frontiers in Education

TYPE Original Research
PUBLISHED 27 February 2026
DOI 10.3389/feduc.2026.1778718

OPEN ACCESS

EDITED BY
Michael Cassidy,
TERC, United States

REVIEWED BY
Fadip Nannim,
University of the Free State, South Africa
Mashite Tshidi,
University of Pretoria, South Africa

*CORRESPONDENCE
Jose-Manuel Sáez López
jmsaezlopez@edu.uned.es

RECEIVED 31 December 2025
REVISED 05 February 2026
ACCEPTED 16 February 2026
PUBLISHED 27 February 2026

CITATION
Redondo-Duarte S, Pattier D, Neubauer A and Sáez López J-M (2026) Machine learning and educational robotics, an implementation in initial university teacher training and for practicing teachers in primary education.
Front. Educ. 11:1778718.
doi: 10.3389/feduc.2026.1778718

Machine learning and educational robotics, an implementation in initial university teacher training and for practicing teachers in primary education

Sara Redondo-Duarte[1], Daniel Pattier[2], Adrian Neubauer[1] and Jose-Manuel Sáez López[1]*

[1]Department of Didactics, School Organization and Special Didactics, National University of Distance Education (UNED), Madrid, Spain, [2]Educational Studies, Universidad Complutense de Madrid, Madrid, Spain

Programming and robotics-based training programs have been shown to enhance computational thinking and self-efficacy, yet limited attention has been paid to preparing future teachers to effectively implement these methodologies in educational practice. This study analyses the impact of an educational intervention based on visual block programming, educational robotics, and machine learning on the initial training of pre-service teachers and in-service primary school teachers. A quasi-experimental design was employed. The sample consisted of 170 participants: 83 students enrolled in a Primary Education degree program and 87 in-service primary school teachers. The instructional procedure was implemented through hands-on activities with micro:bit, Maqueen robots, and introductory machine learning concepts. Data were collected using a coding, robotics, and machine learning knowledge test, along with several validated Likert-type scales to assess attitudes toward the curricular integration of these technologies. For the first dimension, Student's t-tests and linear regression analyses were conducted, while correlation analyses and nonparametric tests were applied to the second dimension. The findings revealed significant improvements in the acquisition of basic computational concepts (sequences, loops, and conditionals) and in the understanding of machine learning, with university students outperforming practicing teachers. Comparative tests indicated a greater self-perception of technological competence among university students, particularly in block-based programming and the use of game engines for educational purposes. The results suggest that the structured integration of robotics and machine learning appears to constitute a viable and effective strategy for enhancing teacher training, promoting active methodologies, and fostering an interdisciplinary approach in primary education.

KEYWORDS
educational technology, higher education, machine learning, primary education, robotics

Introduction

Rapid advances in digital technologies have driven the need to integrate new skills into educational processes, including computational thinking, programming, educational robotics, and, more recently, artificial intelligence (AI) and machine learning (ML). Computational thinking, understood as a set of skills for formulating and solving problems through structured and logical processes, has become a key competence in contemporary education. In parallel, the expansion of AI-based technologies has highlighted the importance of fostering AI and ML literacy among both students and teachers, including an understanding of data, models, and algorithmic decision-making, as well as their ethical and social implications.

In this context, teacher education plays a crucial role. Initial teacher training in higher education strongly influences future teachers' beliefs, attitudes, and technological competencies, which in turn affect their willingness and ability to integrate emerging technologies into classroom practice. However, without adequate training, teachers may face difficulties in implementing programming, robotics, and ML-based activities or may resist their curricular integration. This situation underscores the need to analyze educational interventions that combine these technologies within teacher education programs.

Related studies

Empirical research has shown that visual block programming and educational robotics positively impact students' conceptual understanding, computational thinking, motivation, and engagement across educational levels (Chevalier et al., 2022; Wu and Su, 2021; Wong, 2024). In primary education, robotics has been widely associated with STEM learning, particularly mathematics and science, while also supporting interdisciplinary approaches and inclusive practices.

The implementation of robotics and ML in primary education

Schools and educational systems are permeable to change and emerging social needs. For this reason, there has been an increase in the use of robotics and ML in primary school classrooms internationally in recent years. So much so that Sperling et al. (2022), following actor-network theory, point out that complex relationships develop in schools through the interaction between human and non-human actors. In fact, they warn that the latter play a crucial role in teacher performance, curriculum development, and routines, among other aspects.

ML has been used in various ways at this educational level. One trend in academic literature is the use of this technology to predict academic outcomes (Lillo et al., 2024), early school leaving (Musso et al., 2020), and student repetition rates (Constante Amores et al., 2024). Other authors (Alonso-Secades et al., 2022) have sought to improve the effectiveness of education systems in developing countries to provide evidence that could support decision-making from the policy level down to the classroom. Sperling et al. (2022) also used ML to reinforce mathematics learning in Swedish schools. Meanwhile, Villegas-Ch et al. (2024) developed an ML system that provided students with real-time visual and verbal feedback on their writing, which allowed early identification of difficulties (e.g., pressure, consistency, alignment) in writing in students aged 7–11 years.

From another perspective, educational robotics is characterized as a manipulative (Schina et al., 2025), accessible, and effective resource (Moreno-Palma et al., 2025). Its use is usually associated primarily with STEM subjects, as it has proven effective for learning mathematics and fostering students' predisposition toward this and similar disciplines (Ruiz-Ortiz, 2023; Wu and Su, 2021). However, it is important to point out that, alongside an appropriate approach from the teacher, it facilitates interdisciplinarity (Wong, 2024), as demonstrated in an educational experience developed in the Azores (Portugal) by Santos et al. (2023). Another reason for its widespread use is its wide range of advantages, among which three stand out:

1. It fosters the development of computational thinking, scientific thinking, critical thinking, problem-solving, abstraction skills, and creativity. All of these, combined with the promotion of entrepreneurship among students (Vera-Sagredo et al., 2024), are essential skills for facing the challenges of the 21st century and for effectively entering the workforce.
2. It stimulates creativity and motivation (Ruiz-Ortiz, 2023), communication, and cooperation among students (Schina et al., 2025).
3. Finally, educational robotics also contributes to democratizing access to technology (Gavrilas et al., 2025), thus preventing and combating the digital divide.

Despite its positive effects, Vera-Sagredo et al. (2024) highlight the ongoing debate within the educational community regarding how to integrate robotics as part of the official curriculum or through extracurricular activities. Franco Hidalgo-Chacón et al. (2022) state that robotics is one of the most popular cognitive extracurricular activities among students, and these findings align with those of Purković et al. (2022), who indicate that Croatian students support the inclusion of robotics in their country's curriculum.

