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Creating artificial intelligence: An active approach using machine learning in elementary education

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Abstract

Programming and machine learning (ML) education can foster computational thinking, problem-solving, creativity, and artificial intelligence (AI) literacy, equipping learners to engage actively with AI beyond simply using existing tools. This study examines the implementation of an active learning approach based on ML in primary education, where students create and train their own ML models using accessible visual programming environments such as Teachable Machine and Responsible AI for Social Empowerment and Education. A pre-experimental pretest–posttest design was conducted with 996 students aged 10–11 from 11 schools. Learning outcomes were assessed through a knowledge test analyzed with paired-samples *t*-tests and a Likert-scale questionnaire analyzed using the Wilcoxon signed-rank test. Results revealed statistically significant improvements in students' understanding of ML and AI, with higher posttest scores ($t = -16.13$, $p < 0.001$) and a moderate effect size. Questionnaire findings indicated that 97.9% of participants reported that ML activities improved their understanding of AI, while 94.6% reported enjoying the process of creating ML models. The findings suggest that engaging students in designing and training AI models may support computational thinking, creativity, motivation, and a critical understanding of intelligent systems. The study supports the integration of ML through visual programming as a promising strategy for AI literacy in primary education, which may foster active participation and responsible engagement with emerging technologies.

Keywords: Artificial intelligence; Machine learning; Primary education; Computational thinking; Visual programming

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1. Introduction

Artificial intelligence (AI) represents one of the most significant technological transformations of the 21st century, with applications spanning fields from healthcare and industry to education and scientific research. However, integrating AI into education should not focus solely on task automation or efficiency; it should aim to enhance human capabilities such as creativity, critical thinking, and problem-solving. In this context, active AI use means students understand how intelligent systems function and participate in their creation, such as by developing machine learning (ML) models, rather than merely using generative tools.

Programming and ML are increasingly recognized as pedagogical tools for fostering computational thinking, problem-solving, creativity, and AI literacy from the early years of education. Although recent evidence suggests the strongest empirical support concerns the development of computational thinking, studies also report positive effects on problem-solving, creativity, and AI literacy, while broader transfer to other domains and long-term curricular impact require further investigation (Wang *et al*., 2026; Wei *et al*., 2024).

The effectiveness of programming education for fostering computational thinking has been consistently demonstrated across preschool and primary education. A meta-analysis of 32 studies found a moderate overall effect of programming instruction on children's computational thinking (Wei *et al*., 2024). Consistent with these findings, experimental studies have reported improvements in sequencing, error correction, pattern recognition, and algorithmic problem-solving following structured programming and educational robotics activities (Falloon, 2024). Moreover, both plugged and unplugged approaches contribute to these learning gains, although unplugged activities may be particularly beneficial for younger learners (Bati, 2022).

1.1. Programming and machine learning for early artificial intelligence literacy

Building on these findings, recent research suggests that AI literacy can also be successfully introduced during the early years of education when age-appropriate pedagogical approaches and educational tools are employed. These approaches increasingly shift learning from traditional rule-based programming toward data-driven reasoning, enabling students to train ML models, evaluate predictions, and understand how algorithms learn from data (Tedre *et al*., 2021; Yim & Su, 2025). Longitudinal evidence also suggests that project-based experiences, such as game development, can promote creative thinking, critical thinking, and problem-solving, although further research is needed to understand how these competencies transfer beyond programming tasks (Wong & Cheung, 2020).

Artificial intelligence is already embedded in students' everyday lives through virtual assistants, recommendation systems, automated translation tools, and a wide range of digital applications. Despite their frequent interaction with these technologies, most students have only a limited understanding of how AI systems operate (Heeg & Avraamidou, 2023; Laru *et al*., 2025). ML has become a fundamental technology underpinning contemporary AI, driven by advances in data availability, computing power, and algorithm development (Goodfellow *et al*., 2016; Jordan & Mitchell, 2015). Consequently, understanding its basic principles has become essential to AI literacy and to educational initiatives preparing students for an increasingly data-driven society.

This need has also been recognized at the institutional level. Miao *et al*. (2024) have developed the *AI Competency Framework for Students*, while the European Union has established the Artificial Intelligence Act (European Union, 2024), highlighting the importance of promoting a critical, ethical, and informed use of AI technologies (Daher, 2025; Laru *et al*., 2025). Recent empirical evidence also supports these institutional recommendations. Sáez-López, Redondo-Duarte, & García Cervigón (2026) demonstrated that basic ML concepts can be successfully introduced in primary education through active, age-appropriate learning experiences. Using accessible educational tools, students collected data, trained simple ML models (Shamir & Levin, 2026), and explored how algorithms recognize patterns and improve their predictions. These experiences promoted not only conceptual understanding but also critical reflection on the potential, limitations, and ethical implications of AI.

