan

ycyeh@nccu.edu.tw

ABSTRACT

This study designed an AI-integrated collaborative problem-based learning (CPBL) course aimed to bolster programming self-efficacy among undergraduate and to elucidate the underlying psychological mechanisms that drive self-efficacy. A total of 179 Taiwanese undergraduates participated in an 18-week intervention that integrated AI toolkits, CPBL frameworks, and instructional scaffolding to facilitate interdisciplinary application. To achieve our goals, two instruments were developed to measure programming-specific achievement goals and mindsets. The results indicated that the AI-supported CPBL environment effectively fostered a growth mindset, mastery experiences, and self-efficacy in programming. Mediation model analysis revealed that growth mindset and mastery experience functioned as dual mediators linking achievement goal orientation to self-efficacy. Notably, mastery goals exerted a markedly stronger influence on self-efficacy compared to performance goals. The findings highlight the necessity of prioritizing mastery-oriented pedagogy in the design of AI-integrated programming curricula.

KEYWORDS

achievement goal, growth mindset, mastery experience, self-efficacy, programming

1 INTRODUCTION

In recent years, programming education has attracted significant global attention in many developed countries [1], particularly in the current digital era, where programming ability has become an essential interdisciplinary competence [2]. Despite its importance, programming is characterized by a steep learning curve and high cognitive demand. Even among computer science majors, the complexity of syntax and logical abstraction often leads to significant attrition or course withdrawal [3]. This challenge is further compounded for non-specialist students, who may lack

Tzou, W.-S., Ma, C.-H., Yeh, Y., Simarmata, M. T. A. (2026). Achievement Goal Motivation Influences Self-Efficacy in AI-Supported Collaborative Programming: Mediating Roles of Growth Mindset and Mastery Experience. *International Journal of Engineering Pedagogy (iJEP)*, 16(5), pp. 125–143. https://doi.org/10.3991/ijep.v16i5.62296

Article submitted 2026-05-12. Revision uploaded 2026-07-14. Final acceptance 2026-07-20.

the foundational mental models required for rapid proficiency. It has been found that non–computer science majors tend to exhibit low programming self-efficacy [4]. Developing programming self-efficacy [5] is therefore critical for fostering programming competence. To cultivate learners' programming self-efficacy, both instructional factors and learners' psychological characteristics must be considered. By understanding key psychological mechanisms, instructors can design more effective training that enhances learners' resilience, confidence, and long-term success in programming education.

To improve the effectiveness of programming instruction, research has increasingly focused on the development of instructional tools and techniques [6]. In response, this study developed a training course integrating AI toolkits into collaborative project-based learning (CPBL). The goal was to explore the psychological factors that may influence the development of programming self-efficacy in an AI-supported learning environment. To ensure the robustness of the learning environment, training effects were also examined.

This study focused on three psychological factors: achievement goals, growth mindset, and mastery experience. Achievement goal theory is one of the most prominent and empirically supported frameworks for understanding learning motivation [7]. Growth mindset refers to the belief that one's abilities can be developed over time [8]. A strong achievement goal orientation may foster a growth mindset. Together, these two motivation-related traits can influence the development of mastery experiences. Furthermore, mastery experience is considered the most powerful source for enhancing self-efficacy [9], [10]. Based on these theoretical connections, we hypothesize that growth mindset and mastery experience serve as mediators between achievement goals and programming self-efficacy in an AI-supported learning context.

Achievement goals are generally categorized into mastery goals, which focus on improving one's own competence, and performance goals, which focus on demonstrating competence relative to others [7]. While mastery goals are consistently found to benefit learning, the effects of performance goals are more variable [11]. Accordingly, this study examines how different achievement goal orientations influence programming self-efficacy through the mediating roles of growth mindset and mastery experience in an AI-supported Python programming environment.

2 LITERATURE REVIEW

2.1 Constructs of achievement goals

Achievement goal theory generally distinguishes between two primary goal orientations. Mastery goals emphasize learning and self-improvement. Learners with mastery goals tend to adopt deep learning strategies and persist in the face of challenges. In contrast, performance goals focus on demonstrating competence relative to others. Learners with performance goals often prioritize outcomes and may avoid challenging tasks to protect their self-image [12], [13].

To extend the explanatory power of the theory, Elliot and McGregor [14] proposed a 2 × 2 model that differentiates between approach and avoidance orientations within both mastery and performance goals. The four resulting categories are: (1) Mastery-approach (e.g., striving to fully understand learning content); (2) Mastery-avoidance (e.g., striving to avoid missing important concepts);

(3) Performance-approach (e.g., striving to outperform others); and (4) Performance-avoidance (e.g., trying to avoid being judged poorly for poor performance). Among these orientations, mastery-approach goals are most consistently associated with adaptive outcomes, including higher self-efficacy, greater intrinsic motivation, and sustained academic achievement [15], [16].

Research has shown that achievement goal orientation plays a crucial role in computer-supported collaborative learning [17]. Furthermore, peer cooperation and competition have both been found to be positively related to mastery-approach goals [18]. Although achievement goal theory has been widely applied across educational domains, its application in programming education remains limited. To address this gap, the present study incorporates achievement goals to examine their role in programming learning. For this purpose, we first developed an inventory to measure programming achievement goals.

2.2 Constructs of mindsets

Mindset theory offers a valuable framework for understanding how students interpret challenges and respond to setbacks [19]. Originally, the concept of mindset referred to an individual's beliefs about intelligence [8]. Two core beliefs define this construct: a fixed mindset, in which intelligence is viewed as static, and a growth mindset, in which intelligence is seen as malleable and capable of development through effort and effective strategies [8], [20]. Students who endorse a growth mindset are more likely to embrace challenges as opportunities for development [21]. This belief promotes adaptive learning behaviors, such as persistence, self-regulation, and the adoption of effective learning strategies [22]. Furthermore, a growth mindset is positively associated with academic performance [23].

Importantly, mindset is domain-specific; individuals may hold different beliefs across different areas. Consequently, mindset research has expanded to diverse fields, such as creativity [24] and STEM education [25]. However, mindset has rarely been examined in the context of programming education.

To specify the explanatory power of creativity mindsets, Yeh et al. [26] proposed a 2×2 model that distinguishes between growth and fixed mindsets with internal and external attributions. The four types of mindsets are as follows: (1) Growth–internal mindset: Belief that ability can be improved through self-directed learning; (2) Growth–external mindset: Belief that ability can be improved through supportive learning environments or assistance from others; (3) Fixed–internal mindset: Belief that ability is an innate talent and cannot be improved through self-directed learning; and (4) Fixed–external mindset: Belief that ability cannot be improved even with strong external support. Based on this theoretical framework, this study developed an inventory to measure programming mindset.

2.3 The relationship between programming achievement goals, growth mindset, mastery experience, and self-efficacy during training

Programming self-efficacy, defined as a learner's belief in their ability to successfully design, structure, implement programming solutions, and solve problems, is a critical factor influencing motivation and achievement in programming education [27], [4]. For students from non-computer science backgrounds, low self-efficacy is often associated with anxiety, disengagement, and even course attrition [28]. Fostering programming self-efficacy is therefore essential for supporting these learners.

Prior research has suggested that programming self-efficacy is associated with students' prior programming experiences and performance outcomes [29], [30]. Meta-analytic evidence also indicates that mastery experience is the most influential source of self-efficacy [31]. Mastery experiences enhance learners' sense of competence and self-confidence, particularly when tasks are iterative, feedback-rich, and demand active problem-solving [32]. In programming education, mastery experience involves acquiring coding skills and applying them to solve real problems. It is, therefore, crucial for building programming self-confidence.

Furthermore, social cognitive theory posits that self-efficacy is shaped by an interplay of personal, behavioral, and environmental influences [33]. Motivation serves as the foundation for learner engagement in programming tasks and shapes their mindset [34]. Research indicates that highly motivated learners, particularly those with a mastery goal orientation, are more likely to adopt a growth mindset, believing that programming skills can be developed through persistence [35]. In the same vein, it is found that students with a growth mindset are more likely to persist through errors and debugging, achieving incremental successes in programming tasks [36]. This mindset, in turn, fosters sustained engagement and the accumulation of mastery experiences, which ultimately strengthen programming self-efficacy.

In summary, the relationship between programming motivation and self-efficacy can be conceptualized as a serial mediation model: achievement goal motivation → growth mindset → persistence and mastery experience → enhanced programming self-efficacy.

2.4 Artificial intelligence-supported CPBL

Collaborative project-based learning promotes both knowledge acquisition and teamwork by engaging learners in real-world problem-solving projects. CPBL emphasizes process-oriented, context-related, and student-centered learning [37]. Research on CPBL has shown that collaboration fosters shared responsibility, motivation, and essential teamwork skills [38]. Active peer interaction enables students to articulate ideas, solve problems collectively, and, in turn, develop confidence and self-efficacy [39].

In programming education, CPBL provides opportunities for guided practice, allowing students to build mastery experiences that strengthen their self-efficacy [40]. This approach is particularly effective for non–computer science majors, as it situates programming within meaningful, interdisciplinary contexts [41], [42]. Moreover, CPBL enables students to collaboratively engage in authentic, complex projects that promote the development of knowledge and skills while systematically completing interconnected learning tasks to achieve the project goals. This approach has been shown to significantly enhance college students' programming performance [37].

On the other hand, the interdisciplinary nature of CPBL further encourages learners to integrate IT and programming skills into broader problem-solving contexts [41], [42]. The integration of AI support into CPBL offers additional benefits. AI can provide instant assistance, personalized feedback, and adaptive guidance, all of which have been shown to enhance programming performance [43]. For example, the use of a generative AI tool, MindScratch, has been found to help learners complete creative programming projects [44]. Moreover, it was found that incorporating

ChatGPT into weekly programming practices improved students' programming self-efficacy [4]. Building on these strengths, the present study developed an AI-supported CPBL framework aimed at enhancing learners' growth mindset, mastery experience, and programming self-efficacy.

2.5 Present study and hypotheses

Given the growing importance of Python programming and the potential of AI-supported CPBL, we designed an 18-week training course, by which we examined how achievement goals influence programming self-efficacy. To achieve these objectives, we developed two instruments: the inventory of programming motivation (IPMo) and the inventory of programming mindsets (IPM).

