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A practical framework for selecting educational robotics platforms to foster skills in higher education

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Abstract

Educational robotics (ER) has great potential to develop both computational thinking (CT) and 21st-century skills in higher education (HE). However, structured frameworks that help educators align platform selection with desired learning outcomes are still lacking. This study presents a competency-oriented framework that organizes ER platforms along a functional continuum based on the dominant mode of student interaction. Rather than applying rigid classifications, the framework places platforms on a spectrum ranging from screen-based programming environments to systems in which behavioral logic is integrated into the physical morphology of the robot. Based on the analysis of thirty-two empirical studies, the framework connects interaction modalities with groups of CT dimensions and cross-cutting skills, such as creativity, collaboration, adaptability, leadership, and ethical reasoning. CT is conceptualized as a scaffold that mediates the development of these skills through embedded interaction with robotic systems. The resulting structure offers a practical tool for curriculum planning, platform selection, and instructional design in university settings. By mapping how different types of ER platforms support specific learning processes, the framework contributes to a more intentional and evidence-based integration of robotics in HE, aligned with educational goals and workforce demands across disciplines.

Keywords: educational robotics, computational thinking, 21st-century skills, higher education, curriculum design

Introduction

In the 21st century, the integration of emerging technologies into education has transformed the way students acquire knowledge and develop professional skills. Among these technologies, Educational Robotics (ER) has gained prominence as a powerful tool



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to foster both technical and transversal skills through hands-on, interdisciplinary learning experiences. While the benefits of ER in K–12 education are well documented (Benitti, 2012; Eguchi, 2016; Lotriet & Gouws, 2025; Ouyang & Xu, 2024), its application in higher education (HE) institutions has been less extensively studied, particularly with regard to structured curriculum design and strategic platform selection (Boya-Lara et al., 2023; Pereira et al., 2026; Phokoye et al., 2024; Spolaôr & Benitti, 2017).

Higher education institutions are increasingly tasked with preparing students for automated, interdisciplinary, and AI- and robotics-driven professional environments (Chen et al., 2020; Crompton & Burke, 2023; Dong & Wang, 2026; Jaiswal et al., 2022; Sáez-López et al., 2026). These scenarios demand not only foundational technical knowledge but also a strong portfolio of 21st-century skills such as creativity, collaboration, problem-solving, adaptability, and digital literacy (*P21 Resources | 21st Century Learning Resources | Battelle for Kids*, 2025; Thornhill-Miller et al., 2023; World Economic Forum, 2025). As part of this challenge, educational technologies must be not only engaging but also strategically aligned with specific learning outcomes and workforce expectations.

ER has emerged as a promising instructional medium to bridge theory and practice, enabling students to develop both technical and transversal skills through hands-on, project-based learning (Barak & Assal, 2016; Boya-Lara et al., 2023; Karalekas et al., 2020; Kim et al., 2015). Despite its increasing integration across university curricula, the existing literature largely emphasizes adoption trends, technological affordances, and institutional conditions. However, there is still a notable absence of pedagogical frameworks that clearly connect the selection of robotics platforms with the development of targeted skills. This disconnect is especially relevant in HE, where platform diversity and interdisciplinary demands require more precise instructional alignment (Phokoye et al., 2024). The lack of such frameworks becomes even more critical given the wide range of available platforms, from commercial kits such as LEGO Mindstorms and mBot to highly customized and bio-inspired systems, each offering distinct learning affordances (Boya-Lara et al., 2022).

In this context, the development of computational thinking (CT) has emerged as a central educational objective associated with ER, given its emphasis on core problem-solving skills such as decomposition, abstraction, pattern recognition, algorithmic thinking, and debugging (Anwar et al., 2019; Shute et al., 2017; Wing, 2006, 2008). These skills are critical in engineering and computer science, but also increasingly valued in interdisciplinary fields like data science, health technology, and sustainability (Rao & Bhagat, 2024). ER platforms are well-positioned to promote CT through hands-on problem-solving, especially when embedded in project-based learning models (Bertacchini et al., 2022; Sáez-López et al., 2026). Yet, there is limited guidance on how

specific types of ER platforms reinforce distinct facets of CT and how these are connected to the development of transversal skills that remain underrepresented in current implementations, such as ethical awareness, leadership, and intercultural collaboration.

This study addresses the current disconnect between platform selection and skills development by introducing a competency-based framework. It is based on 32 studies that use different physical ER platforms as the main teaching resource for developing different skills in HE. This framework aims to support curriculum designers, educators, and policymakers in making informed pedagogical decisions about integrating platforms in line with specific learning outcomes.

Specifically, this article contributes by:

1. Introducing a novel competency-oriented mapping framework that supports the intentional selection of ER platforms based on their alignment with targeted CT and 21st-century skills in HE.
2. Organizing ER platforms along a functional continuum defined by interaction modality and openness and linking these dimensions to recurring patterns in student learning processes identified across thirty-two empirical studies.
3. Associating platform types with distinct clusters of CT and transversal skills, including algorithmic thinking, digital literacy, creativity, adaptability, leadership, and ethical reasoning.

Conceptual background

Computational thinking in higher education

CT has emerged as a foundational skill for the 21st century, often compared to reading, writing, and arithmetic in its educational relevance (J. M. Wing, 2006). Broadly defined, CT refers to the thought processes involved in formulating problems and their solutions in ways that can be carried out by an information-processing agent (J. Wing, 2011). While its origins lie in computer science, CT is now recognized as a cross-disciplinary competence that extends well beyond programming (Aho, 2012; Barr et al., 2011; Weintrop et al., 2016). CT includes core practices such as abstraction, decomposition, pattern recognition, algorithmic thinking, simulation, and debugging, each representing a cognitive strategy that enables individuals to model, analyze, and solve complex problems across domains (Shute et al., 2017).

Despite the growing prominence of CT, several authors have noted that the majority of CT research and instructional frameworks remain concentrated in K–12 and early education contexts, with comparatively limited attention to HE. Previous reviews consistently highlight this imbalance (Grover & Pea, 2013; Phokoye et al., 2024; Shute et

al., 2017; Spolaôr & Benitti, 2017), noting that CT in HE is often addressed indirectly, embedded within disciplinary courses, or treated as an implicit outcome rather than an explicit design construct. This gap underscores the need for conceptual structures that articulate CT processes in ways that are pedagogically meaningful for higher education settings.

This limited theoretical and curricular development is further accentuated by empirical studies that highlight gaps in how CT is currently implemented in HE programs. For instance, the relationship between CT skills and academic performance in computer science has been reported as weak or inconsistent (John Lemay et al., 2021), suggesting that these skills are not being systematically cultivated through existing curricula. Similarly, undergraduate engineering students were found to demonstrate skills such as abstraction and algorithm design, while skills such as troubleshooting remained underdeveloped (Zhu et al., 2025). These findings reinforce the need for more intentional instructional design that supports a comprehensive development of CT across disciplinary contexts.

Promoting robust CT development in HE requires moving beyond abstract definitions and translating CT into observable, domain-specific learning outcomes. This task demands the support of guiding frameworks that define what CT entails, how it can be taught, and how it aligns with learning objectives across disciplines. Several peer-reviewed studies have provided important foundations in this regard. A validated model comprising six core CT components—decomposition, abstraction, algorithm design, debugging, iteration, and generalization—has been proposed in the literature (Shute et al., 2017). A systematic review categorized CT constructs according to educational level and type of assessment (Tang et al., 2020), emphasizing the predominance of skill-based approaches in K–12 and the lack of adapted frameworks for HE. CT has also been extended to STEM disciplines through four practical categories: data practices, modeling and simulation, computational problem-solving, and systems thinking (Weintrop et al., 2016). Psychometric evidence has also linked CT to cognitive factors such as spatial reasoning and fluid intelligence (Román-González et al., 2017).

While these contributions provide valuable insights, most of them were developed in K–12 settings or offer generalized constructs that are not tailored to the instructional realities of HE. Within this landscape, a systematic mapping study provides a more targeted examination of how CT is taught in university contexts (Tikva & Tambouris, 2021). Their review of 41 empirical studies on CT through programming in HE revealed fragmented implementation, a lack of cohesive instructional models, and limited availability of validated assessment tools. To help structure this emerging body of work, they proposed the CTPHE model (Computational Thinking through Programming in Higher Education), which adapts categories from existing K–12 frameworks to organize

CT-related research in HE along dimensions such as instructional methods, assessment, contextual factors, and teacher development. Although the model offers a useful analytical structure, the authors emphasize that the field still lacks comprehensive frameworks to support CT as a fully integrated competency in HE programs.

