HJSTEM
Hellenic Journal of STEM Education, 2025, 4(1), 1-9

http://www.hellenicstem.com/
ISSN 2832-840X

RESEARCH ARTICLE

AI–Based Models for Assessing STEAM Engineering Literacy for University Students: The Case of Digital Systems for Precision Agriculture

Apostolos Xenakis University of Thessaly, GREECE

Abstract

Nowadays, the growing intersection between artificial intelligence (AI) models and its usage within education, has paved the way for innovative approaches to assess and improve engineering education initiatives, particularly those that rely on STEAM epistemology principles and, therefore, based on the core elements of Computational Thinking (CT). Projects aligned with CT goals, utilize a problem – based solving methodology, inspired by computer science concepts. This approach is not limited to coding, but applied to tackling complex open engineering problems, across various disciplines, including science, technology, engineering and mathematics, using strategies that are suitable for automation or computational modeling. A well-known framework, applicable within STEAM projects, which consists of a series of steps that students follow, in order to design a prototype artifact and find a solution to a complex problem is the Engineering Design Process (EDP). This paper investigates the impact of AI based methods and tools (i.e. GenAI tools) on STEAM engineering literacy among University students, especially within the content of next generation digital systems, sensors and low power devices for precision agriculture application domain. Utilizing a rubric – based assessment and applying EDP process, the study evaluates two student teams tasked to design and implement a smart greenhouse, equipped with various sensors, actuators, automation and digital systems and data driven analytics capabilities. In particular, team A completed the project without using GenAI assistance, while team B employed GenAI tools throughout their design and implantation process. Comparative analysis of rubric based outcomes, indicates that GenAI assisted team demonstrates superior performance across all key STEAM engineering literacy dimensions, including analytical thinking, innovation and practical application of digital systems. Additionally using a pre and post - test design, the study measures knowledge acquisition related to digital automation systems, alongside student engagement, confidence in learning and AI tool effectiveness. Post - test results demonstrate a significant improvement in STEAM literacy, as well as positive shifts in engagement and confidence. Overall, our findings underscore the potential of GenAI, to significantly enhance students' ability to tackle complex, semi – defined engineering problems, highlighting its relevance for modern engineering education curricula.

Keywords

STEAM literacy, Digital Systems, Engineering activities, GenAI tools, Computational Thinking, Automation, Sensors, Engineering Design Process

- Received 17 April 2025 - Revised 4 June 2025 - Accepted 10 July 2025

Introduction

The integration of the 21st century competencies into STEAM (Science, Technology, Engineering, Arts and Mathematics) education has become a fundamental component in preparing students for the complexities of an increasingly dynamic and technologically advanced world. Such an orientation aligns with the global emphasis on fostering critical thinking, collaboration, creativity and adaptability, collectively referred to as the "4Cs", which are essential for innovation and sustaining economic competitiveness (Alismail & McGuire, 2015; Fajrina, Lufri, & Ahda, 2020).

Contemporary research underscores the potential of STEAM – based frameworks in aligning educational objectives with the evolving requirements of the 21st century. Wulandari (2021) demonstrates how learning models, such as discovery learning, problem – based learning and project – based learning foster student – centered education, while cultivating higher – order-thinking skills (Wulandari, 2021). In the same direction, Krüger and Chiappe (2021), argue that STEAM environments facilitate gamification and inquiry – driven strategies, thereby enriching both formative assessment and collaborative experiences (Krüger & Chiappe, 2021).

The intersection of artificial intelligence (AI) and STEAM education introduces transformative possibilities to redefine both assessment practices and instructional strategies. The adoption of AI – driven technologies, in particular, offers significant potential for scalable, adaptive and personalized learning experiences. AI can assist in analyzing and evaluating project proposals, identifying alignment with STEAM principles and generating constructive and targeted feedback. Such systems not only evaluate teaching techniques and resource utilization but also suggests tailored improvements that enhance compliance with established STEAM educational standards. For example, Jang et al. (2022) demonstrated that AI infused STEAM programs effectively bolster students' problem – solving skills and positively influence their attitude towards technology. Aadditionally, the World Economic Forum (2015), highlights the transformative potential of educational technologies in addressing skill gaps, underscoring the value of adaptive learning environments to foster persistence, communication and critical thinking.

The rapid evolution of digital technologies and AI is reshaping education, particularly within the STEAM disciplines. Engineering literacy encompasses the ability to apply theoretical knowledge to practical, real – world problems and to effectively integrate digital systems (Johnson & Adams, 2016; Martin et al., 2020). Precision agriculture automations, increasingly reliant on digital technologies, such as Internet of Things (IoT) and sensor networks, represents an ideal training paradigm for cultivating engineering literacy among University students (Gebbers & Adamchuk, 2010).

Nonetheless, significant challenges remain in establishing standardized assessment mechanisms and global benchmarks for evaluating educational outcomes within STEAM contexts. Variations in teacher training, availability of educational resources and National policies affects the implementation of STEAM frameworks. Notably, disparities in student STEAM engagement are noted across countries like U.S., Malaysia and Australia, indicating the need for tailored interventions and robust measurement tools to ensure equality and optimize impact (Maizatulliza & Seng, 2019; Sheffield, et al., 2018). Emerging trends suggest that leveraging AI and Large Language Models (LLMs) hold significant potential challenges by facilitating scalable assessments and providing insights into STEAM literacy. AI – driven analytics could assist educators in diagnosing learning gaps in student understanding, deliver personalized feedback and monitor student progress over time. Such innovations are crucial for the realization of a "closed – loop" instructional model that continuously adapts to learners' needs (Wulandari, 2021). Recently, GenAI tools have emerged as powerful support for education, capable of enhancing creativity, analytical reasoning and real problem-solving skills (Brown et al., 2020; Floridi & Chiriatti, 2020). However, the specific impacts of these tools on engineering literacy within STEAM education remain underexplored, particularly regarding their practical integration into project-based learning contexts.

https//doi.org/10.51724/hjstemed.v4i1.37

In light of these insights, this work investigates the impact of AI based models and tools on STEAM literacy, among University students, especially within the content of solving open or semi – defined engineering problems, focused on digital precision systems for primary production using, sensors, low power IoT devices and actuators. It examines the effectiveness of GenAI tools in enhancing STEAM engineering literacy among students, working with interdisciplinary subjects. In particular, a comparative analysis quantifies the influence of GenAI tools on STEAM literacy, within the context of computational thinking (CT) dimensions, including analytical design thinking, innovation and integration of next generation digital systems. CT emphasize decomposition, pattern recognition, abstract, algorithmic thinking and data visualization, as foundations for cultivating interdisciplinary problem – solving competencies and promote real – world application skills. Utilizing a rubric – based assessment and applying the Engineering Design Process (EDP), the study evaluates the performance of two student teams, tasked to design and implement smart greenhouse automations, using various sensors, actuators, digital systems and data driven analytics capabilities. The findings of this study will provide valuable insights for educators aiming to integrate AI – driven tools into STEAM curricula effectively.