It is also worth highlighting some of the educational robotics initiatives that have been developed internationally in primary education. According to Moreno-Palma et al. (2025), the most widely used robotics kits are Bee-Bot, LEGO, and mBot. For example, Bee-Bot was used by Caballero González and García-Valcárcel Muñoz-Repiso (2020) in Spain, while Demetroulis et al. (2023) used the LEGO WeDo 2 kit. Experiences with other materials can also be identified, such as the application of CreaCube with primary education students in France (Schina et al., 2025). Finally, Santos et al. (2023) made various materials available to students and teachers, and they concluded that Botley was more widely used than Bubble due to its usability without requiring programming knowledge.

Training appears to be the main difficulty teachers face in implementing educational robotics in their classrooms. There is broad consensus in the academic literature regarding the lack of initial and ongoing teacher training in robotics (Moreno-Palma et al., 2025; Santos et al., 2023; Vera-Sagredo et al., 2024), which contrasts with the fact that teachers demonstrate a positive attitude, interest, and high motivation to integrate robotics into their classrooms. It is important to note that there is also a correlation between the predisposition to use robotics and teachers' digital self-esteem (Gavrilas et al., 2024).

There are also other limitations that hinder the application of robotics in educational centers, such as the lack of resources and the excessive preparation time required from teachers (Gavrilas et al., 2025). Beyond these barriers, Santos et al. (2023) offer four general guidelines for implementing the use of educational robotics: (a) ensure continuity in these experiences—that is, ensure that they are not an anecdotal and sporadic activity; (b) their application should be gradual and progressive; (c) it is important to acquire and use diverse materials; and, finally, (d) primarily acquire materials that require a lower degree of programming knowledge to introduce students and teachers to this field.

Robotics, coding, and ML in initial teacher training in higher education

The literature on higher education emphasizes that initial teacher training plays a crucial role in developing computational thinking and preparing future teachers to integrate programming, robotics, and, progressively, ML into their educational practices. Various studies focused on pre-service teachers have shown that experiences with programming and robotics provide suitable environments for fostering digital skills, positive attitudes, and a pedagogical understanding linked to computational thinking. Along these lines, Esteve-Mon et al. (2019) analyzed an intervention using educational robots that was designed using a design-based research methodology to promote computational thinking in student teachers. Their proposal combines unplugged, playing, making, and remixing activities, ultimately demonstrating the potential of incorporating hands-on robotics experiences into initial teacher training as a way to strengthen their digital teaching competence. Similarly, Villalustre and Cueli (2023) assessed the computational thinking of 164 prospective teachers using the computational thinking test (CTT); they identified significant differences based on gender and prior experience in robotics programming. Their results showed that men scored higher than women, and that prior experience in robotics programming is a determining factor in the level of development of computational thinking, thus providing relevant information for tailoring training programs to the diverse profiles of university students.

In addition to technical skills, the literature highlights the importance of motivational, affective, and cognitive factors in the disposition of pre-service teachers toward programming, AI, and ML. From an expectancy-value theory perspective, Weber et al. (2022) show that expectations of success and emotional costs influence the intention to teach computational thinking; university-level interventions can strengthen these expectations and values. Similarly, de Vink et al. (2023) demonstrate that peer-teaching experiences in higher education can improve students' motivation, perceptions, and confidence in contexts related to computational thinking.

The specific field of ML has also begun to receive attention in the context of initial teacher training. Laru et al. (2025) provide relevant empirical evidence by analysing the background of AI literacy in prospective teachers. They found that elements such as knowledge of the ML process, attitudes toward AI, and perceived ability to use AI-powered applications are central components of this literacy. They emphasize that understanding the ML workflow (including data preparation, model training, and interpretation of algorithmic outputs) predicts prospective teachers' ability to critically evaluate AI-based technologies and use them in an informed manner. Positive attitudes toward AI are also associated with higher levels of ML literacy, thus underscoring the importance of addressing both conceptual and affective/attitudinal aspects in university teacher training.

Along these same lines, Daher (2025) points out that initial teacher training must explicitly incorporate AI literacy; future teachers need a critical and ethical understanding of how AI-based technologies work in addition to technical skills. Daher warns that developing the ability to interpret and evaluate systems such as ML models is essential to avoid inequalities and ensure responsible educational integration, thus broadening the training focus beyond programming and robotics toward a comprehensive view of AI in education.

In parallel, training programs have been developed explicitly aimed at developing computational thinking in pre-service teachers. For example, Uzumcu and Bay (2020) propose a program based on interest-driven creator theory, composed of unplugged activities and computerized and robotic tasks, with the objective of improving the computational skills of pre-service teachers. In a broader context, Tsai et al. (2023) show that a programming course based on the GAME model (which integrates gamification, assessment, modeling, and inquiry) improves self-efficacy and performance in basic programming concepts among university students without a prior technological background, providing useful evidence for designing accessible and progressive learning experiences. On the other hand, studies focused on compulsory education, such as those by AUTHOR, demonstrate the potential of visual block programming and robotics to foster conceptual understanding, active student participation, and the development of computational thinking. Although situated in school contexts, their conclusions reinforce the need for future teachers to know and understand these methodologies to apply them appropriately in their professional practice.

These studies converge on the idea that initial teacher training in higher education should consider three interrelated axes. The first is the incorporation of practical proposals with educational programming and robotics, allowing future teachers to experience computational thinking and understand its formative potential (Esteve-Mon et al., 2019; Uzumcu and Bay, 2020; Villalustre and Cueli, 2023). The second is designing interventions that address motivational, affective, and cognitive-attitudinal dimensions, while considering expectations, values, perceptions, self-efficacy, and emotions associated with computational thinking and ML (de Vink et al., 2023; Laru et al., 2025; Weber et al., 2022). Finally, the third is the articulation of these experiences with curricular frameworks and empirical results in compulsory education, such that future teachers can establish links between programming and robotics practices and the learning of specific content in various areas of knowledge (Sáez-López et al., 2021; Wong, 2024).

Theoretical framework

This study is grounded primarily in Papert's Constructionism, developed by Seymour Papert in the late 20th century (Papert, 1980). Constructionism builds upon constructivist learning theories and posits that learners construct knowledge most effectively when they actively create tangible artifacts that can be shared, reflected upon, and revised. According to this theory, programming and interaction with technological artifacts enable learners to externalize their thinking, engage in problem-solving, and develop deeper conceptual understanding.

Computational thinking, conceptualized as a set of skills for formulating, decomposing, and solving problems in a structured way, has become a central component of contemporary curricula. Its foundations can be traced back to Papert's (1980) constructionist approach, which argued that interaction with programming languages and technological artifacts allows students to actively and meaningfully construct knowledge.

Key tenets of constructionism include learning through making, the importance of meaningful contexts, and the role of technology as a cognitive tool rather than a mere instructional aid. These principles are directly applicable to educational robotics, block-based programming, and ML activities, where learners design programs, manipulate physical devices, and iteratively refine their solutions.