Although often associated with broader 21st-century skills (Barr et al., 2011; *P21 Resources* | *21st Century Learning Resources* | *Battelle for Kids*, 2025), CT should not be understood as a single skill or learning outcome. Rather, CT functions as a pedagogical framework that supports the development of interrelated cognitive abilities through structured learning experiences. The CT literature therefore provides a conceptual foundation for organizing these processes in ways that are interpretable, coherent, and relevant to higher education contexts.

21st century skills

In the HE context, preparing students for increasingly complex and technology-driven environments requires more than disciplinary expertise. It involves cultivating a broad set of cognitive, interpersonal, and digital skills commonly referred to as 21st-century skills. According to the P21 Framework (*P21 Resources* | *21st Century Learning Resources* | *Battelle for Kids*, 2025), these skills are organized into three overarching categories: Learning and Innovation Skills, Digital Literacy Skills, and Life and Career Skills. The first category, Learning and Innovation Skills, comprises the foundational “4Cs”: critical thinking and problem solving, creativity and innovation, communication, and collaboration. These are essential for navigating complex problems, generating novel solutions, and working effectively in multidisciplinary teams. The second category, Digital Literacy Skills, focuses on the ability to engage critically with information and technology, and includes information literacy, media literacy, and ICT (Information and Communication Technology) literacy. The third, Life and Career Skills, emphasizes adaptive and ethical capacities such as flexibility, initiative, cross-cultural communication, accountability, and leadership.

These skills have become increasingly relevant in a global workforce shaped by automation, data-driven decision-making, and team-based complexity (Thornhill-Miller et al., 2023; World Economic Forum, 2025). Employers consistently prioritize attributes such as analytical thinking, adaptability, and collaboration, which are now regarded as equally important as technical knowledge (McGunagle & Zizka, 2020; Sánchez Carracedo et al., 2018). However, these studies also emphasize that the integration of 21st-century skills in HE remains uneven, as such skills are often addressed through peripheral activities or elective courses rather than embedded systematically into core academic curricula.

Unlike CT, which functions as a pedagogical framework, 21st-century skills represent a set of desirable learning outcomes. They serve as a competency framework that identifies the attributes and capabilities students are expected to develop in order to thrive in modern academic, professional, and civic contexts. This distinction is central to the approach adopted in this study: while CT provides structured strategies for teaching and learning, the 21st-century skills framework is used both to situate educational robotics within broader competency-oriented curricula and to support the systematic analysis of reported skill development in the reviewed literature.

ER as a bridge between CT and 21st century skills

ER has been shown to support the development of both 21st-century skills and CT in HE (Amri et al., 2022; Sáez-López et al., 2026). Although these subjects are often addressed separately in academia, robotics creates a natural convergence through hands-on, project-based learning. Students engage in technical tasks while simultaneously practicing teamwork, iteration, and communication. Rather than treating programming and collaboration as isolated outcomes, robotics encourages the simultaneous development of these competencies within meaningful, context-rich scenarios. These experiences foster embodied and experiential learning, allowing students to apply theoretical knowledge through design, construction, and debugging. They also promote leadership, initiative, and critical reflection, aligning closely with the kinds of challenges professionals face in dynamic and interdisciplinary environments (Barak & Assal, 2016; Coşkun & Filiz, 2023).

ER can be implemented through three complementary approaches: as an object of study, as a medium for teaching disciplinary content, and as a tool for developing transversal skills (Muñoz-Repiso & Caballero-González, 2019). These roles are not mutually exclusive and often overlap depending on instructional design and learning objectives. Recognizing these three dimensions provides a strategic foundation for designing robotics-based learning experiences that are aligned with diverse educational goals. However, different robotics platforms support these roles in distinct ways. Commercial kits such as LEGO Mindstorms, NAO, or mBot typically emphasize structured programming, logical abstraction, and scaffolded problem solving (Budiyanto et al., 2020; Gomez-De-Gabriel et al., 2015; Piedade et al., 2020). These platforms are well suited to support the development of CT through formal algorithmic logic.

In contrast, platforms that emphasize direct hardware interaction such as BEAM robotics, Arduino-based systems, or other microcontroller kits focus more on physical reasoning, sustainable design, and hands-on experimentation (Boya-Lara et al., 2022; Carrasco-Navarro et al., 2022; Chatzopoulos et al., 2022, 2023). These systems allow students to derive abstractions from schematics, construct functional logic in hardware,

and debug systems in real time. Such processes provide a concrete foundation for algorithmic understanding, especially valuable in engineering and technical education contexts (Amri et al., 2022).

In addition, these physically grounded platforms align with theories of embodied learning and perceptual grounding, which argue that cognitive development is enhanced through active interaction with physical systems (Abrahamson & Lindgren, 2022; Day & Goldstone, 2012; Goldstone & Son, 2005; Weintrop et al., 2016). In the case of BEAM robotics, students interpret the behavior of analog circuits and mechanical components, constructing abstract knowledge through exploration and feedback. This process exemplifies what Day and Goldstone (2012) characterize as the development of generalizable knowledge from concrete experience, where learners extract underlying principles through physical manipulation and perceptual variation, reinforcing the cognitive value of tangible, embodied engagement with real-world systems (Day & Goldstone, 2012).

To examine how ER platforms relate to the development of CT and 21st-century skills, this study introduces a functional continuum based on the dominant mode of student interaction. Rather than applying rigid categories, platforms were placed along a spectrum defined by two key dimensions: the degree of abstraction required for control and the level of physical engagement involved in learning. At one end of the continuum are platforms that rely primarily on screen-based environments and structured programming languages where emphasis is placed on algorithmic logic and digital sequencing, often mediated by graphical or textual code. At the other end are platforms where robotic behavior arises directly from the physical structure of the robot. In these systems, the morphology, circuitry, or configuration of materials determines how the robot responds to stimuli, meaning that the design of the body itself encodes behavior. Between these two poles are hybrid platforms that integrate both approaches, allowing students to alternate between coding and manipulating physical components. These systems enable fluid transitions between abstraction and action, fostering iterative problem solving, embodied reasoning, and perceptual grounding.

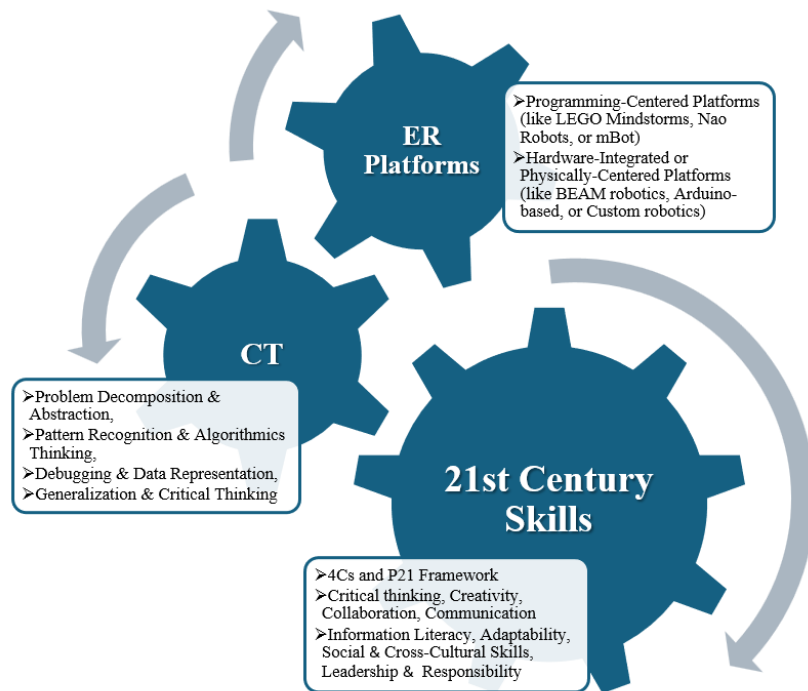
1. **Coding-centered platforms**, such as LEGO Mindstorms or mBot, are based primarily on software programming and are typically designed to support structured, algorithmic learning.
2. **Hybrid platforms**, exemplified by Arduino-based kits, integrate programmable components with closely related hardware elements, allowing students to combine coding tasks with physical construction and system-level thinking.
3. **Hardware-integrated platforms**, such as BEAM robots, embed control logic within the physical morphology of the robot itself, fostering direct sensorimotor interaction and reasoning through analog mechanisms or bioinspired behaviors.

This typology reflects not only technological variation, but also distinct pedagogical affordances that shape the kinds of cognitive and transversal skills students are likely to develop through each approach.

Figure 1 synthesizes this relationship by illustrating how each platform type supports different configurations of CT and 21st-century skill development. Coding-centered platforms tend to reinforce structured algorithmic reasoning and digital literacy. Hybrid platforms contribute to collaborative problem solving and system-level understanding, especially when students alternate between code and hardware manipulation. Hardware-integrated platforms promote situated abstraction, creativity, and adaptability, particularly when students must infer logic from the robot's physical behavior. These distinctions, while not rigid, reflect the pedagogical trajectories afforded by each platform type.