Background and Motivation

Computational Thinking (CT) and Problem Solving

Computational Thinking (CT) emerges as a critical area of exploration within the context of an increasingly digitized world. It is about solving real problems, designing and testing systems, by applying fundamental computer science (CS) principles (Wing, 2008). CT is considered as a universal skill that complements thinking in science, mathematics and engineering, with a focus on systems (Wing, 2008). Contemporary perspectives conceptualize CT as a distinctive approach to problem solving that originates from the field of CS. It is regarded as a cognitive process that blends both inductive and deductive reasoning and supports the design of systems, as well as, the comprehension of domain – specific solutions (Palomés et. al. 2024). Within the context of education, CT is recognized as a *transformative* force, often described as the next significant evolution. Although CT may encompass a variety of interpretations, in this study, it is conceptualized as a core competency that enables students to address problems effectively through the application of advanced system design and structured methodologies (Lodi et. al, 2021; Montiel et. al 2021). In their work, Breeman and Resnick (2012) introduced the *dimensions* of CT, which include *abstraction, pattern recognition, problem decomposition* and *algorithmic design.* Following, we highlight the meaning of these dimensions:

1. **Abstraction** refers to the process of omitting extraneous or context-specific details in order to highlight the essential characteristics and behaviors of a broader, more intricate system. Proficiency in abstraction is a foundational skill in system design, as it enables the development of generalized models that can be applied across multiple scenarios (Rodríguez, 2021)
2. **Decomposition** entails the systematic division of complex problems or datasets into smaller, more manageable units. This analytical strategy facilitates a deeper understanding of the problem by isolating its constituent parts. Furthermore, components derived through decomposition may be reused across different sections of the same system or even in entirely distinct applications (Angeli el. al., 2020)
3. **Pattern recognition** involves drawing upon prior knowledge to identify similarities, regularities, or recurring trends within new problems or datasets. The ability to relate a novel challenge to a previously encountered one can significantly simplify the problem-solving process. Mastery of this skill contributes to more efficient reasoning and solution development (S. Bocconi el al., 2022)
4. **Algorithm design** lies at the heart of computational problem solving. It encompasses the creation of clear, precise, and logically ordered sets of instructions intended to resolve a problem within a finite timeframe. This component is essential for developing reliable and effective computational solutions (S. Bocconi el al., 2022)

However, Weese and Feldhausen (2017) and Feldhausen, et al. (2018) redefine the *computational thinking* concepts by proposing the following CT concepts, with a focus on the concepts related to CS principles:

- Abstraction and Problem Decomposition (**ABS**): It refers to the generalized representation of a complex problem.
- Algorithmic Thinking (**ALG**): It refers to the discrete sequence of logical steps, necessary to complete the solution.
- Parallelism (**PAR**): It refers to parallel processing of a task.
- Decomposition (**DEC**): It refers to breaking a problem into smaller parts and pieces that can be solved independently of each other.
- Flow Control (**CON**): Flow control directs algorithmic steps towards problem solution completion.
- Data Collection (**DAT**): It refers to the data collection from various sources, like sensors, their representation and the analytics.
- Testing and Debugging (**TAD**): Testing system performance and fixing problems while developing a prototype solution.

STEAM Education and Engineering Literacy

At the core of STEAM education, lies the process of addressing solutions for real – world problems, as illustrated in **Fig. 1**. This approach emphasizes *computational thinking* along with *hands – on* experimentation, within a *cross – thematic* and *interdisciplinary* framework. The epistemology of STEAM education reflects a paradigm shift from a disciplinary knowledge to a transdisciplinary that embraces real – world complexity. At its core, STEAM epistemology correlates logic with creativity and science with art, and promotes a holistic and integrative model of learning (Yakman, 2008). It emphasizes the co – construction of knowledge through design, experimentation, iteration and collaborative problem – solving, which foster deeper cognitive engagement. STEAM learning is rooted in constructionist theories, which suggest that students actively build their understanding through *hands – on* experiences and dialogue (Papert, 1980). STEAM learning promotes a cohesive model grounded in practical applications and authentic challenges.

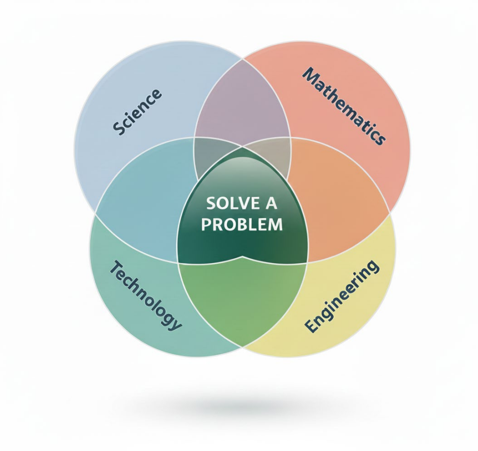

Figure 1. The heart of STEAM education

STEAM education extends beyond traditional STEM, by including "A"rts as a critical domain of human creativity and design thinking. This integration allows for more inclusive and diverse learning experiences (Land, 2013).STEAM activities help change the learning process by involving appropriate artifacts. The key characteristics of STEAM education involve the following goals (Henriksen, 2014):

- **Interdisciplinary learning**: Project and challenges require integration of science fields with mathematics, engineering and artistic design expression.
- **Creativity and imagination**: Emphasis is given on designing, prototyping and testing solutions, by applying analytical thinking. Innovation is linked to imagination
- **Problem solving**: Students are engaged with real – world, open – ended, authentic problems (i.e. smart agriculture, health technologies, industry 4.0, smart cities, environmental sustainability etc.)
- **Inclusion and equity**: STEAM framework foster student participation from various underrepresented groups through differentiated culturally responsive pedagogies (Bequette & Bequette, 2012).

Engineering literacy is defined as the ability to understand, evaluate and apply engineering concepts and systems to solve problems and make decisions (National Academy of Engineering, 2009). It encompasses not only technical skills but also awareness of the social, ethical and environmental dimensions of engineering. Engineering literacy is vital in STEAM education, as it transforms knowledge integration into tangible project outcomes. Following, in this work, we will present our use case, focused on smart greenhouse design and automation, in which students are required to apply *engineering* principles in combination with data analytics, sensor networks and automation, thereby bridging *theory* and *practice* (Martinez & Stager, 2013). The key components of engineering literacy include:

- **Problem solving and design thinking**: Ability to define problems, generate solutions, and iterate based on feedback.
- **Systems thinking**: Understanding how components interact within larger systems (e.g., smart cities, precision agriculture).
- **Application of scientific and mathematical principles**: Translating theory into practical, workable solutions.
- **Collaboration and communication**: Working in teams and effectively sharing technical knowledge.