In the context of this study, constructionism provides the pedagogical foundation for the hands-on intervention implemented with micro:bit, robotics kits, and introductory ML tools. By engaging both pre-service and in-service teachers in active creation processes, the intervention aligns with constructionist principles and supports the development of computational thinking, technological competence, and reflective pedagogical practices.

Aims

The overall objective of this study is to analyze the impact of an intervention focused on the acquisition of computational concepts, robotics, and ML on prospective and practicing primary school teachers. The specific objectives are:

- To assess participants' knowledge of fundamental computational concepts (sequences, loops, conditionals, and sensors) and ML using the coding, robotics and machine learning test (CRMT) instrument;
- To examine variations in attitudes toward integrating programming, ML, and robotics into the primary education curriculum using validated Likert-type scales; and
- To determine the feasibility of implementing robotics-based learning activities within initial teacher training programs and in schools, considering participant feedback and the results of the implementation process.

Methods

Design of the study

As randomization in the selection and assignment of participants to the groups could not be ensured, the study adopts a quasi-experimental design with a control group and an experimental group in both dimensions (Pérez Juste, 2006). Although such designs involve lower internal validity than true experimental designs, their applicability to naturally occurring groups makes them widely used in educational research (Tejedor, 2000).

Participants

The study was conducted in seven primary schools and at a Spanish public university within the primary education degree program. The study population consisted of undergraduate pre-service teachers enrolled in the first year of a Primary Education degree program at a public university and in-service primary school teachers working in public schools.

A non-probabilistic, purposive sample of 170 participants was used, including 83 first-year undergraduate pre-service teachers and 87 in-service primary school teachers from the city of Madrid. Participants were assigned based on the availability of educational centers and existing class groups rather than through random selection.

The undergraduate pre-service teacher group was composed of 92.8% female and 7.2% male participants, reflecting the gender imbalance typically observed in primary teacher education programs. Their mean age was 19.35 years, and the group was highly homogeneous in terms of age and educational background, as all participants were in their first year of university studies. The group of in-service primary school teachers consisted of 48.3% female and 51.7% male teachers, representing a more balanced gender distribution.

Instrumentations

Data were collected using a coding, robotics, and machine learning knowledge test, along with several validated Likert-type scales to assess attitudes toward the curricular integration of these technologies. The instrument was structured into two dimensions, addressing cognitive and attitudinal aspects of teacher training.

Dimension 1 encompasses knowledge of ML, computational concepts, and robotics. The content validity of the CRMT instrument was evaluated considering the criteria of relevance and appropriateness by 11 expert judges, obtaining Aiken's V coefficient values ($V = S/[n(c-1)]$) greater than 0.75 for all items. Likewise, Cronbach's alpha reliability coefficients exceeded 0.80, thus indicating an acceptable level of internal consistency (Hair et al., 1998).

Dimension 2, ML and educational robotics in teacher training, focused on the knowledge and understanding of practicing teachers and university students in the primary education degree program regarding computational concepts, educational robotics, and ML. The attitudes and perceptions of these groups toward the use of educational robotics and block programming in teacher training were analyzed using three Likert-type scales. Content validity was assessed qualitatively by 11 expert judges, considering the criteria of relevance and suitability of the instrument. Aiken's V coefficient ($V = S/[n(c-1)]$) values greater than 0.75 were obtained for all items. Cronbach's alpha reliability coefficients were 0.918 for teachers and 0.911 for university students, exceeding 0.80, which indicates an acceptable level of internal consistency (Cronbach, 1951).

Instructional procedure (study procedure)

The project was carried out during the 2024–2025 academic year in seven schools, training practicing primary school teachers. The four sessions (see Appendix) focused on building a series of projects related to the micro:bit using the Maqueen kit. Temperature and light sensors were used with the micro:bit, along with the Visual Basic block-based programming environment using "micro:bit MakeCode" (see Figure 1). Participants programmed their projects and worked with basic computational concepts (sequences, loops, conditionals) using devices and robots.

Given the quasi-experimental nature of the study and the absence of random assignment, several strategies were implemented to control for potential extraneous variables that could threaten internal validity.

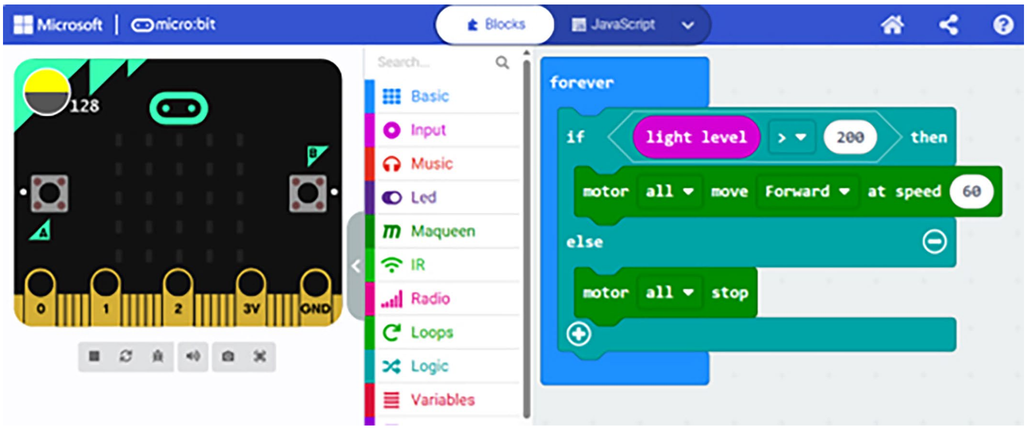

FIGURE 1
Visual block programming: light car in micro:bit MakeCode.

First, both groups (undergraduate pre-service teachers and in-service primary school teachers) followed the same instructional intervention, with identical content, materials, duration, sequencing of activities, and learning objectives, thus minimizing instructional and procedural variability. Second, data collection instruments were standardized, validated, and administered under comparable conditions to reduce measurement bias. Although causal inference remains limited due to the use of naturally occurring groups, the combination of design consistency and statistical control contributes to reducing the influence of extraneous variables and enhances the interpretability of the results.

The same implementation and activities were carried out at the University of La Laguna with undergraduate students in the primary education teaching degree program. In the sessions, participants created basic programs using the micro:bit (dice, temperature sensor, light sensor), understanding block programming elements, basic computational concepts, sensors, and actuators. The Maqueen kit was also used with the micro:bit to build a robot that moves (actuators/motors) when light levels are high, simulating a solar car (Figures 1, 2). As seen in the conditional statement, if light levels are low, the motors stop.

Method of data analysis

Data analysis was conducted using IBM SPSS Statistics. Prior to inferential analyses, data were screened for missing values, outliers, and violations of statistical assumptions. Descriptive statistics (means, standard deviations, frequencies, and percentages) were calculated to summarize participants' demographic characteristics, test scores, and questionnaire responses (Table 1).