Several educational tools have been developed to facilitate these learning experiences. Recent reviews identify environments such as Teachable Machine, Machine Learning for Kids, LearningML, PopBots, Scratch, and Python as suitable resources for introducing AI concepts throughout K–12 education, with some applications already appropriate for primary school (Yim & Su, 2024). Visual ML tools are frequently integrated with block-based programming environments such as Scratch or App Inventor, enabling students to develop image-recognition models embedded in games or mobile applications (Von Wangenheim *et al*., 2021).

The educational potential of these tools is further supported by recent empirical studies in both early childhood and primary education. Block-based environments such as ScratchJr have been shown to improve preschool children's understanding of algorithms, representation, and hardware and software concepts, although not all dimensions of computational thinking develop at the same pace (Louka & Papadakis, 2024). Likewise, hybrid instructional approaches combining unplugged and plugged activities have demonstrated significant gains in computational thinking skills among primary school students (Wong, 2024), while tangible robot programming has proven effective in strengthening debugging abilities, including both syntactic and semantic understanding, in preschool learners (Misirli & Komis, 2023).

Taken together, these findings suggest that programming

and ML activities offer an effective pathway to foster AI literacy throughout compulsory education while underscoring the importance of pedagogically grounded, developmentally appropriate learning experiences.

Despite these advances, significant challenges remain, including limited theoretical grounding, a lack of rigorous empirical evaluation, insufficient teacher preparation (Redondo-Duarte *et al*., 2026), and the need for stronger pedagogical frameworks addressing ethics (Martinez-Requejo *et al*., 2025), transparency, and the diverse learning needs of younger students (Yim & Su, 2024).

1.2. Pedagogical foundations for machine learning

Papert (1991)'s theory of constructionism provides an important pedagogical foundation for integrating programming and AI into education. Building on Piaget's constructivist theory, constructionism argues that learning is enhanced when students actively create meaningful artifacts, such as computer programs, robots, or digital media, that can be shared, refined, and reflected upon (Papert, 1980). Within this framework, technology is not merely a learning tool but a medium for creating "objects-to-think-with" that foster reflection, creativity, and conceptual understanding (Papert, 1991; Resnick, 2020).

This pedagogical perspective has been further developed by Mitch Resnick, director of the Lifelong Kindergarten Group at the MIT Media Lab. During the webinar *Putting Students First in the Age of AI* (hosted by LEGO Education), Resnick argued that education in the age of AI should preserve learners' most human capabilities, including creativity, curiosity, and empathy. Rather than replacing human reasoning, AI should support learning by expanding students' capacity to investigate, create, and solve problems. Central to this approach is human agency, in which students make decisions, express their ideas, and maintain ownership of the learning process.

Building on these constructionist principles, engaging students in developing ML models is an effective way to introduce AI because it lets them explore a fundamental technology through direct experimentation. Unlike the passive use of AI applications, designing and training ML models requires learners to understand how algorithms learn from data, identify patterns, generate predictions, and recognize the limitations of intelligent systems (Alpaydin, 2020; Bishop & Nasrabadi, 2006; Houngue *et al*., 2022; Sanusi *et al*., 2024; Shamir & Levin, 2026; Triantafyllou, 2025). This process also helps students understand concepts such as data quality, model training, and generalization, enabling them to critically evaluate AI-generated outputs and make informed decisions.

A key characteristic of constructionist ML activities is that, rather than relying on predefined datasets, students often create or curate their own training data, connecting model development to their prior knowledge and authentic, real-world problems. Using self-generated, meaningful datasets helps learners understand how data quality and data selection influence model behavior, fostering deeper AI literacy and critical reflection on algorithmic decision-making (Kim *et al*., 2025; Zhdanovskaya *et al*., 2023). Collaborative dataset refinement and iterative evaluation further strengthen this learning process by enabling students to improve model performance through data inspection, transfer learning, and the analysis of classification errors (Tseng *et al*., 2024).

A further principle of constructionist learning concerns the educational value of error. Resnick (2020) argues that meaningful learning does not involve using AI to eliminate all difficulties but instead preserves challenges that promote deep understanding and creativity. Likewise, Carney *et al*. (2020) suggest that students are more willing to engage with complex problems when these are personally meaningful. In ML education, classification errors, overfitting, and low model accuracy become valuable learning opportunities, encouraging students to analyze algorithmic behavior, refine training data, and progressively improve model performance.

