

Article

Exploring Artificial Intelligence Through Robotics and Machine Learning: Perceptions of Pre-Service Teachers, Elementary School Students, and In-Service Teachers

Sara Redondo-Duarte ¹, José-Manuel Sáez-López ^{1,*}, Mario Pena-Garrido ¹ and María-Belén Morales-Cevallos ²

¹ Faculty of Education, Universidad Nacional de Educación a Distancia (UNED), 28040 Madrid, Spain; sara.redondo@edu.uned.es (S.R.-D.); mpena@edu.uned.es (M.P.-G.)

² Faculty of Communication, Humanities, and Creativity, Universidad Ecotec, Samborondón 092302, Ecuador; mmoralesc@ecotec.edu.ec

* Correspondence: jmsaezlopez@edu.uned.es

Abstract

This study examined how educational robotics and machine learning activities contributed to the understanding of artificial intelligence (AI) among elementary school students, pre-service teachers, and practicing teachers. The intervention involved 1207 participants, including 1009 fifth-grade students, 93 practicing elementary school teachers, and 105 pre-service teachers. Participants engaged in a series of structured activities focused on educational robotics, visual block-based programming, and machine learning concepts. A pre-experimental design was employed to assess changes in understanding and to explore participants' perceptions of the learning experience. Statistical analyses included Student's *t*-tests, the Kruskal–Wallis H test, and Bonferroni-corrected post hoc comparisons. Results indicated pre–post gains in elementary school students' understanding of machine learning, AI modeling processes, and fundamental computational concepts following participation in the intervention. Across the three groups, participants reported positive perceptions of the activities and recognized their value for learning about AI. Elementary school students reported higher motivation and stronger engagement in coding-related tasks, likely reflecting their previous experience with Scratch in school settings. Practicing teachers expressed a more interdisciplinary perspective on the educational applications of AI, whereas pre-service teachers demonstrated stronger conceptual understanding of the underlying principles. Overall, the findings suggest that educational robotics and machine learning activities are associated with positive learning experiences and observed gains in AI-related understanding. However, given the pre-experimental design without a control group or random assignment, the results should be interpreted as evidence of observed changes and participant perceptions rather than demonstrated effectiveness.



Academic Editors: Jiyeon Yoon and Peggy Semingson

Received: 16 June 2026

Revised: 23 July 2026

Accepted: 28 July 2026

Published: 30 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: elementary education; educational technology; higher education; machine learning; robotics

1. Introduction

Since the contributions of Seymour Papert (1980) and constructionism, it has been emphasized that learning is more effective when learners are actively involved in building something tangible and meaningful, and that experience is more powerful when it translates into the creation of objects for thought, when something concrete is created, whether it be a

robot or even a text. From the perspective of elementary education, [Resnick et al. \(2009\)](#), who led the creation of the Scratch block-based programming language at MIT, highlight that computer programming is an extension of writing, and that it is beneficial for young people to learn to program. Visual block-based programming environments facilitate ease of use by allowing users to drag and drop graphical blocks to compose simple programs ([Chevalier et al., 2022](#); [Maloney et al., 2008](#); [Noh & Lee, 2020](#)).

Educational robotics is considered a manipulative, accessible, and effective resource ([Schina et al., 2025](#)) that is particularly effective for teaching mathematics ([Wu & Su, 2021](#)), although it facilitates interdisciplinarity with an appropriate approach ([Gavrilas et al., 2024](#); [Wong, 2024](#)). Several authors ([Israel et al., 2015](#); [Sáez-López et al., 2026a, 2026b](#)) highlight its advantages in elementary education, with statistically significant improvements in the understanding of computational concepts and projects of particular interest in art education, natural sciences, and social sciences.

The importance of machine learning has also been emphasized. This implementation used “Machine Learning for Kids,” created by Dale Lane, which is integrated with Scratch 3.0 and facilitates the creation of artificial intelligence (AI) and block-based code. The application of machine learning in education is not new. [Sperling et al. \(2022\)](#) conducted a study and concluded that machine learning is beneficial for learning mathematics, while [Villegas-Ch et al. \(2024\)](#) developed a machine learning system that provides students with real-time feedback on their handwriting by identifying difficulties in pressure or alignment.

Meanwhile, [Laru et al. \(2025\)](#) provide relevant empirical evidence in the context of initial university teacher training by analyzing the history of AI literacy among future teachers. [Daher \(2025\)](#) points out that initial teacher training should explicitly incorporate AI literacy, including the ability to interpret machine learning models, thus broadening the training approach beyond programming and robotics toward a comprehensive view of AI in education. In considering the inclusion of coding and robotics in initial university teacher training, [Uzumcu and Bay \(2021\)](#) proposed unplugged activities and robotics with the aim of improving the computational skills of pre-service teachers. Meanwhile, [Tsai et al. \(2023\)](#) present a programming course based on a model that integrates gamification with basic programming concepts. This is of interest because incorporating programming and educational robotics in the training of future teachers allows them to experience computational thinking and machine learning, as well as understand their formative potential ([Esteve-Mon et al., 2019](#); [Villalustre & Cueli, 2023](#); [Uzumcu & Bay, 2021](#)) through interventions that address the motivational and cognitive-attitudinal dimensions associated with these skills ([de Vink et al., 2023](#); [Laru et al., 2025](#); [Weber et al., 2022](#)) alongside their practical applications in diverse areas of knowledge ([Wong, 2024](#)).

The Horizon Report, Teaching and Learning Edition ([Robert et al., 2025](#)) highlights the importance of robotics in cognitive processes and fostering autonomy among students working on projects, while enabling them to manage different information resources and making them more adaptable to change. Technology is also enabling new ways of documenting student learning and success ([Giannakoulas & Xinogalos, 2024](#); [Robert et al., 2025](#)). Key technologies include programmable boards, which are electronic devices that can control sensors and actuators through block-based programming, thus fostering creativity and innovation ([Bers, 2008](#); [Chevalier et al., 2022](#); [Noh & Lee, 2020](#)). This study used the micro:bit board (<https://makecode.microbit.org/> accessed on 22 July 2026) and robotics kits (Maqueen and Nezha), which allow for simple and adaptable assembly, as well as working with visual block-based programming.

2. Objectives

The main objective of the study was to assess the importance and use of machine learning and educational robotics in initial university teacher training and in elementary school contexts. The specific objectives were:

- To verify the importance of machine learning for understanding AI in school and university contexts
- To assess the feasibility of using visual block programming for learning robotics among future teachers, elementary school students, and practicing teachers
- To evaluate the knowledge of future teachers, practicing elementary school teachers, and elementary school students regarding educational robotics
- To assess the attitudes of future teachers, elementary school students, and practicing teachers toward the implementation of educational robotics and machine learning

3. Materials and Methods

Two dimensions of analysis are proposed (Table 1). For the first dimension—knowledge of computational concepts, robotics, and machine learning—the 10-question Coding, Robotics, Machine Test (CRMT) was administered to 1009 primary school students and the results were then analyzed. The group was homogeneous because the students were practically the same age (10 years old), from the same context (schools in the Community of Madrid), and at the same educational level (fifth grade).

Table 1. Dimensions, Indicators, and Instruments (Sáez-López et al., 2026a, 2026b).

Dimensions	Indicators	Instruments
1. Knowledge of computational concepts, robotics, and machine learning	-Machine learning -Sequence -Iteration (looping) -Conditional statements -Sensors	Coding, Robotics, and Machine Learning Test (CRMT) Descriptive analysis Student's <i>t</i> -test
2. Educational robotics and machine learning in the training of primary school teachers and students	-Mastery of educational robotics -Understanding of machine learning -Computational concepts -Application in curricular areas	Scale Descriptive analysis Kruskal–Wallis Post hoc Bonferroni correction

A pre-experimental design with related samples was used. Pretest and posttest scores from the experimental group were compared using a paired-samples *t*-test, with statistical significance defined as $p < 0.05$. The reliability calculated using Cronbach's alpha coefficient was 0.78 for this first dimension, which is considered acceptable (Hair et al., 1998). In assessing the content validity of the CRMT instrument, Aiken's *V* coefficient values ($V = S/[n(c - 1)]$) greater than 0.75 were obtained in all items. Content validity was established through expert judgment involving 11 university faculty members with expertise in educational technology, computational thinking, educational robotics, artificial intelligence in education, educational measurement, and educational research. Each expert independently evaluated every item according to three criteria—relevance, clarity, and representativeness—using an 11-point rating scale ranging from 0 (not relevant at all) to 10 (highly relevant), allowing for greater discrimination in expert judgments. Aiken's *V* coefficient was calculated for each item to quantify the degree of expert agreement. All CRMT items obtained Aiken's *V* values greater than 0.75, indicating satisfactory content validity.