To analyze differences in conceptual knowledge between undergraduate pre-service teachers and in-service primary school teachers, an independent-samples Student's *t*-test was applied to the scores of the Coding, Robotics and Machine Learning Test (CRMT). Levene's test was used to assess the homogeneity of variances; when $p > 0.05$, equality of variances was assumed. Statistical significance was set at $p < 0.05$, and Cohen's d was calculated to estimate effect size, interpreted as small (0.20), medium (0.50), or large (0.80).

To examine predictors of CRMT performance, a multiple linear regression analysis was conducted, including group membership (pre-service vs. in-service teachers), gender, and teaching experience as independent variables. The model was evaluated using the *F*-test, R^2 and adjusted R^2, and standardized beta coefficients. Assumptions of normality, linearity, multicollinearity (tolerance and VIF), and independence of errors (Durbin–Watson statistic) were examined.

FIGURE 2
Maqueen kit with micro:bit.

TABLE 1 Indicators and instruments used in each dimension of the study.

Dimensions	Indicators	Instruments
1. Knowledge of ML, computational concepts, and robotics	ML Sequence Iteration (looping) Conditional statements Sensors	Coding, robotics, and ML test (CRMT) Descriptive analysis Student's *t*-test Linear regression
2. ML and educational robotics in teacher training	Visual block programming and robotics Computational concepts Application in curricular areas	Scale Correlations Descriptive analysis Mann–Whitney *U* Test

ML, machine learning.

Regression coefficients were considered statistically significant at $p < 0.05$.

For the analysis of Likert-scale questionnaire data, non-parametric Mann–Whitney *U* tests were used to compare groups due to the ordinal nature of the data. A conservative significance level of $p < 0.01$ was adopted, and effect sizes were calculated using r, interpreted as small (0.10), medium (0.30), or large (0.50). Relationships between variables were explored using Spearman's rank-order correlation coefficients, with only correlations of $\rho \geq 0.50$ and $p < 0.01$ reported.

TABLE 2 Results of the linear regression for the prediction of test_CRMT ($N = 170$).

Predictor	B	SE B	β	t	p	95% CI
Constant	3.836	0.979	—	3.917	<0.001	[1.903, 5.769]
Teaching experience	0.025	0.026	0.118	0.948	0.345	[−0.027, 0.076]
Gender	0.199	0.317	0.054	0.630	0.530	[−0.426, 0.824]
Group (teachers vs. students)	1.132	0.438	0.337	2.584	0.011	[0.267, 1.997]

Dependent variable: test_CRMT. Coding: Group_M_AL (1 = teachers, 2 = students); $R = 0.233$—$R^2 = 0.054$—adjusted $R^2 = 0.037$ $F(3,166) = 3.19$, $p = 0.025$.

Results

Dimension 1: knowledge of ML, computational concepts, and robotics

The CRMT was administered to assess knowledge of ML, coding, and robotics; the average scores of university students and practicing teachers who had worked with the described training implementation were then compared. The average score for university students was 6.31 out of 10, while the teachers obtained an average of 5.59 out of 10. Statistical comparison allowed us to verify whether there were significant improvements between the two groups after the intervention. The scores on the 10-item test emphasize the importance of an educational design that includes visual programming languages, as well as the implementation of educational robotics and ML to foster the acquisition of computational concepts. Given that the significance value of Levene's test is $p = 0.053$ (>0.05), equality of variances is assumed. The Student's *t*-test revealed statistically significant differences between the groups ($p = 0.002$), with higher scores in the university student group. The effect size was small to medium, with a Cohen's *d* value of 0.441.

Linear regression

Multiple linear regression was performed to predict test_CRMT scores based on teaching experience (exp_docente), gender (Genero), and group membership (1 = Teachers; 2 = Students). After excluding cases with missing data, the analysis was performed on $N = 170$. The pooled model was found to be significant, $F(3,166) = 3.19$, $p = 0.025$, and explained 5.4% of the variance in test_CRMT ($R^2 = 0.054$; adjusted $R^2 = 0.037$). Although the overall effect size was small, the model achieved statistical significance (see Table 2). Of the included predictors, only the group (teachers vs. students) variable was significant ($B = 1.132$, $\beta = 0.337$, $t = 2.58$, $p = 0.011$), which indicates that, controlling for experience and gender, students scored on average 1.13 points higher on the CRMT than teachers. The coefficients for teaching experience ($B = 0.025$, $p = 0.345$) and gender ($B = 0.199$, $p = 0.530$) did not reach statistical significance in the model (see Table 2).

Standardized residuals remained within the acceptable range (−2.82 to 2.29), and no extreme outliers were detected that would compromise the assumptions. Collinearity tests (tolerance and VIF) showed no serious problems: maximum VIF ~ 2.99. The Durbin–Watson statistic = 0.82 suggests some autocorrelation in residuals that should be considered in future models (e.g., hierarchical modeling or inclusion of covariates that capture temporal or group structure). Thus, belonging to the student group (vs. teachers) predicted a higher score on test_CRMT with a moderate standardized effect ($\beta = 0.337$), while neither teaching experience nor gender explained relevant added variance in the presence of the group effect.

Dimension 2: ML and educational robotics in teacher training

On average, university students scored higher than teachers on most items, particularly in Sections 1 and 2 of the questionnaire, which relate to knowledge of ML and programming, and computational concepts (Table 3). In Section 1, these differences were observed in programming knowledge (1.1), knowledge of ML (1.2), and perceived importance of ML (1.3). Furthermore, students achieved higher scores in block programming (1.5), with a high standard deviation in both groups, which reflects the significant heterogeneity in experience with this type of tool, especially among practicing teachers. In basic computational concepts, this trend is maintained in knowledge of sequences (2.1), loops (2.2), and conditionals (2.3); we can highlight, here, the case of loops, where, in addition to a higher mean, students showed less dispersion (SD = 0.75) than the teachers (SD = 1.02), which indicates greater homogeneity in the mastery of this concept among future teachers.

Regarding curriculum application, students achieved higher scores in robotics learning (3.1), block-based programming content (3.2), and art and music (3.6), while teachers obtained a slightly higher average in natural sciences (3.4). Finally, the assessment of the inclusive potential of programming (3.9) was high in both groups, although students showed a higher average and less dispersion, which demonstrates greater agreement in the perception of programming as a resource for educational inclusion.

Tables 4, 5 show the strongest correlations ($\rho \geq 0.50$; $p < 0.01$) between the questionnaire variables for university students and practicing teachers. In both groups, a high degree of consistency was observed in basic programming knowledge, with very strong associations between sequences, loops, and conditionals (e.g., in teachers: $\rho = 0.781$, $\rho = 0.697$, and $\rho = 0.819$; in students: $\rho = 0.760$, $\rho = 0.696$, and $\rho = 0.628$). Likewise, in both samples, strong associations were identified between educational innovation based on programming and robotics and learning with robotics, as well as with its application in curricular areas, especially in the natural sciences and social studies.