We further anticipated that different types of achievement goal motivation—specifically, mastery goals and performance goals—might exert distinct effects on self-efficacy. The following hypotheses were proposed:

- H1: Growth mindset would mediate the influence of achievement goal motivation on programming self-efficacy among non–computer science college students.
- H2: Mastery experience would mediate the influence of achievement goal motivation on programming self-efficacy among non–computer science college students.
- H3: Growth mindset and mastery experience would jointly mediate the influence of achievement goal motivation on programming self-efficacy among non–computer science college students.
- H4: Mastery goal motivation would exhibit stronger overall explanatory power in predicting programming self-efficacy compared to performance goal motivation.

Notably, in an exploratory manner, we also examined the training effects on mastery experience and self-efficacy in programming, as well as fixed and growth mindsets toward programming. The effects of achievement goal motivation were not assessed because the study did not include any manipulation of this construct. Instead, we assumed that achievement goal motivation would influence students' learning processes during the training.

3 METHOD

3.1 Participants

A total of 179 college students (88 females, 80 males, and 11 unspecified) who had participated in the inventory development also took part in the training course. All participants were undergraduate students from the School of Life Science, with a mean age of 19.45 years (*SD* = 8.74), enrolled in the liberal education course Programming Language and Data Processing offered by the Department of Bioscience and Biotechnology at a public university in Taiwan. This study was conducted as part of a regular university course. Participation involved no risk beyond normal educational activities. All data were anonymized before analysis. Participation in research analysis was voluntary, and informed consent was obtained from all participants at the outset of the study. Each participant received a reward equivalent to approximately USD 7.

3.2 Instruments

Four instruments were used in this study: the IPMo, the IPM, the *Inventory of Programming Mastery Experience (IPME)*, and the *Inventory of Programming Self-Efficacy (IPSE).* The first two inventories were developed in this study. All instruments employed a 6-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree).

IPMo and IPM. The development of the IPMo and IPM involved a series of reliability and validity analyses to assess internal consistency and construct validity. The final version of the IPMo consisted of nine items across two factors: Mastery goal (5 items) and Performance goal (4 items) (refer to Table 1). The IPM comprised ten items across two factors: Growth mindset (5 items) and Fixed mindset (5 items) (refer to Table 2). Details of the scale development process are provided in Section 4.1.

IPME and IPSE. The IPME [45] was used to measure participants' mastery experience in Python programming. The scale was validated through both exploratory and confirmatory factor analyses. It comprised five items across two factors: Foundational ability (3 items) and Advanced ability (2 items). The correlation between the two factors was .810 (p < .001), and the correlations between each factor and the total score were .965 and .936 (ps < .001). Cronbach's α coefficients were .930 for the overall scale, .909 for Foundational ability, and .857 for Advanced ability. Example items include: "I can apply basic programming syntax in my code" (Foundational ability) and "I can use programming to explore what interests me" (Advanced ability).

The IPSE [45] was used to assess participants' self-efficacy in Python programming. The scale was validated through both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). It consists of seven items across two factors: Application self-efficacy (4 items) and Learning self-efficacy (3 items). The correlation between the two factors was .843 (p < .001), and the correlations between each factor and the total score were .973 and .945 (ps < .001). Cronbach's α coefficients indicated excellent internal consistency, with values of .943 for the overall scale, .912 for Application self-efficacy, and .899 for Learning self-efficacy. Example items include: "I believe I can adapt example code to solve similar problems" (Application self-efficacy) and "I believe I can learn and understand basic programming syntax" (Learning self-efficacy).

3.3 Experimental design and procedures

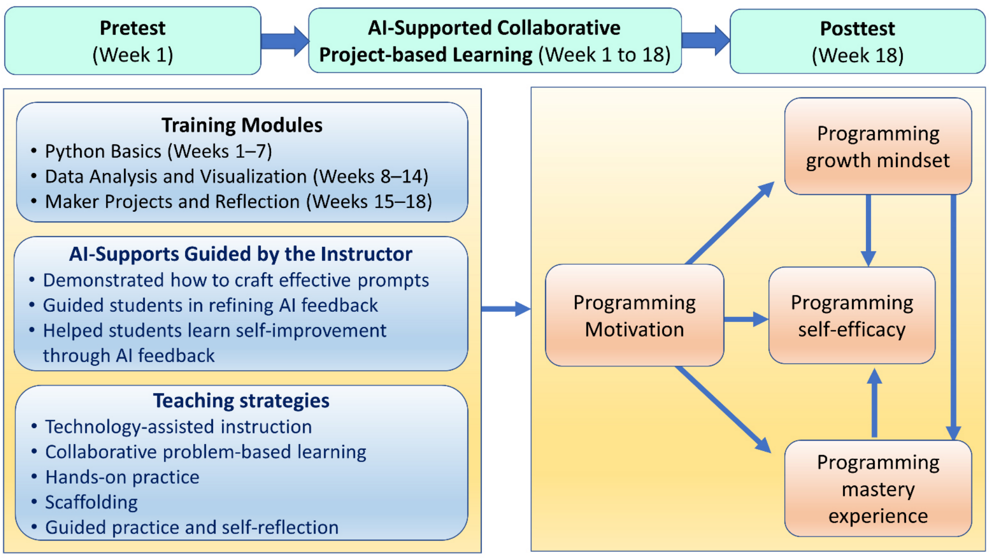

Fig. 1. Experimental design and key features of the instructional design

Data for inventory development were collected via SurveyCake (https://www.surveycake.com), with no time constraints imposed on participants. For the experimental teaching, the study aimed to enhance students' growth mindset, mastery experience, and self-efficacy through an 18-week instructional course. During the first week, participants completed a pretest assessing achievement goal motivation, growth mindset, mastery experience, and self-efficacy. They then engaged in the 18-week training course, after which they completed a posttest containing the same measures as the pretest. We anticipated that the training course would enhance participants' programming motivation, growth mindset, mastery experiences, and self-efficacy. See Figure 1 for the experimental design and the key features of the instructional design.

The course was conducted in a blended learning format via the TronClass teaching platform. The instructor—also the first author—has over 20 years of experience teaching the Programming Language and Data Processing course. The instructional design was organized into three stages:

1. Python basics (Weeks 1–7): This stage introduced fundamental Python syntax and the use of comments. Problem-based learning was emphasized through hands-on coding exercises, weekly assignments, and group discussions.
2. Data analysis and visualization (Weeks 8–14): This stage focused on progressively developing students' data analysis skills, including data visualization with Matplotlib, exploring relationships among variables, and applying linear regression models. Learning activities centered on practical applications of the taught techniques.
3. Maker projects and reflection (Weeks 15–18): This stage implemented CBPL using the Flag's Maker Workshop: Learning Python Through Maker Activities kit. Students engaged in peer sharing, discussion sessions, and reflective practices throughout the project process. Three projects were completed with an ESP32-powered AI maker kit: a Morse Code Communicator, a Lie Detector, and a Pulse Oximeter. The Morse Code Communicator required students to program LED blink patterns to simulate Morse code. The Lie Detector used a galvanic skin response (GSR) sensor to detect changes in skin conductivity, analyzing fluctuations to infer stress levels and potential deception. Finally, the Pulse Oximeter employed an optical sensor to measure blood oxygen saturation (SpO_2) and pulse rate, with real-time data processing and display via the ESP32. Together, these projects showcased how sensing technologies and microcontrollers can be applied in interactive and wearable systems. Examples of applications using the AI kit are illustrated in Figure 2.

To support active learning, the course integrated multiple technologies—including Python, multimedia resources, PowerPoint slides, and a software development kit—aimed at strengthening conceptual understanding, facilitating hands-on practice, promoting collaboration and discussion, and enhancing problem-solving skills and confidence. A central resource was the kit *Flag's Maker Workshop*, which provided structured tasks to increase student engagement and reinforce practical Python skills and self-efficacy through group CPBL. The instructional design followed a scaffolding approach, gradually guiding students from foundational concepts to applied projects and reflection. Notably, throughout the course, students participated in peer sharing, collaborative project development, and in-class presentations.

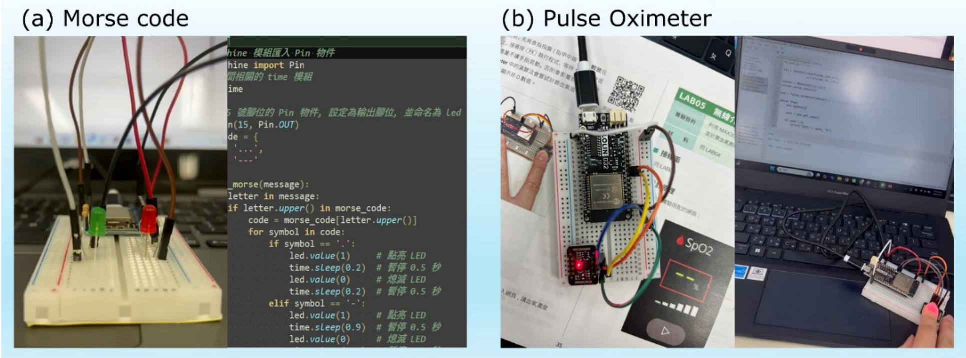

Fig. 2. Examples of applications using the kit of "Flag's Maker Workshop: Learning Python Through Maker Activities"

Notes: The Morse code for SOS was coded into the LED lights to send a message. The letter S (· · ·) is shown by three quick flashes, and the letter O (– – –) is shown by three long flashes. Together, the short and long flashes spell out SOS.

Notably, generative AI—primarily ChatGPT—was systematically integrated to support students' learning in both individual and group assignments. At the beginning of the course, the instructor demonstrated how to formulate effective prompts. Throughout the learning process, the instructor also provided explicit guidance when students were unable to obtain useful responses from the generative AI on their own, particularly during the final Maker Project. In addition, students were taught how to improve their programming skills by interpreting and refining the feedback generated by ChatGPT. Within this AI-supported, collaborative problem-solving environment, students learned to leverage generative AI effectively to enhance and facilitate their learning.

4 RESULTS

4.1 Inventory development

For both inventories, internal consistency reliability and EFA with Promax rotation were conducted to establish reliability and preliminary construct validity. Subsequently, CFA using maximum likelihood estimation, along with inter-factor correlation analyses, was performed to further validate the construct structure.