Figure 1

Conceptual model illustrating how educational robotics (ER) platforms support computational thinking (CT) processes, which in turn scaffold the development of 21st-century skills in higher education contexts. Source: Author's own elaboration.



Summary of related frameworks and positioning of the present study

Existing research on ER in HE has produced a range of frameworks and conceptual models aimed at classifying platforms, instructional strategies, or learning outcomes. As summarized in Table 1, prior work has contributed valuable insights by focusing on specific dimensions such as learning theories, project-based approaches, embodied

interaction, programming complexity, or curricular alignment. These contributions have been instrumental in establishing the educational value of robotics across diverse contexts. However, the reviewed frameworks tend to address these dimensions in isolation, often emphasizing instructional levels or disciplinary settings without offering an integrative structure that connects platform characteristics to both computational thinking processes and transversal skill development in higher education. In particular, few models explicitly align modes of interaction, degrees of learner autonomy, and targeted competencies within a unified pedagogical framework.

Table 1

Comparative scope and contribution of prior studies and the present framework. Source: Author's own elaboration

Study	Scope and Contribution of Prior Work	What This Study Adds
(Spolaôr & Benitti, 2017)	Provided a foundational map of ER research in HE, organized by educational level and learning theory	Builds on their categorization by introducing a functional typology linking platform characteristics to learning outcomes
(Barak & Assal, 2016)	Highlighted the value of creativity and open-ended learning in robotics-based STEM education	Integrates creativity within a broader framework that connects platform interaction with transversal skills
(Karalekas et al., 2020)	Demonstrated interdisciplinary potential of ER in engineering education through Arduino-based project learning	Generalizes these insights to create a typology applicable across platforms and institutional contexts
(Phokoye et al., 2024)	Explored the alignment between ER use and curriculum outcomes, with a focus on contextual instructional goals	Expands this alignment by incorporating platform types, CT processes, and transversal skill mapping
(Budiyanto et al., 2020)	Showed how ER supports CT and competence development in teacher training environments	Extends the scope to HE, offering a structured model to connect interaction modality with targeted skills
(Abrahamson & Lindgren, 2022)	Provided a theoretical foundation for embodied learning and sensorimotor interaction in education	Applies embodied cognition principles to categorize ER platforms by physical engagement and learning potential
(Shute et al., 2017)	Established a validated CT taxonomy widely used for assessment and curriculum design	Links CT components to physical robotics interaction and embeds them into a skill-oriented framework for HE

In contrast to these prior contributions, the present study consolidates recurring constructs into a four-dimensional, competency-oriented decision-support framework that links platform interaction, openness, CT processes, and transversal outcomes for higher-education instructional planning.

The present study builds on these foundational contributions by proposing a multidimensional framework that brings together interaction modality, level of openness, computational thinking components, and 21st-century skills. Rather than replacing

existing models, it seeks to synthesize and extend them, providing a structured lens to support platform selection and instructional design in higher education.

Methodology

The purpose of this section is to explain how the study identifies, organizes, and analyzes empirical evidence to construct a framework that links ER platforms with the development of CT and 21st-century skills in HE. To achieve this goal, the study adopts a conceptual methodology supported by systematic evidence analysis. A total of thirty-two peer-reviewed empirical studies were selected based on their relevance to hardware-based ER in university contexts. These studies were identified through a structured and transparent process informed by the PRISMA 2020 framework, which provides updated guidelines for reporting systematic evidence syntheses and reinforces methodological clarity and reproducibility (Page et al., 2021).

Data collection and identification of studies

To identify the most relevant empirical studies for this analysis, an extensive search was conducted in the following academic databases: Web of Science, Scopus, ScienceDirect, IEEE Xplore, Wiley Online Library, and SpringerLink. These sources were selected for their comprehensive coverage of peer-reviewed literature in educational technology, engineering education, and CT. The search included publications from 2015 to 2026, a period aligned with the rapid growth of ER applications in HE and the increasing demand for future-ready skills.

The following search terms and Boolean operators were used:

1. "educational robotics" AND "higher education"
2. "computational thinking" AND "21st-century skills" AND "robotics"
3. "university" AND "robots"
4. "curriculum" AND "robotics programming"
5. "robotics platforms" AND "electronics"
6. "STEM" AND "education"

The initial query retrieved 2,462 articles. After removing duplicates, book chapters, and conference proceedings, 133 publications remained for screening. A first review of titles and abstracts excluded studies centered on pre-university education or software-only ER implementations. This process reduced the pool to 72 full-text articles. A second round of evaluation applied the following inclusion and exclusion criteria to identify the final selection of studies:

Inclusion criteria:

1. Studies explicitly focused on ER in HE

2. Publications that specify the use of physical, hardware-based robotics platforms (e.g., LEGO Mindstorms, Arduino, NAO, Raspberry Pi, or custom-built systems)
3. Empirical studies with a well-defined research design (e.g., experimental, quasi-experimental, case study)
4. Articles addressing curricular models, CT skills, or 21st-century skills.
5. Peer-reviewed journal articles published between 2015 and 2026.
6. Only peer-reviewed journal articles published in English were retained for analysis.

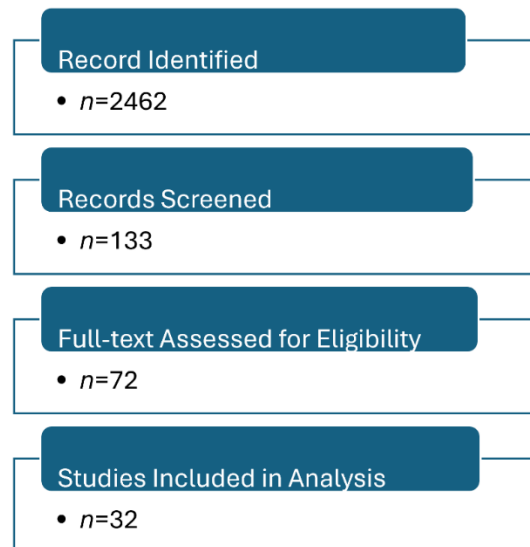
Exclusion criteria:

1. Studies focused exclusively on primary or secondary education.
2. Publications based on software-only or simulation-based platforms.
3. Articles without empirical data or with insufficient methodological description
4. Non-peer-reviewed or duplicate works

After applying these criteria, 32 studies were retained for final analysis. Figure 2 illustrates the complete selection process.

Figure 2

The flow diagram showing the identification, screening, and selection of studies included in the analysis. Source: Author's own elaboration. Adapted from the PRISMA 2020 flow diagram (Page et al., 2021).



Analytical classification of studies

The analytical classification was designed to convert the heterogeneous evidence reported across the selected studies into a common structure that could support systematic comparison and subsequent framework development. The coding structure was established before the study-level analysis and was grounded in the conceptual synthesis

presented in Section 2. The prior frameworks summarized in Table 1 were examined to identify recurring CT constructs and areas of conceptual overlap. These constructs were then consolidated into the five main CT categories and associated subskills presented in Table 2. In parallel, the P21 framework was adopted to organize transversal competencies into the three domains and corresponding subskills presented in Table 3. The platform interaction continuum defined in Section 2.3 provided the basis for distinguishing coding-centered, hybrid, and hardware-integrated forms of interaction. Together, these elements defined the analytical references used to classify the selected studies.

Each of the 32 studies was then examined individually using a common extraction and coding procedure. For each study, information was recorded on the robotic platform used, the instructional activities and objectives, the pedagogical approach, the assessment procedures, and the reported learning outcomes. CT processes were coded by matching the evidence reported in each study with the operational definitions established in Table 2. A CT skill was assigned when it was explicitly identified by the authors or when the described activity, assessment, or learning outcome corresponded directly to the relevant operational definition. The same procedure was applied to 21st-century skills using Table 3 (*P21 Resources* | *21st Century Learning Resources* | *Battelle for Kids*, 2025). Multiple codes were permitted when a study provided independent evidence for more than one CT process or transversal competency. Platform type was determined from the dominant mode of student interaction with the robotic system, while the pedagogical model was recorded according to the instructional approach described in the study.

Table 2

Synthesized conceptual taxonomy of CT processes derived from established frameworks in Table 1.