From the above, we understand that there is a close relationship among engineering literacy and STEAM education. In essence, STEAM epistemology underpins a learner – centered vie of knowledge creation, while STEAM education offers the pedagogical tools to cultivate engineering literacy. In this direction, *STEAM engineering literacy* refers to students' ability to effectively integrate concepts from STEAM to creatively solve complex and real – world engineering problems. It empowers students to tackle real – world challenges through interdisciplinary problem – solving and innovation. STEAM education is inherently interdisciplinary; therefore, engineering literacy is the *application – oriented core* that connects scientific knowledge, technological tools and mathematical models to design, to build and to test functional solutions. In our use case related to a smart greenhouse project, students use **science** to understand the climate conditions, **math** to model optimal growing conditions, **technology** to use sensors, embedded systems and microcontrollers, **engineering** to design automated systems and **art** to ensure usability and environmental sustainability. Engineering literacy move concepts from design to creation, within the STEAM interdisciplinary process.

STEAM Engineering Literacy Assessment

A crucial part of our work is to measure engineering literacy and estimate how our students adopt STEAM pedagogy in combination with CT principles. STEAM engineering literacy assessment can be approached through several effective methods related to:

Rubric – based assessment: In this work, we apply two kinds of rubrics to assess the degree of students' engagement into STEAM engineering literacy activities. The **first one** relates to NGSS engineering design – aligned rubric (Archieve, Inc. 2016; NGSS Lead States. 2013). The Next Generation Science Standards (NGSS) is a set of science content standards, developed to improve science education in the U.S., by emphasizing deep understanding, practical application and integration across disciplines. A central feature of this framework is the integration of *engineering design* into the science standards and the development of a strand of engineering and technology standards. The key features of NGSS are:

1. Three dimensional learning:
   - *Disciplinary Core Ideas (DCIs)*: Key content in physical, earth, life and engineering sciences
   - *Science and Engineering Practices (SEPs)*: Identifies what scientists and engineers actually do (i.e. the process of asking questions, how to analyze data etc.)
   - Crosscutting Concepts (CCCs): Ideas that apply across disciplines (i.e. systems, patterns etc.)
2. Performance Expectations (PEs): The PEs describe what students are expected to be able to do after an instruction
3. Engineering and Technology Integration: Engineering design is treated as a *core discipline*, not just an add – on.

The NGSS provides an agreed – upon set of education standards that place a heavy emphasis on practice by outlining *eight* science and engineering practices with which students need to engage. These are: (1) Ask questions and define problems, (2) Develop and use models, (3) Plan and carry out investigations, (4) Analyze and interpret data, (5) Use mathematics and computational thinking, (6) Construct explanations and design solutions, (7) Engage in argument from evidence, and (8) Obtain, evaluate, and communicate information. Our NGSS rubric, as appears in **Table 1**, aligns with these eight practices and reflect the three – dimensional learning (i.e. DCIs, SEPs, CCCs).

Table 1. Engineering design NGSS – aligned Rubric (Archieve, Inc. 2016; NGSS Lead States. 2013)

Criteria	Exceeds Expectations (3)	Meets Expectations (2)	Needs Improvement (1)
1. Integration of Science and Engineering Practices (SEPs)	Multiple SEPs are authentically embedded and students actively engage with them throughout the lesson	At least one SEP is included in a meaningful way	SEPs are minimally present or superficially included
2. Use of Crosscutting Concepts (CCCs)	Lesson explicitly integrates one or more CCCs to help students make connections across domains	At least one CCC is identified and loosely tied to the lesson content	CCCs are not identified or connected to learning outcomes
3. Disciplinary Core Ideas (DCIs)	Lesson targets grade-appropriate DCIs with clear, explicit alignment to NGSS content	At least one DCI is targeted and partially aligned with lesson goals	DCI alignment is unclear, missing, or not aligned to standards
4. Engineering Design Integration	Engineering design is central to the lesson, with students defining problems, designing solutions, and iterating	Engineering is included, but limited to one or two phases of the design process	No evidence of engineering design integration
5. Real-World Relevance and Problem-Solving	Lesson presents an authentic, real-world problem that requires critical thinking and interdisciplinary solutions	Some real-world connection exists but may lack depth or complexity	Lesson is abstract with little or no real-world context
6. Student-Centered and Inquiry-Based Learning	Students make decisions, ask questions, and explore ideas through hands-on, inquiry-driven activities	Some opportunities for student inquiry are present, but teacher-directed instruction dominates	Lesson is mostly lecture-based or procedural with limited inquiry
7. Use of Data and Evidence	Students collect, analyze, and use data to support claims or refine designs	Data is used in a limited way (e.g., pre-collected or demonstration only)	No meaningful use of data or evidence in student learning
8. Communication and Collaboration	Students communicate ideas clearly through writing, visuals, or presentations and collaborate effectively	Some communication and group work included	No structured opportunities for collaboration or communication

The **second** rubric, used in this work as **Table 2** shows, relies on the work of Kalovrektis et al. (2023) and is used to measure students' engagement degree with CT activities, within the STEAM framework. The rubric's main pillars are based on CT's dimensions and the evaluation is organized in four levels. The educator is free to adjust grade *weights* (in %) in order to measure a *weighted average* as a final evaluation metric. Rubric – based assessment is an overall assessment mechanism.

Artifacts Portfolios: Students produce tangible artifacts, by using 3D design programs and 3D printers (i.e. smart greenhouse structures). Portfolios document the design process; depict the series of decisions made, challenges and final solutions. Along with the artifacts, portfolios include deliverables, which highlight the design process, the solution steps and how student overcome challenges. EDP is considered a contemporary project based teaching method, appropriate for STEAM interdisciplinary use cases. In essence, students collaborate as *engineers* and follow a series of steps (or phases) to propose a solution to a real – problem

Engineering Design Process (EDP)

The *Engineering Design Process (EDP)* is a structured, iterative method, applied by engineers, and problem solvers to identify needs, generate solutions, solve complex problems, develop new products and systems and optimize systems for real – world applications. Unlike scientific inquiry, which aims to help natural phenomena understanding, EDP is project – oriented, aiming to design functional products, processes and systems, to meet specific constraints (National Research Council [NRC], 2012). EDP consists of several unique modes of thinking that teachers use to elaborate and deconstruct the concepts during a project, such as understanding the prompt, design concept, iteration, conceptualization, prototyping, discovery, assessment, iteration, manufacturing development and final product. To this end, EDP is a series of eight phases to find a solution to a problem. The phases include problem definition, information gathering for background research, specifying requirements and constraints, team collaboration, brainstorming, solutions evaluation, and communication. According to **Fig. 2**, the eight EDP phases (P) are the following:

P1: Identify the problem, meaning to understand the nature of the problem and its relationship with specific scientific and technology/engineering principles.

P2: Search or research about the given problem, to understand its nature and to gather information, i.e. from e – books, papers, internet sources, GenAI tools, libraries etc. In this phase, students work either inside or outside the lab.