Development of the IPMo. Exploratory factor analysis results for the IPMo revealed a two-factor structure—Mastery goal and Performance goal—across nine items. Factor loadings ranged from .697 to .966, accounting for 75.606% of the total variance (refer to Table 1). The correlation between the two factors was .575 ($p < .001$), and the correlations between each factor and the total score were .892 and .883 ($ps < .001$). Cronbach's α coefficients indicated strong internal consistency, with values of .913 for the overall scale, .897 for the Mastery goal, and .916 for the Performance goal. Item–total correlations ranged from .591 to .788, further supporting the reliability of the scale.

Confirmatory factor analysis further supported the two-factor structure of the IPMo. The model fit indices were: χ^2 ($N = 193$, $df = 26$) = 124.151, $p < .001$; goodness-of-fit index (GFI) = .877; adjusted goodness-of-fit index (AGFI) = .788; standardized root mean square residual (SRMR) = .059; root mean square error of approximation (RMSEA) = .140; comparative fit index (CFI) = .926; and normed fit index (NFI) = .909. The composite reliability (CR) values for the Mastery goal and Performance goal factors were .895 and .917, respectively, and the average variance extracted (AVE) values were .647 for Mastery goal and .738 for Performance goal.

Table 1. Test items and factor loadings of the IPMo

No.	Factors and Items During the Learning of Programming	Factor Loadings 1	2
	Factor 1: Mastery goal (α = .897)		
3	I strive to avoid missing any important concepts during my learning.	.923	
2	I do my best to learn as many important concepts from class as possible.	.893	
6	I make an effort to integrate what I've learned, hoping to apply it effectively.	.876	
1	I try hard not to take a perfunctory approach, so as not to reduce the effectiveness of my learning.	.802	
7	I strive to avoid a superficial understanding that prevents true comprehension and integration.	.697	
	Factor 2: Performance goal (α = .916)		
9	I put in great effort to perform well so others won't look down on me.		.966
5	I work hard to avoid being ridiculed by others.		.912
8	I strive to perform well to impress others.		.908
4	I make an effort to perform well in hopes of gaining others' recognition.		.717

The development of IPM. Exploratory factor analysis revealed a two-factor structure—Fixed Mindset and Growth Mindset—across ten items. Factor loadings ranged from .814 to .902, accounting for 77.283% of the total variance (refer to Table 2). The correlation between the two factors was –.381 (p < .001). The correlations between each factor and the total score were .551 (p < .001) for Fixed Mindset and .562 (p < .001) for Growth Mindset (refer to Table 2). Cronbach's α coefficients indicated excellent internal consistency, with values of .929 for Fixed Mindset and .920 for Growth Mindset. Item–total correlations ranged from .758 to .851 for Fixed Mindset and from .744 to .846 for Growth Mindset.

Confirmatory factor analysis further supported the two-factor structure of the IPM. The model fit indices were: χ^2 (N = 193, df = 34) = 133.550, p < .001; GFI = .871; AGFI = .791; SRMR = .046; RMSEA = .123; CFI = .937; and NFI = .918. CR values were .930 for Fixed Mindset and .919 for Growth Mindset, with AVE values of .702 and .727, respectively.

Table 2. Test items and factor loadings of IPM

No.	Factors and Items	Factor Loadings 1	2
	Factor 1: Growth mindsets (α = .920)		
8	If I have good learning opportunities, my programming skills can improve significantly.	.897	
7	As long as I am willing to learn, I can improve my programming skills.	.886	
4	If I have a good learning environment, my programming skills can improve.	.859	
2	With the help of teachers and teaching assistants, my programming skills will improve.	.823	
1	My programming skills can be improved through self-learning, and it's never too late to start learning now.	.814	

(Continued)

Table 2. Test items and factor loadings of IPM *(Continued)*

No.	Factors and Items	Factor Loadings	
		1	2
	Factor 2: Fixed mindsets (α = .929)		
6	Even if there is a good learning environment, it's still difficult for me to improve my programming skills.		.902
5	Even if I am willing to learn, it's still hard for me to improve my programming skills.		.879
10	Even if I have great learning opportunities, my programming skills won't improve much.		.869
9	Even if I study very hard on my own, my programming skills won't improve significantly.		.867
3	It's hard for me to improve my programming skills; self-learning doesn't help either.		.815

4.2 Improvement of programming self-efficacy, mastery experience, and mindset

To assess the effects of the training course, repeated measures ANOVA was performed with pretest and posttest scores as within-subject variables for programming self-efficacy, mastery experience, growth mindset, and fixed mindset. Means and standard errors are presented in Figure 3. Results showed significant improvements in the overall and subscale scores of programming self-efficacy, Fs(1, 166) = 7.538–48.906, ps < .01, η_p^2 = .090–.228. Participants' growth mindset also significantly increased, F(1, 166) = 5.248, p = .023, η_p^2 = .031, whereas their fixed mindset significantly decreased, F(1, 166) = 4.625, p = .033, η_p^2 = .027 (refer to Table 3).

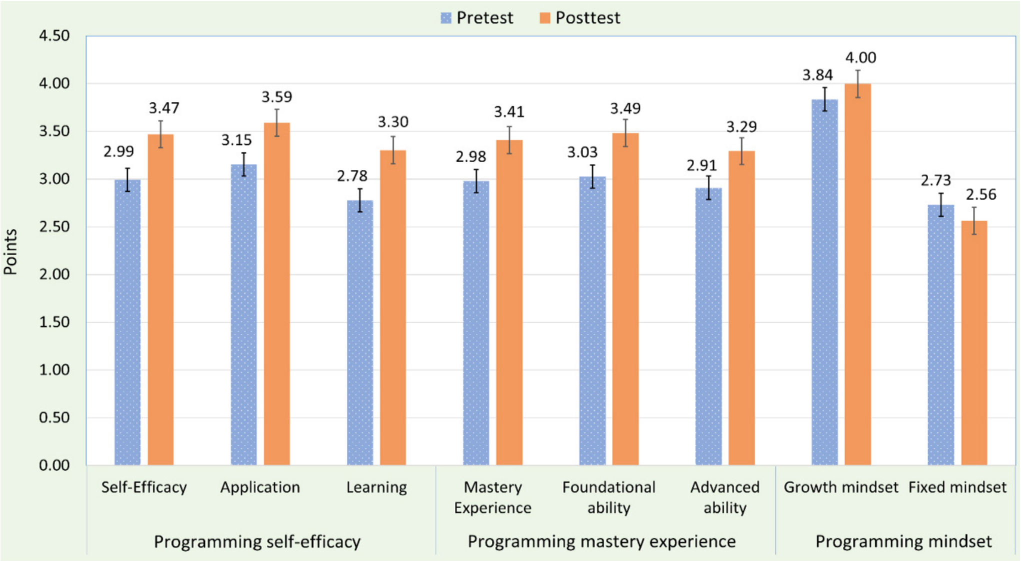

Fig. 3. Means and standard errors of programming self-efficacy, mastery experience, and growth mindset in the pretest and posttest

Table 3. Results of repeated measures ANOVA examining improvements in programming self-efficacy, mastery experience, growth mindset, and fixed mindset

Source	MS	$F(1, 166)$	p	η_p^2	Comparison
Self-Efficacy	18.821	48.906***	.000	.228	Posttest > Pretest
Application	15.955	34.829***	.000	.173	Posttest > Pretest
Learning	23.010	53.597***	.000	.244	Posttest > Pretest
Mastery experience	7.701	12.584***	.001	.142	Posttest > Pretest
Foundational ability	8.107	14.785***	.000	.163	Posttest > Pretest
Advanced ability	5.651	7.538**	.008	.090	Posttest > Pretest
Mindset					
Growth mindset	2.183	5.248*	.023	.031	Posttest > Pretest
Fixed mindset	2.415	4.625*	.033	.027	Posttest < Pretest

Notes: $^{*}p < .05$. $^{**}p < .05$. $^{***}p < .05$.

4.3 The process model of motivation, growth mindset, mastery experience, and self-efficacy

We employed SPSS PROCESS to examine the potential mechanisms underlying the enhancement of programming self-efficacy during the training. Because we assumed that a fixed mindset would be negatively correlated with the other variables, we did not include it in the model. The correlation between the two types of achievement goals was .575 ($p < .001$). The mean scores (and standard deviations) for the overall motivation scale, mastery goal, and performance goal were 3.58 (0.80), 3.79 (0.83), and 3.31 (1.00), respectively. To assess whether mastery goal and performance goal motivations exerted distinct influences within the PROCESS framework, we conducted separate analyses for each motivational type. In the following model descriptions, The proposed mediation models are presented in Figures 4 and 5.

Model 1 (see Figure 4) examined the influence of mastery goal motivation on growth mindset, mastery experience, and programming self-efficacy. Three significant indirect pathways were identified: (1) Mastery goal → Growth mindset → Self-efficacy: Mastery goal positively predicted growth mindset ($\beta = .696$, $p < .001$), which in turn predicted self-efficacy ($\beta = .438$, $p < .001$); total indirect effect = .305. (2) Mastery goal → Mastery experience → Self-efficacy: Mastery goal directly predicted mastery experience ($\beta = .388$, $p < .001$), which subsequently predicted self-efficacy ($\beta = .456$, $p < .001$); total indirect effect = .177. (3) Mastery goal → Growth mindset → Mastery experience → Self-efficacy: Mastery goal predicted growth mindset ($\beta = .696$, $p < .001$), which predicted mastery experience ($\beta = .485$, $p < .001$), which then predicted self-efficacy ($\beta = .456$, $p < .001$); total indirect effect = .154.

Again, the direct effect of Mastery goal on self-efficacy was not significant ($\beta = .051$, $p = .361$). Overall, the total indirect effect was significant ($\beta = .635$), and the total effect of Mastery goal on self-efficacy was strong ($\beta = .687$, $p < .001$), explaining 47.1% of the variance ($R^2 = .471$).