Source: Author's own elaboration

Main Category	CT skills
Problem Decomposition & Abstraction	Abstraction (Identifying the essential details while ignoring irrelevant information) Decomposition (Breaking down complex problems into smaller, manageable parts)
Pattern Recognition & Algorithmic Thinking	Pattern Recognition (Identifying trends, similarities, and repeated sequences in data or problems) Algorithmic Thinking (Creating step-by-step instructions or algorithms to solve problems)
Debugging & Optimization	Debugging (Identifying and fixing errors in a process, program, or system) Evaluation & Optimization (Assessing different solutions and improving efficiency)
Simulation & Data Representation	Simulation & Modeling (Creating models to predict behavior or analyze complex systems) Data Representation (Using visual or structured formats to organize and interpret data)
Generalization & Critical Thinking	Generalization (Applying solutions from one problem to another similar context) Persistence (Developing resilience and perseverance in problem-solving) Critical Thinking (Analyzing and reasoning to make logical decisions based on evidence)

Table 3

Categories and subcategories of 21st-century skills based on the P21 framework. Note: Adapted from P21 (*P21 Resources / 21st Century Learning Resources / Battelle for Kids*, 2025)

Category	Subcategories / Skills
Learning and Innovation Skills	Critical Thinking and Problem Solving Creativity and Innovation Communication Collaboration
Digital Literacy Skills	Information Literacy Media Literacy ICT (Information and Communication Technology) Literacy
Life and Career Skills	Flexibility and Adaptability Initiative and Self-Direction Social and Cross-Cultural Skills Productivity and Accountability Leadership and Responsibility

For the study-level analysis, four complementary analytical dimensions were therefore considered: platform type, CT skills, 21st-century skills, and pedagogical model. The same decision rules were applied across the complete corpus to maintain consistency and comparability among studies.

1. **Platform type:** ER platforms were classified according to their dominant mode of interaction. Coding-centered platforms emphasize structured software-based programming through graphical or text-based interfaces; hybrid platforms combine programmable logic with physical prototyping and modular hardware elements; and hardware-integrated platforms emphasize direct sensorimotor interaction and embedded reasoning through analog, electronic, or bioinspired control systems. Classification was based on the dominant form of student interaction rather than on platform brand or technical architecture alone.
2. **CT skills supported:** The five-category structure presented in Table 2 was applied as an a priori coding scheme. A CT process was assigned only when the evidence reported in the study corresponded to the operational definition of the relevant category or subskill. Evidence could derive from the instructional activity, learning objective, assessment procedure, or reported outcome. Multiple CT codes could be assigned to the same study when independently supported by the evidence.
3. **21st-century skills:** The categories and subcategories presented in Table 3 were used to identify transversal competencies addressed in each study. A skill was coded when it was explicitly reported or when the intervention or reported outcome showed a direct correspondence with the relevant P21 category. Multiple skills could be assigned to the same study when separately supported by the reported evidence.
4. **Pedagogical model:** The instructional approach was coded to capture how learning with the robotic platform was organized in each study. This dimension included approaches such as Project-Based Learning (PjBL), Problem-Based Learning (PBL), Inquiry-Based Learning (IBL), Design-Based Research (DBR), and challenge-based or sustainability-focused strategies. When the study explicitly identified a pedagogical model, that classification was retained; when no formal label was provided, the model was inferred from the structure and implementation of the instructional intervention described by the authors.

All coding decisions were documented in a structured study-level coding record, linking each classification to the corresponding evidence extracted from the original study. The same definitions and decision rules were applied across the corpus to maintain consistency and traceability throughout the classification process. The procedure was not structured as an independent parallel-coding exercise; therefore, inter-rater reliability was not calculated. Consequently, the analysis prioritized transparent, evidence-based classification and consistent application of the predefined coding criteria.

Each study was assigned a code (P1 to P32) to facilitate identification throughout the analysis. A full summary of the selected studies, including platform type, instructional model, and research design, is presented in Appendix A.

Linking robotics platforms to learning outcomes: Results and framework proposal

This section presents the analytical results derived from the methodology. The goal is to identify how different types of robotics platforms contribute to the development of CT and 21st-century skills. It examines the patterns observed across platform categories in relation to specific cognitive and transversal skills. Then, it introduces a competency-oriented framework that integrates these patterns into a structured tool to guide platform selection and instructional planning. The final part of the section illustrates how the framework can be applied in practice, using representative platform examples to highlight variations in skill development and educational potential.

Mapping results

The analysis of thirty-two empirical studies revealed clear patterns linking robotics platforms to specific cognitive and transversal skills. The classification confirms that platform characteristics influence not only the presence but also the type of skills developed by students. Table 4 shows the distribution of CT skills across ER platforms, using the five-category taxonomy introduced in Section 2.1. Each study is identified by its code (P1 to P32), allowing traceability with Appendix A.

Table 4

Mapping robotics platforms with CT skills developed. Source: Author's own elaboration

ER Platforms	CT Skills	Research Papers (Codes)
LEGO Mindstorms (NXT/EV3/Spike Prime), mBot	Abstraction	P1, P8, P9, P23, P24, P29
	Decomposition	
	Pattern Recognition	
	Algorithmic Thinking	
Arduino, Raspberry Pi, micro:bit-based Platforms	Debugging	P3, P12, P17, P21, P32
	Evaluation & Optimization	
	Generalization	
	Critical Thinking	
Custom-Built Robots (Bioinspired, BEAM, Multi-Agent Systems)	Simulation & Modeling	P4, P11, P18, P20, P27, P31
	Data Representation	
	Generalization	
	Persistence	
Industrial & Research Prototypes (PUMA 560, Hexapod Phantom X)	Abstraction	P2, P7, P26
	Decomposition	
	Simulation & Modeling	
	Critical Thinking	
IoT & AI-integrated Platforms (FOSSBot, MEIoT 2D-CACSET, Smart Home Robots)	Pattern Recognition	P5, P12, P22, P25
	Algorithmic Thinking	
	Debugging	
	Evaluation & Optimization	

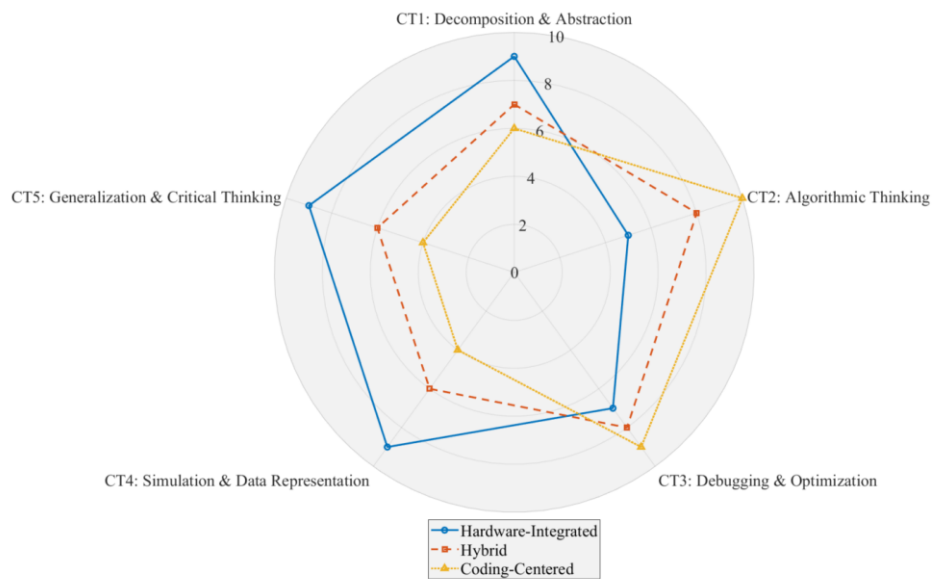
Table 4 indicates that most platforms address multiple CT dimensions, though with varying degrees of emphasis. However, the type of cognitive engagement supported by a platform depends strongly on its interaction modality. Platforms centered on software programming tend to prioritize algorithmic logic and debugging. In contrast, platforms that involve hardware manipulation or analog behavior promote more diverse forms of reasoning, such as abstraction, simulation, and critical thinking. These differences suggest that the affordances of each platform shape how CT skills are activated and practiced, consistent with theories of embodied cognition and perceptual grounding.

To synthesize these distinctions, Figure 3 presents a radar chart that compares the CT skill profiles of three functional types of ER platforms: coding-centered, hybrid, and hardware-integrated. The chart displays the relative emphasis placed on each of the five CT dimensions, based on the patterns observed in the selected studies. The results show that coding-centered platforms strongly reinforce algorithmic thinking and structured problem solving. Hybrid platforms, which combine software with hardware design, display a more balanced emphasis across categories. Hardware-integrated platforms exhibit the broadest cognitive profile, particularly in areas related to abstraction,

modeling, and generalization. These findings reinforce the pedagogical importance of aligning platform selection with intended CT outcomes.