Among ML paradigms, supervised learning is particularly relevant in educational settings because it lets students see how algorithms learn from labeled examples and generalize to unseen data (Carney *et al*., 2020). Visual programming environments such as Teachable Machine and Responsible AI for Social Empowerment and Education (RAISE) make these concepts accessible through block-based programming activities, allowing students to experiment with supervised learning while making abstract AI concepts tangible and understandable (Mustafa *et al*., 2024; Yuan *et al*., 2024). Consequently, implementing supervised ML through accessible visual programming environments provides a pedagogically sound framework for introducing AI concepts in primary education.

1.3. Objectives

The main objective of this study is to evaluate the educational outcomes of an ML-based intervention in primary education. The specific objectives are:

(i) To assess learning through an understanding of ML in elementary education.
(ii) To analyze the participants' acquisition of basic concepts regarding ML model training.

2. Data and methods

2.1. Data collection

A pre-experimental pretest–posttest design with related samples was employed to evaluate the educational intervention. The study involved 996 students aged 10–11 years enrolled in primary schools in the Madrid region (Spain). A purposive, non-probabilistic sampling strategy was used, resulting in a sample drawn from 17 classrooms across 11 schools. The sample comprised 49.4% girls and 50.6% boys.

Learning outcomes were assessed using a 10-item knowledge test administered before and after the intervention. The knowledge test consisted of 10 multiple-choice items (**Appendix**). Each correct answer received one point, yielding total scores ranging from 0 to 10. The instrument was adapted from Redondo-Duarte *et al.* (2026) and Sáez-López, Redondo-Duarte, Neubauer Esteban, & Pena Garrido (2026) and was designed to assess students' knowledge of ML together with the computational concepts (e.g., programming logic and event-based programming) required to develop and use ML applications. Therefore, the total score should be interpreted as representing foundational knowledge for educational ML rather than ML knowledge in isolation. Pretest–posttest differences on the knowledge test were analyzed using paired-samples Student's *t*-tests, with statistical significance established at $\alpha = 0.01$. Statistical analyses were conducted using the Statistical Package for Social Sciences software (version 30.0).

Students also completed a four-point Likert-scale questionnaire designed to examine their perceptions of the learning experience. Internal consistency, estimated using Cronbach's alpha, was 0.67 for the second dimension, indicating acceptable reliability. The questionnaire was administered before and after the intervention. At pretest, items referring to ML activities were intended to capture students' initial perceived understanding and expectations regarding these activities, as participants had no prior experience with the instructional approach. At posttest, the same items assessed perceptions based on direct participation in the intervention. Questionnaire responses were analyzed using the Wilcoxon signed-rank test. Although the questionnaire included multiple items, the present study focused on three items that directly assessed students' understanding of and perceptions of ML, as these were predefined as the questionnaire items most closely aligned with the objectives of the present study.

2.2. Implementation

The intervention comprised four instructional sessions of approximately 60 minutes each, delivered over a two-week period. Session 1 introduced the fundamental concepts of AI and supervised ML and familiarized students with the Teachable Machine environment. During Session 2, students collected and labeled image data and trained their first image-classification models. Session 3 focused on evaluating model performance, identifying classification errors, and improving the models by refining the training dataset. In Session 4, students integrated their trained models into interactive projects using the RAISE visual programming environment, allowing them to apply ML within block-based programming activities.

The activities were delivered by classroom teachers following a common instructional protocol. Prior to implementation, instructors received brief training/materials to ensure consistency in the delivery of the intervention. Students worked individually, using the same software, instructional materials, and activity sequence in all 17 classrooms. The knowledge test was administered immediately before the first session (pretest) and immediately after the fourth session (posttest) under comparable classroom conditions.

The sessions introduced primary education students to the development of image classification models using block-based visual programming environments. Using an active learning approach, the activities engaged students in training and testing their own ML models while introducing them to fundamental ML principles through hands-on experimentation.

Two educational tools were employed: Teachable Machine (Figure 1) and RAISE (Figure 2). Teachable Machine is a web-based interface that allows users to train their own ML classification models without the need for coding, using images, sound, or a webcam. It employs transfer learning, an ML technique that adapts a pre-trained model using user-generated data. This approach enables learners to identify patterns in images or audio and rapidly create simple classification models through an accessible and intuitive interface.

Responsible AI for Social Empowerment and Education is a block-based visual programming environment developed by the Massachusetts Institute of Technology. As an extension of the Scratch programming language, it incorporates AI and ML functionalities, enabling students to integrate trained ML models into interactive programming projects while reinforcing computational thinking and problem-solving skills.

Both tools followed the design principles of a "low floor, high ceiling, and wide walls" (Brennan & Resnick, 2012), meaning that they are easy for beginners to use (low floor),

support increasingly complex projects (high ceiling), and enable a wide variety of creative applications (wide walls). These characteristics align with the constructionist principles described by Papert (1991) and Resnick (2020), as they encourage exploration, creativity, and increasingly sophisticated computational thinking.