The second dimension, educational robotics and machine learning in the training of primary school teachers and students, focused on the knowledge and understanding regarding computational concepts, educational robotics, and machine learning among practicing teachers and students in a primary education degree program. The attitudes and perceptions of these groups toward the use of educational robotics and block-based programming in teacher training were analyzed. Participants completed a 15-item attitude and perception questionnaire using a four-point Likert-type scale ranging from 1 = strongly disagree to 4 = strongly agree. Item scores were analyzed individually; higher scores indicated more positive perceptions of educational robotics, programming, and machine learning. Descriptive statistics were analyzed, average ranks were calculated for each group, the Kruskal–Wallis H test was performed along with effect size, and post hoc comparisons were conducted using Bonferroni correction. The content validity of this dimension was assessed considering the instrument’s relevance and suitability criteria, with Aiken’s V coefficient ($V = S/[n(c - 1)]$) values greater than 0.75 for all items. Cronbach’s alpha reliability coefficient was 0.71, indicating an acceptable level of internal consistency. Both instruments were developed based on previous studies conducted by the authors (Sáez-López et al., 2026a, 2026b) and subsequently refined for the objectives of the present study.

3.1. Participants

The study population consisted of undergraduate students in primary education, practicing teachers, and primary school students from the Community of Madrid. The non-probabilistic, purposive sample comprised 1207 participants: 1009 fifth-year primary education students, 93 practicing primary school teachers, and 105 pre-service teachers. Participants attended 13 schools and two universities in the Community of Madrid. The group was 51.3% female and 47.8% male.

3.2. Implementation

The activities and sessions related to machine learning and educational robotics were conducted in 2025. The intervention consisted of eight face-to-face sessions. Each session lasted approximately 60 min and followed a progressive sequence, beginning with basic programming concepts, sensors, and conditionals, continuing with educational robotics projects using the micro:bit, Maqueen, and Nezha platforms, and concluding with introductory machine learning activities using Machine Learning for Kids integrated with Scratch 3.0. Full descriptions of the sessions are provided in Appendix A. The same sessions were implemented for university students, practicing teachers, and primary school students. The eight sessions focused on working with “Machine Learning for Kids,” creating a model with Scratch 3.0, building a light-powered robot with the Maqueen kit, constructing a barrier with a traffic light and an obstacle-avoiding car with the Nezha kit, and using the micro:bit board to program a die or a temperature sensor. The sessions emphasized problem-solving, understanding computational and practical elements, and fostering motivation, enthusiasm, and participation among the participants. To illustrate the intervention, the activity in which a camera recognizes objects and displays a number on the micro:bit, using the “Smart AI Lens” micro:bit and the Nezha kit, is highlighted (Figure 1).

Another key project involved LEGO Technic blocks, which were programmed using the micro:bit board. Coherent construction is important for this project, as is detailing conditionals, sensors, and actuators in the programming (Figure 2).

All of these projects sought to foster work that would enhance logical and analytical thinking, problem-solving, and the debugging and correction of errors (trial and error). Using devices, programming, and machine learning, the projects also promote learning

about how machines work and develop digital competence. Further information about all sessions and projects is provided in the Appendix A.

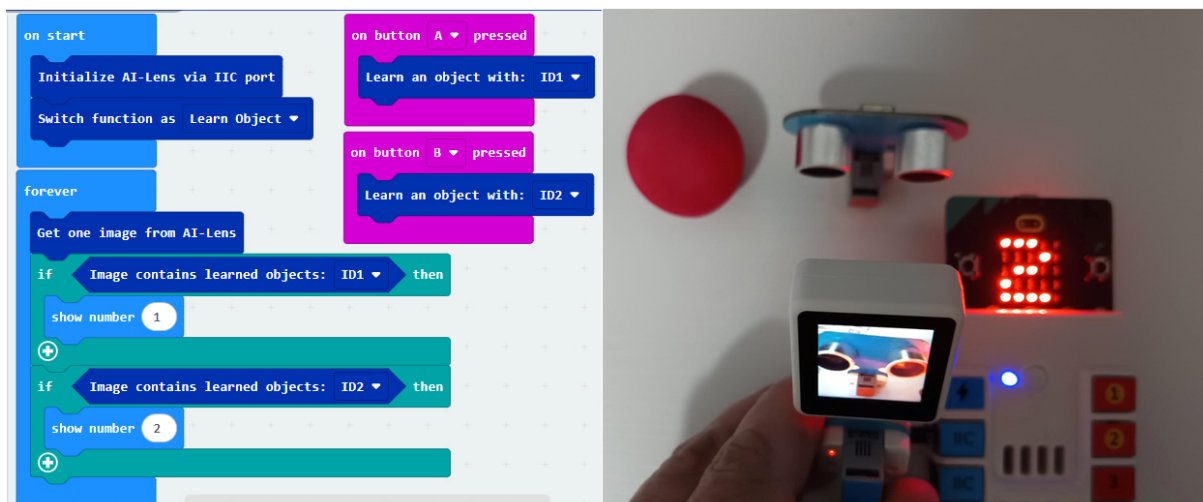


Figure 1. Object recognition activity using the Smart AI Lens integrated with the micro:bit platform during the introductory machine learning session.

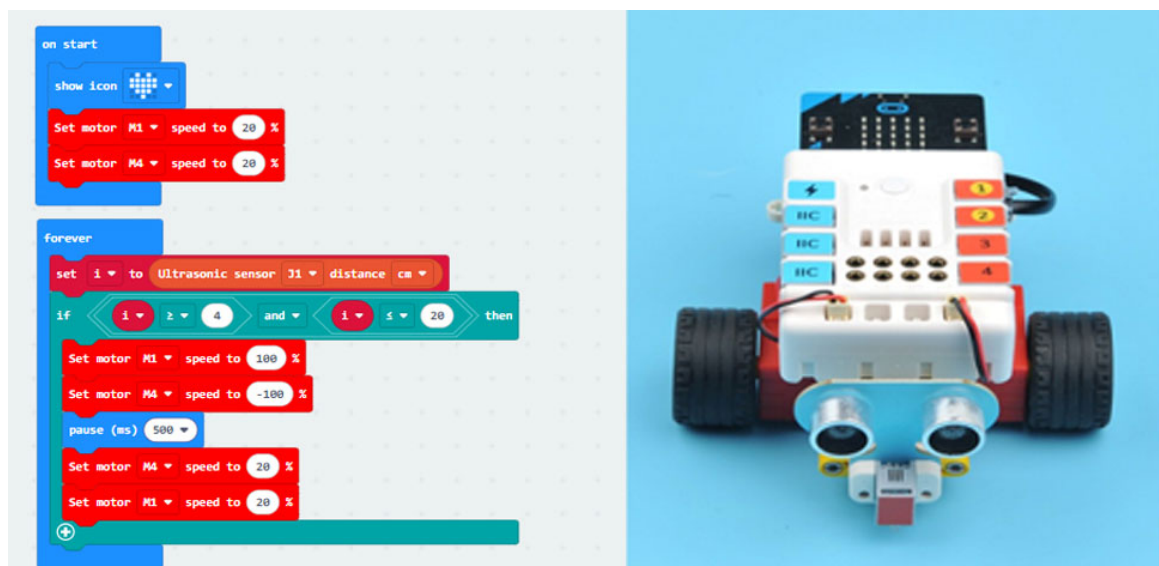


Figure 2. Obstacle avoidance car built with the Nezha Inventor's Kit and ultrasonic sensor. Adapted from ELECFREAKS WIKI, Case 12: Obstacle Avoidance Car.