P3: Develop possible solution(s) to the given problem.

P4: Select one optimal solution, according to criteria or rubric(s).

P5: Prototype construction, which means that students built a working prototype artifact.

P6: Test and evaluate solution, which means to test the proposed solution of P4, P5 and proceed with its evaluation.

P7: Solution communication, which relates to a soft skill that engineers need to have when discuss with a client. Students prepare appropriate test reports and inform about their prototype functionality, according to assessment data.

P8: Redesign the solution. This phase relates to a potential feedback loop, in case students need to alter and redesign parts of the solution provided, to better meet optimization criteria.

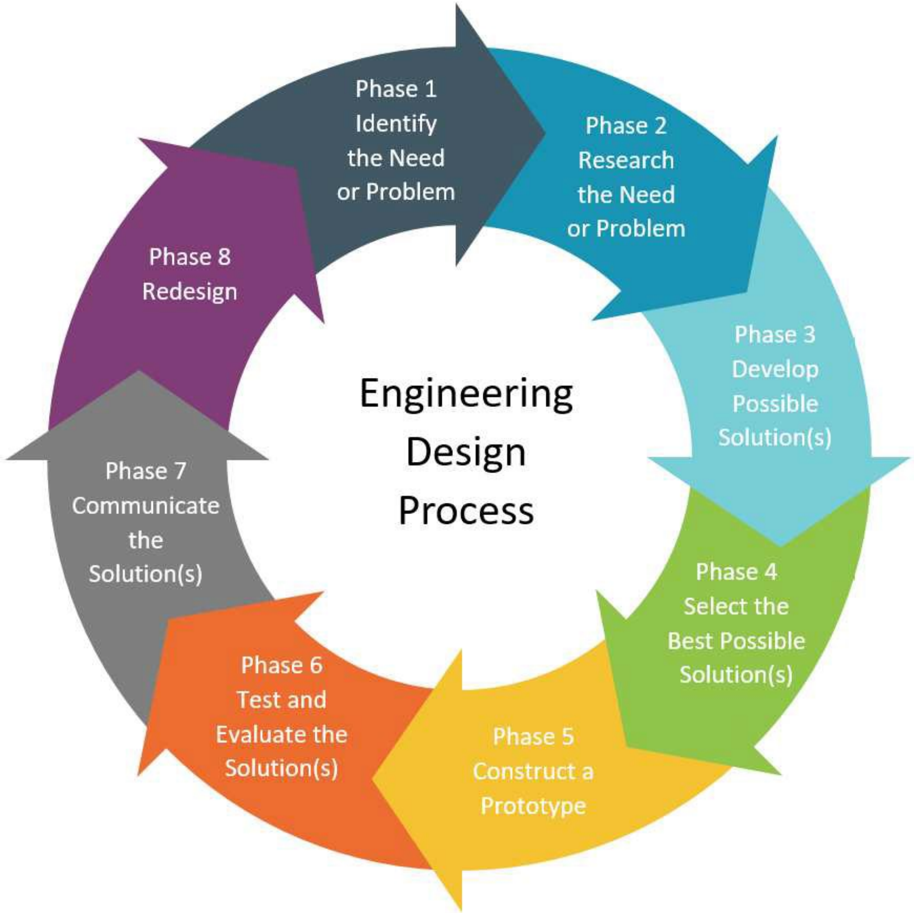

Figure 2. The eight phases of EDP (Psycharis et. al 2023)

Table 2. Computational Thinking Concepts aligned Rubric as proposed in (Kalovrektis et. al, 2023)

Criteria	Level-1	Level-2	Level-3	Level-4	CT concepts
Decomposes a problem into chunks of subproblems driving to a solution based on the subproblems' solutions.	Ineffectively tries to notionally separate the initial problem.	Formulates a partly acceptable decomposed problem solution.	Formulates a series of individual subproblems which are part of the initial problem.	Designs solvable individual subproblems which results in the initial problem solution.	DE, AL, AB
Finds similari-ties/differences during a problem analysis (pattern recognition)	Cannot identify similarities and/or differences in a problem solution.	Identifies some of the similarities and/or differences in a problem solution.	Can transform the similarities to patterns.	Successfully applies the recognized patterns to the final problem solution.	GE, AL
Data, information analysis and evaluation	Cannot recognize the role of accurate data in a problem's solution.	Partly effectively uses the notions of data and information.	Can collect, organize, store data, and evaluate the resulting information.	Evaluates the received feedback and improves the offered solution.	EV
Designs and creates artefacts	Inadequately designs artefacts.	Designs adequate artefacts but faces difficulties in the implementation phase.	Creates "weak" digital artefacts (lack of stability, trust worthless, not tested, etc.).	Creates solid digital artefacts, effective and well-designed.	AL, AB
Exploitation and usage of procedures	Has no clear image of a procedure usage.	Knows that a procedure can be used to hide the detail with subsolution.	Inadequately uses the procedures in a program solution (still needs improvement).	Perfectly designs, writes and debugs programs using procedures.	AL, DE, AB, GE
Propose solutions which are based on the solutions of smaller instances of the initial problem (Recursion).	Has no clear image of a recursion notion.	Cannot identify the recursion problem parts.	Ineffective uses the recursion (no results, high delays).	Perfectly uses the recursion.	AL, DE, AB, GE

Large Language Models (LLMs) and Generative AI (GenAI) tools in Education

Large Language Models (LLMs) are considered advanced AI models, designed to comprehend and generate human – like language. They are trained on massive datasets of *textual* content, enabling them to understand and generate human – like text (U. Kamath el. al, 2024). LLMs are about to revolutionize both teaching and learning. These models manage a large volume of parameters, are trained to be able to process and generate *natural language* (Kasneci et. al, 2023). The real operational innovation is that they ground their processing and generation abilities upon large document volumes, being able to operate on the principles of statistical regularities of natural language, like grammar and vocabulary. LLMs represent one of the most effective systems currently available for a wide range of educational applications, including generating content, such as multiple – choice questions, essays, and solutions to mathematical problems; adapting assessments to individual learners; and providing accurate automated feedback (Kasneci et. al, 2023; X.Zhai, 2022). Compared to other automated tools, they stand out for their ability to produce longer, more fluent and coherent texts, and for generating credible and logically consistent narratives.

One of the most significant potentials of large language models lies in their capacity to enable personalized learning within real educational environments. By leveraging a fine-tuned model with billions of parameters and incorporating a student's entire interaction history, such systems can offer tailored guidance, simulations, and problem-solving approaches that address individual needs and proficiency levels (Kasneci et. al, 2023). However, the integration of large language models in education raises several open questions. These include ethical concerns, such as the ease of generating original, plagiarism-free AI-produced texts, and technical challenges, particularly in deploying reliable software for automated assessment and instructional support. Despite these issues, with appropriate safeguards and regulatory frameworks, the thoughtful use of large language models in educational contexts is both attainable and highly promising. Their potential to enrich teaching and learning processes is increasingly recognized by the educational research community. To summarize, the main usage of LLMs relates to *writing assistance* and *content generation*, *tasks summarization* and *code generation*. Students may work with LLM tools, mainly on EDP's phase 2 and gather ideas about prototype construction phase.