These projects illustrate how block-based programming can be effectively combined with AI to create interactive educational applications. In this example, RAISE Playground (Figure 3) serves as the development environment, while Google Teachable Machine provides the image classification model that enables the real-time recognition of fruits through a webcam. By integrating these two environments, students can develop interactive applications that incorporate ML models without requiring prior knowledge of ML algorithms or text-based programming.

The development process begins in Google Teachable Machine, where students create an image classification model using supervised learning. The model is trained by collecting multiple image samples for each fruit category (e.g., apple, banana, and orange), together with a background class. Teachable Machine then applies transfer learning to adapt a pre-trained model using the collected data, resulting in a custom image classification model capable of recognizing the selected categories. Once the training process is complete, the model is published, generating a URL that can be imported into RAISE Playground for integration into a block-based programming project.

Within RAISE Playground, the trained model is integrated through dedicated AI blocks by importing the URL generated in Google Teachable Machine. Instead of implementing image recognition algorithms directly, the platform accesses the published ML model and continuously captures webcam images. Each captured frame is analyzed by the model, which returns the predicted class together with its confidence score. The block-based program then uses these predictions as inputs, enabling the application to respond dynamically to objects detected by the camera.

Programming in RAISE Playground is based on an event-driven paradigm using graphical blocks. The application begins by initializing the webcam, loading the external ML model, and defining game variables such as score, time, and game status. During execution, it continuously requests predictions from the AI model and stores the detected labels. Conditional blocks then evaluate whether the predicted fruit matches the expected game object and whether the confidence score exceeds a predefined threshold. When these conditions are met, the application triggers the corresponding actions, including updating the score, displaying animations, playing sound effects, and generating new fruit objects on the screen.

This architecture clearly separates the ML stage from application development. The image classification model is created and trained externally using Google Teachable Machine, whereas RAISE Playground manages the interaction logic through block-based visual programming.

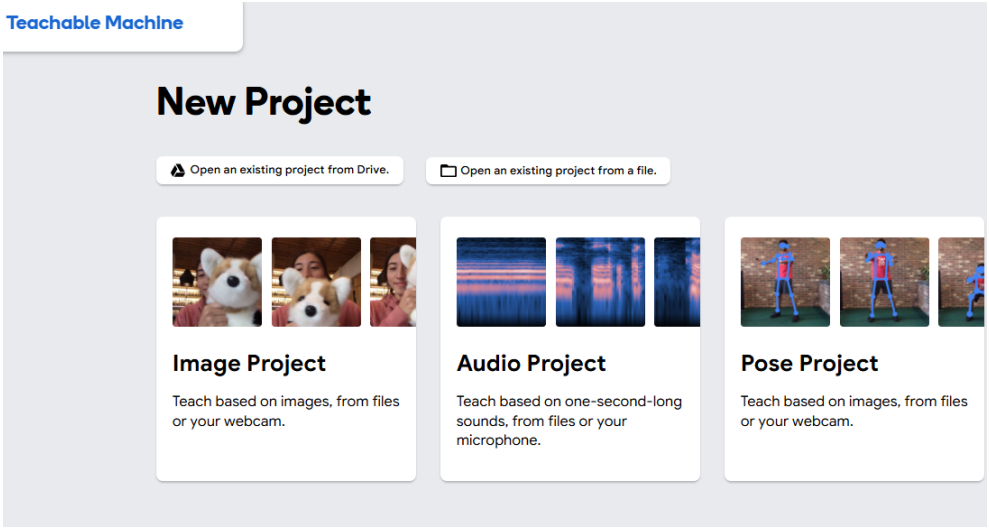


Figure 1. Teachable Machine platform for training models. https://teachablemachine.withgoogle.com/train. Teachable Machine provides a machine learning (ML) environment for creating image and text recognition models that can be integrated into applications developed using the Responsible AI for Social Empowerment and Education-Scratch visual block-based programming environment.