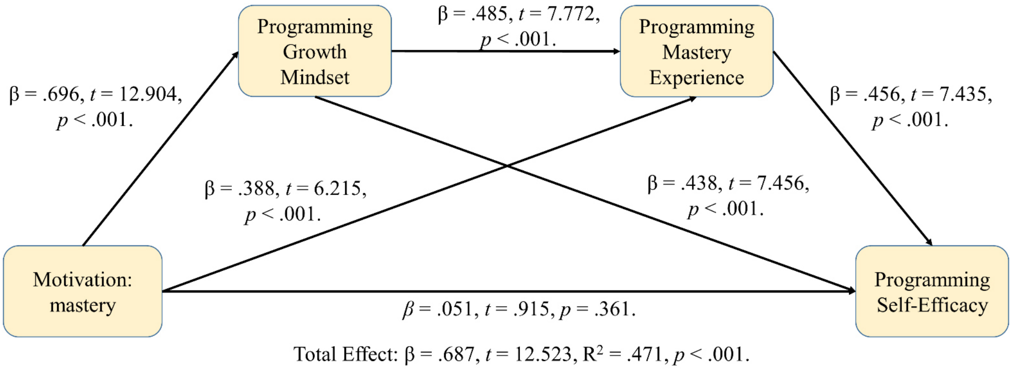

Fig. 4. PROCESS model of mastery goal, growth mindset, mastery experience, and programming self-efficacy

Model 2 (see Figure 5 examined the influence of performance goal motivation on growth mindset, mastery experience, and programming self-efficacy. Three significant indirect pathways emerged: (1) Performance goal → Growth mindset → Self-efficacy: Performance goal positively predicted growth mindset (β = .359, $p < .001$), which in turn predicted self-efficacy (β = .444, $p < .001$); total indirect effect = .159. (2) Performance goal → Mastery experience → Self-efficacy: Performance goal did not significantly predict mastery experience (β = .097, $p = .066$), although mastery experience predicted self-efficacy (β = .468, $p < .001$); total indirect effect = .045. (3) Performance goal → Growth mindset → Mastery experience → Self-efficacy: Performance goal predicted growth mindset (β = .359, $p < .001$), which predicted mastery experience (β = .720, $p < .001$), which then predicted self-efficacy (β = .468, $p < .001$); total indirect effect = .121.

Notably, the direct effect of performance goal on self-efficacy was not significant (β = .056, $p = .361$). Overall, the total indirect effect was significant (β = .323), while the total effect of motivation on self-efficacy was weaker than in the other two models (β = .382, $p < .001$), explaining 14.6% of the variance ($R^2 = .146$).

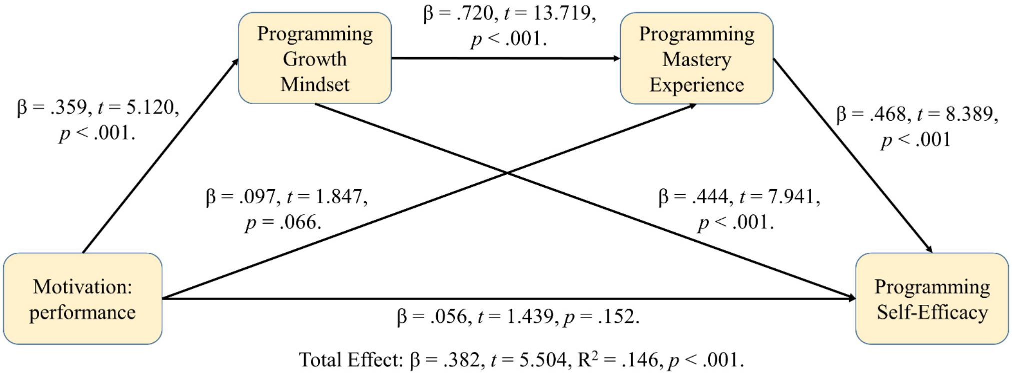

Fig. 5. PROCESS model of performance goal, growth mindset, mastery experience, and programming self-efficacy

5 DISCUSSION

5.1 Inventory development

Two inventories were developed in this study—the Inventory of Programming Achievement Goals and the IPM. Both demonstrated good reliability and validity.

Achievement goals are critical for fostering the ability to tackle challenging tasks [12], [11]. Accordingly, we created the Inventory of Programming Achievement Goals, initially developing items based onElliot and McGregor's 2 × 2 model [14], which distinguishes mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance goals. However, following reliability and validity testing, the items converged into two factors—Mastery goal and Performance goal—consistent with the earlier two-factor conceptualization of goal orientation [8].

Additionally, drawing on Yeh et al.'s 2 × 2 mindset framework [26], we developed items to measure four types of programming mindsets: Growth–internal, Growth–external, Fixed–internal, and Fixed–external. After reliability and validity analysis, these items also converged into two factors—Growth mindset and Fixed mindset—supporting the two-construct theory of mindset [19]. These two mindsets demonstrated a moderate negative correlation (r = –.649), indicating that they represent distinct, independent dimensions that should be assessed separately.

5.2 Instructional effects on programming growth mindset, mastery experience, and self-efficacy

In an exploratory manner, we examined the training effects on mastery experience and self-efficacy in programming, as well as fixed and growth mindsets toward programming. The effects of achievement goal motivation were not assessed because the study did not include any manipulation of this construct and only the pretest data were collected. To address the need for cultivating Python programming self-confidence among non-computer science majors, we designed and implemented an 18-week integrative training course. The results suggest that the instructional strategies, such as AI-assisted CPBL, scaffolding, hands-on activities, the use of an online learning platform, multimedia presentations, and reflective practices, effectively enhanced participants' growth mindset, mastery experience, and self-efficacy in Python programming, while reducing their fixed mindset.

The course integrated diverse technologies to strengthen conceptual understanding, foster collaboration and discussion, and develop problem-solving skills and confidence. A key component was the use of *Python Maker Activities* within a CPBL framework, which provided hands-on, real-world problem-solving experiences. These activities, combined with continuous feedback, created repeated opportunities for success, thereby building students' sense of competence and self-efficacy. This aligns with findings that CPBL supports mastery experiences and self-efficacy development [40].

The results also support prior evidence that AI-supported tools and adaptive learning platforms enhance personalization and engagement, enabling learners to improve their programming performance [43] and programming self-efficacy [4], as well as to complete creative programming projects [44]. Furthermore, the findings are consistent with research showing that project-based learning strengthens self-efficacy [40] and programming performance [37]. Overall, these results underscore the value of thoughtfully designed, AI-supported CPBL that actively engages learners, promotes reflective practice, and scaffolds both self-learning and psychological growth.

5.3 Relationship of motivation, growth mindset, mastery experience, and programming self-efficacy in collaborative and AI-supported learning

The PROCESS results showed that both forms of achievement goals, particularly mastery goals, demonstrated strong explanatory power for self-efficacy through growth mindset and mastery experience in Python programming. The findings revealed that achievement goal motivation influenced self-efficacy through one direct pathway and three indirect pathways. Although none of the "achievement goal → self-efficacy" direct effects were significant, all total indirect effects were significant.

Regarding the first indirect path (achievement goal → growth mindset → self-efficacy), mastery goal motivation yielded the largest total effect (.305), compared to performance goal (.159), with a particularly strong effect on growth mindset (β = .696, $p < .001$). For the second indirect path (achievement goal → mastery experience → self-efficacy), the mastery goal also had a larger total effect (.177) than the performance goal (.045). Notably, although the total indirect effect was significant, the influence of performance goal on mastery experience was not significant. Finally, regarding the third indirect path (achievement goal → growth mindset → mastery experience → self-efficacy), mastery goal also had a larger total effect (.154) than performance goal (121). For the *overall total effects* (direct plus indirect), mastery goal motivation again produced the strongest effect (β = .687, R^2 = .471), substantially exceeding that of performance goal motivation (β = .384, R^2 = .146).

Overall, growth mindset and mastery experience consistently emerged as critical mediators between achievement goal motivation and programming self-efficacy, suggesting the view that self-efficacy is shaped by the interplay of motivation, mindset, and mastery experience. Moreover, the findings support that motivation plays a foundational role in shaping mindset [34].

Among the motivational types, mastery goal motivation produced the most coherent and effective pathway for enhancing programming self-efficacy. Within the CPBL framework of this training—characterized by reflective thinking, peer collaboration, and AI-supported activities—students with mastery goals appeared more willing to embrace challenges, thereby strengthening their growth mindset. This finding aligns with research showing that learners with a mastery goal orientation are more likely to adopt a growth mindset [35] and that the growth mindset serves as a key mediator between motivation and mastery experience [24]. It also supports the view that the quality of achievement goals plays a crucial role in shaping learners' cognition, emotions, behavior, and ultimately, achievement outcomes [11].

In sum, the findings reinforce that effective programming instruction should address not only technical skill development but also the psychological readiness to persevere and succeed. This study provides an empirical profile of how non–computer science students' achievement goal orientations interact with technology- and AI-supported training activities to build programming self-efficacy.

6 CONCLUSIONS

Collaborative problem-based learning with AI-supported training holds strong potential for enhancing programming performance and self-confidence. In this study, these strategies and AI toolkits were integrated into an 18-week training course. Although the instructional effects required further examination, the findings suggest that AI-supported CPBL fosters a supportive learning environment with rich hands-on activities, contributing to the development of a growth mindset, mastery experience, and self-efficacy in programming. Importantly, growth mindset and mastery experience emerged as key mediators linking achievement goal motivation to self-efficacy.

In conclusion, this study contributes to programming education in the following aspects: (1) Developing an AI-supported CPBL framework: It demonstrates how AI toolkits, CPBL, technological support, and scaffolding can be integrated to enhance Python learning and its interdisciplinary applications. (2) Revealing psychological mechanisms in programming learning: Growth mindset and mastery experience emerged as key mediators linking achievement goal motivation to self-efficacy, offering insights into how programming self-confidence is built among non–computer science majors. (3) Clarifying the role of achievement goal types: It highlights that mastery goals exert a substantially stronger influence on programming self-efficacy than performance goals, highlighting the need to distinguish goal types in AI-supported CPBL design. (4) Conceptualizing and measuring programming mindsets: This study is among the first to conceptualize, distinguish, and validate the dual dimensions of programming mindsets, providing robust instruments for future research and instructional design in programming education.

7 LIMITATIONS AND SUGGESTIONS

Although the training effects were examined, the primary focus of this study was to investigate how achievement goal motivation shapes programming self-efficacy through the mediation of growth mindset and mastery experience in an AI-supported collaborative learning environment. Consequently, a control group was not included. Nevertheless, the substantial instructional effects observed provide partial evidence of the effectiveness of our instructional framework, which may serve as a model for teaching students who are apprehensive about programming. Future research could incorporate a control group and compare outcomes across different AI tools (e.g., MindScratch) to evaluate relative learning benefits.

As the adoption of generative AI becomes increasingly widespread, it is no longer sufficient to simply teach students how to use AI for programming tasks. More critically, educators must scaffold learners in applying AI tools to solve authentic, real-world problems through programming. Incorporating AI tools into CPBL warrants further empirical research to establish a stronger theoretical foundation. In doing so, personal traits such as motivation and mindset should be carefully considered, along with other potentially important psychological variables.