Generative AI (GenAI) are considered a broader class of AI systems, designed to generate various forms of content, not limited to text, but video, music, even complex digital artifacts. To this end, the typical use cases of GenAI based tools relates to generating *visual art and graphics, video and animation synthesis, music composition, text and audio combinations etc.* GenAI is transforming numerous sectors, with education emerging as one of the most significant impacted areas. As AI technology continues to evolve rapidly, educators and students now have access to advanced tools that can significantly enhance the effectiveness and efficiency of both teaching and learning process. Consequently, AI has the potential to significantly redefine the way education is delivered and assessed, fostering more effective and student – centered outcomes. As AI technologies advance, they offer innovative solutions to persistent challenges in traditional education systems – most notably by facilitating personalized learning paths, reducing administrative burdens and improving overall quality (Pedro et. al, 2019). The role of AI in education is projected to expand considerably, evolving from simple automation towards a more active influence on pedagogical strategies and student engagement.

GenAI is emerging as a transformative force in STEAM education, enabling more dynamic, personalized and problem – based learning experiences. GenAI tools empower students to engage more deeply with semi – defined and open real – problems, by supporting tasks such as content creation, simulation, data analysis and feedbacks. These technologies, not only streamline time – consuming processes (writing, coding, data modeling and analysis), but also foster creativity, self – directed learning and iterative thinking, which are core to STEAM frameworks (Henriksen, 2014; Holmes et al., 2022). As an example, when students design a smart greenhouse system, GenAI can assist in code generation for embedded IoT systems, interpret environmental data from sensors, propose a 3D design for the greenhouse housing, thereby allowing students to focus more on innovation, system – level thinking and optimization subjects. Additionally, GenAI support differentiated instruction by customizing challenges to individual students' levels and needs, helping them bridge knowledge gaps in interdisciplinary contexts (Zawacki-Richter et al., 2019). In this way, GenAI serves as both a cognitive and creative AI agent, enhancing students' ability to solve complex, real – world problems with greater efficiency.

Methodology

In this section, we focus on the course of Precision Systems Applications for Primary Production course, as a use case, to measure to which extend students met the learning objectives by working in STEAM real – projects to design and implement smart greenhouse and automations. In essence, the course is an undergraduate course taught at the department of Digital Systems, University of Thessaly, Greece. Students form two main teams, A and B, and follow the principles of EDP during their project solution process. We are mainly interested in assessing how students met learning requirements and acquire engineering literacy, by measuring the impact of AI tools during the process. For our qualitative results, we consult the two STEAM based rubrics, as shown in **Table 1** and **Table 2**.

Learning Objectives and Project Teams

Automation and Communications engineers design and implement advanced technologies, which may lead to sophisticated systems. The technical skills students should develop for the course of applications of precision systems for primary production relates to system design, automations programming, sensors, IoT, control and communication systems. These elements make the course interdisciplinary and well candidate for STEAM course. The learning objectives (LO) of this course are closely related to sensors, automation and control, data analytics and smart systems design for primary production environments, with a focus on precision agriculture applications such as smart greenhouse. Additionally, students may cultivate design skills for the greenhouse housing system. In particular, LO objectives (i.e. what students need to know) associated are as follows:

1. Technical Design Skills:
    - LO1.1: Describe the principles and components of precision agriculture and smart farming systems
    - LO1.2: Identify and select appropriate sensors, actuators and embedded systems for monitoring and control
    - LO1.3: Design a smart greenhouse prototype system by integrating automation and communication technologies
2. Communication Technologies:
    - LO2.1: Explain the role of IoT in precision agriculture applications
    - LO2.2: Implement wireless communication protocols (i.e. LoRA, ZigBee) suitable for sensor networks in agricultural domains.
    - LO2.3: Set up a data acquisition and remote control system for environmental variables
3. Data Collection and Decision Support:
    - LO3.1: Collect and visualize sensor data
    - LO3.2: Apply statistical analysis and decision making
4. System Integration and Automation:
    - LO4.1: Integrate embedded low power IoT devices (i.e. Arduino, Raspberry Pi)
    - LO4.2: Program the devices and develop control algorithms for automated environmental management.
    - LO4.3: Troubleshoot and optimization automation workflows

To test CT and engineering literacy in practice, se give students an open and real – world problem, related to: *design a smart greenhouse with sensors, actuators, automations, and communication and IoT technologies to ensure production sustainability.* Initially, students were divided into two teams: **team A** that makes no use of AI tools, and **team B** that uses AI tools during design and solution process. Both teams work in parallel, following EDP phases. As mentioned before, in EDP we focus on problem solving process, in which students participate in groups and work their solution out, in an iterative way, until they reach the best solution, which meets problem requirements. Within both teams, we also create three groups, to better facilitate the engineering solution process. These are:

1. **Design Group (DES-G)**: Focuses on the design of the smart greenhouse, including materials and architecture. Problems also relate with 3D modelling and components testing
2. **Control and Circuits Group (CC – G):** Focuses on the sensors circuitry and precision systems automation
3. **Programming Group (PROG – G)**: Focuses on the programming, development and testing of algorithms and decision making
4. **Communications Group (COMM – G**): Focuses on the communication infrastructure, the sensor network, IoT and protocols.

For bigger projects, we suggest adding more groups, related to: *Project Management* for efficient project planning, deliverables submission and resource allocation, *Research and Development* for exploring innovative technologies and advancements and taking part in several competitions.

The Use Case: Digital Systems for Precision Agriculture

In this study, 126 undergraduate students from the Department of Digital Systems, University of Thessaly. In particular, as shown in **Table 3**, the gender distribution is 72.2% males (91 students) and 27.7% females (35 students). As noted above, we evenly distribute students in team A and B. Within each team we further distribute students among groups. According to **Table 3**, 67% of students feel familiar with using GenAI based tools. The STEAM scenario lasted approximately one semester and all students engaged themselves for one month, as a preparatory phase, to familiarize themselves with all necessary digital tools and technological concepts, necessary to develop the project's solution.

Table 3. Participant Students

Age	Gender	Experience with AI tools	Mean Prior experience with AI
Mean ± SD: 21.3 ± 1.9 years	Male: 91 students (72.2%)	Prior experience with AI tools: 48 students (67%)	10.1 +- 1.9 months
18-25 years: 118 students (93%)	Female: 35 students (27.7%)	Prior experience with STEAM projects: 21 students (16.6%)	

Following the work from Chatzopoulos el. al (2024), in **Fig. 3** we depict the problem decomposition into several areas, as several sub – problems, following CT dimensions philosophy of decomposition. In essence, we recognize two sub – problems per student group, which focuses properly on each group. Each group is illustrated with a difference color code, same as each sub – problem. During the first two EDP phases, each group, from team A and B, works in parallel to gather information and categorize information about the nature of the problem. Let us recall that only team B has access to GenAI tools additionally along the way. In the sequel, in phase 3, groups focus on several tasks, each of which relates to the nature of each sub – problems.