Figure 3

Radar chart illustrating the relative prominence of CT categories across the reviewed ER platforms. Each axis corresponds to one CT category, and the radial scale represents the frequency with which that category is reported or emphasized across the analyzed studies. Source: Author's own elaboration.



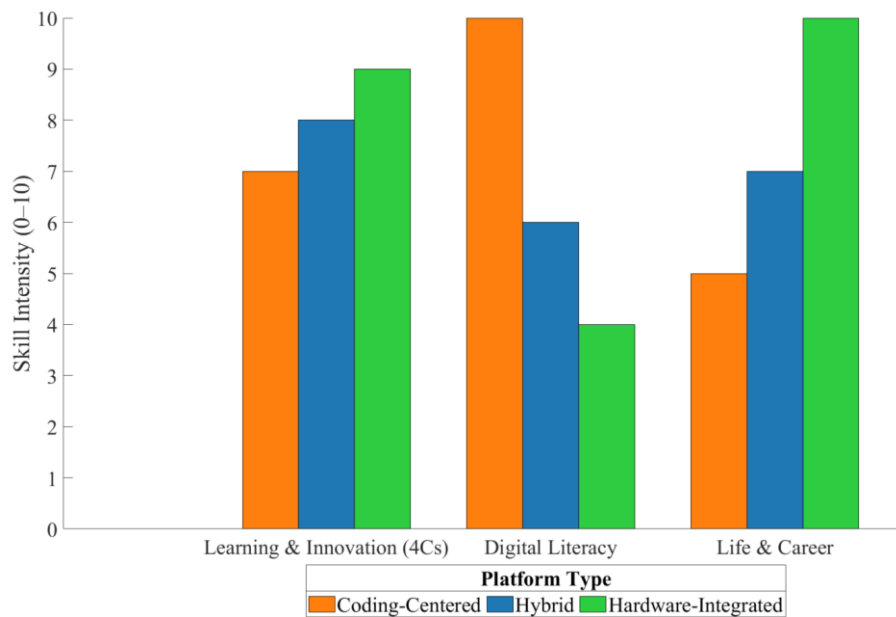
Beyond cognitive development, Appendix B (Table B) presents the detailed coding of how individual ER platforms support the development of 21st-century skills, categorized according to the P21 Framework. The analysis reveals that certain skills, such as critical thinking, collaboration, and creativity, appear more frequently across the studies. Others, including social and cross-cultural communication, initiative, and leadership, remain less systematically represented. These disparities suggest that while ER environments offer fertile ground for transversal skill development, their impact is uneven and strongly shaped by platform type.

To illustrate this relationship, Figure 4 compares the distribution of 21st-century skills reinforced by each of the three types of platforms: coding-centered, hybrid, and hardware-integrated. Here, we define skill intensity as the frequency with which a 21st-century skill is identified in each study and the specific platform used, as documented in Appendix B. The chart shows that coding-centered platforms are strongly associated with digital literacy and collaboration, but less so with adaptability or initiative. Hybrid platforms have a more balanced profile, while hardware-integrated platforms stand out for supporting creativity, flexibility, and leadership. These patterns reflect the different pedagogical possibilities offered by each type of technological configuration.

This typological alignment reinforces the idea that platform selection should be based not only on technical features, but on how different systems facilitate the integration of transversal skills into instructional practice.

Figure 4

Distribution of 21st-century skills associated with ER platforms across the reviewed studies. Values represent the frequency with which each skill is explicitly addressed or reported as a learning outcome in the analyzed literature. Source: Author's own elaboration.



Framework construction

The proposed framework is developed as a synthesis of the analytical findings derived from the systematic classification of the thirty-two empirical studies reviewed in this work (Section 3). Its purpose is to support decision-making in HE by organizing ER platforms according to their pedagogical affordances and their capacity to foster CT and 21st-century skills. Rather than categorizing platforms based on technical specifications or brand-specific features, the framework emphasizes the underlying modes of interaction and learning processes through which competencies are developed.

Specifically, the framework is structured around four pedagogically relevant dimensions that emerged consistently from the cross-study analysis:

1. **Type of technological interaction:** This refers to the primary modality through which students engage with the platform. Some systems emphasize coding and algorithm design through graphical or script-based programming interfaces. Others require direct physical engagement with hardware, such as wiring, component assembly, or analog logic construction. A third group combines both modalities in

hybrid configurations. These distinctions are pedagogically significant because they influence how students conceptualize problems, build representations, and construct knowledge. Platforms that promote tangible interaction are particularly aligned with embodied learning principles, as they ground cognitive development in sensorimotor feedback and iterative manipulation.

2. **Level of openness and learner autonomy:** This dimension captures the degree of design freedom, programmability, and learner autonomy afforded by the platform. In this framework, openness is understood as a pedagogical property rather than a technical or licensing characteristic, reflecting how constrained or flexible the learning environment is in terms of student agency and exploration.
 - *Low openness:* Platforms operate within highly structured environments where tasks, behaviors, and solution paths are largely predefined. Learner interaction follows prescribed sequences, and modifications are typically limited to parameter tuning or rule-based programming. These platforms support controlled learning experiences and the development of foundational computational thinking skills.
 - *Medium openness:* Platforms combine structured guidance with opportunities for modification and exploration. Learners can extend functionalities, adjust components, or experiment within a defined system architecture. This level supports iterative design, problem decomposition, and collaborative experimentation while maintaining pedagogical scaffolding.
 - *High openness:* Platforms offer minimal predefined structure and afford extensive learner autonomy in both physical configuration and behavioral logic. Learning emerges through exploration, prototyping, and interaction with material and social constraints, fostering creativity, adaptability, initiative, and emergent problem-solving strategies.
3. **CT skills supported:** Based on the taxonomy outlined in Section 2.1, this includes core processes such as decomposition and abstraction, algorithmic thinking, debugging and optimization, simulation and data representation, and generalization.
4. **21st-century skills reinforced:** Following the P21 Framework discussed in Section 2.2, this includes creativity, collaboration, digital literacy, adaptability, initiative, and leadership. These transversal skills are essential for preparing students to thrive in dynamic, interdisciplinary, and technology-rich environments.

Application of the framework

To demonstrate practical use, the framework can be applied as a simple decision flow:

1. Define intended learning outcomes by selecting priority CT processes and 21st-century skills.
2. Choose the desired interaction modality (coding-centered, hybrid, or hardware-integrated) based on the required cognitive–sensorimotor engagement.
3. Set an openness level (low, medium, high) consistent with the desired degree of learner autonomy.
4. Select or design a platform that matches these constraints and verify alignment using Table 5.

Illustrative example: if an instructor aims to strengthen decomposition, simulation/data representation, and initiative within a project-based course, a hybrid platform with medium openness is typically appropriate, as it supports iterative prototyping while maintaining manageable scaffolding. Conversely, if the priority is algorithmic thinking and debugging under tightly guided laboratory sessions, a coding-centered platform with low openness is a better fit. If the goal is exploratory design emphasizing creativity and adaptability through direct circuit-level experimentation, a hardware-integrated platform with high openness is more consistent with the framework.

Table 5

Pedagogical typologies and competency profiles of representative ER platforms. Source: Author's own elaboration.

Pedagogical Typology	Platform Example	Interaction Type	Openness Level	Key CT Skills	Key 21st-Century skills
Coding-centered	LEGO Mindstorms	Graphical/text-based coding	Low	Algorithmic thinking, debugging	Collaboration, digital literacy
Hardware-integrated	BEAM Robots	Direct manipulation of hardware	High	Abstraction, generalization, physical reasoning	Creativity, adaptability, leadership
Hybrid	Arduino-based kits	Combined hardware-software	Medium	Decomposition, simulation, data representation	Problem solving, initiative, tech fluency

In studies involving LEGO Mindstorms, for example, the platform is consistently associated with structured programming, logical sequencing, and collaborative debugging. Its closed design and high degree of instructional scaffolding support algorithmic thinking and teamwork, especially in foundational or teacher training programs (e.g., P1, P8, P29). These features reflect the coding-centered typology, where interaction is primarily mediated through screen-based programming environments and the learning path follows a well-defined structure.

By contrast, platforms that fall under the hardware-integrated typology, such as BEAM robots or other analog and bioinspired systems, encourage students to engage directly

with physical components and sensorimotor logic. These platforms typically offer high levels of openness and promote exploratory reasoning through tactile manipulation and real-time feedback. The learning processes observed in these contexts often emphasize abstraction, generalization, and creative problem solving. Studies such as P11 and P20 show that these systems tend to foster adaptability, leadership, and systems-level thinking, particularly in environments concerned with sustainability and engineering design.