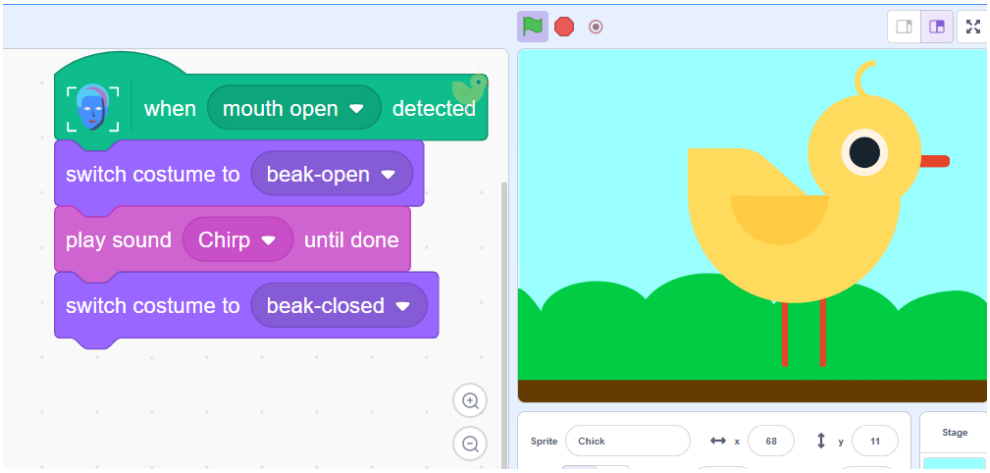


Figure 2. Responsible AI for Social Empowerment and Education (based on Scratch 3.0) with integrated Teachable Machine models. https://playground.raise.mit.edu/. Data can be added to or removed from the model as needed, and various interactive, creative projects are carried out using visual block-based programming.

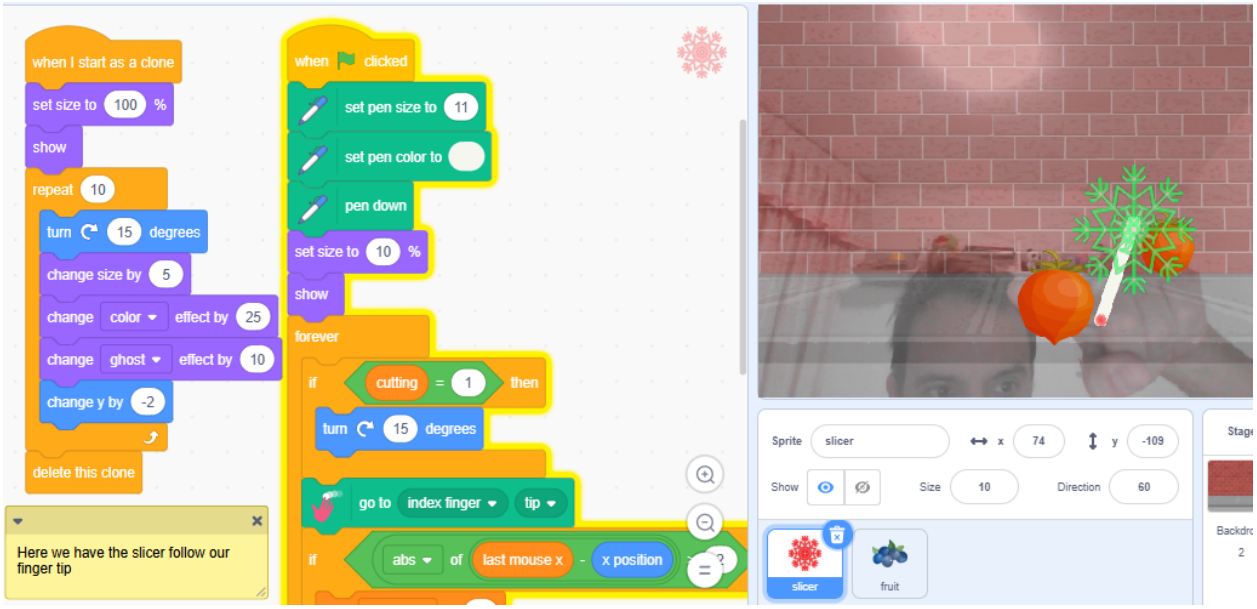


Figure 3. Responsible AI for Social Empowerment and Education (based on Scratch 3.0) with integrated Teachable Machine models. "Slicer fruit project" https://playground.raise.mit.edu/.

This separation helps students understand that ML models can be integrated as reusable components within software applications, illustrating the practical relationship between ML and programming.

By eliminating the syntactic barriers associated with conventional programming languages, RAISE Playground allows learners to focus on algorithmic reasoning, event-driven logic, and the design of interactive systems. Consequently, this approach provides an accessible pedagogical framework for promoting AI literacy and computational thinking through the development of interactive ML applications.

This study is part of a broader research project investigating the integration of ML activities in primary education. A previous publication (Sáez-López, Redondo-Duarte, Neubauer Esteban, *et al.*, 2026) reported findings

from an earlier intervention conducted within the same research program. Although some schools participated in both studies, the interventions, participant samples, and datasets are different. The present manuscript reports the results of a separate educational intervention and addresses a distinct dataset and research objectives. This clarification is provided to ensure transparency regarding the relationship between the two publications.