Finally, this study did not assess peer interaction during or outside the training course. Given its central role in CPBL, future research should examine the nature and impact of peer collaboration, potentially leveraging generative AI to facilitate or analyze these interactions.

7.1 Statements and declarations

Financial interests: The authors declare that they have no financial interests.

7.2 Declaration of generative AI and AI-assisted technologies

During the preparation of this work, the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

8 REFERENCES

[1] F. H. Tsai, "Using a physical computing project to prepare preservice primary teachers for teaching programming," *SAGE Open,* vol. 13, no. 4, 2023. https://doi.org/10.1177/21582440231205409

[2] U. Tellhed, F. Bjorklund, and K. K. Strand, "Sure I can code (but do I want to?). Why boys' and girls' programming beliefs differ and the effects of mandatory programming education," *Computers in Human Behavior*, vol. 135, pp. 1–11, 2022. https://doi.org/10.1016/j.chb.2022.107370

[3] M. Öztürk, "The effect of self-regulated programming learning on undergraduate students' academic performance and motivation," *Interactive Technology and Smart Education*, vol. 19, pp. 319–337, 2022. https://doi.org/10.1108/ITSE-04-2021-0074

[4] R. Yilmaz and F. G. K. Yilmaz, "The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy, and motivation," *Computers and Education: Artificial Intelligence*, vol. 4, p. 100147, 2023. https://doi.org/10.1016/j.caeai.2023.100147

[5] J. Liu, Q. Li, X. Sun, Z. Zhu, and Y. Xu, "Factors influencing programming self-efficacy: An empirical study in the context of Mainland China," *Asia Pacific Journal of Education,* vol. 43, pp. 835–849, 2021. https://doi.org/10.1080/02188791.2021.1985430

[6] Kanika, S. Chakraverty, and P. Chakraborty, "Tools and techniques for teaching computer programming: A review," *Journal of Educational Technology Systems,* vol. 49, no. 2, pp. 170–198, 2022. https://doi.org/10.1177/0047239520926971

[7] R. Rinas, M. Dresel, and M. Daumiller, "Faculty subjective well-being: An achievement goal approach," *International Journal of Educational Research,* vol. 115, p. 101942, 2022. https://doi.org/10.1016/j.ijer.2022.101942

[8] C. S. Dweck, "What having a 'growth mindset' actually means," *Harvard Business Review,* vol. 13, pp. 213–226, 2022.

[9] N. J. Beatson, S. T. M. Sithole, P. de Lange, B. O'Connell, and J. K. Smith, "Sources of self-efficacy beliefs in learning accounting: Does gender matter?" *Journal of International Education in Business*, vol. 18, no. 2, pp. 196–217, 2025. https://doi.org/10.1108/JIEB-02-2024-0014

[10] N. Hampel, K. Sassenberg, A. Scholl, and L. Ditrich, "Enactive mastery experience improves attitudes towards digital technology via self-efficacy – a pre-registered quasi-experiment," *Behaviour & Information Technology,* vol. 43, no. 2, pp. 298–311, 2023. https://doi.org/10.1080/0144929X.2022.2162436

[11] S. Schweder, G. Hagenauer, L. Grahl, and D. Raufelder, "Achievement goal profiles and profile transitions in teacher- and self-directed learning and the association with self-efficacy and interest," *Motivation and Emotio*n, vol. 49, no. 5, pp. 593–623, 2025. https://doi.org/10.1007/s11031-025-10142-0

[12] M. Daumiller, "Achievement goals: The past, the present, and possible future of achievement goal research in the context of learning and teaching," in *Motivation and Emotion in Learning and Teaching Across Educational Contexts*, G. Hagenauer, R. Lazarides, and H. Järvenoja, Eds., Routledge, 2024, pp. 35–53. https://doi.org/10.31234/osf.io/xn2v5

[13] P. R. Pintrich and D. Schunk, *Motivation in Education: Theory, Research, and Applications*, 2nd ed. Upper Saddle River, NJ: Prentice-Hall, 2002.

[14] A. J. Elliot and H. A. McGregor, "A 2 × 2 achievement goal framework," *Journal of Personality and Social Psychology*, vol. 80, no. 3, pp. 501–519, 2001. https://doi.org/10.1037/0022-3514.80.3.501

[15] Y. K. Lee and E. Seo, "Trajectories of implicit theories and their relations to scholastic aptitude: A mediational role of achievement goals," *Contemporary Educational Psychology,* vol. 59, p. 101800, 2019. https://doi.org/10.1016/j.cedpsych.2019.101800

[16] A. Camacho, R. A. Alves, J. R. Daniel, F. De Smedt, and H. Van Keer, "Structural relations among implicit theories, achievement goals, and performance in writing," *Learning and Individual Differences,* vol. 100, p. 102223, 2002. https://doi.org/10.1016/j.lindif.2022.102223

[17] K. Wang, B. Duan, X. Li, and Y. Xue, "A profile analysis of computer-supported collaborative learning motivation in Chinese higher education: Integrating achievement goal and expectancy-value perspectives," *Interactive Learning Environments*, vol. 34, no. 3, pp. 1355–1377, 2025. https://doi.org/10.1080/10494820.2025.2521342

[18] Y. Chen, J. Li, H. Chui, and R. B. King, "Peer cooperation and competition are both positively linked with mastery-approach goals: An achievement goal perspective," *British Journal of Educational Psychology,* vol. 95, no. 4, pp. 941–961, 2025. https://doi.org/10.1111/bjep.12784

[19] K. Bernecker and V. Job, "Mindset theory," in *Social Psychology in Action: Evidence-Based Interventions from Theory to Practice*, K. Sassenberg and M. L. W. Vliek, Eds., Springer, Charm, 2019, pp. 179–191. https://doi.org/10.1007/978-3-030-13788-5_12

[20] A. Kapasi and J. Pei, "Mindset theory and school psychology," *Canadian Journal of School Psychology,* vol. 37, no. 1, pp. 57–74, 2021. https://doi.org/10.1177/08295735211053961

[21] C. J. Fong *et al*., "Do socializers' mindset beliefs matter for student mindset and achievement? A meta-analysis," *Learning and Individual Differences,* vol. 121, p. 102709, 2025. https://doi.org/10.1016/j.lindif.2025.102709

[22] J. B. Sarrasin, L. Nenciovici, L. M. B. Foisy, G. Allaire-Duquette, M. Riopel, and S. Masson, "Effects of teaching the concept of neuroplasticity to induce a growth mindset on motivation, achievement, and brain activity: A meta-analysis," *Trends in Neuroscience and Education,* vol. 12, pp. 22–31, 2018. https://doi.org/10.1016/j.tine.2018.07.003

[23] D. Platte, K. M. Xu, and R. H. M. de Groot, "The effect of fostering a growth mindset in primary school children: Does intervention approach matter?" *Education Sciences,* vol. 15, no. 3, p. 327, 2025. https://doi.org/10.3390/educsci15030327

[24] Y. S. Ting and Y. Yeh, "Growth-mindset intervention effects and the relationship of mindset, hope belief, and self-efficacy during creativity game-based learning," *Interactive Learning Environments*, vol. 32, no. 7, pp. 3146–3162, 2024. https://doi.org/10.1080/10494820.2023.2170418

[25] A. Chouvalova *et al*., "Undergraduates' reactions to errors mediate the association between growth mindset and study strategies," *International Journal of STEM Education,* vol. 11, p. 26, 2024. https://doi.org/10.1186/s40594-024-00485-4

[26] Y. Yeh, Y. S. Ting, and J. L. Chiang, "Influence of growth mindset, fixed mindset, grit, and self-determination on self-efficacy in game-based creativity learning," *Educational Technology & Society,* vol. 26, no. 1, pp. 62–78, 2023. https://doi.org/10.30191/ETS.202301_26(1).0005

[27] S. Boguslawski, R. Deer, and M. G. Dawson, "Programming education and learner motivation in the age of generative AI: Student and educator perspectives," *Information and Learning Sciences,* vol. 126, nos. 1–2, pp. 91–109, 2025. https://doi.org/10.1108/ILS-10-2023-0163

[28] H. Y. Durak, F. G. K. Yilmaz, and R. Yilmaz, "Computational thinking, programming self-efficacy, problem solving and experiences in the programming process conducted with robotic activities," *Contemporary Educational Technology*, vol. 10, no. 2, pp. 173–197, 2019. https://doi.org/10.30935/cet.554493