Among teachers, these relationships show high values between educational innovation and mathematical and scientific learning (e.g.,

TABLE 3 Descriptive statistics of the questionnaire items for practicing teachers (n = 87) and university students (n = 83).

Items	Teachers		Students	
	Media	DT	Media	DT
1.1. Programming knowledge	2.71	0.85	3.12	0.90
1.2. I know what machine learning is	2.36	0.95	2.81	0.88
1.3. Machine learning is important	2.82	0.76	3.19	0.74
1.4. Creativity	3.47	0.70	3.47	0.69
1.5. I have worked with block programming	1.98	1.03	2.47	0.95
2.1. I know what a sequence is in programming	3.10	0.86	3.25	0.79
2.2. I know what a loop is in programming	3.01	1.02	3.33	0.75
2.3. I know what a conditional is in programming	2.69	1.14	3.07	0.82
2.4. Educational innovation	3.32	0.80	3.43	0.67
2.5. I know how to program game engines	2.25	1.01	2.87	0.79
3.1. Learning with robotics	3.06	0.83	3.28	0.72
3.2. Content with visual block programming	3.07	0.77	3.41	0.64
3.3. Mathematical learning	3.40	0.75	3.49	0.67
3.4. Natural sciences	3.13	0.79	3.01	0.83
3.5. Social studies	3.09	0.80	3.16	0.79
3.6. Art and music	3.00	0.84	3.39	0.69
3.7. Interest in coding	3.07	0.82	3.20	0.79
3.8. Active participation	3.49	0.68	3.47	0.72
3.9. Students with special educational needs	3.07	0.79	3.45	0.72

TABLE 4 Significant spearman correlations between questionnaire variables in practicing teachers (n = 87).

Related variables	ρ	p
2.1–2.2 I know what a sequence is – I know what a loop is	0.781**	<0.001
2.1–2.3 I know what a sequence is – I know what a conditional is	0.697**	<0.001
2.2–2.3 I know what a loop is – I know what a conditional is	0.819**	<0.001
1.4–3.3 Creativity – Mathematical learning	0.595**	<0.001
2.4–3.1 Educational innovation – Learning with robotics	0.556**	<0.001
2.4–3.3 Educational innovation – Mathematical learning	0.663**	<0.001
2.4–3.4 Educational innovation – Natural sciences	0.575**	<0.001
2.4–3.5 Educational innovation – Social studies	0.567**	<0.001
3.1–3.4 Learning with robotics – Natural sciences	0.724**	<0.001
3.1–3.5 Learning with robotics – Social studies	0.731**	<0.001
3.1–3.6 Learning with robotics – Art and music	0.595**	<0.001
3.1–3.7 Learning with robotics – Interest in coding	0.529**	<0.001
3.1–3.9 Learning with robotics – Support for students with special educational needs	0.556**	<0.001
3.7–3.9 Interest through coding – Attention to students with special educational needs	0.604**	<0.001

**p < 0.01. Only correlations with $\rho \geq 0.50$ are presented.

ρ = 0.663 with mathematics and ρ = 0.575 with natural sciences), as well as with social studies (ρ = 0.567). Among students, block-based programming learning is strongly associated with content work in primary education (ρ = 0.558). In the motivational and inclusive sphere, strong relationships are observed between interest in coding, active student participation, and attention to students with special educational needs, both among teachers (ρ = 0.604 between interest and attention to special educational needs; ρ = 0.518 between interest and participation) and students (ρ = 0.579 between interest and participation; ρ = 0.533 between participation and attention to special educational needs). The pattern of correlations among practicing teachers is more consistent between educational innovation based on programming and robotics and the various curricular areas, while among university students, the associations between block-based

TABLE 5 Significant spearman correlations between questionnaire variables in university students pursuing the primary education degree (n = 83).

Related variables	ρ	p
2.1–2.2 I know what a sequence is – I know what a loop is	0.760**	<0.001
2.1–2.3 I know what a sequence is – I know what a conditional is	0.696**	<0.001
2.2–2.3 I know what a loop is – I know what a conditional is	0.628**	<0.001
2.4–2.6 Educational innovation – Game engines are possible in practice	0.604**	<0.001
3.1–3.2 Learning with block-based programming – Primary school content with visual block-based programming	0.558**	<0.001
3.1–3.4 Learning with robotics – Natural Sciences	0.498**	<0.001
3.1–3.7 Learning with robotics – Interest in coding	0.546**	<0.001
3.7–3.8 Interest in coding – Active participation	0.579**	<0.001
3.8–3.9 Active participation – Support for students with special educational needs	0.533**	<0.001
3.7–3.9 Interest in coding – Support for students with special educational needs	0.525**	<0.001

**$p < 0.01$. Only correlations with $\rho \geq 0.50$ are presented.

TABLE 6 Differences between teachers (n = 87) and university students (n = 83) in programming and robotics variables (Mann–Whitney U).

Variable	Range teachers	Range students	U	Z	p	r
1.1. Programming knowledge	74.19	97.36	2,626.50	−3.262	0.001**	0.25
1.2. I know what machine learning is	75.13	96.37	2,708.00	−2.951	0.003**	0.23
1.3. Machine learning is important	74.61	96.92	2,663.00	−3.208	0.001**	0.25
1.5. I have worked with block programming	73.99	97.56	2,609.50	−3.247	0.001**	0.25
2.5. I know how to program game engines	71.43	100.25	2,386.50	−4.001	<0.001**	0.31
3.2. Block programming in primary education	75.63	95.84	2,752.00	−2.926	0.003**	0.22
3.6. Art and music	74.68	96.84	2,669.50	−3.182	0.001**	0.24
3.9. Students with special educational needs	74.13	97.42	2,621.00	−3.349	<0.001**	0.26

**$p < 0.01$.

programming, content teaching in primary education, and student engagement are particularly prominent.

Regarding curricular areas, both groups demonstrate a significant association between social studies and art education, which is explainable by their cultural, historical, and humanistic connections. Likewise, the relationship between the natural sciences and social studies is evident, highlighting an interrelationship between the different areas of knowledge and allowing for the interpretation of an interdisciplinary and interconnected educational approach. Methodological approaches such as holistic approaches, project-based learning, and integrated subject areas could thus facilitate the incorporation of technological elements from a cross-curricular perspective. Finally, it is observed that there is a relationship between educational innovation and the use of game engines among university students, a relationship not found in the group of practicing teachers.

The Mann–Whitney U test showed statistically significant differences between teachers and university students in 10 of the variables analyzed (Table 6). From a rigorous and conservative perspective, a significance level of 0.01 ($p < 0.01$) was adopted. In all cases, the average ranks were higher in the university student group, which reflects a greater self-perception of technological competence and the educational potential of programming and robotics in this group. The greatest differences were observed in programming game engines for educational purposes ($U = 2386.50$), with a medium effect size ($r = 0.31$). Significant differences were also found in the perceived need for programming instruction, knowledge of ML, the importance of ML in primary education, and the use of block-based programming in practice, all with small to medium effect sizes ($r \approx 0.23$–0.25).