3. Results

Pretest and posttest scores from the 996 participating students were compared using paired-samples Student's *t*-tests. The analysis revealed a statistically significant improvement following the intervention. Mean posttest scores (mean = 6.24, standard deviation = 1.41) were significantly higher than pretest scores (mean = 5.54, standard deviation = 1.74) ($t[995] = -16.13$, $p < 0.001$). The mean difference between measurements was −0.70 points, with a 99% confidence interval (CI) of [−0.82, −0.59]. Effect size estimates indicated a moderate effect, according to both Cohen's d ($d = -0.51$, 99% CI: −0.60, −0.42) and Hedges' correction ($g = -0.509$, 99% CI: −0.60, −0.42), supporting the observed pretest–posttest improvement following the intervention.

Students' perceptions of the intervention were assessed using a four-point Likert-scale questionnaire. Table 1 presents the questionnaire results, which show significant shifts in students' responses; however, Items 1.2 and 1.3 should be interpreted as shifts from anticipated pretest perceptions to experience-based posttest perceptions, rather than as direct pretest–posttest improvements in a stable construct.

As shown in Table 1, most students selected "Agree" or "Strongly agree" for all three items. For Item 1.1 ("I understand what machine learning is"), 81.8% of participants agreed or strongly agreed that they understood the concept. Agreement was even higher for Item 1.2 ("I understand artificial intelligence better through machine learning activities"), with 97.9% selecting "Agree" or "Strongly agree." Likewise, 94.6% of students agreed or strongly agreed that they enjoyed creating ML models (Item 1.3).

All three questionnaire items showed statistically significant shifts in students' responses ($p < 0.001$). However, Items 1.2 and 1.3 should be interpreted as changes from anticipated perceptions at pretest to experience-based perceptions at posttest, rather than as direct pretest–posttest improvements in a stable construct.

Effect sizes ranged from small for Item 1.1 ($r = 0.15$) to large for Item 1.3 ($r = 0.69$) and very large for Item 1.2 ($r = 0.81$). Posttest responses were predominantly concentrated in the two highest response categories, particularly for Items 1.2 and 1.3.

4. Discussion

The findings of the present study indicate that engaging primary education students in the design and training of ML models was associated with significant improvements in students' understanding of AI while generating high levels of motivation toward learning. These findings provide an opportunity to reflect on one of the key competencies required in the age of AI: creativity. Rather than replacing human capabilities, educational approaches based on ML may create meaningful opportunities for students to investigate authentic problems, design technological solutions, and actively participate in the development of intelligent systems.

Creativity has become one of the most important competencies in the age of AI. Rather than diminishing its importance, AI reinforces the need to develop learners' capacity to generate original ideas, solve authentic problems, and design innovative solutions. In this context, Resnick (2020) argues that creativity should remain at the center of education and proposes the "Four Ps" model of creative learning (Projects, Passion, Peers, and Play).

Designing ML models may enable students to formulate authentic problems, collect and organize data, train models, evaluate predictions, and iteratively refine their solutions. Through this process, learners engage in problem-solving, technological innovation, and AI literacy (Laru *et al*., 2025; Mustafa *et al*., 2024; Sperling *et al*., 2022). The high levels of agreement observed among participants regarding their understanding of AI and their enjoyment of creating ML models are consistent with this constructionist perspective, in which learning occurs through the active creation of meaningful technological artifacts (Papert, 1991; Resnick, 2020).

These theoretical arguments are further supported by recent empirical evidence. Research conducted by Sáez-López, García-Jiménez, & García-Cervigón (2026) and Sáez-López, Redondo-Duarte, Neubauer Esteban, & Pena Garrido (2026) demonstrates the educational value of combining programming and ML as an active learning strategy. Their findings suggest that engaging students in designing and training ML models creates authentic opportunities for creative thinking, problem-solving, and technological innovation. From this perspective, creativity extends beyond artistic expression and can be understood as the capacity to generate original ideas, develop innovative solutions, and approach authentic problems from multiple perspectives.

Table 1. Student perceptions of the machine learning before and after the intervention

Item	Pretest				Posttest				*Z*	*r*	*p*
	1	2	3	4	1	2	3	4			
1.1. Understand machine learning	15.1	40.4	35.4	9.1	10.4	7.8	72.2	9.6	−4.572	0.15	<0.001
1.2. Understand artificial intelligence through machine learning activities	18.6	8.6	69.5	3.3	0.4	1.8	15.8	82.1	−25.565	0.81	<0.001
1.3. Enjoy creating models to train machine learning	0.9	57.4	15.3	26.4	0.6	4.8	16.5	78.1	−21.627	0.69	<0.001

Note: Values represent percentages. Likert scale: 1 = Strongly disagree, 2 = Disagree, 3 = Agree, 4 = Strongly agree. Z = Wilcoxon signed-rank test statistic. Effect size was calculated as $r = |Z|/\sqrt{N}$.