[29] Y. T. Kuo and Y. C. Kuo, "African American students' academic and web programming self-efficacy, learning performance, and perceptions towards computer programming in web design courses," *Education Sciences*, vol. 13, no. 12, pp. 1–17, 2023. https://doi.org/10.3390/educsci13121236
[30] Y. T. Kuo and Y. C. Kuo, "Learning programming: Exploring the relationships of self-efficacy, computational thinking, and learning performance among minority students," *Frontiers in Education*, vol. 10, p. 1623415, 2025. https://doi.org/10.3389/feduc.2025.1623415
[31] H. P. Phan and B. H. Ngu, "Sources of self-efficacy in academic contexts: A longitudinal perspective," *School Psychology Quarterly*, vol. 31, pp. 548–564, 2016. https://doi.org/10.1037/spq0000151
[32] A. L. Kleppang, A. M. Steigen, and H. S. Finbråten, "Explaining variance in self-efficacy among adolescents: The association between mastery experiences, social support, and self-efficacy," *BMC Public Health*, vol. 23, p. 1665, 2023. https://doi.org/10.1186/s12889-023-16603-w
[33] A. Bandura, *Self-Efficacy: The Exercise of Control.* New York, NY: W. H. Freeman, 1997. https://doi.org/10.1037/0033-295X.84.2.191
[34] D. S. Yeager and C. S. Dweck, "Mindsets that promote resilience: When students believe that personal characteristics can be developed," *Educational Psychologist*, vol. 47, no. 4, pp. 302–314, 2012. https://doi.org/10.1080/00461520.2012.722805
[35] Q. Liu and T. Kamioka, "The effects of employees' digital growth mindset and supervisors' coaching behaviour on digital self-efficacy," *Technology in Society,* vol. 81, p. 102875, 2025. https://doi.org/10.1016/j.techsoc.2025.102875
[36] S. Yang, M. Baird, E. O'Bourke, K. Brennan, and B. Schneider, "Decoding debugging instruction: A systematic literature review of debugging interventions," *ACM Transactions on Computing Education*, vol. 24, no. 4, pp. 1–44, 2024. https://doi.org/10.1145/3690652
[37] S. Yeom, N. Herbert, and R. Ryu, "Project-based collaborative learning enhances students' programming performance," *Computer Science Education*, vol. 1, pp. 248–254, 2022. https://doi.org/10.1145/3502718.3524779
[38] A. Zamecnik, V. Kovanović, S. Joksimović, G. Grossmann, D. Ladjal, and A. Pardo, "The perception of task cohesion in collaborative learning teams," *International Journal of Computer-Supported Collaborative Learning,* vol. 19, pp. 369–393, 2024. https://doi.org/10.1007/s11412-024-09424-5
[39] C. Crook, "CSsCL: The performance of collaborative learning," *International Journal of Computer-Supported Collaborative Learning,* vol. 17, pp. 169–183, 2022. https://doi.org/10.1007/s11412-022-09364-y
[40] L. Wijnia, G. Noordzij, L. R. Arends, R. M. J. P. Rikers, and S. M. M. Loyens, "The effects of problem-based, project-based, and case-based learning on students' motivation: A meta-analysis," *Educational Psychology Review,* vol. 36, p. 29, 2024. https://doi.org/10.1007/s10648-024-09864-3
[41] T. T. Wu, N. A. R. M. Sari, A. P. R. Z. Putri, H. R. Chen, and Y. M. Huang, "Fostering undergraduate accounting students' educational attainment through CT-enhanced collaborative project-based learning," *The International Journal of Management Education,* vol. 23, no. 3, p. 101195, 2025. https://doi.org/10.1016/j.ijme.2025.101195
[42] B. Tangney, K. Sullivan, and J. Lawlor, "Online collaborative PBL-The Bridge21 approach," *Computers and Education Open,* vol. 7, p. 100114, 2024. https://doi.org/10.1016/j.caeo.2024.100224
[43] L. Yan, S. Greiff, J. M. Lodge, and D. Gašević, "Distinguishing performance gains from learning when using generative AI," *Nature Reviews Psychology,* vol. 4, pp. 435–436, 2025. https://doi.org/10.1038/s44159-025-00467-5

[44] Y. Chen, S. Xiao, Y. Song, Z. Li, L. Sun, and L. Chen, "MindScratch: A visual programming support tool for classroom learning based on multimodal generative AI," *International Journal of Human–Computer Interaction*, vol. 41, no. 21, pp. 13650–13668, 2025. https://doi.org/10.1080/10447318.2025.2475991

[45] W. S. Tzou, Y. C. Yeh, C. H. Ma, and X. Yu, "Mastery experience bridges computational thinking and self-efficacy in programming among non-computer science majors," in *The 4th Paris Conference on Education*, 2025, pp. 10–14.

9 AUTHORS

Wen-Shyong Tzou is a Professor in the Department of Bioscience and Biotechnology at National Taiwan Ocean University. His research interests include translational genomics, computational protein structure modeling, bioinformatics, and generative AI–driven protein design, integrating nature-inspired algorithms to advance biomolecular engineering (E-mail: wstzou@mail.ntou.edu.tw).

Chia-Hsiang Ma is a PhD. Candidate of the Department of Psychology, National Chengchi University. His research interests focus on bilingual word recognition, with particular emphasis on logographic writing systems. He also works on several natural language processing topics, such as sentence similarity and applications of BERT (E-mail: 110752501@nccu.edu.tw).

Yu-chu Yeh is a distinguished Professor in the Institute of Teacher Education and a Research Fellow at the Research Center for Mind, Brain, and Learning at National Chengchi University. Her interdisciplinary research focuses on the intersection of generative AI-enhanced instruction, game-based learning, and neuroeducation. With a foundation in educational, cognitive, and positive psychology, she specializes in fostering creativity and critical thinking within modern learning environments (E-mail: ycyeh@nccu.edu.tw; ycyeh@mail2.nccu.tw).

Melissa T. A. Simarmata was a postdoctoral researcher at National Chengchi University, where she contributed to projects related to AI ethics, motivation, and digital learning systems. Her research interests include personal innovativeness, knowledge management, and educational technology (E-mail: melissasimarmata@gmail.com).

Online-Journals.org

iJEP International Journal of Engineering Pedagogy

iJEP | eISSN: 2192-4880 | Vol. 16 No. 5 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijep.v16i5.62782

PAPER

Re-Engineering Supply Chain Education: A Theoretical Framework for Integrating Financial Asymmetry and Systems Thinking

Jiří Strouhal[1,2] (✉),
Gabriel Xiao-Guang Yue[3,4],
Vaiva Kiaupaite-Grušniene[1],
Josef Horák[2]

[1]TalTech, Tallinn, Estonia

[2]Pan-European University, Prague, Czech Republic

[3]Sohar University, Sohar, Oman

[4]Turon University, Karshi, Uzbekistan

jiri.strouhal@taltech.ee

ABSTRACT

Modern industrial and systems engineering curricula excel at teaching students to mitigate physical supply-side disruptions, yet frequently fail to address the intra-supply-chain allocation of financial distress. This theoretical paper proposes a novel, problem-based learning curriculum framework designed to bridge the gap between operational logistics and financial risk-shifting. It critiques the pedagogical reliance on traditional bankruptcy prediction models, demonstrating how they systematically misclassify capital-intensive original equipment manufacturers (OEMs) into distress zones due to the structural liabilities of captive financial divisions. Grounded in systems thinking and Kolb's experiential learning theory, the proposed framework introduces dynamic industry benchmarks into the classroom, specifically utilizing the Strouhal Credibility Index (SCI). By structuring a pedagogical module around the 2020–2022 automotive crisis, and utilizing descriptive statistical comparisons rather than complex econometrics, this framework equips engineering educators with an accessible blueprint to teach the financial bullwhip effect. This ensures future engineering managers understand the structural vulnerabilities embedded within hierarchical supply chains and the limits of OEM-driven supply chain finance.

KEYWORDS

engineering education, systems thinking, problem-based learning, financial bullwhip effect, supply chain finance

1 PEDAGOGICAL BACKGROUND AND THE CURRICULUM GAP

The COVID-19 pandemic and subsequent supply chain disruptions tested the financial resilience of global manufacturing ecosystems, exposing severe vulnerabilities in how liquidity and distress are transmitted across hierarchical value chains. Within modern industrial and systems engineering education, curricula are

Strouhal, J., Yue, G. X.-G., Kiaupaite-Grušniene, V., Horák, J. (2026). Re-Engineering Supply Chain Education: A Theoretical Framework for Integrating Financial Asymmetry and Systems Thinking. *International Journal of Engineering Pedagogy (iJEP)*, 16(5), pp. 144–153. https://doi.org/10.3991/ijep.v16i5.62782

Article submitted 2026-06-29. Revision uploaded 2026-07-16. Final acceptance 2026-07-20.

highly adept at addressing the physical manifestations of these crises. The operational consequences of supply-side shocks, such as semiconductor shortages and production bottlenecks, are well-documented and extensively modelled in the classroom. However, this intensive focus on operational optimization has created a critical pedagogical blind spot. The intra-supply-chain allocation of financial distress remains underexplored in engineering management coursework. Future supply chain designers are rarely challenged to evaluate systemic financial questions, such as whether final assemblers with superior market power absorb macroeconomic shocks, or whether they insulate their balance sheets by shifting working capital burdens upstream to their suppliers via the trade credit channel. When engineering programs do attempt to bridge this interdisciplinary gap by introducing corporate distress management, they typically rely on legacy frameworks that are ill-suited for modern industrial contexts. Empirically testing financial dynamics requires a highly precise measure of corporate financial stability. Unfortunately, the default pedagogical tools often include traditional bankruptcy prediction models, most notably Altman's Z-score [2], which exhibit a severe downward bias when applied to capital-intensive transportation sectors. In practice, automotive original equipment manufacturers (OEMs) frequently operate large captive financial service divisions. These divisions artificially inflate consolidated balance sheet liabilities. By continuing to teach these traditional models without contextual adjustment, educators inadvertently train students to utilise metrics that systematically penalize structurally sound original equipment manufacturers.

The consequence of this reliance on outdated models is a mathematically invalid classroom experience. Students are actively taught to misclassify capital-intensive OEMs into distress zones due to the structural liabilities of captive financial divisions. Because cross-sectional comparisons across the value chain are rendered mathematically invalid under these traditional metrics, students cannot accurately measure the distribution of risk. This represents a severe methodological flaw in engineering education that must be resolved. If students cannot accurately diagnose the baseline financial health of a supply chain apex, they are fundamentally unequipped to understand how financial distress ripples through the broader ecosystem.

To adequately prepare the next generation of industrial engineers, modern curricula must transition away from static, flawed metrics and adopt dynamic frameworks. Resolving this methodological flaw requires introducing measures of financial stability that utilize an average linkage approach to benchmark firms against dynamic, empirically derived industry averages. By recognizing the structural vulnerabilities embedded within hierarchical supply chains and acknowledging the limits of OEM-driven supply chain finance, educators can completely reimagine capstone design projects. This paper proposes a theoretical curriculum framework to correct this gap, enabling students to accurately identify the asymmetric transmission of exogenous macroeconomic shocks and ultimately design more holistically resilient manufacturing networks.

2 LITERATURE REVIEW

The integration of complex financial dynamics into industrial and systems engineering curricula represents a critical, yet underexplored, frontier in modern technical education. While the COVID-19 pandemic and subsequent supply chain disruptions exposed severe vulnerabilities in global manufacturing ecosystems, engineering education has historically struggled to unify physical supply chain optimization with its underlying financial realities. This literature review synthesizes the current pedagogical paradigms in engineering management, critiques the persistent reliance on legacy corporate distress models, and establishes the theoretical necessity for a curriculum framework grounded in systems thinking and experiential learning.

2.1 The operational bias in engineering management curricula

Historically, supply chain management coursework within industrial engineering programs has prioritized physical network optimization. Rooted in operations research, these curricula train students to mitigate physical bottlenecks, optimize inventory routing, and reduce cycle times. While this foundational knowledge is essential, it creates a pedagogical silo where the financial mechanics of corporate distress are frequently relegated exclusively to business and finance programs.