The study employed a pre-experimental design without a control group or random assignment. Consequently, although pretest-posttest comparisons provide evidence of changes observed after the intervention, the design does not permit causal inferences regarding the effectiveness of the intervention. The findings should therefore be interpreted as indicative of associations between participation in the activities and the observed learning outcomes.

4. Results

4.1. Dimension 1: Knowledge of Computational Concepts, Robotics, and Machine Learning

For this dimension, a pre-experimental design was used, employing a paired-samples t-test. The CRMT was administered at two points in time—pretest and posttest—to determine if there were significant improvements in the acquisition of computational concepts

after the intervention. The CRMT was administered to 1009 fifth-grade students before and after the intervention. The paired-samples analysis included all matched pretest–posttest cases, as complete data were available for both assessment occasions for every participant. Therefore, no cases were excluded, no attrition occurred, and no missing-data procedures were required. The analytical sample was identical to the full sample of elementary school students.

This statistical analysis allowed us to examine whether participants showed statistically significant pre–post differences in their understanding of computational concepts following participation in the intervention.

The results obtained from the 10 items of the instrument indicated positive pre–post changes in scores following the training activities, suggesting improved performance on the assessed computational concepts, which integrate machine learning activities and educational robotics, while reinforcing the role of these technologies as educational resources for the progressive acquisition of computational thinking skills.

The results of the administered Student's *t*-test yielded a value ($t = 15.250$; $p = 0.001$) that indicated significant improvements. The paired-samples analysis included 1009 matched pretest–posttest cases. Students obtained a mean pretest score of 4.95 ($SD = 1.26$) and a mean posttest score of 5.99 ($SD = 1.68$) on the CRMT. A paired-samples *t*-test indicated that posttest scores were significantly higher than pretest scores, $t([df]) = 15.25$, $p < 0.001$, with a mean difference of -1.03 points (95% CI 1.16, 0.90). The effect size was moderate, Cohen's $d = 0.48$ (Hedges' $g = 0.48$), indicating a meaningful improvement in students' understanding of computational concepts, robotics, and learning following participation in the intervention.

Higher posttest scores were observed following participation in the intervention, indicating statistically significant pre–post gains in the assessed computational concepts. The effect size was $d = -0.48$, both in the Cohen's d estimate and when using Hedges' correction, with a 95% confidence interval between -0.55 and -0.42 . According to the conventional criteria, this value corresponds to a moderate effect size, which indicates that statistically significant pre–post differences were observed following participation in the intervention.

The negative sign does not imply an adverse effect but rather reflects the direction of the difference based on the order of the means (pretest–posttest); in this case, it suggests an improvement in the posttest compared to the pretest. The agreement between the Cohen's d and Hedges' correction reinforces the stability of the estimate, and the confidence interval, which does not include zero, confirms that the observed effect is statistically consistent and not attributable to chance. Overall, these results indicate statistically significant pre–post gains of moderate magnitude following participation in the intervention. Given the pre-experimental design, these findings should be interpreted as observed changes rather than evidence of causal effects.

4.2. Dimension 2: Educational Robotics and Machine Learning in the Training of Primary School Teachers and Students

Descriptive Analysis and Statistical Inference with Kruskal–Wallis H and Post Hoc Comparisons with Bonferroni Correction

The descriptive results (Table 2) showed a generally positive trend in perceptions of programming, robotics, and machine learning. In this second dimension, most items had high median scores ($Mdn = 4$), especially those related to understanding concepts linked to AI through machine learning activities (Items 1.3 and 1.4) and activation and motivation of learning provided by robotics in the classroom (e.g., Items 3.1, 3.2, 3.6, and 3.7). Beyond the differences between groups, there was a generally favorable assessment of the educational

potential of robotics and programming, both for fostering conceptual understanding and for energizing teaching and learning processes.

Table 2. Descriptive Statistics for Dimension 2.

Item	Mean	Median	SD
1.1 Programming and working with robots gives me new ideas.	2.64	2.00	1.084
1.2 I understand how machine learning works.	2.77	3.00	0.782
1.3 I understand AI through machine learning activities.	3.67	4.00	0.603
1.4 I enjoy creating models to train with machine learning.	3.59	4.00	0.737
2.1 I know what a “loop” is.	2.81	3.00	0.713
2.2 I have worked with Scratch at school.	2.68	2.00	0.961
2.3 With robotics, you do new things in class.	3.70	4.00	0.575
2.4 I understand what a conditional statement is in programming.	3.63	4.00	0.674
3.1 You learn a lot with robotics.	3.67	4.00	0.601
3.2 You learn a lot about math with programming and robotics.	3.72	4.00	0.550
3.3 Programming and robotics help you learn natural sciences.	3.66	4.00	0.618
3.4 Programming and robotics help you learn social sciences.	2.69	2.00	0.897
3.5 Programming and robotics help you learn art and music.	3.04	3.00	0.915
3.6 With programming and robotics, class is more interesting.	3.66	4.00	0.611
3.7 With programming and robotics, I feel more active.	3.71	4.00	0.557

However, some items, such as “programming and robotics help in learning social sciences” (Item 3.4), showed lower medians ($Mdn = 2$), which indicates a more limited perception of the potential of these technologies in the humanities. Likewise, items about prior experience, such as having worked with Scratch (Item 2.2), showed greater variability ($SD = 0.961$), which reflects the notable differences in the educational backgrounds of the participants. These results seem to indicate that the development of skills in programming and robotics is still at an early stage for some participants, while confidence in their motivational and educational capacity is perceived as more consolidated.

When these trends are analyzed together with the average ranks per agent derived from the Kruskal–Wallis test (Table 3), consistent differences emerged among the groups analyzed (primary school students, primary school teachers, and university students). University students tended to rank higher on items related to creativity, solution design, and technical understanding (Items 1.1, 1.4, and 3.5), while primary school teachers showed higher ranks on items associated with cross-curricular educational application, particularly in curricular areas such as social sciences and art education (Items 3.4 and 3.5), due to their curricular experience and interdisciplinary teaching practice. However, they showed more moderate and, in some cases, lower values, particularly on items related to technical understanding (Items 1.3 and 1.4), which could be associated with less specific training. Primary school students, for their part, showed intermediate scores on most items, thus confirming that they valued robotics positively, but not to the same extent as the other groups. It is worth noting that they showed higher scores on items related to motivation, interest, and active participation in the classroom (Items 2.3, 3.6, and 3.7), thus reinforcing the idea that educational robotics acts as a particularly powerful stimulus at early ages in promoting learning through exploration, manipulation of materials, and guided discovery.

Table 3. Average Ranks per Agent by Item (Kruskal–Wallis).

Items	Students (<i>n</i> = 1009)	Teachers (<i>n</i> = 93)	Pre-Service_S. (<i>n</i> = 105)
1.1 Programming and working with robots gives me new ideas.	585.40	633.05	757.00
1.2 I understand how machine learning works.	619.62	440.68	598.58
1.3 I understand AI through machine learning activities.	662.14	234.34	372.71
1.4 I enjoy creating models to train with machine learning.	649.76	206.24	516.52
2.1 I know what a “loop” is.	566.66	737.88	844.28
2.2 I have worked with Scratch at school.	628.96	389.67	554.02
2.3 With robotics, you do new things in class.	632.36	446.81	470.69
2.4 I understand what a conditional statement is in programming.	635.65	493.33	397.85
3.1 You learn a lot with robotics.	647.80	338.10	418.62
3.2 You learn a lot about math with programming and robotics.	630.08	462.54	478.63
3.3 Programming and robotics help you learn natural sciences.	653.90	365.01	336.16
3.4 Programming and robotics help you learn social sciences.	575.36	705.81	789.08
3.5 Programming and robotics help you learn art and music.	604.64	458.38	726.80
3.6 With programming and robotics, class is more interesting.	647.03	352.20	413.49
3.7 With programming and robotics, I feel more active.	624.19	504.34	498.22

The results of the Kruskal–Wallis test showed statistically significant differences between the groups (primary school students, teachers, and university students) on all analyzed items (Table 4), which indicates that the perception of the educational potential of programming, robotics, and machine learning varied depending on the educational agent. Analysis of effect size using epsilon-squared (ϵ^2) revealed predominantly small to moderate effects, which indicates that, although the groups differ systematically, belonging to an educational profile (i.e., primary school student, teacher, or university student) only partially explains the observed behavior in the scores. The strongest effects were observed in items related to the understanding and application of machine learning, particularly in “I understand AI through machine learning activities” ($\epsilon^2 = 0.244$) and “I like creating models to train with machine learning” ($\epsilon^2 = 0.190$). These values, which were close to the moderate-to-high effect threshold, suggest that prior training and academic exposure to computational content have a significant impact on the development of advanced conceptual skills.