Between these two typologies, Arduino-based kits exemplify the hybrid typology by combining coding tasks with hands-on prototyping. Their medium openness allows students to iterate between digital and physical representations, supporting skills such as decomposition, simulation, and data interpretation. The literature suggests that these platforms are especially valuable in interdisciplinary, project-based settings where students develop initiative, problem-solving abilities, and technological fluency (e.g., P12, P21, P28).

Together, these three cases demonstrate how the proposed framework can guide the selection and implementation of ER platforms in HE. The distinctions among platform types are not rigid categories, but evidence-based trends that highlight how specific technological and pedagogical configurations shape the emergence of both cognitive and transversal skills. By aligning platform selection with curricular goals and learning outcomes, the framework provides educators with a practical tool for designing instruction that addresses the complex demands of 21st-century education.

Discussion

This study addresses the disconnect between ER platform selection and competency development in HE by proposing a framework that links platform characteristics with recurring patterns of CT and 21st-century skills. The results indicate that interaction modality and level of openness are associated with different competency profiles, supporting their use as practical criteria for instructional planning. This extends previous work in HE that has emphasized the educational potential of robotics, curriculum integration, and competency development, but has generally examined these dimensions separately rather than as part of an integrated platform-selection framework (Coşkun & Filiz, 2023; Phokoye et al., 2024; Spolaôr & Benitti, 2017). In this sense, the framework does not replace previous classifications; it brings these dimensions together to support better alignment between platform selection and intended learning outcomes.

The mapping of the thirty-two studies shows that the three platform types are associated with different, although overlapping, competency profiles. Coding-centered platforms show a stronger emphasis on algorithmic reasoning, structured problem solving, debugging, digital literacy, and collaboration. Representative cases within the corpus include studies using LEGO Mindstorms, mBot, and related programmable systems (e.g.,

P8 and P29), where learning activities were organized primarily around programming and structured computational tasks. The more recent micro:bit-based intervention in P32 extends this pattern by combining visual programming with progressively more complex robotics activities. These cases illustrate the tendency observed in Figures 3 and 4. Beyond the analyzed corpus, this interpretation is consistent with established CT models that identify algorithm design and debugging as central computational processes (Shute et al., 2017). It is also supported by evidence that university robotics activities can foster cognitive, autonomous, cooperative, and innovation-related skills (Coşkun & Filiz, 2023). Taken together, these findings suggest that coding-centered platforms provide a particularly suitable environment when instructional objectives emphasize structured computational reasoning and digitally mediated problem solving.

Hybrid platforms show a broader distribution across the CT dimensions because students move repeatedly between software representations and the behavior of the physical system. Within the reviewed corpus, P12 and P21 provide representative examples. Physical robotic interaction was combined with virtual, graphical, and abstract representations in an IoT-enabled mechatronics environment (Carrasco-Navarro et al., 2022), while students were required to apply CT-related processes across virtual and physical robotics tasks in another study (Chichekian et al., 2024). These cases illustrate how programming, sensing, actuation, and physical prototyping can become part of the same learning sequence. This interpretation is also compatible with previous work emphasizing the educational value of modular and extensible robotic systems that integrate programming, sensors, hardware, and system-level interaction (Karalekas et al., 2020). The comparatively balanced profile observed for hybrid platforms therefore appears to reflect the need to coordinate several forms of representation and problem solving rather than work predominantly within either software or hardware alone.

Hardware-integrated platforms show a different pattern, with stronger associations with abstraction, modeling, generalization, creativity, and adaptability. Representative cases in the corpus include BEAM and other custom or bioinspired systems (e.g., P11, P20, and P31), where students interact directly with circuits, components, materials, and physical behavior. In P31, for example, CT-related processes were addressed through circuit construction, physical debugging, iterative redesign, and the reuse of electronic components rather than through conventional software programming (Boya-Lara et al., 2026). This provides a concrete example of the broader pattern identified in the mapping rather than independent confirmation of it. The interpretation is supported theoretically by embodied learning perspectives, which associate conceptual development with physical interaction, perceptual feedback, and reflection on action (Abrahamson & Lindgren, 2022). From this perspective, the stronger representation of abstraction, generalization, and creative exploration in hardware-integrated platforms can be

understood because of students having to infer and modify system behavior directly through the physical artifact.

The level of openness adds a second layer to the interpretation of these platform differences. The results do not indicate that greater openness is inherently preferable, but rather that different levels of openness are better suited to different instructional purposes. More structured environments can provide useful scaffolding when students are developing foundational skills or working within tightly defined learning objectives, whereas more open platforms allow greater freedom to modify components, test alternatives, and construct different solutions. This interpretation is consistent with earlier work showing that the educational value of robotics depends strongly on task structure and the degree of learner autonomy allowed within the activity (Barak & Assal, 2016). More recent evidence from HE also shows growing interest in modular, DIY, and open-source platforms that expose students to hardware assembly, sensor integration, and hardware–software co-design rather than restricting interaction to closed configurations (Pereira et al., 2026). In practical terms, openness therefore functions in the framework as a pedagogical criterion that can be adjusted according to the amount of learner autonomy, experimentation, and design freedom intended in the course.

The distribution of 21st-century skills follows a similar pattern. Coding-centered platforms are more frequently associated with digital literacy and collaboration, while hybrid and hardware-integrated systems show broader representation of creativity, flexibility, initiative, and related competencies. Within the reviewed corpus, these tendencies appear across different instructional settings rather than being tied to a single platform. External evidence also supports the idea that robotics can contribute to several transversal competencies at the same time. For example, significant improvements in cognitive, autonomous, cooperation and flexibility, and innovation skills were reported following a university robotics intervention (Coşkun & Filiz, 2023), although these competencies were not equally related to robotic achievement. This distinction is important for the proposed framework because it reinforces that ER does not produce a uniform set of transversal outcomes; the competency profile depends on how the platform, the task, and the degree of learner autonomy are combined.

A notable finding of the analysis is the comparatively limited representation of ethical reasoning, intercultural collaboration, leadership, and other Life and Career skills. These competencies are not entirely absent from the reviewed studies, but they appear much less frequently than problem solving, creativity, collaboration, or digital literacy. The pattern therefore seems to reflect what is being explicitly targeted and assessed in ER activities rather than a technical limitation of the platforms themselves. A related conclusion was reached in a systematic review of educational human–robot interaction (Tekerek et al., 2026), which reported positive outcomes in learning, motivation, and

social interaction while also identifying weak pedagogical grounding and limited attention to ethical issues in many interventions. For the framework, this means that platform selection alone is insufficient when these less represented competencies are intended outcomes. They need to be deliberately incorporated through the instructional design, for example through team responsibilities, leadership roles, ethical or sustainability constraints, stakeholder-based problems, or reflective activities.

These findings are also relevant as ER expands into a wider range of HE contexts. Beyond engineering and computer science, recent studies have applied robotics in teacher education, sustainability-oriented learning, and other interdisciplinary settings. For example, robotics, visual programming, and introductory machine learning have been integrated into initial teacher education (Sáez-López et al., 2026), while hardware-centered robotics has been connected with CT and sustainability through WEEE reuse in a multidisciplinary university cohort (Boya-Lara et al., 2026). Robotics and AI have also begun to appear in areas further removed from conventional STEM education, including second-language teaching in HE (Dong & Wang, 2026). This broader use strengthens the relevance of selecting platforms according to intended competencies and learning processes rather than according to disciplinary tradition or platform popularity alone.

From a practical perspective, the value of the framework lies in translating these recurring patterns into a more informed basis for platform selection. If the intended outcomes emphasize structured algorithmic reasoning, debugging, and digital literacy, a coding-centered platform may provide the most direct fit. When the objectives combine programming with prototyping, simulation, system integration, and problem solving, a hybrid platform offers a broader range of interactions. If the emphasis is placed on physical reasoning, exploratory design, creativity, adaptability, and higher learner autonomy, hardware-integrated platforms may be more appropriate. The level of openness can then be adjusted according to the amount of scaffolding and design freedom required. In this way, the framework does not begin with the question of which robot is technically more advanced, but with which combination of platform characteristics is better aligned with the competencies that the instructor intends to prioritize.

These relationships should not be interpreted as fixed or deterministic. The same platform can support different outcomes depending on the instructional design, assessment strategy, disciplinary context, and activities assigned to students. The framework is therefore intended as a heuristic decision-support tool rather than as a predictive model. Its contribution is to make explicit the associations identified across the reviewed studies and to organize them in a form that can support pedagogical reasoning in HE. Rather than establishing a hierarchy among platforms, it provides a structured way to connect intended learning outcomes with interaction modality, openness, and the competency profiles most frequently associated with each type of ER platform.