Programming and creating ML models may provide an appropriate context for developing this competency. When students design a program or develop a technological solution to a real-world problem, they engage in creative processes involving planning, experimentation, and continuous improvement (Shamir & Levin, 2026).

Programming, as a tool for active learning, may provide a tangible experience that facilitates the understanding of abstract concepts and significantly enhances students' motivation. The ability to build and program models transforms learning into an active and meaningful experience. This interpretation aligns with the high levels of enjoyment participants reported after the intervention.

From an educational perspective, AI should support, not replace, human creativity. Before using AI-based tools, learners should first define the objectives, identify the problem, and reflect on possible solutions. Only after this human-centered process should AI be used to support the generation of alternatives and enrich decision-making. This approach is encapsulated in the principle *"Prompt the human before the machine*," emphasizing that understanding the problem should precede the use of AI as a cognitive support tool.

Working with ML models allows these issues to be addressed from a practical perspective, as students experiment directly with data selection, bias detection, and the critical evaluation of algorithmic behavior. AI should be integrated into education through a people-centered approach rather than one focused exclusively on technology. Building ML models can promote active learning, creativity, critical thinking, and real-world problem-solving (Franceschelli & Musolesi, 2024; Said-Metwaly *et al*., 2017; Sanusi *et al*., 2024; Shamir & Levin, 2026). Rather than using AI only to get immediate answers, students need to understand how it works, participate in its development, and reflect on its ethical and social implications.

Ultimately, working with ML models may help cultivate citizens who can think creatively, design innovative solutions, critically interpr*et al*gorithmically generated information, and use AI as a tool for empowerment.

5. Limitations

The pre-experimental one-group pretest–posttest design limits the conclusions that can be drawn from the findings. Although knowledge scores increased following the four instructional sessions, these gains cannot be confidently attributed to the intervention itself because the study did not include a control or comparison group. Alternative explanations, including maturation, testing effects, concurrent classroom instruction, teacher-related influences, and other contextual factors, cannot be ruled out. Accordingly, the findings should be interpreted as evidence of a pretest–posttest change observed following the intervention rather than as definitive evidence of its causal effectiveness. Future studies employing randomized or quasi-experimental designs with appropriate comparison groups are needed to strengthen causal inferences regarding the educational value of this instructional approach. Students' prior experience with programming, Scratch, or ML was not formally assessed and therefore may have influenced individual learning outcomes.

An additional limitation concerns the hierarchical structure of the data. Students were nested within 17 classrooms across 11 schools, whereas the statistical analyses were conducted at the individual student level. Consequently, the analyses did not account for potential dependence within classrooms or schools, which may have affected standard error estimates and statistical significance.

Future research should employ multilevel modeling or cluster-robust analytical approaches to appropriately account for the nested structure of educational data and to provide more robust estimates of intervention effects.

The observed pretest–posttest gain should be interpreted with caution because its educational significance depends on the measurement quality of the knowledge test. Although statistically significant differences were observed, further evidence regarding the test's reliability, validity, and sensitivity to detect learning gains would strengthen confidence in the interpretation of these findings. Future studies should either report the complete questionnaire results or clearly justify the a priori criteria used for item selection.

Furthermore, using a purposive sample from schools in a single region may limit the generalizability of the findings. In addition, the intervention was limited to four instructional sessions, and no delayed follow-up assessment was conducted; therefore, the long-term durability of the observed learning gains remains unknown.

6. Conclusion

Recent research (Redondo-Duarte *et al*., 2026; Sáez-López, Redondo-Duarte, Neubauer Esteban, & Pena Garrido, 2026; Shamir & Levin, 2022; Touretzky *et al*., 2023) demonstrates that programming and ML can be successfully incorporated into primary education through active, student-centered methodologies.

The two outcome measures assessed different constructs and should be interpreted accordingly. The knowledge test provided an objective measure of students' conceptual knowledge, whereas the questionnaire captured students' self-reported perceptions of their understanding and learning experience. Consequently, increases in perceived understanding should not be interpreted as direct evidence of gains in conceptual knowledge but rather as students' subjective evaluations of their learning. The convergence between both measures is encouraging; however, each provides distinct evidence and should be interpreted independently.

Programming and ML may provide tangible experiences that help students understand complex concepts and boost motivation; furthermore, they allow accessible introductions to AI fundamentals, contributing to deeper, more critical AI literacy. The findings of the present study support the following conclusions:

(i) Students demonstrated statistically significant pretest–posttest improvements in AI knowledge following the ML activities. Although the mean posttest score for the knowledge test (mean = 6.24) reflects the conceptual complexity of the content, statistically significant improvements were observed following the intervention. These findings suggest that primary education students can successfully understand fundamental AI concepts by creating and training their own ML models using accessible visual programming environments such as Teachable Machine and Raise.