Similarly, items related to the perception of learning through robotics in the natural sciences (Item 3.3; $\epsilon^2 = 0.173$) or to the motivation and interest generated by robotics in the classroom (Items 3.1 and 3.6; $\epsilon^2 \geq 0.128$) also showed effects of significant magnitude, which suggests that educational experience influences how the pedagogical potential of these technologies is valued. In contrast, items linked to prior experience or basic computer literacy (such as Item 2.2, $\epsilon^2 = 0.040$, or 3.5 art and music, $\epsilon^2 = 0.026$) showed more modest

effects, which indicates that differences between groups are determined less by educational background and more by other formative or contextual factors.

Table 4. Kruskal–Wallis Test and Effect Size (ϵ^2) by Item.

Items	H	G1	Asymp. Sign	ϵ^2
1.1 Programming and working with robots gives me new ideas.	26,154	2	<0.001	0.020
1.2 I understand how machine learning works.	32,032	2	<0.001	0.025
1.3 I understand AI through machine learning activities.	296,390	2	<0.001	0.244
1.4 I enjoy creating models to train with machine learning.	230,895	2	<0.001	0.190
2.1 I know what a “loop” is.	119,237	2	<0.001	0.097
2.2 I have worked with Scratch at school.	49,949	2	<0.001	0.040
2.3 With robotics, you do new things in class.	71,602	2	<0.001	0.057
2.4 I understand what a conditional statement is in programming.	89,189	2	<0.001	0.072
3.1 You learn a lot with robotics.	167,871	2	<0.001	0.138
3.2 You learn a lot about math with programming and robotics.	62,625	2	<0.001	0.050
3.3 Programming and robotics help you learn natural sciences.	209,673	2	<0.001	0.173
3.4 Programming and robotics help you learn social sciences.	51,822	2	<0.001	0.041
3.5 Programming and robotics help you learn art and music.	33,196	2	<0.001	0.026
3.6 With programming and robotics, class is more interesting.	156,152	2	<0.001	0.128
3.7 With programming and robotics, I feel more active.	37,175	2	<0.001	0.029

Post hoc comparisons with Bonferroni correction (Table 5) allowed us to identify which pairs of agents explain these overall discrepancies. Consistently, university students (PRE-SERVICE) differed significantly from both primary school students (STUDENTS) and teachers (TEACHERS) on most of the conceptual and creativity items related to machine learning (Items 1.1, 1.3, 1.4, 3.1, 3.6, and 3.7), repeatedly achieving the highest scores. These results indicate that greater educational specialization contributes to a stronger understanding of the concepts and greater technical confidence in the use of these technologies.

Post hoc pairwise comparisons indicated significant differences between elementary school students and pre-service teachers, between elementary school students and practicing teachers, and between pre-service teachers and practicing teachers on the corresponding items, after adjustment for multiple comparisons.

Primary school teachers, on the other hand, showed relatively higher scores on items related to cross-curricular areas, such as social sciences (Item 3.4) and art and music (Item 3.5). Thus, teaching experience, daily practice, and pedagogical knowledge could foster a greater perception of the usefulness of programming and robotics in interdisciplinary contexts, even when their technical training is less specialized than that of university students. Regarding primary school students, post hoc comparisons showed that, although their assessments do not reach the levels of university students in most conceptual items, they do score significantly higher than those of teachers in aspects related to motivation, interest, and active participation (e.g., Items 3.1, 3.6, and 3.7). This result complements the descriptive findings and suggests that robotics continues to act as a highly motivating stimulus at early ages, even when conceptual understanding is still developing.

Table 5. Kruskal–Wallis Post Hoc Group Comparisons by Item. Pairwise post hoc comparisons with Bonferroni-adjusted *p*-values.

Items	Pairwise Comparison	Test Statistic	Bonferroni-Adjusted <i>p</i>
1.1 Programming and working with robots gives me new ideas.	STUDENTS–TEACHERS	−47.65	0.557
	STUDENTS–PRE-SERVICE	−171.60	<0.001
	TEACHERS–PRE-SERVICE	−123.95	0.026
1.2 I understand how machine learning works.	TEACHERS–PRE-SERVICE	−157.90	<0.001
	TEACHERS–STUDENTS	178.93	<0.001
	PRE-SERVICE–STUDENTS	21.04	1.000
1.3 I understand AI through machine learning activities.	TEACHERS–PRE-SERVICE	−138.37	0.001
	TEACHERS–STUDENTS	427.80	<0.001
	PRE-SERVICE–STUDENTS	289.43	<0.001
1.4 I enjoy creating models to train with machine learning.	TEACHERS–PRE-SERVICE	−310.28	<0.001
	TEACHERS–STUDENTS	443.52	<0.001
	PRE-SERVICE–STUDENTS	133.24	<0.001
2.1 I know what a “loop” is.	STUDENTS–TEACHERS	−171.23	<0.001
	STUDENTS–PRE-SERVICE	−277.62	<0.001
	TEACHERS–PRE-SERVICE	−106.39	0.021
2.2 I have worked with Scratch at school.	TEACHERS–PRE-SERVICE	−164.35	0.001
	TEACHERS–STUDENTS	239.29	<0.001
	PRE-SERVICE–STUDENTS	74.94	0.069
2.3 With robotics, you do new things in class.	TEACHERS–PRE-SERVICE	−23.87	1.000
	TEACHERS–STUDENTS	185.55	<0.001
	PRE-SERVICE–STUDENTS	161.68	<0.001
2.4 I understand what a conditional statement is in programming.	PRE-SERVICE–TEACHERS	95.48	0.041
	PRE-SERVICE–STUDENTS	237.80	<0.001
	TEACHERS–STUDENTS	142.32	<0.001
3.1 You learn a lot with robotics.	TEACHERS–PRE-SERVICE	−80.52	0.106
	TEACHERS–STUDENTS	309.70	<0.001
	PRE-SERVICE–STUDENTS	229.18	<0.001
3.2 You learn a lot about math with programming and robotics.	TEACHERS–PRE-SERVICE	−16.09	1.000
	TEACHERS–STUDENTS	167.54	<0.001
	PRE-SERVICE–STUDENTS	151.45	<0.001
3.3 Programming and robotics help you learn natural sciences.	PRE-SERVICE–TEACHERS	28.84	1.000
	PRE-SERVICE–STUDENTS	317.74	<0.001
	TEACHERS–STUDENTS	288.90	<0.001
3.4 Programming and robotics help you learn social sciences.	STUDENTS–TEACHERS	−130.46	0.001
	STUDENTS–PRE-SERVICE	−213.72	<0.001
	TEACHERS–PRE-SERVICE	−83.26	0.209
3.5 Programming and robotics help you learn art and music.	TEACHERS–STUDENTS	146.26	<0.001
	TEACHERS–PRE-SERVICE	−268.42	<0.001
	STUDENTS–PRE-SERVICE	−122.16	0.001

Table 5. Cont.

Items	Pairwise Comparison	Test Statistic	Bonferroni-Adjusted <i>p</i>
3.6 With programming and robotics, class is more interesting.	TEACHERS–PRE-SERVICE	−61.28	0.342
	TEACHERS–STUDENTS	294.83	<0.001
	PRE-SERVICE–STUDENTS	233.55	<0.001
3.7 With programming and robotics, I feel more active.	PRE-SERVICE–TEACHERS	6.12	1.000
	PRE-SERVICE–STUDENTS	125.97	<0.001
	TEACHERS–STUDENTS	119.85	<0.001

Note. Pairwise comparisons were conducted following the Kruskal–Wallis test. Reported *p* values are Bonferroni-adjusted for multiple comparisons. All significance values are asymptotic and based on two-sided tests.