In the curricular field, university students obtained higher scores in the teaching of content through block programming, in the learning of art and music through programming and robotics, as well as in the perception of providing help to students with special educational needs, with effect sizes between $r = 0.22$ and $r = 0.26$. Differences were also observed in the understanding of computational concepts, in the knowledge of the concept of ML and in its importance for learning in primary education (Items 1.1, 1.2, and 1.3), as well as in the greater use of visual block programming compared to practicing teachers (Item 1.5).

Finally, university students assigned greater value to the innovative implementation of game engines, block-based programming in primary education, support for students with special educational needs, and the contributions of programming to art education (Items 2.5, 3.2, 3.6, and 3.9). In the other curricular areas analyzed, no statistically significant differences were observed between the two groups, which indicates a similar assessment of the technological implementation.

Discussion

This study examined the impact of an educational intervention integrating visual block programming, educational robotics, and introductory machine learning (ML) on undergraduate pre-service teachers and in-service primary school teachers. The discussion is organized around the main research objectives guiding the study.

Differences in computational knowledge and ML understanding

A central finding is that undergraduate pre-service teachers achieved significantly higher scores than in-service teachers on the Coding, Robotics and Machine Learning Test (CRMT), particularly in basic computational concepts (sequences, loops, and conditionals), programming logic, educational robotics, and ML. This result suggests that recent exposure to formal learning environments and structured training in digital technologies may play a key role in conceptual understanding.

A plausible explanation lies in the proximity of university students to assessment-oriented learning contexts and their recent engagement with formal instruction, which may facilitate test performance. This interpretation aligns with research on “teaching to the test” effects (Zakharov, 2021) and with the protégé effect, whereby learning with the intention of teaching enhances conceptual encoding and retention (Fiorella and Mayer, 2013). The absence of a significant effect of teaching experience is consistent with evidence indicating that professional experience does not necessarily translate into higher performance on theoretical or conceptual assessments (Kini and Podolsky, 2016).

These findings are consistent with previous studies showing that early and systematic exposure to visual programming and robotics positively influences computational thinking development (Wei et al., 2021; Wu and Su, 2021; Noh and Lee, 2020).

Predictors of performance in computational concepts and ML

The multiple linear regression analysis indicated that group membership (pre-service vs. in-service teachers) was the only significant predictor of CRMT performance, while gender and teaching experience were not significant. Although the effect size was moderate, the explained variance was low, suggesting that performance in computational concepts and ML is influenced by multiple interacting factors, such as motivation, learning strategies, prior training, and cognitive styles (Brydges, 2019).

This finding reinforces the idea that formal training opportunities, rather than accumulated teaching experience alone, are critical for developing emerging digital competencies. It also highlights the need for continuous professional development programs that explicitly address robotics, programming, and ML for in-service teachers, as emphasized in recent reports on educational innovation and digital transformation (Robert et al., 2025).

Attitudes toward programming, robotics, and game-based learning

Another relevant finding concerns the higher self-perception of technological competence among undergraduate pre-service teachers, particularly regarding block-based programming and the use of game engines for educational purposes. University students reported greater confidence and motivation to integrate game-based digital tools into teaching, which may reflect their greater familiarity with contemporary digital environments and interactive media.

These results are consistent with prior research showing that game-based learning environments enhance computational thinking, motivation, and active participation (Giannakoulas and Xinogalos, 2024). Studies combining Scratch, robotics, and game engines in teacher education have similarly reported improvements in both technical skills and innovative pedagogical design (Rich et al., 2022; Sáez-López et al., 2023).

In contrast, in-service teachers demonstrated a more consolidated pattern of curriculum-oriented integration but lower confidence in advanced digital tools, reflecting a persistent training gap identified in the literature (Moreno-Palma et al., 2025; Robert et al., 2025).

Curricular integration, interdisciplinarity, and inclusion

The results also revealed strong associations between basic programming knowledge, educational robotics, and pedagogical innovation in both groups, as well as between robotics use and its application across curricular areas, particularly mathematics, natural sciences, and social studies. These relationships support an interdisciplinary view of computational thinking, as proposed by Wing (2006).

Notably, undergraduate pre-service teachers assigned higher value to the use of programming and robotics in artistic and musical learning and in supporting students with special educational needs. This finding reinforces the inclusive and cross-curricular potential of these tools, in line with studies highlighting their effectiveness in promoting engagement, creativity, and participation when appropriate guidance and feedback are provided (Chevalier et al., 2022; Wu and Su, 2021).

From a theoretical perspective, these results align with Papert’s constructionism (Papert, 1980), which emphasizes learning through active creation, problem-solving, and interaction with meaningful technological artifacts.

Educational implications

The findings of this study have several educational implications. First, they highlight the importance of strengthening initial teacher education through systematic, hands-on experiences with block-based programming, educational robotics, and introductory ML. Early exposure appears to foster both conceptual understanding and positive attitudes toward technological integration.

Second, the results underscore the need for targeted professional development programs for in-service teachers that address emerging technologies beyond basic digital literacy, particularly ML and game-based programming environments. Such programs should adopt progressive, structured, and pedagogically grounded approaches to reduce the identified training gap.

Finally, the strong links observed between programming, student engagement, interdisciplinarity, and inclusion suggest that robotics and ML can serve as powerful tools for promoting active, inclusive, and innovative teaching practices across the primary education curriculum.

Limitations of the study

This study has several limitations that should be considered. First, the use of non-probabilistic purposive sampling, as well as the assignment of groups based on pre-existing groupings and availability in educational centers, may restrict the generalizability of the results and generate potential selection bias. Although equivalence between groups was verified, the absence of a randomization process limits the possibility of establishing robust causal inferences. Future research should consider random or stratified sampling designs to strengthen the external validity of the findings.

Second, the marked gender imbalance in the sample, characteristic of teacher training programs, could influence the interpretation of the results, especially those related to attitudes toward programming and robotics. While this distribution accurately reflects the current student body composition, it hinders the analysis of potential gender-related differences in response to the intervention. Future studies could benefit from more balanced samples or from a specific analysis of the interaction between gender and learning outcomes in educational robotics and ML contexts.

Finally, the research was conducted in a limited number of institutions and during a relatively short intervention period, which restricts the evaluation of both the long-term retention of learning and its transfer to actual teaching practice. Longitudinal and multicenter studies are recommended to validate and expand upon the results obtained in this research.

Conclusion

This study demonstrates that the structured integration of visual block programming, educational robotics, and introductory machine learning constitutes an effective approach for developing computational understanding and positive attitudes in teacher education. Undergraduate pre-service teachers showed higher levels of conceptual knowledge, technological self-perception, and openness to innovative and game-based methodologies than in-service teachers, highlighting the critical role of initial training.