Through the lens of systems thinking [6], [14], this operational bias is highly problematic. Systems thinking requires students to view supply chains not merely as linear pipelines of material flow, but as complex, interconnected socio-technical and financial networks [5]. When engineering students are not taught how financial asymmetry dictates operational decisions, their understanding of the system remains incomplete. For example, while students are frequently taught the operational bullwhip effect—how small fluctuations in consumer demand cause massive physical inventory swings upstream [9]—they are rarely exposed to its financial counterpart. Consequently, graduates enter the workforce unable to recognize that the intra-supply-chain allocation of financial distress is strategically managed by final assemblers. Therefore, a modern curriculum must evolve to teach students that physical inventory optimization cannot be decoupled from working capital management, risk-shifting, and liquidity preservation.

2.2 Pedagogical flaws in teaching corporate distress measurement

When engineering management curricula do attempt to bridge this interdisciplinary gap by introducing financial stability metrics, they typically default to foundational frameworks. However, teaching these legacy models presents a severe pedagogical risk. Traditional bankruptcy prediction models, most notably Altman's Z-score [2], exhibit a severe downward bias when applied to capital-intensive transportation sectors. In practice, automotive OEMs frequently operate large financial service divisions, which artificially inflate consolidated balance sheet liabilities. Continuing to teach Altman's Z-score without significant industry adjustment means educators are passing down a captive finance penalty to their students. From a constructivist learning perspective S [12], teaching students to apply a universally flawed model actively hinders their ability to assess real-world engineering problems, rendering cross-sectional comparisons across the value chain mathematically invalid.

Critics may argue that modern corporate distress prediction has evolved far beyond foundational ratio analysis, frequently employing machine learning algorithms [3], [10] or Merton-based structural models [4], [11]. However, while these advanced probabilistic models offer superior predictive accuracy for quantitative analysts, they present a severe black box problem in the engineering classroom [13]. Constructivist pedagogy requires students to understand the underlying mechanical relationship of a system [12]. If an engineering student feeds OEM data into a neural network, the algorithm may correctly classify the firm, but the student remains blind to the intra-supply-chain mechanics driving that classification. Therefore, replacing legacy models with dynamic ratio adjustments, such as the Strouhal Credibility Index (SCI), represents a state-of-the-art pedagogical intervention. By utilizing an average linkage approach, it maintains the mathematical transparency required for students to manually trace how captive finance liabilities distort baseline stability, bridging the gap between high-level predictive accuracy and classroom comprehensibility.

2.3 Experiential learning and dynamic industry benchmarks

To resolve these methodological flaws in the classroom, educators must adopt dynamic teaching tools that resonate with how engineering students learn best. The proposed curriculum framework leverages Kolb's experiential learning theory [8], which posits that knowledge is created through the transformation of experience. Kolb's continuous cycle consists of four stages: (1) concrete experience, (2) reflective observation, (3) abstract conceptualization, and (4) active experimentation. Traditional lecture-based financial instruction often traps engineering students in passive conceptualization, failing to connect the mathematics to real-world systemic failures.

Incorporating dynamic industry benchmarks aligns perfectly with Kolb's framework and problem-based learning methodologies. By transitioning away from static legacy models and introducing tools that utilize an average linkage approach, educators can provide students with raw, standardized financial reporting data (based on IFRS or US GAAP framework) and task them with mathematically equalizing fundamental dimensions of financial stability. This active engagement allows students to explicitly test the asymmetric transmission of exogenous macroeconomic shocks. By performing comparative statistical analyses to identify the financial bullwhip effect, students transition from passive recipients of legacy theories into active analysts of modern supply chain crises.

2.4 Alignment with global engineering accreditation standards

Finally, the necessity of this pedagogical shift is reinforced by the stringent requirements of global engineering accreditation bodies. Frameworks established by ABET in the USA and the EUR-ACE framework in Europe explicitly mandate that engineering graduates must possess the ability to design complex systems within realistic constraints, prioritizing economic, environmental, and ethical considerations [1], [7].

To satisfy these rigorous outcomes, engineering management students must look beyond baseline profitability and evaluate the ethical and long-term economic implications of risk-shifting within hierarchical supply chains. The curriculum must illustrate that corporate resilience in final manufacturers is heavily subsidized by the liquidity of upstream partners. By studying empirical data from systemic supply-side contractions, students must be challenged to recognize that optimizing a supply chain through OEM-centric working capital management can structurally degrade the financial health of the supplier base, ultimately threatening long-term supply chain viability. Integrating these advanced financial realities into the curriculum is not merely an interdisciplinary enhancement; it is a fundamental requirement for producing competent, ethically aware engineering leaders capable of safeguarding the entire manufacturing ecosystem.

3 THE PROPOSED INSTRUCTIONAL FRAMEWORK: THE FINANCIAL BULLWHIP MODULE

To bridge the gap between theoretical knowledge and practical application, this paper outlines a highly structured, three-phase problem-based learning module that educators can implement within senior-level industrial engineering or supply chain management capstone courses. The primary objective of this instructional framework is to translate advanced financial realities into an accessible pedagogical blueprint. The module begins with dataset formulation and the critical deconstruction of legacy financial models. Educators are advised to provide students with a proprietary panel dataset comprising consolidated financial data from 40 global market leaders in the mobility and transportation manufacturing sectors. To facilitate a robust comparative analysis, educators should ensure the sample is stratified into three distinct sub-industries: (I) Top 20 automotive OEMs, (ii) Top 10 automotive suppliers, and (iii) Top 10 aircraft manufacturers and suppliers. Furthermore, the instructional data must span a six-year period from 2017 to 2022, extracted from annual reports prepared under standardized reporting frameworks (IFRS or US GAAP). Pedagogically, this timeframe is critical because it strategically encapsulates a full macroeconomic cycle, including the pre-pandemic baseline, the acute COVID-19 exogenous shock, and the subsequent supply chain disruption phase. Armed with this data, educators task students with analyzing the firms using traditional bankruptcy prediction models, demonstrating how captive divisions artificially inflate consolidated balance sheet liabilities.

Once students recognize that traditional tools systematically penalize structurally sound OEMs and misclassify them into the distress zone, the module transitions into its second phase: the application of dynamic industry benchmarks. To overcome this methodological limitation, educators introduce the SCI, which relies on an average linkage approach to benchmark firms against dynamic, empirically derived industry averages. To ensure complete replicability and transparency within the classroom environment, students are required to rely exclusively on publicly available, audited consolidated financial data prepared under standardized reporting frameworks, strictly avoiding subjective or proprietary managerial estimates. The core activity tasks students with calculating six fundamental dimensions of financial stability:

profitability $$R_1 = \frac{EBIT}{Sales}$$

capital structure $$R_2 = \frac{Equity}{Assets}$$

long-term financing $$R_3 = \frac{Equity}{Non-Current\ Assets}$$

asset turnover $$R_4 = \frac{Sales}{Assets}$$

current ratio $$R_5 = \frac{Current\ Assets}{Current\ Liabilities}$$

internal financing $$R_6 = \frac{Retained\ Earnings}{Assets}$$

For each ratio i, students calculate the pooled industry average $\overline{R_i}$ across the entire sample to establish a macroeconomic baseline. Educators then guide the cohort to formulate the index as the arithmetic mean of a firm's relative outperformance or underperformance across these six dimensions:

$$SCI_{j,t} = \frac{1}{6}\sum_{i=1}^{6}\frac{R_{i,j,t}}{\overline{R_i}}$$

By performing this mathematical equalization, students stratify the sample firms into three distinct financial health zones based on their scores:

high credibility (outperformers)	SCI > 1.20
the stable grey zone	0.80 < SCI < 1.20
low credibility (distress)	SCI < 0.80

In the final phase of the module, students apply their newly constructed index to simulate the financial bullwhip effect. Having established a robust, sector-neutral measure of financial stability, educators guide the classroom to utilize it to test the asymmetric transmission of exogenous shocks across the automotive value chain. The instructional design leverages the COVID-19 pandemic as a quasi-natural experiment. Students are challenged to quantitatively test a specific operational hypothesis: that during systemic supply-side crises, final car manufacturers insulated their own financial credibility by pushing margin compression and inventory burdens upstream to their Tier 1 suppliers. By calculating the mean credibility scores and standard deviations of final OEMs against Tier 1 suppliers across the pre- and post-shock periods, students trace the divergence in financial stability. The culminating pedagogical moment occurs when students visually and statistically observe the asymmetric impact of the shock. They discover firsthand that while OEM credibility scores stabilize or recover, Tier 1 suppliers absorb a disproportionate liquidity shock, suffering a severe and statistically observable credibility penalty relative to the historical sample mean.

While contemporary supply chains face evolving disruptions—such as geopolitical fragmentation or algorithmic demand shocks—the 2020–2022 automotive crisis provides a pedagogically pristine quasi-natural experiment. This specific timeframe strategically encapsulates a completely closed macroeconomic cycle—a stable pre-shock baseline, a severe exogenous contraction, and a subsequent recovery phase—allowing students to isolate and observe the pure mechanics of the financial bullwhip effect without the confounding variables of ongoing, unresolved modern crises.

4 PROPOSED ASSESSMENT AND EVALUATION STRATEGY

To provide educators with a clear blueprint for deployment, Table 1 outlines the complete curriculum map for the financial bullwhip module, aligning Kolb's experiential learning cycle with specific engineering learning objectives, instructional activities, and assessment mechanisms.

Table 1. Curriculum map for the financial bullwhip module

Module Phase	Kolb's Cycle Alignment	Learning Objective	Instructional Activitiy	Assessment Mechanism
Phase I: Deconstructing the Penalty	Concrete Experience and Reflective Observation	Identify and critique the structural liabilities of captive financial divisions within legacy metrics	Students calculate Altman's Z-score on a panel dataset comprising 40 market leaders and identify OEM misclassifications	Formative: peer-reviewed data workshops debating the limitations of traditional bankruptcy prediction models
Phase II: Applying Dynamic Benchmarks	Abstract Conceptualisation	Calculate and apply dynamic measures of financial stability utilising an average linkage approach	Students calculate six fundamental dimensions of financial stability and establish a pooled macroeconomic baseline using the Strouhal Credibility Index	Formative: A cohort cross-examination of the mathematical equalisation and stratification of the sample firms into distinct financial health zones
Phase III: Simulating the Shock	Active Experimentation	Quantify the asymmetric transmission of exogenous macroeconomic shocks using descriptive statistics	Students compare mean index scores pre- and post-shock to prove OEMs insulated their financial credibility by pushing burdens upstream	Summative: executive policy memo detailing the economic magnitude of the divergence and proposing supply chain finance interventions

Source: Author's own elaboration based on [8].