In summary, the results suggest that robotics and programming are valued positively by all stakeholders; however, the way in which this value is expressed, as well as its conceptual depth, differs depending on educational background and role. While specialized academic training is linked to a more solid technical understanding, teaching experience tends to focus on the curricular potential of these technologies, prioritizing their integration into different areas of knowledge over their technical dimension. In contrast, in the early stages of education, the enthusiasm and motivation that robotics inspires predominate, thus reinforcing its role as a dynamic learning resource.

5. Conclusions and Discussion

Regarding the first dimension, the results from the CRMT showed statistically significant improvements in the understanding of concepts related to programming, robotics, and machine learning after the intervention. This reinforces the idea that even content traditionally considered complex, such as machine learning, can be addressed meaningfully at an early age when using hands-on, visual, and project-based approaches. These results align with previous research highlighting the effectiveness of block-based programming and educational robotics for developing computational thinking in primary education (Chevalier et al., 2022; Wu & Su, 2021).

This research also highlights key findings regarding machine learning and educational robotics in educational contexts for learning computational concepts. Significant pre–post gains and generally positive scores were observed across both dimensions. These findings suggest that participation in the robotics and machine learning activities was associated with positive learning experiences and improved understanding of the assessed concepts.

Participants showed improvements in conceptual understanding and reported positive perceptions following the intervention. However, because the study employed a pre-experimental design without a control group, these findings should be interpreted cautiously and cannot be considered evidence of causal effectiveness. Thus, these findings suggest that this approach represents a promising educational strategy associated with positive learning experiences and observed gains in understanding AI, coding, and robotics; however, further controlled research is required to establish its effectiveness.

Previous research has analyzed the possibilities of visual block programming in pedagogical contexts with positive and significant results (Israel et al., 2015; Sáez-López et al., 2026a). Based on the analysis of the present results, and through data triangulation across different sources and tests, we can present the following conclusions:

1. Primary school students showed improved results with the intervention of this study. When applying the CRMT, scores close to 6 were observed, which can be considered moderately high due to the difficulty of the content; however, statistically significant improvements were noted. The primary school students thus improved their under-

- standing of machine learning and how AI is modeled, and they grasped computational concepts and the implementation of educational robotics (Dimension 1).
2. In the second dimension, the results of the descriptive analysis and the Kruskal–Wallis test showed generally positive assessments of machine learning and educational robotics by all three groups analyzed, although there were significant differences depending on the educational background.
 3. Regarding machine learning, most participants understood AI by creating models with machine learning (Items 1.2 and 1.3) and enjoyed these activities (Item 1.4). Primary school students particularly enjoyed these activities. Creativity and new ideas (Item 1.1) received more modest scores, which indicates that this may be difficult for primary school students. In contrast, university students generated new ideas more easily (Tables 3–5).
 4. Considering the effect sizes (Table 4), the participants appeared to improve in terms of their understanding and application of machine learning, which further helped them understand AI (Items 1.2 and 1.3, $\varepsilon^2 = 0.244$), and they also enjoyed these activities (Item 4, $\varepsilon^2 = 0.190$).
 5. The participants understood computational concepts, loops, and conditionals (Items 2.1 and 2.4), and they also believed that robotics allows them to do new things (Item 2.3) and learn a lot (Item 3.1). The elementary school students had worked more with Scratch at school (Item 2.2), which was why they obtained higher scores than the other groups on these items. The teachers obtained acceptable, but significantly lower scores.
 6. Primary school teachers highlighted the potential for cross-curricular educational application, particularly in curricular areas such as social studies and art education (Items 3.4 and 3.5), due to their curricular experience and interdisciplinary teaching practice. However, they obtained lower scores on items related to understanding concepts and applying these practices (Items 1.3, 1.4, 2.2, and 3.1), which could be interpreted as areas for improvement or a need to update teacher training, given that these are recent emerging technologies.
 7. The class with robotics and programming was very interesting to primary school students (while teachers showed lower values) and they felt more active, thus highlighting the motivating, activating, and commitment elements of educational robotics (Items 3.6 and 3.7).

Proper implementation and guidance were associated with higher levels of understanding of AI-related concepts observed after the intervention; however, causal conclusions cannot be drawn from the present design. Learning visual block programming and educational robotics can thus be fostered in educational contexts, which in turn promotes active learning, motivation, and interest. The fact that primary school students have worked with Scratch at school (Item 2.2) is highlighted as a fundamental element in this intervention; this considerably influenced the students' positive attitudes and opinions toward these approaches. They also emphasized that these approaches are effective in mathematics and natural sciences, although primary school teachers tended to have a more interdisciplinary perspective.

An important finding of this study is that many elementary school students had prior experience with Scratch, which appears to have been a key facilitating factor in their positive performance and attitudes toward educational robotics and machine learning activities. This previous exposure to visual block-based programming likely reduced the cognitive demands associated with learning new computational concepts, allowing students to focus more effectively on understanding robotics and introductory AI concepts. Although this relationship should not be interpreted as causal, it suggests that the progressive introduction

of block-based programming in the primary curriculum can provide a valuable foundation for subsequent learning in robotics and AI.

From an educational policy perspective, these findings support the systematic integration of computational thinking, visual programming, educational robotics, and introductory AI literacy across the primary education curriculum. Educational authorities should consider promoting the early adoption of age-appropriate programming environments such as Scratch, together with sustained investment in teacher professional development, curricular resources, and technological infrastructure. Such measures would help ensure that students progressively develop the computational and AI literacy competencies required for future learning and active participation in an increasingly technology-driven society.

University students demonstrated higher levels of conceptual understanding and affinity for the design and training of machine learning models, which can be attributed to their greater academic exposure and a more advanced level of digital literacy. This result is consistent with studies underscoring the importance of initial teacher training for developing competencies related to AI and computational thinking (Esteve-Mon et al., 2019; Villalustre & Cueli, 2023; Weber et al., 2022). Primary school teachers, for their part, particularly valued the cross-curricular potential of robotics and programming in areas such as social sciences and art education. However, they showed more moderate scores on items related to the technical understanding of machine learning. This finding highlights the need to strengthen ongoing professional development for teachers in emerging technologies, especially in an educational context increasingly influenced by AI (Daher, 2025; Robert et al., 2025). Such professional development could be structured around hands-on, practice-oriented workshops that combine foundational AI concepts with classroom applications, including educational robotics, block-based programming, and introductory machine learning activities. Continuous support through collaborative learning communities and opportunities to design, implement, and reflect on AI-integrated lessons may further enhance teachers' confidence and their ability to incorporate these technologies into interdisciplinary teaching practices.

Although primary school students demonstrated a still-developing conceptual understanding, they stand out for their high levels of motivation, interest, and participation during the activities. These results further confirm the role of educational robotics as a powerful motivational resource that fosters active learning and student engagement, as indicated by recent studies on robotics and project-based learning (Giannakoulas & Xinogalos, 2024; Wei et al., 2021; Wong, 2024).

Overall, the effect sizes obtained indicate that understanding machine learning and AI is one of the aspects most sensitive to the intervention, especially when working through the creation and training of models. This result reinforces the idea that literacy in machine learning and AI should go beyond the instrumental use of technology and focus on understanding its basic principles, limitations, and educational possibilities (Laru et al., 2025; Sperling et al., 2022). The results of this research thus reaffirm numerous studies highlighting the importance of integrating AI and educational robotics from the earliest school years. Practices that integrate visual block programming and collaborative project work should thus be considered beneficial in elementary education (Holmes et al., 2025). Likewise, an approach focused on coding and modeling with machine learning improves students' competence for an educational approach to AI, while their perceptions of AI may be influenced by their perceived competence in these areas, as those with higher levels of AI competence tend to approach risks more systematically (Heilala et al., 2025).

These conclusions are reinforced by several studies that demonstrated the importance of acquiring basic computer programming concepts in elementary education, where future teachers will work (Israel et al., 2015; Sáez-López et al., 2026b). University education

and initial teacher training must therefore be adapted to the demands of today's society, considering the emerging trends that future professionals will encounter in their immediate future. These interventions and initiatives generate an emerging innovative approach in pedagogical contexts, with several studies coinciding with the results of this research (Chevalier et al., 2022; Giannakoulas & Xinogalos, 2024; Israel et al., 2015; Noh & Lee, 2020; Rich et al., 2022; Wei et al., 2021; Wong, 2024; Wu & Su, 2021). Based on this work and the contributions consistent with our findings, we suggest that educational authorities implement machine learning activities to enhance the understanding of AI, coding, and robotics, so that dynamic and active learning activities can be developed.