Limitations and future research

This study is subject to several limitations that should be considered when interpreting its findings and applying the proposed framework in HE contexts. First, the synthesis is based on peer-reviewed journal articles indexed in major international databases and published in English. As a result, relevant research reported in other languages may not be fully represented, potentially limiting the visibility of regionally situated pedagogical practices and culturally specific approaches to ER in HE.

Second, the reviewed literature shows a notable concentration of studies conducted within engineering education and teacher training programs. This disciplinary focus may influence the observed associations between ER platforms and targeted competencies by emphasizing technical, computational, and problem-solving outcomes while providing less evidence from other areas of HE.

Third, the analytical classification relied on predefined coding criteria and a structured study-level coding record, but the procedure was not conducted as an independent parallel-coding exercise. Consequently, inter-rater reliability was not calculated, and some degree of researcher judgment remained unavoidable when classifying reported activities and outcomes across heterogeneous studies. To reduce this source of variability, the same operational definitions and decision rules were applied consistently across the complete corpus, with each coding decision linked to evidence extracted from the corresponding study. Future applications of the framework could strengthen this aspect through independent multi-coder replication and formal assessment of coding agreement. Fourth, the proposed framework is intended as an evidence-informed decision-support structure rather than as an empirically predictive model. It synthesizes recurring associations between platform interaction, openness, CT processes, and transversal skills, but these relationships should not be interpreted as causal. The framework has not yet been directly evaluated through controlled implementation across different instructional settings.

Future research should therefore examine the framework in a wider range of disciplinary, institutional, and cultural contexts. Empirical studies could test whether platform selections guided by the framework produce the competency profiles anticipated by the mapping and could compare different combinations of interaction modality and openness under equivalent instructional conditions. Qualitative and mixed-method approaches would also be useful for examining competencies that remain less visible in the current literature, particularly ethical reasoning, intercultural collaboration, leadership, and inclusion. In parallel, replication of the coding process by independent researchers would provide additional evidence regarding the robustness and reproducibility of the analytical structure.

Conclusion

This study proposed a competency-oriented framework that systematically links ER platforms with the development of CT and 21st-century skills in HE. By reviewing and analytically classifying thirty-two empirical studies, the framework clarifies how platform characteristics related to interaction modality and openness are associated with distinct learning processes and competency profiles. In doing so, it addresses a persistent gap in the literature between platform selection and pedagogically grounded competency development.

The synthesis revealed consistent patterns across platform types. Coding-centered systems were most frequently associated with structured algorithmic reasoning, digital literacy, and collaborative problem solving, whereas hybrid and hardware-integrated platforms were more strongly linked to creativity, adaptability, and systems-level thinking. These patterns underscore the importance of considering interaction modality and learner autonomy when selecting ER platforms to support specific educational goals in HE.

At the same time, the analysis highlighted a systematic underrepresentation of competencies related to ethical reasoning, intercultural communication, leadership, and inclusion. This finding suggests that the current use of ER in HE often prioritizes technical and cognitive outcomes, while broader developmental goals remain insufficiently addressed. The framework offers a means to make such gaps visible and to support more intentional pedagogical design when integrating robotics into higher education curricula.

Beyond its analytical contribution, the proposed framework provides a structured decision-support tool for instructors and curriculum designers seeking to align ER platforms with targeted CT processes and transversal skills in HE. Rather than functioning as a deterministic or predictive model, the framework is intended to guide pedagogical reasoning by making explicit the empirically grounded associations between platform interaction modalities, levels of openness, and competency development. By supporting more transparent and intentional instructional design decisions, the framework contributes to evidence-informed curriculum planning while remaining adaptable to diverse disciplinary, institutional, and cultural contexts.

Future research should apply and empirically evaluate the framework across a wider range of academic fields, methodological approaches, and institutional contexts. Qualitative and mixed-method studies could deepen understanding of how complex competencies such as ethical judgment, identity formation, and inclusive collaboration emerge in ER-based learning environments. Addressing gender dynamics and equity-oriented instructional strategies also represents an important direction for advancing socially responsive applications of ER in HE.

Overall, this work positions ER not merely as a technological enhancement, but as a pedagogical resource whose educational value depends on informed design choices. By articulating how different platforms support specific CT processes and transversal competencies, the proposed framework contributes a practical and theoretically grounded tool for preparing future-ready graduates in diverse higher education contexts.

Appendix A. Summary of the selected studies

This appendix provides a detailed overview of the thirty-two studies analyzed in this research. Each study is identified by a unique code (P1 to P32), along with information about the ER platform used, study context, instructional model, and key outcomes. These codes are used throughout the main text and tables to ensure traceability and consistency.

Table A

Summary of the selected papers. Each paper is assigned a code, which will be used for its identification and simplification of the analysis. Also, the type of hardware platform for ER is highlighted. AR (Augmented Reality), PjBL (Project-Based Learning), PBL (Problem-Based Learning), IBL (Inquiry-Based Learning). HoP (Hands-on Programming), TAM (Technology Acceptance Model), CS (Computer Science). Source: Author's own elaboration based on the reviewed studies.

Code	Paper name	ER platform	Curricular Model	Study Design	Participants
P1	Mobile Robot Lab Project to Introduce Engineering Students to Fault Diagnosis in Mechatronic Systems (Gomez-De-Gabriel et al., 2015)	LEGO Mindstorms NXT	Lab-Based Learning	Experimental	45 Engineering Students
P2	A Multidisciplinary Industrial Robot Approach for Teaching Mechatronics-Related Courses (Garduno-Aparicio et al., 2018)	Industrial robot prototype	PjBL	Quasi-Experimental	60 Students
P3	Educational Robot for Principles of Electrical Engineering (Rahnavard et al., 2018)	Custom educational robot	PBL	Experimental	35 First-Year Students

P4	Mona: an Affordable Open-Source Mobile Robot for Education and Research (Arvin et al., 2019)	Mona (low-cost, open-source robot)	IBL	Case Study	25 University Students
P5	Development of an Easy-to-Use Multi-Agent Platform for Teaching Mobile Robotics (Farias et al., 2019)	Custom-Built Multi-Agent Robotic Platform	Challenge-Based Learning	Quasi-Experimental	50 Students
P6	The Development of Computational Thinking in Student Teachers through an Intervention with Educational Robotics (Esteve-Mon et al., 2019)	Makey-Makey, Bee-Bots, mBots, Scratch, mBlock	Aligns with Technology, Pedagogy, and Content Knowledge with Computational Thinking (TPACK-CT) framework.	Design-Based Research (DBR)	116 Student Teachers
P7	What's in the Box: Design of an Open Didactic Robot Environment (Jokić et al., 2020)	PUMA 560 Robot (Custom-Built Didactic Environment)	Didactic Robotics	Case Study	24 University Students
P8	On Teaching Programming Fundamentals and Computational Thinking with Educational Robotics: A Didactic Experience with Pre-Service Teachers (Piedade et al., 2020)	mBot, LEGO Mindstorms NXT, Dash & Dot, Anprino, Codey Rocky, Zow	HoP	Experimental	26 Pre-Service Teachers
P9	Hands-on Learning In STEM: Revisiting Educational Robotics as a Learning Style Precursor (Budiyanto et al., 2020)	LEGO Mindstorms	Kolb's Learning Styles	Quasi-Experimental	50 STEM Students

P10	An Associational Study: Preschool Teachers' Acceptance and Self-Efficacy Towards Educational Robotics in a Pre-Service Teacher Training Program (Schina et al., 2021)	Blue-Bot	TAM	Survey-Based	78 Female, 38 Male
P11	Development of a Course Based on BEAM Robots to Enhance STEM Learning in Electrical, Electronic, and Mechanical Domains (Boya-Lara et al., 2022)	BEAM Robots (Custom-Built, Bioinspired Robotics Platform)	PjBL	Experimental	40 Engineering Students
P12	MEIoT 2D-CACSET: IoT Two-Dimensional Cartesian Coordinate System Educational Toolkit Align with Educational Mechatronics Framework (Carrasco-Navarro et al., 2022)	MEIoT 2D-CACSET (Custom-Built ER Platform with IoT and Mechatronics Integration)	IoT-Integrated Learning	Experimental	30 Mechatronics Students
P13	A Novel, Modular Robot for Educational Robotics Developed Using Action Research Evaluated on Technology Acceptance Model (Chatzopoulos et al., 2022)	Custom-Built Modular Educational Robot (Open-Source, Low-Cost)	Action Research in ER	Experimental	116 University Students
P14	A Project Based Learning Approach for Improving Students' Computational Thinking Skills (Bertacchini et al., 2022)	NAO Robot	PjBL	Experimental	30 Engineering Students