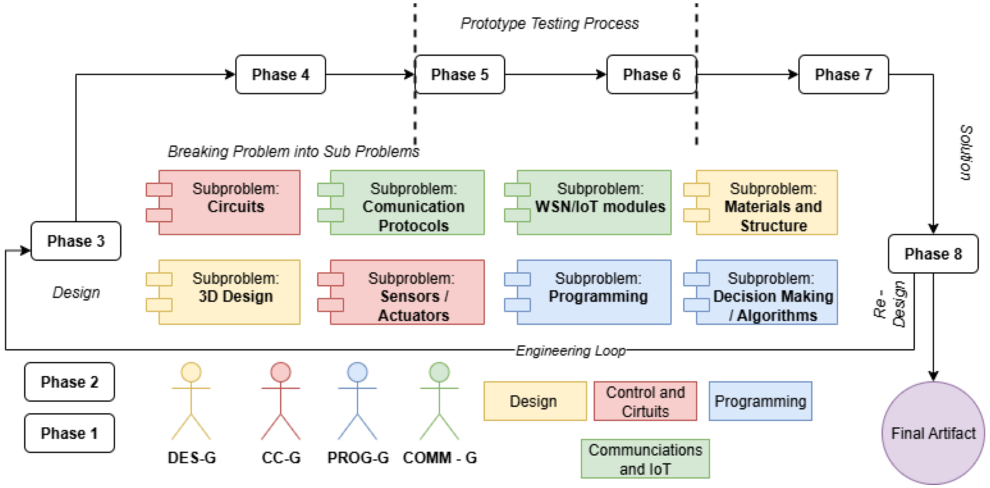

Figure 3. Smart Greenhouse problem decomposition according to EDP (Chatzopoulos et. al 2024)

In the sequel, in phases 5 and 6, groups work with the solution design and prepare their prototype. In **Figures 4** and **5**, we depict paradigms of the teams' greenhouse design and part of the sensors and circuitry automation during design and implementation phases of EDP. Following, in phase 7, students prepare technical reports and communicate their findings. Finally, in phase 8 a feedback loop is activated and decision making is done as to whether the final artifact meets the criteria and solves the initial problem.

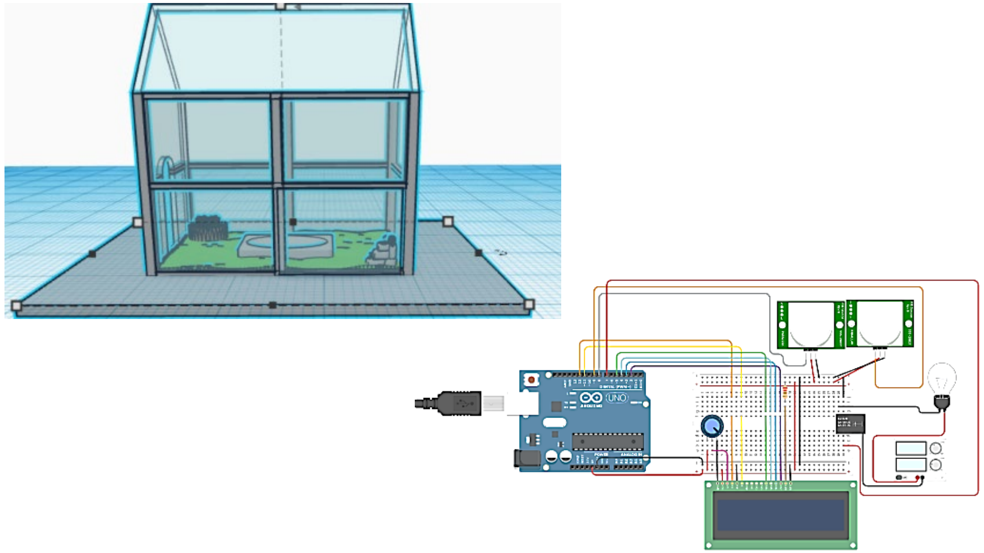

Figure 4. Smart Greenhouse design prototype (left) and circuit for motion sensors (right)

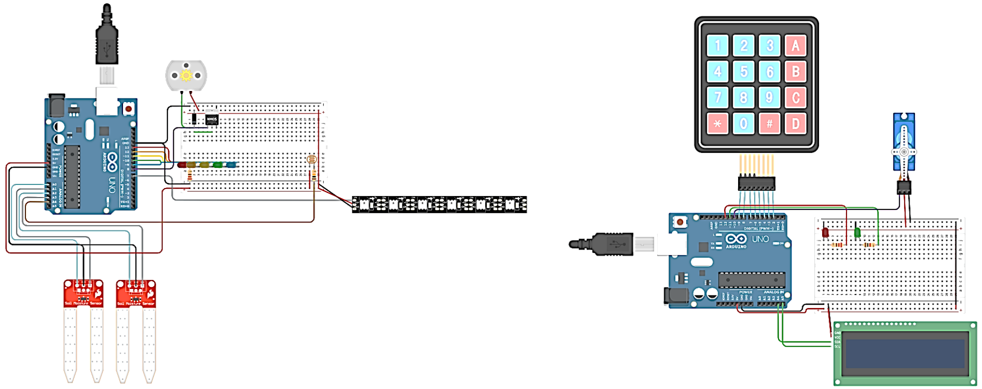

Figure 5. Soil moisture sensor circuitry (left) and password protected shields automation (right)

Results and Discussion

In order to examine if both student teams achieved the expected learning outcomes, we firstly test the functionality of their final artifact. We use the NGSS engineering design related rubric in **Table 1** to compare team A and team B and to quantify the impact of GenAI based tools during problem solving process. According to **Table 1**'s rubric, 3 points mean *exceeds expectations,* 2 points mean *meets expectations* and 1 point mean *need improvement.* Clearly from **Fig. 6**, we understand that the impact of using GenAI tools has a positive impact on the students' performance, across all sub – groups. According to **Fig. 6**, team B scored higher than team A in all CT criteria, with mean = 2.19 and std = 0.36 for team A and mean = 2.77 and std = 0.22 for team B.