This study has several limitations that should be considered when interpreting the findings. First, the sample was selected using a non-probabilistic, purposive sampling strategy, which limits the statistical generalizability of the results beyond the participants included in the study. Although the large and diverse sample of elementary school students, pre-service teachers, and practicing teachers provides valuable evidence regarding the educational potential of robotics and machine learning, the findings should be interpreted as representative of the participating educational contexts rather than the broader population. Future research should employ probabilistic sampling strategies and include participants from different geographical regions and educational settings to strengthen the external validity of the findings.

In conclusion, the findings indicate that machine learning and educational robotics represent promising educational approaches for promoting AI literacy, understanding computational concepts, and fostering active engagement. Nevertheless, future research using experimental or quasi-experimental designs with control groups and random assignment, where feasible, is needed to establish causal evidence regarding their effectiveness. Future studies employing more rigorous research designs are needed to establish the effectiveness and generalizability of these approaches across broader educational contexts.

Author Contributions: Conceptualization, J.-M.S.-L.; methodology, J.-M.S.-L. and S.R.-D.; software, J.-M.S.-L. and M.P.-G.; validation, M.-B.M.-C. and S.R.-D.; formal analysis, J.-M.S.-L. and S.R.-D.; investigation, S.R.-D.; resources, M.P.-G. and M.-B.M.-C.; data curation, M.P.-G.; writing—original draft preparation, S.R.-D., M.-B.M.-C. and M.P.-G.; writing—review and editing, J.-M.S.-L. and S.R.-D.; visualization, S.R.-D.; supervision, S.R.-D. and J.-M.S.-L.; project administration, J.-M.S.-L.; funding acquisition, J.-M.S.-L. All authors have read and agreed to the published version of the manuscript.

Funding: 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.

Institutional Review Board Statement: The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and the applicable institutional and national regulations governing research involving human participants and approved by the Ethics Committee of UNED under certificate reference number 09-SISH-EDU-2024. Date: 20 March 2024.

Informed Consent Statement: Written informed consent was obtained from all participating teachers and pre-service teachers. For elementary school students, written informed consent was obtained from their parents or legal guardians before participation, and verbal or written assent was obtained from the children in accordance with their age and institutional requirements. Participation was voluntary, and participants were informed that they could withdraw from the study at any time without consequence. All data were anonymized prior to analysis, treated confidentially, and processed in compliance with the applicable data protection regulations.

Data Availability Statement: Data available on request from the authors. The data that support the findings of this study are available from the corresponding author, J.-M.S.-L., upon reasonable request.

Conflicts of Interest: The authors have no competing interests to declare that are relevant to the content of this article.

Appendix A

Session 1–2—Conditional Reasoning and Sensor-Driven Programming

Participants are introduced to conditional control structures based on “if–then” logic alongside foundational work with environmental sensors, including light and temperature inputs. Students design interactive programs that respond dynamically to real-time data, such as displaying measured values or activating visual feedback when pre-defined thresholds are met. The session prioritizes the development of computational decision-making processes and highlights the functional connection between physical inputs and digital outputs.

Learning focus: Logical decision structures and input–output interactions.

Practical activities:

1. Environmental data display: Students program the micro:bit to present temperature or light intensity readings when Button A is activated.
2. Threshold-based alert systems: Learners develop programs that initiate visual or audio signals when sensor values surpass or fall below established limits.
3. “If–Then” applied challenges: Short problem-solving tasks require students to construct conditional responses to real-life scenarios, such as modeling weather-based alerts.
4. Digital dice simulation: Participants create a virtual dice generator using randomized output triggered by the micro:bit’s motion sensor (shake function), introducing sequencing and event-driven logic.
5. Assemble and build a car with the Nezha kit; the car should avoid obstacles with the ultrasonic distance sensor.

Session 3–4—Foundations of Educational Robotics with the Maqueen Kit

Students transition from screen-based programming to hands-on robotics by working with the Maqueen robot. Following assembly, the learners program basic motor commands to produce controlled movement patterns along predefined pathways. The instruction focuses on principles of directional control, action sequencing, and spatial reasoning. The core pedagogical objective is to connect abstract programming concepts with observable physical actions performed by a robotic system.

Learning focus: Motor coordination and physical execution of algorithms.

Practical activities:

1. Robot construction workshop: Students assemble the Maqueen robot and integrate the micro:bit controller.
2. Movement sequencing exercises: Learners program forward motion, directional turns, and timed stops to navigate structured routes.
3. Light-based navigation challenge: Students design, implement, and refine control programs that enable the Maqueen robot to navigate toward a target location by responding to variations in ambient light detected by the micro:bit’s built-in light sensor (Figure A1). Through the use of conditional statements, the robot adjusts its movement based on light intensity levels. Learners engage in iterative testing and debugging to optimize sensor thresholds and improve navigation accuracy and responsiveness.

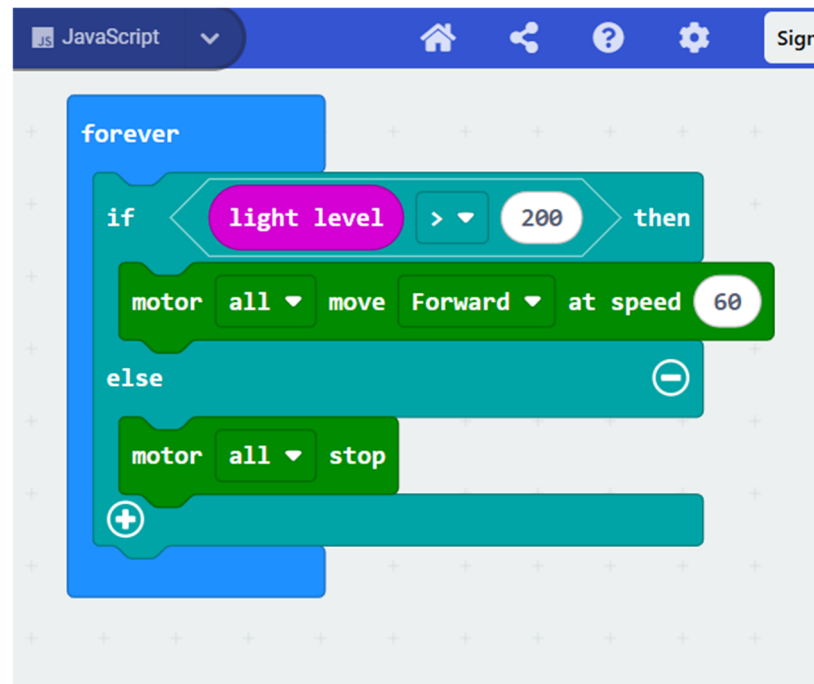


Figure A1. Visual block program developed in micro:bit MakeCode for the light-guided robot navigation project. https://makecode.microbit.org/_4yR150LbpWvm (accessed on 22 July 2026).

Session 5–6—Conditional Control of an Automated Barrier System Using Sensors and Actuators

This session advances students' understanding of robotic systems through the design and programming of an automated barrier with an integrated traffic-light mechanism, using the micro:bit and Nezha platform. Learners focus on the use of an ultrasonic sensor to detect approaching objects and apply conditional logic to control system responses, such as activating a servo motor to raise or lower the barrier and switching LED signals to represent traffic states (red, yellow, and green).

Students develop programs that enable the robotic system to make real-time decisions based on distance measurements, thus reinforcing the relationship between sensor input, conditional structures, and actuator output. The session emphasizes computational thinking, logical sequencing, and systematic debugging within a real-world automation context.

Learning focus: Real-time decision-making and conditional control in sensor-driven robotic systems.