Within the context of problem-based learning, educators must deploy both formative and summative evaluation mechanisms that move beyond rote memorization of formulas. Formative assessment should occur continuously during the data analysis workshops, specifically targeting the students' ability to critique traditional models and accurately compute dynamic benchmarks. Educators can evaluate collaborative student teams on their capacity to calculate the pooled industry average across the entire sample to establish a macroeconomic baseline. Peer-review sessions serve as an excellent formative tool, allowing cohorts to debate their justifications for stratifying firms into distinct financial health zones. This collaborative evaluation ensures that students have thoroughly comprehended the underlying mechanics of the SCI before advancing to comparative modelling.

For the summative assessment, educators must design an evaluative instrument that forces students to interpret their mathematical findings through the lens of a senior engineering manager. Traditional multiple-choice examinations are inadequate for this level of analytical synthesis. Instead, educators should assign a comprehensive policy memo or an executive board presentation. In this capstone deliverable, students must articulate the real-world economic magnitude of their comparative estimates. Specifically, they must translate the diverging index scores into actionable supply chain intelligence, explaining how Tier 1 suppliers absorb a disproportionate liquidity shock. To achieve a high level of proficiency, students must explicitly contextualize the variance between the two tiers, demonstrating how the supplier penalty significantly deviates from the historical sample mean. By requiring students to articulate these specific quantitative outcomes, the assessment confirms their mastery over the concept of the financial bullwhip effect and proves their ability to link macroeconomic exogenous shocks to downstream operational vulnerabilities. Finally, the summative assessment must require students to transition from diagnosing a systemic failure to proposing structural engineering solutions. A core tenet of modern engineering accreditation is the ability to design and improve systems to mitigate identified risks. Therefore, the evaluation rubric must heavily weight a student's capacity to formulate strategic countermeasures that protect the most vulnerable nodes of the ecosystem.

Educators should instruct students to explore the mitigating role of foundational supply chain finance instruments—such as reverse factoring—to determine whether proactive liquidity interventions by OEMs can effectively dampen this upstream transmission. Mastering these traditional interventions provides the critical cognitive scaffolding required before students can subsequently evaluate state-of-the-art, technologically driven solutions, such as blockchain-enabled deep-tier supply chain finance or smart contract liquidity provisioning.

5 CONCLUSIONS AND FUTURE DIRECTIONS

This theoretical curriculum framework set out to resolve a persistent methodological flaw in corporate distress measurement as it is currently taught within industrial engineering and supply chain management programs. By proposing a problem-based learning module centered on the SCI, this paper demonstrates that training students to evaluate capital-intensive firms against dynamic industry benchmarks successfully eliminates the captive finance penalty that plagues traditional bankruptcy models. For engineering educators, implementing this shift ensures that students accurately perceive the stark asymmetry in how exogenous macroeconomic shocks are absorbed within the automotive value chain. By embedding these comparative statistics into classroom simulations, academic programs can provide students with robust quantitative evidence of a financial bullwhip effect, proving that corporate resilience in final OEMs is heavily subsidized by the liquidity of upstream partners.

Equipping engineering graduates with this interdisciplinary knowledge yields critical implications for future corporate practitioners and policymakers. When students independently calculate the divergence in credibility scores, they tangibly internalize the systemic risk of OEM-centric working capital management. This instructional design forces future supply chain managers to confront the reality that while pushing inventory and payment terms upstream protects short-term OEM liquidity, it structurally degrades the financial health of the supplier base, potentially threatening long-term supply chain viability. Furthermore, training engineers to view supply chains as interconnected financial networks ensures that future policymakers recognize that during macroeconomic crises, liquidity interventions targeted solely at final manufacturers may fail to reach the most vulnerable nodes of the ecosystem. Students learn firsthand that targeted relief must account for the upstream accumulation of financial distress.

While, this framework offers a rigorous blueprint for modernizing engineering syllabi, educators must remain cognizant of its pedagogical limitations. First, the proposed instructional dataset is restricted to 40 global market leaders. While these specific firms represent the vast majority of global market capitalization and production volume in the automotive and aerospace sectors, expanding the sample to include smaller, peripheral firms would introduce unobservable structural heterogeneity and dilute the macroeconomic significance of evaluating the true supply chain apex. Educators must caution students that the findings may not fully generalize to small- and medium-sized enterprises (SMEs) operating on the periphery of these ecosystems. Additionally, the financial bullwhip effect compounds further upstream, but the lack of consolidated public data for private Tier 2 and Tier 3 suppliers limits the direct observation of these deeper nodes within a classroom setting.

These limitations highlight several critical paths for future educational research. Most immediately, engineering education scholars must empirically test this theoretical curriculum framework within active classrooms to measure student learning outcomes, assessing the cognitive load required for engineering cohorts to master dynamic modelling. Methodologically, the teaching modules should be expanded and empirically tested across other highly capital-intensive sectors burdened by unique balance sheet structures, such as telecommunications infrastructure. Future studies utilizing proprietary procurement datasets could illuminate whether the supplier penalty is passed down further to Tier 2 and Tier 3 manufacturers. Finally, educational researchers should explore the mitigating role of supply chain finance instruments—such as reverse factoring—to determine whether proactive liquidity interventions by OEMs can be effectively taught as standardized engineering design solutions. By continuously refining how financial risk-shifting is taught, academic institutions can cultivate a new generation of supply chain leaders fully equipped to navigate, neutralize, and ultimately solve complex systemic vulnerabilities.

6 REFERENCES

[1] ABET, *Criteria for Accrediting Engineering Programs (2022–2023)*, 2021. [Online]. Available: https://www.abet.org/wp-content/uploads/2022/01/2022-23-EAC-Criteria.pdf

[2] E. L. Altman, "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy," *The Journal of Finance*, vol. 23, no. 4, pp. 589–609, 1968. https://doi.org/10.2307/2978933

[3] F. Barboza, H. Kimura, and E. Altman, "Machine learning models and bankruptcy prediction," *Expert Systems with Applications*, vol. 83, pp. 405–417, 2017. https://doi.org/10.1016/j.eswa.2017.04.006

[4] S. T. Bharath and T. Shumway, "Forecasting default with the merton distance to default model," *The Review of Financial Studies*, vol. 21, no. 3, pp. 1339–1369, 2008. https://doi.org/10.1093/rfs/hhn044

[5] E. F. Crawley, J. Malmqvist, S. Östlund, and D. R. Brodeur, *Rethinking Engineering Education: The CDIO Approach*. New York, NY: Springer, 2014. https://doi.org/10.1007/978-3-319-05561-9

[6] C. L. Dym, A. M. Agogino, O. Eris, D. D. Frey, and L. J. Leifer, "Engineering design thinking, teaching and learning," *Journal of Engineering Education*, vol. 94, no. 1, pp. 103–120, 2005. https://doi.org/10.1002/j.2168-9830.2005.tb00832.x

[7] European Network for Accreditation of Engineering Education, *EUR-ACE Framework Standards and Guidelines*, 2021. [Online]. Available: https://www.enaee.eu/wp-content/uploads/2022/03/EAFSG-04112021-English-1-1.pdf

[8] D. A. Kolb, *Experiential Learning: Experience as the Source of Learning and Development*. Englewood Cliffs, NJ: Prentice Hall, 1984.

[9] H. L. Lee, V. Padmanabhan, and S. Whang, "The bullwhip effect in supply chains," *MIT Sloan Management Review*, vol. 38, no. 3, pp. 93–102, 1997.

[10] F. Mai, S. Tian, C. Lee, and L. Ma, "Deep learning models for bankruptcy prediction using textual disclosures," *European Journal of Operational Research*, vol. 274, no. 2, pp. 743–758, 2019. https://doi.org/10.1016/j.ejor.2018.10.024

[11] R. C. Merton, "On the pricing of corporate debt: The risk structure of interest rates," *The Journal of Finance*, vol. 29, pp. 449–470, 1974. https://doi.org/10.1111/j.1540-6261.1974.tb03058.x

[12] J. Piaget, *To Understand Is to Invent: The Future of Education*. New York, NY: Penguin Books, 1976.

[13] C. Rudin, "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead," *Nature Machine Intelligence*, vol. 1, no. 5, pp. 206–215, 2019. https://doi.org/10.1038/s42256-019-0048-x

[14] P. Senge, *The Fifth Discipline: The Art and Practice of the Learning Organization*. New York, NY: Doubleday/Currency, 1990.

7 AUTHORS

Jiří Strouhal is Head of Accounting Research group of TalTech School of Business and Governance, Tallinn, Estonia, and currently serves as the Vice-Rector for Research at Department of Finance and Accounting, Pan-European University, Prague, Czechia. Research interests in the fields of international accounting, financial performance, ESG reporting and accounting education (E-mail: jiri.strouhal@taltech.ee).

Gabriel Xiao-Guang Yue is a researcher at Sohar University, Oman, and the Vice Rector for International Cooperation at Turon University, Uzbekistan. Research interests in the fields of AI, sustainability, and AI education (E-mail: xgyue@whu.edu.cn).

Vaiva Kiaupaite-Grušniene is a researcher at TalTech School of Business and Governance, Tallinn, Estonia. Research interests in the fields of accounting education, ESG reporting, performance management and managerial accounting (E-mail: vaiva.kiaupaite-grusniene@taltech.ee).

Josef Horák is a researcher and a Head of the Department of Finance and Accounting, Pan-European University, Prague, Czechia. Research interests in the fields of green accounting, performance management and managerial accounting (E-mail: josef.horak@peuni.cz).

Imprint

iJEP – International Journal of Engineering Pedagogy
Online issue: http://www.i-jep.org

Indexing
International Journal of Engineering Pedagogy (iJEP) is indexed
in Elsevier Scopus, Clarivate Analytics ESCI, EBSCO, and DBLP.

Publication Frequency
Bi-monthly

ISSN
2192-4880

Publisher
International Federation of Engineering Education Societies (IFEES)
IFEES-GEDC Secretariat
c/o George Mason University
Volgenau School of Engineering
4400 University Drive, MS 4A3
Fairfax, VA 22030
USA

Editorial Office
CTI Global
Frankfurt, Vienna, New York, Bengaluru, Hong Kong
Madrider Strasse 4
60327 Frankfurt am Main
Germany