At the same time, the findings reveal a persistent training gap among practicing teachers, reinforcing the need for ongoing professional development focused on emerging digital technologies. Overall, the results support the adoption of progressive, constructionist-based training models that combine technical competence with pedagogical application, contributing to innovative, interdisciplinary, and inclusive educational practices aligned with current educational demands.

Recommendations

Based on the findings of this study, several recommendations are proposed for teacher education, educational practice, and future research.

First, initial teacher education programs should systematically incorporate visual block programming, educational robotics, and introductory machine learning as core components of the curriculum. These experiences should be progressive, starting with basic computational concepts and gradually advancing toward more complex applications, including game-based learning and ML-supported activities. Early and structured exposure can strengthen both conceptual understanding and positive attitudes toward technological integration.

Second, professional development programs for in-service teachers should be expanded and updated to address emerging technologies, particularly machine learning and educational robotics. Training initiatives should emphasize hands-on, practice-oriented approaches aligned with classroom realities, enabling teachers to translate technological knowledge into meaningful pedagogical applications across different curricular areas.

Third, educational institutions and policymakers should support interdisciplinary and inclusive uses of programming and robotics, promoting their integration beyond STEM subjects into areas such as the arts, social sciences, and special education. Providing adequate resources, time, and institutional support is essential to ensure sustainable implementation.

Finally, future research should adopt longitudinal and experimental designs to examine the long-term effects of robotics and ML interventions on teaching practice and student learning. Studies with larger and more diverse samples are recommended to enhance generalizability and to explore additional factors influencing teachers' technological competence, such as motivation, self-efficacy, and prior experience.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by UNED Ethics Board. Approved in the I+D+i project. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation in this study was provided by the participants' legal guardians/next of kin.

Author contributions

SR-D: Validation, Formal analysis, Supervision, Visualization, Writing – review & editing, Writing – original draft, Investigation.

DP: Supervision, Writing – review & editing, Validation, Investigation. AN: Writing – original draft, Visualization, Validation, Software. J-MS: Methodology, Supervision, Writing – review & editing, Conceptualization, Software, Writing – original draft, Formal analysis, Project administration, Funding acquisition.

Funding

The author(s) declared that financial support was received for this work and/or its publication. Competitive I+D+I project: Creative programming in primary education. Development of materials and proposals for block coding, game engines, machine learning, and robotics (PID2022-136442OB-I00). Knowledge Generation Projects 2022 (MICINN). Ministry of Science, Innovation and Universities of Spain.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that Generative AI was not used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2026.1778718/full#supplementary-material

References

Alonso-Secades, V., López-Rivero, A.-J., Martín-Merino-Acera, M., Ruiz-García, M.-J., and Arranz-García, O. (2022). Designing an intelligent virtual educational system to improve the efficiency of primary education in developing countries. *Electronics* 11:1487. doi: 10.3390/electronics11091487

Brydges, C. R. (2019). Effect Size Guidelines, Sample Size Calculations, and Statistical Power in Gerontology. *Innovation in Aging, 3.* doi: 10.1093/geroni/igz036

Caballero González, Y. A., and García-Valcárcel Muñoz-Repiso, A. (2020). Strengthening computational thinking and social skills through learning activities with educational robotics in early school levels. Pixel-Bit. *Revista De Medios Y Educación,* 58, 117–142. doi: 10.12795/pixelbit.75059

Chevalier, M., Giang, C., El-Hamamsy, L., Bonnet, E., Papaspyros, V., Pellet, J. P., et al. (2022). The role of feedback and guidance as intervention methods to foster computational thinking in educational robotics learning activities for primary school. *Comput. Educ.* 180:104431. doi: 10.1016/j.compedu.2022.104431

Constante Amores, I. A., Arroyo Resino, D., Sánchez Munilla, M., and Asensio Muñoz, I. (2024). Contribution of machine learning to the analysis of grade repetition in Spain: a study with PISA data. *Rev. Esp. Pedagog.* 82, 539–562. doi: 10.22550/2174-0909.4014

Cronbach, L. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika* 16, 297–334. doi: 10.1007/bf02310555

Daher, R. (2025). Integrating AI literacy into teacher education: a critical perspective paper. *Discov. Artif. Intell.* 5:217. doi: 10.1007/s44163-025-00475-7

de Vink, I. C., Tolboom, J. L. J., and van Beekum, O. (2023). Exploring the effects of near-peer teaching in computational thinking education in higher education. *Inf. Educ.* 22, 329–350. doi: 10.15388/infedu.2023.10

Demetroulis, E. A., Theodoropoulos, A., Wallace, M., Poulopoulos, V., and Antoniou, A. (2023). Collaboration skills in educational robotics: a methodological approach—results from two case studies in primary schools. *Educ. Sci.* 13:468. doi: 10.3390/educsci13050468

Esteve-Mon, F. M., Adell-Segura, J., Llopis-Nebot, M. A., Valedolivas-Novella, G., and Pacheco-Aparicio, J. (2019). The development of computational thinking in student teachers through an intervention with educational robotics. *J. Inf. Technol. Educ. Innov. Pract.* 18, 140–152. doi: 10.28945/4442

Fiorella, L., and Mayer, R. E. (2013). The relative benefits of learning by teaching and teaching expectancy. *Contemp. Educ. Psychol.* 38, 281–288. doi: 10.1016/j.cedpsych.2013.06.001

Franco Hidalgo-Chacón, J. P., Rodríguez-Arteche, I., and Martínez-Aznar, M. M. (2022). What do Spanish primary school students do outside of school hours? Extracurricular activities. *Rev. Complut. Educ.* 33, 459–474. doi: 10.5209/rced.74490

Gavrilas, L., Kotsis, K. T., and Papanikolaou, M. S. (2024). Exploration of the prospective utilization of educational robotics by preschool and primary education teachers. *Pedagog. Res.* 9, em0181. doi: 10.29333/pr/14049

Gavrilas, L., Kotsis, K. T., and Papanikolaou, M. (2025). The challenges encountered by preschool and primary educators in implementing educational robotics. *Res. Sci. Technol. Educ.*, 1–29. doi: 10.1080/02635143.2025.2578308

Giannakoulas, A., and Xinogalos, S. (2024). Studying the effects of educational games on cultivating computational thinking skills to primary school students: a systematic literature review. *J. Comput. Educ.* 11, 1283–1325. doi: 10.1007/s40692-023-00300-z

Hair, J. F., Anderson, R. E., Tatham, R. L., and Black, W. C. (1998). *Multivariate data analysis*. 5th Edn. Upper Saddle River, NJ: Prentice Hall.

Kini, T., and Podolsky, A. (2016). *Does teaching experience increase teacher effectiveness? A review of the research*: Learning Policy Institute.