Practical activities:

1. Ultrasonic-based barrier control: Students program the ultrasonic sensor to measure distance and use conditional statements to determine when the servo motor should raise or lower the barrier (e.g., opening the barrier when a vehicle is detected within a predefined range).
2. Traffic-light signaling with actuators (Figure A2): Learners integrate LED indicators to simulate a traffic-light system, coordinating color changes with barrier movement through conditional logic (e.g., red light when the barrier is closed, green light when it is open).
3. Testing, debugging, and optimization: Teams intentionally modify distance thresholds, servo angles, and timing parameters to observe system behavior, identify logical or sensor-related errors, and refine their programs to ensure accuracy, reliability, and smooth operation.

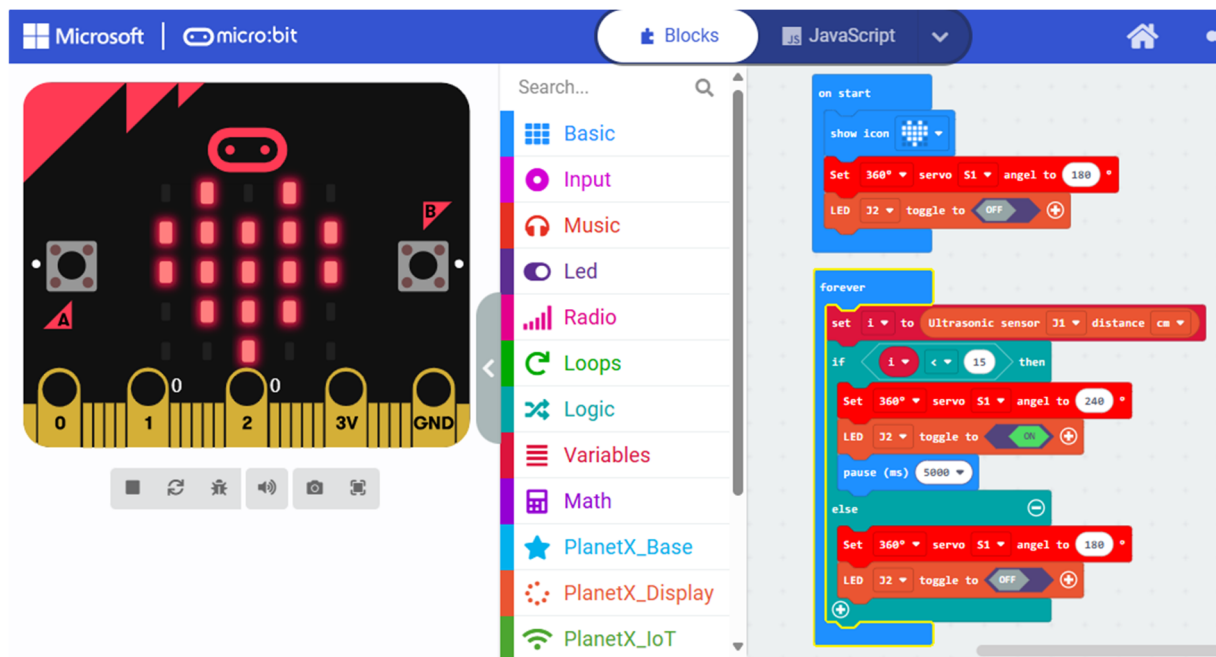


Figure A2. Visual block program developed in micro:bit MakeCode for controlling the automated barrier and traffic light system using an ultrasonic sensor and servo motor (Sáez-López et al., 2026a, 2026b).

Session 7–8—Introductory Machine Learning through Visual Programming

Students explore introductory machine learning concepts using the “Machine Learning for Kids” platform alongside Scratch 3.0, focusing on supervised classification models based on image recognition. Through the “Shy Panda” project, participants progress through dataset creation, model training, and live inference testing. Pedagogical emphasis is placed on understanding the essential machine learning pipeline, data collection and labeling, training, evaluation, and iterative refinement, rather than technical coding complexities, thus providing an accessible introduction to artificial intelligence principles (Sáez-López et al., 2026a, 2026b).

Learning focus: Fundamentals of supervised learning and foundational AI literacy.

Practical activities:

1. Learners work on two projects with the Smart AI Lens: recognizing the color of the balls and recognizing objects with the camera (Figure A3).
2. Dataset creation: Students capture and categorize images into two classes (“I see you”/“I don’t see you”) within the “Machine Learning for Kids” platform.
3. Model training and evaluation: Learners train classification models and assess real-time predictive performance using webcam input during the “Shy Panda” activity.
4. Model refinement and bias awareness: Participants revise datasets and retrain models to observe changes in prediction accuracy, facilitating discussion about data bias and model reliability.

In this session, a model is trained using images and the possibilities of machine learning are demonstrated. Scratch 3.0 and “Machine Learning for Kids” (<https://machinelearningforkids.co.uk/>, accessed on 22 July 2026) are used. The “Shy Panda” project was developed; this resource is available on the website and is based on an original idea by Cassie Evans (<https://codepen.io/cassie-codes/pen/jKaVqo>, accessed on 22 July 2026). In this project, learners interact with a shy panda bear. If the character does not feel that it is being watched, it will dance, but if it detects that you are watching it, it will become embarrassed and stop dancing. Ultimately, in this session, participants can understand machine learning and how it is trained with numerous images in two categories, “I see you”

(te veo) and “I don’t see you” (no te veo), to recognize whether the learner is looking at the panda or covering his or her eyes. It is a simple and fun project that allows learners to understand image detection and use visual block programming to explore computational concepts and practices.

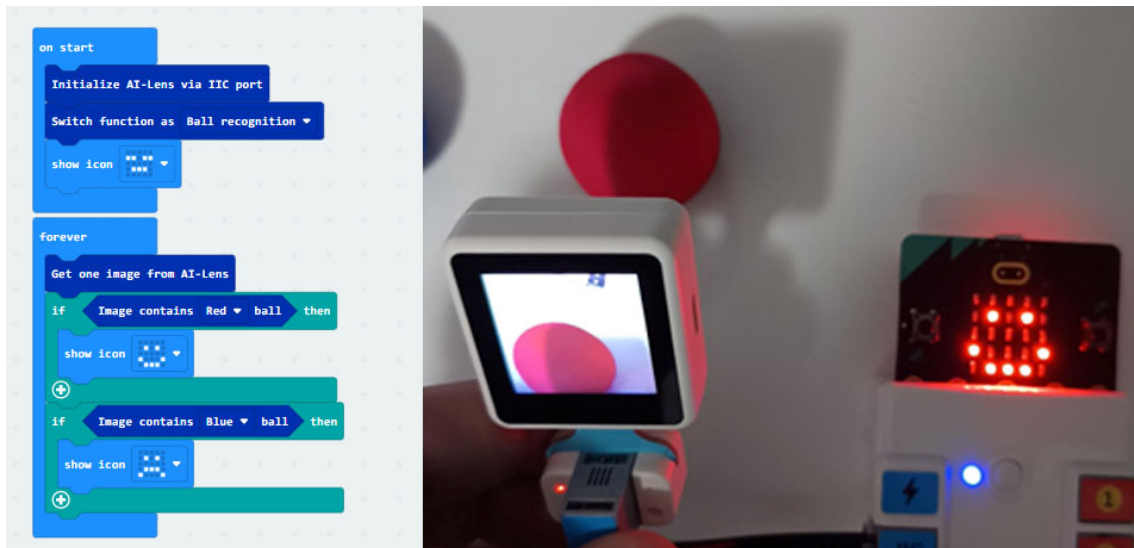


Figure A3. Recognition of a red ball using the Smart AI Lens as part of an introductory object recognition activity.