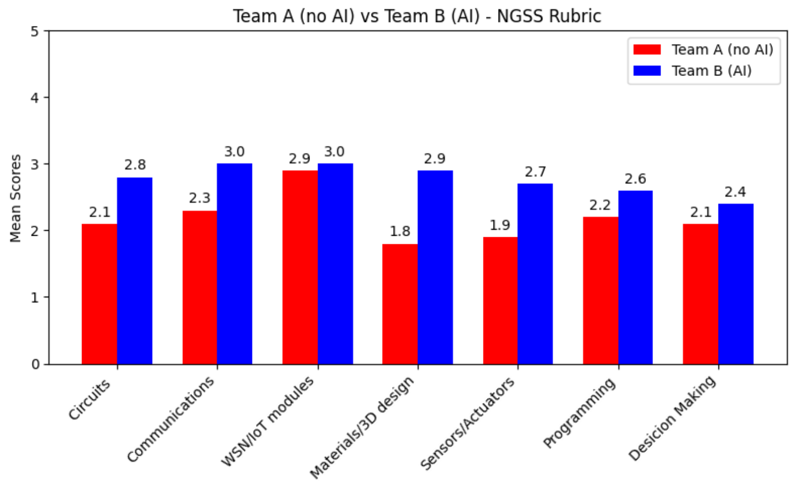

Figure 6. Impact of AI assistance – Comparison of Team A and B (NGSS rubric)

Following, according to the 2nd rubric of **Table 2**, we assess the impact of AI as far as CT criteria is concerned, comparing the scores of both team A and team B. In this scenario, we have six CT criteria and the grading is an average of four distinct levels, ranging from level 4 (perfect) to level 1 (insufficient). According to **Fig. 7**, team B scored higher than team A in all CT criteria, with mean = 3.18 and std = 0.32 for team A and mean = 3.35 and std = 0.1 for team B.

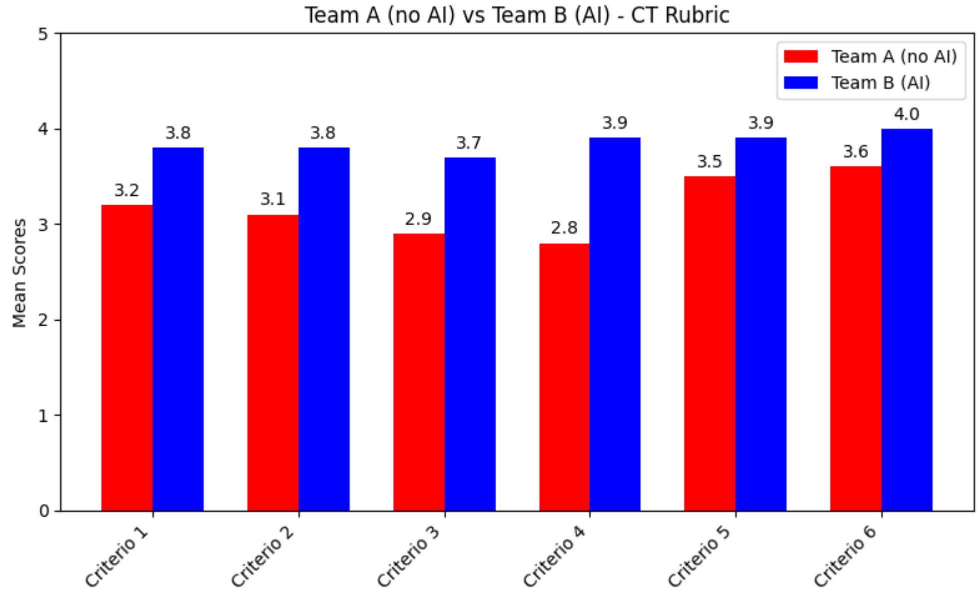

Figure 7. Impact of AI assistance – Comparison of Team A and B (CT rubric)

Finally, we measure students' attitudes towards STEAM pedagogical methodology, as combined with EDP and CT dimensions. To this end, we gave both teams (A and B) a Likert 5 – scale questionnaire, ranging from 1 (strongly disagree) to 5 (strongly agree). According to **Fig. 8**, the majority of students strongly agree and agree that STEAM as combined with EDP process and hands – one activities, helps them better understand the nature of the open problem. Additionally, sub – problems related to *communication protocols*, *sensors* and *circuits* pose the biggest difficulty to students, as far as implementation is concerned.

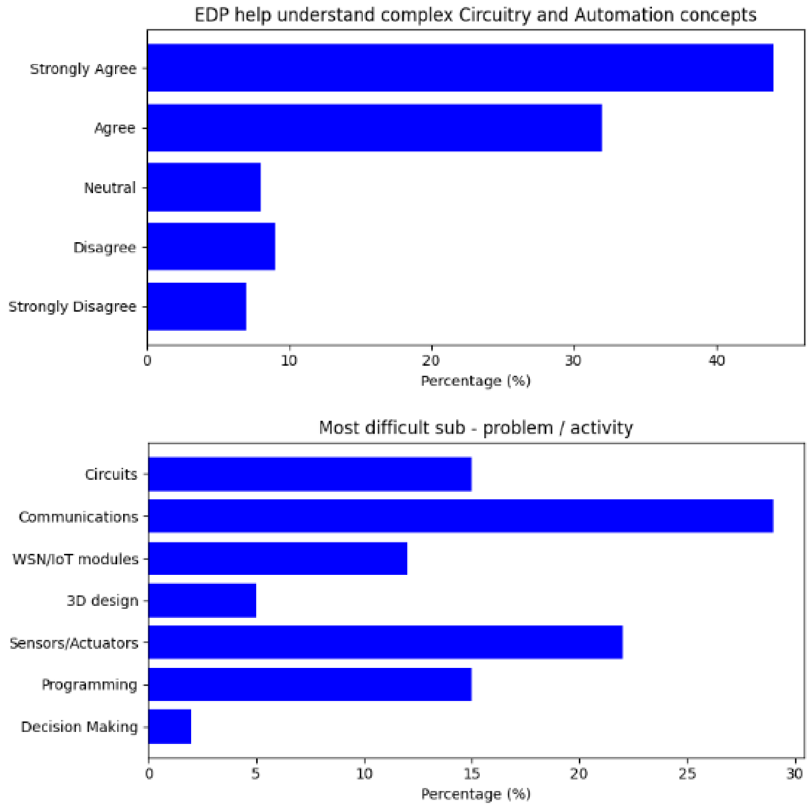

Figure 8. Evaluate STEAM and EDP efficiency (left) and most difficult activity (right)

Conclusions

In conclusion, the integration of GenAI based tools into educational settings demonstrates significant potential in supporting students to achieve their learning outcomes, in a more efficient way. GenAI empowers learners to navigate complex tasks with greater clarity and confidence, by providing personalized assistance, immediate adaptive feedback and intelligent content creation. This kind of support, not only enhances academic performance, but also fosters deeper engagement with interdisciplinary content, especially in the cases of semi – defined and open project – based learning materials. Specifically, GenAI proves to be a valuable asset in cultivating STEAM engineering literacy. According to our findings, it enables students to bridge theoretical knowledge with practical applications, by guiding them through iterative problem – solving and system design – key dimensions of engineering thinking. As students leverage GenAI to explore real-world challenges, such as designing smart agricultural systems, they develop the cognitive and technical skills essential to STEAM fields. Ultimately, the use of GenAI tools not only enriches learning experiences but also equips students with the competencies needed to innovate and collaborate in increasingly technology-driven environments