(ii) Students reported statistically significant shifts in their perceived understanding of AI concepts and high levels of enjoyment following the intervention. The questionnaire results showed statistically significant pretest–posttest shifts in students' self-reported perceptions ($p < 0.001$), rather than direct evidence of improvements in conceptual knowledge. For Items 1.2 and 1.3, these shifts should be interpreted specifically as changes from anticipated perceptions at pretest to experience-based perceptions at posttest, rather than as direct pretest–posttest improvements in a stable construct. These findings suggest that active, ML-based activities were associated with more positive self-reported perceptions of understanding and enjoyment during the creation and training of ML models.

However, the study did not directly measure motivation, computational thinking, creativity, critical thinking, or responsible engagement; therefore, these outcomes should be considered potential implications of the approach rather than demonstrated effects. In particular, enjoyment should not be interpreted as direct evidence of increased motivation.

In summary, the findings confirm that integrating ML into primary education is not only feasible but also educationally valuable when grounded in visual programming, active learning, and critical reflection. Ultimately, preparing students for an AI-driven society requires an educational approach that combines technical understanding and the capacity to design innovative solutions to authentic problems.

As Mitch Resnick (2020) has argued, not knowing how to program is like learning to read but never learning to write; coding, even with visual block-based programming, is fundamental to understanding the technological world. We truly learn about AI by understanding and building our own models, thereby grasping the possibilities and limitations these systems offer. In this context, ML emerges as a powerful tool for supporting essential educational processes, including content adaptation, educational data analysis, and personalized learning. However, its educational value depends not only on technological innovation but also on fostering critical AI literacy that

combines technical understanding with ethical reflection.

Given the educational benefits observed in this study, educational authorities and schools should promote the integration of ML activities into primary education through active, hands-on learning experiences. Beyond increasing student motivation and engagement, this pedagogical approach helps students understand how AI works.

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Conflict of interest

The authors have no competing interests relevant to the content of this article.

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Ethics approval and consent to participate

The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of UNED (protocol code/certificate reference number 09-SISH-EDU-2024, date of approval: March 20, 2024). Participants' legal guardians provided consent for their participation.

Consent for publication

Participants' legal guardians provided consent for their data to be published.

Availability of data

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

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Appendix. Test of the first dimension: Knowledge of machine learning

The knowledge test was adapted from Redondo-Duarte *et al.* (2026) and Sáez-López, Redondo-Duarte, Neubauer Esteban, & Pena Garrido (2026). It consisted of 10 multiple-choice items designed to assess primary school students' understanding of the machine learning concepts addressed during the instructional intervention.

1. What is "machine learning"?

a) It is a repeating loop in programming.
b) Training machines so they can learn on their own and perform tasks (correct).
c) It is a sequence and an event.
d) It is a robot turning with a servo sensor upon encountering an obstacle.

2. When training a machine learning model to identify a cat, it is important to:

a) Provide few photos of cats.
b) Provide many photos of dogs and mice.
c) Provide many photos of cats; the more, the better (correct).
d) Include an LED motor.

3. Which of these examples is a sensor?

a) It is a constantly nested conditional statement.
b) It is a motor in a car-robot.
c) It is a constantly shining red LED.
d) An ultrasonic distance device (eyes) (correct).

4. What computational concept do you see in the image?

a) Sequence (correct).
b) Loop.
c) Conditional.
d) Event.

5. What computational concept do you see in the image?

a) Sequence.
b) Loop (correct).
c) Conditional.
d) Event.

6. What computational concept do you see in the image?

a) Sequence.
b) Loop.
c) Conditional (correct).
d) Event.

7. What computational concept do you see in the image?

a) Sequence.
b) Loop.
c) Conditional.
d) Event (correct).

8. For the chick to open and close its beak at the same time as I open and close my mouth in the camera, the following is required:

a) Tap the taco pointer and set the color effect.
b) Tap the taco pointer and set the position (y–10).
c) Facial recognition and two ML categories from the Teachable Machine (correct).
d) Move the chick to X=40 and change its costumes with the sound.

9. In RAISE, the following is required

a) Introduce a model with different categories (correct).
b) Introduce Python and C#.
c) Separate loops and operators.
d) Building parallelism.

10. In Teachable Machine, what does the "dataset" that users upload or capture during the creation of a model represent?

a) A set of programming instructions that the model executes automatically.
b) A collection of training data (images, sounds, or poses) that the model uses to learn to classify patterns.
c) A history of the predictions made by the model after training.
d) A database of users who will access the model online.

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