Appendix B

Test (CRMT) of the first dimension: Knowledge of machine learning, computational concepts and robotics:

- What is “machine learning”?
It is a repeating loop in programming.
Training machines so they can learn on their own and perform tasks (correct).
It is a sequence and an event.
It is a robot turning with a servo sensor upon encountering an obstacle.
- When training a machine learning model to identify a cat, it is important to:
Provide few photos of cats.
Provide many photos of dogs and mice.
Provide many photos of cats; the more, the better (correct).
Include an LED motor.
- Which of these examples is a sensor?
It is a constantly nested conditional statement.
It is a motor in a car-robot.
It is a constantly shining red LED.
An ultrasonic distance device (eyes) (correct).
- Which of these examples is an actuator?
It is a constantly nested conditional statement.
It is a motor in the wheels of a robot/car (correct).
It is a variable.
An ultrasonic distance device (eyes).
- What computational concept do you see in the image?
Sequence (correct)
Loop

- Conditional
- Event
- 6. What computational concept do you see in the image?
 - Sequence
 - Loop (correct)
 - Conditional
 - Event
- 7. What computational concept do you see in the image?
 - Sequence
 - Loop
 - Conditional (correct)
 - Event
- 8. What computational concept do you see in the image?
 - Sequence
 - Loop
 - Conditional
 - Event (correct)
- 9. If you want to place a character in the upper right part of the scene, you must configure:
 - Go to X = −150, Y = 150
 - Go to X = 150, Y = 150 (correct)
 - Go to X = 150, Y = −150
 - Go to X = −150, Y = −150
- 10. To train a model with Machine Learning for Kids, the steps are:
 - Go to X = −150, Y = 150
 - Train, Learn & Test, Make (correct)
 - Sequences, loops, and conditional
 - Keyboard input, Scratch 3.0, and Python

References

- Bers, M. U. (2008). *Blocks to robots: Learning with technology in the early childhood classroom*. Teachers College Press.
- Chevalier, M., Giang, C., El-Hamamsy, L., Bonnet, E., Papaspyros, V., Pellet, J. P., Audrin, C., Romero, M., Baumberger, B., & Mondada, F. (2022). The role of feedback and guidance as intervention methods to foster computational thinking in educational robotics learning activities for primary school. *Computers & Education*, 180, 104431. [\[CrossRef\]](#)
- Daher, R. (2025). Integrating AI literacy into teacher education: A critical perspective paper. *Discover Artificial Intelligence*, 5, 217. [\[CrossRef\]](#)
- de Vink, I. C., Tolboom, J. L. J., & van Beekum, O. (2023). Exploring the effects of near-peer teaching in robotics education: The role of STEM attitudes. *Informatics in Education*, 22(2), 329–350. [\[CrossRef\]](#)
- Esteve-Mon, F. M., Adell-Segura, J., Llopis-Nebot, M. A., Valedolivas-Novella, G., & Pacheco-Aparicio, J. (2019). The development of computational thinking in student teachers through an intervention with educational robotics. *Journal of Information Technology Education: Innovations in Practice*, 18, 139–152. [\[CrossRef\]](#) [\[PubMed\]](#)
- Gavrilas, L., Kotsis, K. T., & Papanikolaou, M. S. (2024). Exploration of the prospective utilization of educational robotics by preschool and primary education teachers. *Pedagogical Research*, 9(1), em0181. [\[CrossRef\]](#) [\[PubMed\]](#)
- Giannakoulas, A., & Xinogalos, S. (2024). Studying the effects of educational games on cultivating computational thinking skills to primary school students: A systematic literature review. *Journal of Computers in Education*, 11, 1283–1325. [\[CrossRef\]](#)
- Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate data analysis* (5th ed.). Prentice Hall.
- Heilala, V., Sikström, P., Setälä, M., & Kärkkäinen, T. (2025). Artificial intelligence competence of K-12 students shapes their AI risk perception: A co-occurrence network analysis. *arXiv*, arXiv:2512.04115.
- Holmes, W., Bialik, M., & Fadel, C. (2025). *Artificial intelligence in education: Promises and implications for teaching and learning*. Springer.
- Israel, M., Pearson, J. N., Tapia, T., Wherfel, Q. M., & Reese, G. (2015). Supporting all learners in school-wide computational thinking: A cross-case qualitative analysis. *Computers & Education*, 82, 263–279. [\[CrossRef\]](#)

- Laru, J., Celik, I., Jokela, I., & 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. *European Journal of Teacher Education*, 48(5), 964–986. [\[CrossRef\]](#)
- Maloney, J., Kafai, Y., Resnick, M., & Rusk, N. (2008). Programming by choice: Urban youth learning programming with scratch. In *39th SIGCSE technical symposium on computer science education, Portland, OR, USA, March 12–15* (pp. 367–371). ACM.
- Noh, J., & Lee, J. (2020). Effects of robotics programming on the computational thinking and creativity of elementary school students. *Educational Technology Research and Development*, 68, 463–484. [\[CrossRef\]](#)
- Papert, S. (1980). *Mindstorms: Children, computers, and powerful ideas*. Basic Books.
- Resnick, M., Maloney, J., Hernández, A. M., Rusk, N., Eastmond, E., Brennan, K., Millner, A., Rosenbaum, E., Silver, J., Silverman, B., & Kafai, Y. (2009). Scratch: Programming for all. *Communications of the ACM*, 52(11), 60–67. [\[CrossRef\]](#)
- Rich, P. J., Bartholomew, S., Daniel, D., Dinsmoor, K., Nielsen, M., Reynolds, C., Swanson, M., Einward, E., & Yauney, J. (2022). Trends in tools used to teach computational thinking through elementary coding. *Journal of Research on Technology in Education*, 56(3), 269–290. [\[CrossRef\]](#)
- Robert, J., Muscanell, N., McCormack, M., Pelletier, K., Arnold, K., Arbino, N., Young, K., & Reeves, J. (2025). *2025 EDUCAUSE horizon report, teaching and learning edition*. EDUCAUSE.
- Sáez-López, J.-M., García-Jiménez, A.-S., & de-Lara-García-Cervigón, S. (2026a). Coding, robots, computational concepts, and machine learning using the microbit card and the Maqueen and Nezha kits: A study in initial teacher training. *Computers and Education Open*, 10, 100366. [\[CrossRef\]](#)
- Sáez-López, J.-M., Redondo-Duarte, S., & De Lara-García Cervigón, S. (2026b). Educational robotics with interactive and environmental projects using “micro:bit” and “Nezha” in nine primary schools. *Eurasia Journal of Mathematics, Science and Technology Education*, 22(3), em2802. [\[CrossRef\]](#) [\[PubMed\]](#)
- Schina, D., Romero, M., & France, N. (2025). Pair interactions and emergent roles in problem-solving with modular robotics in primary education. *Technology, Knowledge and Learning*. [\[CrossRef\]](#)
- Sperling, K., Stenliden, L., Nissen, J., & 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. *European Journal of Education Research, Development and Policy*, 57(4), 584–600. [\[CrossRef\]](#)
- Tsai, C. Y., Chen, Y. A., Hsieh, F. P., Chuang, M. S., & Lin, C. L. (2023). Effects of a programming course using the GAME model on undergraduates' self-efficacy and basic programming concepts. *Journal of Educational Computing Research*, 62(3), 482–504. [\[CrossRef\]](#)
- Uzumcu, O., & Bay, E. (2021). The effect of computational thinking skill program design developed according to interest driven creator theory on prospective teachers. *Education and Information Technologies*, 26, 565–583. [\[CrossRef\]](#)
- Villalustre, L., & Cueli, M. (2023). Assessing the computational thinking of pre-service teachers: A gender and robotics programming experience analysis. *Education Sciences*, 13(10), 1032. [\[CrossRef\]](#)
- Villegas-Ch, W., García-Ortiz, J., & Sánchez-Viteri, S. (2024). Optimizing writing skills in children using a real-time feedback system based on machine learning. *IEEE Access*, 12, 164634–164651. [\[CrossRef\]](#)
- Weber, A. M., Bastian, M., Barkela, V., Mühlhling, A., & Leuchter, M. (2022). Fostering preservice teachers' expectancies and values towards computational thinking. *Frontiers in Psychology*, 13, 987761. [\[CrossRef\]](#) [\[PubMed\]](#)
- Wei, X., Lin, L., Meng, N., Tan, W., Kong, S. C., & Kinshuk. (2021). The effectiveness of partial pair programming on elementary school students' computational thinking skills and self-efficacy. *Computers & Education*, 160, 104023. [\[CrossRef\]](#)
- Wong, G. K. W. (2024). Amplifying children's computational problem-solving skills: A hybrid-based design for programming education. *Education and Information Technologies*, 29, 1761–1793. [\[CrossRef\]](#)
- Wu, S.-Y., & Su, Y.-S. (2021). Visual programming environments and computational thinking performance of fifth- and sixth-grade students. *Journal of Educational Computing Research*, 59(6), 1075–1092. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.