References

Achieve, Inc. (2016). EQuIP rubric for science: Version 3.0. *Next Generation Science Standards*. https://www.nextgenscience.org/resources/equip-rubric-science

Alismail, H. A., & McGuire, P. (2015). 21st century standards and curriculum: Current research and practice. *Journal of Education and Practice, 6*(6).

https://www.researchgate.net/publication/322616880_21st_century_standards_and_curriculum_Current_research_and_practice

Bequette, J. W., & Bequette, M. B. (2012). A place for art and design education in the STEM conversation. *Art Education, 65*(2), 40–47. https://doi.org/10.1080/00043125.2012.11519167

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*. https://arxiv.org/abs/2005.14165

Chatzopoulos, A., Xenakis, A., Papoutsidakis, M., Kalovrektis, K., Kalogiannakis, M., & Psycharis, S. (2024). *Proposing and testing an open-source and low-cost drone under the engineering design process for higher education: The mechatronics course use case*. In 2024 IEEE Global Engineering Education Conference (EDUCON) (pp. 1–7). IEEE. https://doi.org/10.1109/EDUCON60312.2024.10578677

Fajrina, S., Lufri, L., & Ahda, Y. (2020). Science, technology, engineering, and mathematics (STEM) as a learning approach to improve 21st-century skills: A review. *International Journal of Online and Biomedical Engineering, 16*(7), 95–104. https://doi.org/10.3991/ijoe.v16i07.14101

Floridi, L., & Chiriatti, M. (2020). GPT-3: Its nature, scope, limits, and consequences. *Minds and Machines, 30*, 681–694. https://doi.org/10.1007/s11023-020-09548-1

Gebbers, R., & Adamchuk, V. I. (2010). Precision agriculture and food security. *Science, 327*(5967), 828–831. https://doi.org/10.1126/science.1183899

Henriksen, D. (2014). Full STEAM ahead: Creativity in excellent STEM teaching practices. *The STEAM Journal, 1*(2), Article 15. https://doi.org/10.5642/steam.20140102.15

Holmes, W., Bialik, M., & Fadel, C. (2022). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

Jang, J., Jeon, J., & Jung, S. (2022). Development of STEM-based AI education program for sustainable improvement of elementary learners. *Sustainability, 14*(22). https://doi.org/10.3390/su142215178

Johnson, L., & Adams Becker, S. (2016). *The NMC Horizon Report: 2016 Higher Education Edition*. The New Media Consortium. https://library.educause.edu/resources/2016/2/2016-horizon-report

Kalovrektis, K., Dimos, I. A., & Kakarountas, A. (2023). Computational thinking: A proposed formative assessment rubric for physical computing courses. *European Journal of Engineering and Technology Research, 1(CIE)*, 61–65. https://doi.org/10.24018/ejeng.2023.1.CIE.3138

Kamath, U., Keenan, K., Somers, G., Sorenson, S. (2024). *Large Language Models: An Introduction*. In: Large Language Models: A Deep Dive. Springer, Cham. https://doi.org/10.1007/978-3-031-65647-7_1

Kasneci, E., Sessler, K., Betschart, S., Kasneci, G., & Molli, L. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Land, M. H. (2013). Full STEAM ahead: The benefits of integrating the arts into STEM. *Procedia Computer Science, 20*, 547–552. https://doi.org/10.1016/j.procs.2013.09.317

Lodi, M., Martini, S. (2021). Computational Thinking, Between Papert and Wing. *Science & Education, 30*, 883–908. https://doi.org/10.1007/s11191-021-00202-5

Maizatulliza, M., & Seng, G. (2019). Teachers' perspective of 21st century learning skills in Malaysian ESL classrooms. International Journal of Advanced and Applied Sciences, 6(10), 32–37. https://doi.org/10.21833/ijaas.2019.10.006

Martin, L., Polly, D., & Ritzhaupt, A. D. (2020). Exploring the development of engineering literacy in K–16 settings. Journal of Engineering Education, 109(3), 467–483. https://doi.org/10.1002/jee.20331

Martinez, S. L., & Stager, G. S. (2013). Invent to learn: Making, tinkering, and engineering in the classroom. Constructing Modern Knowledge Press.

Montiel, H., & Gomez-Zermeño, M. G. (2021). Educational challenges for computational thinking in K–12 education: A systematic literature review of “Scratch” as an innovative programming tool. Computers. https://www.mdpi.com

National Academy of Engineering. (2009). Engineering in K–12 education: Understanding the status and improving the prospects. National Academies Press. https://doi.org/10.17226/12635

National Research Council. (2012). A framework for K–12 science education: Practices, crosscutting concepts, and core ideas. National Academies Press. https://doi.org/10.17226/13165

NGSS Lead States. (2013). Next Generation Science Standards: For states, by states – Performance expectations and assessment rubrics. The National Academies Press. https://www.nextgenscience.org

Palomés, X. P. I., Verdaguer-Codina, J., Casas, P. F. I., & Rubiés-Viera, J. L. (2024). Physical and digital twin with computational thinking to foster STEM vocations in primary education. In 2024 IEEE Global Engineering Education Conference (EDUCON) (pp. 1–8). IEEE. https://doi.org/10.1109/EDUCON60312.2024.10578918

Papert, S. (1980). Mindstorms: Children, computers, and powerful ideas. Basic Books.

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). Artificial intelligence in education: Challenges and opportunities for sustainable development. UNESCO.

Psycharis, S., Iatrou, P., Kalovrektis, K., & Xenakis, A. (2023). The impact of the computational pedagogy STEAM model on prospective teachers’ computational thinking practices and computational experiment capacities: A case study in a training program. In Lecture Notes in Networks and Systems (pp. 400–411). https://doi.org/10.1007/978-3-031-26190-9_41

Rodríguez del Rey, Y. A. (2021). Developing computational thinking with a module of solved problems. Computer. https://www.researchgate.net

Sheffield, R., Koul, R., Blackley, S., Fitriani, E., Rahmawati, Y., & Resek, D. (2018). Transnational examination of STEM education. International Journal of Innovation in Science and Mathematics Education, 28(8), 67–80. https://openjournals.library.sydney.edu.au/CAL/article/view/13174

Wing, J. M. (2008). Computational thinking and thinking about computing. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 366(1881), 3717–3725.

Wulandari, R. (2021). Characteristics and learning models of the 21st century. In International Conference of Economics Education and Entrepreneurship (ICEEE 2020), 4, 8–16. https://doi.org/10.20961/shes.v4i3.49958

Yakman, G. (2008). STEAM education: An overview of creating a model of integrative education. Purdue University STEM Colloquium.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? International Journal of Educational Technology in Higher Education, 16(1), 1–27. https://doi.org/10.1186/s41239-019-0171-0