Laru, J., Celik, I., Jokela, I., and Mäkitalo, K. (2025). The antecedents of pre-service teachers' AI literacy: perceptions about own AI driven applications, attitude towards AI and knowledge in machine learning. *Eur. J. Teach. Educ.* 48, 964–986. doi: 10.1080/02619768.2025.2535623

Lillo, F., García, L., and Severino-González, P. (2024). Machine learning model for predicting primary school scores based on spatial, socio demographic and school–related information. *Interciencia* 49, 60–67. Available at: https://www.interciencia.net/wp-content/uploads/2024/02/07_7104_Com_Severino_v49n1_8.pdf

Moreno-Palma, N., Berral Ortiz, B., Fernández Fernández, C. R., and Victoria Maldonado, J. J. (2025). Computational thinking in basic education through educational robotics: a systematic review. *Eur. Public Soc. Innov. Rev.* 10, 1–20. doi: 10.31637/epsir-2025-1099

Musso, M. F., Cascallar, E. C., Bostani, N., and Crawford, M. (2020). Identifying Reliable Predictors of Educational Outcomes Through Machine-Learning Predictive Modeling. *Front. Educ.* 5:104. doi: 10.3389/feduc.2020.00104

Noh, J., and Lee, J. (2020). Effects of robotics programming on the computational thinking and creativity of elementary school students. *Educ. Technol. Res. Dev.* 68, 463–484. doi: 10.1007/s11423-019-09708-w

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

Pérez Juste, R. (2006). *Evaluación de programas educativos*. Madrid: La Muralla.

Purković, D., Delač, D., and Kovačević, S. (2022). Interests of Croatian primary school pupils about elective technology teaching and school activities. *Metod. Ogl.* 29, 167–189. doi: 10.21464/mo.29.1.6

Rich, P. J., Bartholomew, S., Daniel, D., Dinsmoor, K., Nielsen, M., Reynolds, C., et al. (2022). Trends in tools used to teach computational thinking through elementary coding. *J. Res. Technol. Educ.* 56, 269–290. doi: 10.1080/15391523.2022.2121345

Robert, J., Muscanell, N., McCormack, M., Pelletier, K., Arnold, K., Arbino, N., et al. (2025). *2025 EDUCAUSE horizon report. Teaching and learning edition.* Boulder, CO: EDUCAUSE.

Ruiz-Ortiz, I. (2023). Robotics in the mathematics area in primary education. A systematic review. *Edutec, Elect. J. Educ. Tech.* 84, 1–17. doi: 10.21556/edutec.2023.84.2889

Santos, A. I., Pereira, D., Botelho, N., Medeiros, P., and Cascalho, J. M. (2023). Robotics for young people in AZORESminiBOT. *Int. J. Inf. Educ. Technol.* 13, 33–41. doi: 10.18178/ijiet.2023.13.1.1777

Sáez-López, J. M., González-Calero, J. A., Cózar-Gutiérrez, R., and del Olmo-Muñoz, J. (2023). Scratch and unity design in elementary education: A study in initial teacher training. *Journal of Computer Assisted Learning,* 39, 1528–1538. doi: 10.1111/jcal.12815

Sáez-López, J. M., Buceta Otero, R., y De Lara García-Cervigón, S. (2021). Introducing robotics and block programming in elementary education. RIED. *Revista Iberoamericana de Educación a Distancia,* 24, 95–113. doi: 10.5944/ried.24.1.27649

Schina, D., Romero, M., and France, N. (2025). Pair interactions and emergent roles in problem-solving with modular robotics in primary education. *Technol. Knowl. Learn.* doi: 10.1007/s10758-025-09907-w

Sperling, K., Stenliden, L., Jörgen, N., and Heintz, F. (2022). Still w(AI)ting for the automation of teaching: an exploration of machine learning in Swedish primary education using actor-network theory. *Eur. J. Educ. Res. Dev. Policy* 57, 584–600. doi: 10.1111/ejed.12526

Tejedor, F. J. (2000). El diseño y los diseños en la evaluación de Programas. *Rev. Investig. Educ.* 2, 319–339. https://revistas.um.es/rie/article/view/121021

Tsai, C. Y., Chen, Y. A., Hsieh, F. P., Chuang, M. S., and Lin, C. L. (2023). Effects of a programming course using the GAME model on undergraduates' self-efficacy and basic programming concepts. *J. Educ. Comput. Res.* 62, 482–504. doi: 10.1177/07356331231206071

Uzumcu, O., and Bay, E. (2020). The effect of computational thinking skill program design developed according to interest driven creator theory on prospective teachers. *Educ. Inf. Technol.* 26, 565–583. doi: 10.1007/s10639-020-10268-3

Vera-Sagredo, A., Constenla-Núñez, J., and Jara-Coatt, P. (2024). Exploratory study of teachers' self-perception of robotics and educational work in primary education: contributions to innovation and entrepreneurship. *Edutec. Electron. J. Educ. Technol.* 90, 1–18. doi: 10.21556/edutec.2024.90.3545

Villalustre, L., and Cueli, M. (2023). Assessing the computational thinking of pre-service teachers: a gender and robotics programming experience analysis. *Educ. Sci.* 13:1032. doi: 10.3390/educsci13101032

Villegas-Ch, W., García-Ortiz, J., and Sánchez-Viteri, S. (2024). Optimizing writing skills in children using a real-time feedback system based on machine learning. *IEEE Access* 12, 164634–164651. doi: 10.1109/ACCESS.2024.3492974

Weber, A. M., Bastian, M., Barkela, V., Mühling, A., and Leuchter, M. (2022). Fostering preservice teachers' expectancies and values towards computational thinking. *Front. Psychol.* 13:987761. doi: 10.3389/fpsyg.2022.987761

Wei, X., Lin, L., Meng, N., Tan, W., Kong, S. C., and Kinshuk (2021). The effectiveness of partial pair programming on elementary school students' computational thinking skills and self-efficacy. *Comput. Educ.* 160:Article 104023. doi: 10.1016/j.compedu.2020.104023

Wing, J. (2006). Computational thinking. *Commun. ACM* 49, 33–35. doi: 10.1145/1118178.1118215

Wong, G. K. W. (2024). Amplifying children's computational problem-solving skills: a hybrid-based design for programming education. *Educ. Inf. Technol.* 29, 1761–1793. doi: 10.1007/s10639-023-11880-9

Wu, S.-Y., and Su, Y.-S. (2021). Visual programming environments and computational thinking performance of fifth- and sixth-grade students. *J. Educ. Comput. Res.* 59, 1075–1092. doi: 10.1177/0735633120988807

Zakharov, A. (2021). Teaching to the test: effects of test-centred preparation on short-term academic performance. *Educ. Meas. Res. Rev.* 9, 45–59. doi: 10.1016/j.ijedudev.2021.102422