P15	Using STEM to Educate Engineers about Sustainability: A Case Study in Mechatronics Teaching and Building a Mobile Robot Using Upcycled and Recycled Materials (Chatzopoulos et al., 2023)	Mechatronics (Custom-Built Educational Mobile Robot)	Sustainability-Focused Learning	Experimental	40 Mechatronics Students
P16	The Promotion of Healthy Hydration Habits through Educational Robotics in University Students (De la Hoz et al., 2023)	Mind Designer Robot	Challenge-Based Learning	Quasi-Experimental	50 Health Science Students
P17	Development of Robotto Improve Learning of Programming Skills among Students (Muazu et al., 2023)	mBot	PBL	Experimental	40 CS Students
P18	Low-Cost Open-Source Robotic Platform for Education (Cehovin Zajc et al., 2023)	Custom-Built 3D-Printed Robotic Manipulator	3D-Printed Learning	Experimental	30 University Students
P19	Analysis of Gender Issues in Computational Thinking Approach in Science and Mathematics Learning in Higher Education (De la Hoz Serrano et al., 2024)	Mind Designer Robot	Experimental Gender Study	Experimental	116 STEM Students
P20	Bridging the gap: bioinspired robotics as catalyst for interdisciplinary education (Cayetano-Jiménez et al.,	Custom-Built Bioinspired Robotics	Bioinspired Learning	Experimental	24 Interdisciplinary Students

	2024)							
P21	Experimenting with computational thinking for knowledge transfer in engineering robotics (Chichekian et al., 2024)	Arduino-Based Mobile Robots (Custom-Built ER Platform)		Knowledge Transfer in Robotics		Experimental	30	Engineering Students
P22	A Holistic Approach to Use Educational Robots for Supporting Computer Science Courses (Mamatnabiyev et al., 2024)	FOSSBot (Open-Source, Custom-Built ER Platform)		Holistic Education	CS	Experimental	50	CS Students
P23	An Educational Robotics Approach to Drawing and Studying Central Trochoids at the University Level (Körei et al., 2024)	LEGO SPIKE Prime		Mathematical Visualization		Experimental	30	Mathematics Students
P24	An Innovative STEAM-Based Method for Teaching Cycloidal Curves in Engineering Higher Education (Szilágyi et al., 2024)	LEGO SPIKE Prime		STEAM-Based Education		Experimental	30	STEAM Students
P25	Evaluation of the Established IoT Smart Home Robot Teaching Module Based on Embedded Thematic-Approach Strategy (Yao et al., 2020)	Custom-Built IoT Smart Home Robot (Developed for the Study, Based on myRIO and LabVIEW)		Thematic-Approach Learning		Experimental	40	Engineering Students
P26	Improving Education in Developing Countries Using Robotic Platforms (Ponce et al., 2019)	Hexapod Phantom X AX Mark II (Custom-Built) and NAO Robot		Hands-on Learning	ER	Experimental	50	Students from Developing Countries
P27	Inquiry-Based	RoboGen		IBL		Experimental	40	AI &

	Learning With (Custom-Built, Open-Source ER Platform)				Robotics Students
	RoboGen: An Open-Source Software and Hardware Platform for Robotics and Artificial Intelligence (Auerbach et al., 2019)				
P28	Introducing a Robotic Hand to Support Lecture-Based Courses on Mechatronics Systems Design at the Undergraduate Level (Garcia et al., 2020)	Custom-Built Robotic Hand (Developed for the Study)	Embedded System Learning	Experimental	30 Mechatronics Students
P29	Learning Programming through Robots: The Effects of Educational Robotics on Pre-Service Teachers' Programming Comprehension and Motivation (Fegely & Tang, 2022)	LEGO Mindstorms EV3	Programming through ER	Experimental	30 Education Students
P30	The Effectiveness of Using Augmented Reality (AR) on Assembling and Exploring Educational Mobile Robot in Pedagogical Virtual Machine (PVM) (AlNajdi et al., 2020)	Buzz-Boards Mobile Robot (Custom-Built ER Platform)	AR-Based Learning	Experimental	40 AR & Robotics Students
P31	From E-Waste to Learning: A Tangible Approach to Computational Thinking and Sustainability Education (Boya-Lara et al., 2026)	BEAM Robots	Hardware-centered and sustainability-oriented learning	Mixed-method intervention study	30 university students
P32	Coding, Robots,	micro:bit,	Constructionist-	Quasi-	144 pre-service

Computational Concepts, and Machine Learning Using the micro:bit Card and the Maqueen and Nezha Kits. A Study in Initial Teacher Training (Sáez-López et al., 2026)	Maqueen and Nezha kits	based educational robotics	experimental	teachers (105 experimental, 39 control)
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Appendix B. Detailed coding of 21st-century skill alignment across ER platforms

This appendix presents the detailed coding of how each ER platform contributes to the development of 21st-century skills, based on the P21 framework. The table includes individual platforms and their reported alignment with three overarching categories: Learning and Innovation (4Cs), Digital Literacy, and Life and Career Skills.

Table B

Distribution of 21st-century skills identified across the thirty-two selected studies, organized by ER platform type. Source: Author's own elaboration based on the reviewed studies.

Code	Robotics Platform	21st-century Skill
P29	LEGO Mindstorms EV3	Communication & Digital Literacy Collaboration & Teamwork
P8	mBot, LEGO NXT, Dash & Dot	Communication & Digital Literacy Collaboration & Teamwork
P6	Makey-Makey, Bee-Bots, mBots	Communication & Digital Literacy Creativity & Innovation
P24	LEGO SPIKE Prime	Creativity & Innovation Flexibility & Adaptability
P1	LEGO Mindstorms NXT	Critical Thinking & Problem-Solving Collaboration & Teamwork
P14	NAO Robot	Critical Thinking & Problem-Solving Communication & Digital Literacy
P23	LEGO SPIKE Prime	Critical Thinking & Problem-Solving Communication & Digital Literacy
P9	LEGO Mindstorms	Critical Thinking & Problem-Solving Flexibility & Adaptability
P17	mBot	Critical Thinking & Problem-Solving Initiative & Self-Direction
P10	Blue-Bot	Social & Cross-Cultural Skills Communication & Digital Literacy
P16	Mind Designer Robot	Social & Cross-Cultural Skills Communication & Digital Literacy
P19	Mind Designer Robot	Social & Cross-Cultural Skills Critical Thinking & Problem Solving
P30	Buzz-Boards Mobile Robot	Information, Media, & Technology Literacy Critical Thinking & Problem Solving

P5	Custom Multi-Agent Platform	Collaboration & Teamwork Critical Thinking & Problem Solving
P4	Mona	Creativity & Innovation Collaboration & Teamwork
P27	RoboGen	Creativity & Innovation Critical Thinking & Problem Solving
P31	BEAM Robots	Creativity & Innovation Critical Thinking & Problem Solving
P11	BEAM Robots	Creativity & Innovation Flexibility & Adaptability
P18	Custom 3D-Printed Robot	Creativity & Innovation Information, Media, & Technology Literacy
P32	micro:bit, Maqueen and Nezha kits	Creativity & Innovation Information, Media, & Technology Literacy
P28	Custom Robotic Hand	Creativity & Innovation Initiative & Self-Direction
P20	Custom Bioinspired Robot	Creativity & Innovation Leadership & Responsibility
P13	Custom Modular Robot	Creativity & Innovation Productivity & Accountability
P21	Arduino Mobile Robots	Critical Thinking & Problem-Solving Collaboration & Teamwork
P12	MEIoT 2D-CACSET	Information, Media, & Technology Literacy Critical Thinking & Problem Solving
P3	Custom Educational Robot	Information, Media, & Technology Literacy Critical Thinking & Problem Solving
P22	FOSSBot	Information, Media, & Technology Literacy Productivity & Accountability
P25	Custom IoT Smart Home Robot	Information, Media, & Technology Literacy Productivity & Accountability
P15	Mechatron	Leadership & Responsibility Flexibility & Adaptability
P7	PUMA 560 Robot	Leadership & Responsibility Information, Media, & Technology Literacy
P2	Industrial Robot Prototype	Leadership & Responsibility Productivity & Accountability
P26	Hexapod Phantom X, NAO	Leadership & Responsibility Social & Cross-Cultural Skills

Abbreviations

ER: Educational Robotics; CT: Computational Thinking; HE: Higher Education; P21: Partnership for 21st Century Learning; STEM: Science, Technology, Engineering, and Mathematics; PjBL: Project-Based Learning; PBL: Problem-Based Learning; IBL: Inquiry-Based Learning; DBR: Design-Based Research; AI: Artificial Intelligence; IoT: Internet of Things.

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Author's contributions

The author conceived the study, conducted the literature review and analysis, developed the framework, interpreted the results, and wrote and revised the manuscript.

Author's information

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Availability of data and materials

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Competing interests

The author declares that there are no competing interests.

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