Enhancing Continuous Professional Development for Science Teachers with Machine Learning Activities

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Abstract

Aligned with the principles of justice, peace, and sustainable development, Artificial Intelligence (AI) has the potential to make learning more equitable, fair, accessible, and inclusive. To achieve this, teachers need specialized training and low-cost, easily accessible educational resources that facilitate their incorporation into pedagogical practice. This article aims to contribute to this goal, specifically in the context of science education. To this end, it presents the design, implementation, and evaluation of a proposal for educational activities intended to enhance the teaching strategies of science teachers by incorporating Supervised Machine Learning. We evaluated the activities in two workshops involving a total of 56 science teachers; the first workshop was conducted online, and the second was held in person. During the evaluation, we examined changes in teachers' self-perception through surveys, with assessments conducted at the beginning and end of both workshops. The results highlight significant improvements in the science teachers' perceptions in key areas, such as knowledge about Machine Learning, the selection of resources to support their teaching, and more positive attitudes towards integrating Machine Learning in the science classroom. Challenges related to the conceptualization and application of Machine Learning in the educational environment were also identified. This study underscores the need for additional support and specific preparation to overcome digital gaps in the adoption of AI in multidisciplinary education. The findings are discussed considering recent professional development trends based on AI teacher training strategies.

Keywords: Artificial Intelligence Teaching and Learning, Machine Learning, Science Education, Continuing Education, ICT Into the Curriculum.

1 Introduction

The potential of emerging technologies, such as Artificial Intelligence (AI) and its subfields like Machine Learning (ML), is internationally recognized as a crucial strategic factor for strengthening educational systems and advancing toward the fulfillment of the Sustainable Development Goals [1, 2, 3]. The global discourse has established that these technologies can help drive equitable growth in society while also addressing some of the complex challenges of the 21st century [4].

From an educational perspective, it has been proposed that educational institutions, particularly schools, should adapt to this technological shift and take the lead in preparing teachers and students to understand, co-create, and promote the responsible use of AI [5, 6, 7]. Classroom interactions, culture, socio-emotional aspects, and creativity are irreplaceable; in this sense, it is clear that AI will never replace teachers or their role in the future [8]. However, it is also evident that AI will become increasingly present in classrooms, used by both students and teachers. The latest AI models not only enrich the learning experience but also enhance teaching efficiency, allowing educators to dedicate more time to student interaction, timely feedback, and the design of innovative pedagogical and curricular approaches [9].

The integration of AI into school curricula is a key governmental strategy for promoting social justice, as it provides equitable learning opportunities for students across diverse regions and contexts. Its inclusion democratizes access to these resources, reduces gaps in their use, and strengthens civic preparedness from an early age, ensuring that everyone can adapt, actively participate, and contribute to a future where AI will play a permanent role. While there is an ongoing debate on the importance of incorporating AI into national curricula, international comparative evidence suggests that this process has been slow and has occurred in only a few regions worldwide [10]. Adaptation mechanisms have been influenced by various ethical challenges [11, 12, 13] and fundamental questions about how teachers and students should interact responsibly with AI to harness its potential for supporting education [13, 14]. There is still no clear consensus on what teachers and students should know about AI in schools or how this technology should be integrated into teaching and learning processes.

Some studies suggest that the limited adoption of AI in the education sector is partly due to the lack of specific educational approaches in research on its use [15], as well as the absence of new theories, models, and methods for its effective integration into pedagogical practice [16]. Another critical factor is the scarcity of empirical evidence, particularly in regions such as Africa, Latin America, and the Caribbean [17]. Most studies and models on AI use originate from high-income countries such as the United States, China, and the United Kingdom. Research on AI in Latin America has primarily focused on its use in higher education or university contexts [18, 19, 20], highlighting the importance and necessity of expanding research into AI in school education within these regions. Few studies have explored teachers' perceptions and the challenges they face in using AI pedagogically [21, 22, 23], despite the significance of mediating factors that influence AI-assisted teaching [24, 25].

Another key factor that could help explain the slow adoption of AI relates directly to the role of teachers and their professional preparation [26]. In general, the potential of AI in educational practices remains underutilized [27], and teachers often feel unprepared or lack confidence in teaching with these technologies [17]. When educators use AI without adequate training, they tend to rely on traditional teaching models based on passive strategies rather than leveraging AI’s potential in combination with active strategies to foster deep learning among students [28]. In practice, studies indicate that the knowledge enabling teachers to mediate AI use in the classroom is fundamental to achieving effective teaching outcomes [29, 30, 31, 32]. Research also emphasizes that the better prepared teachers are in selecting, accessing, and using AI, the more likely they are to utilize these tools to enhance student motivation and engagement [33, 34].

While teacher training is a lifelong process [35], both initial teacher education and continuous professional development programs can contribute to AI preparedness. Specifically, studies by [36, 37] examine factors that support the success of continuous professional development programs, including the implementation of activities with appropriate durations, internal coherence within training activities, and alignment with the school curriculum. In this regard, effective teacher training strategies should not only focus on the technical use of AI or the development of programming skills but also incorporate pedagogical, curricular, disciplinary, and ethical perspectives tailored to each educational setting. When combined, these aspects can help improve teachers' confidence in AI-assisted instruction, promote pedagogical use through constructive approaches, and ensure its responsible integration into teaching practices [38, 39, 40, 41, 42]. However, [43] highlights that there remains a significant research gap in addressing the ongoing professional development needs of teachers as they integrate AI into their instructional practices.

In this context, and to contribute updated evidence, the present study aims to present the design and implementation process of workshops that are part of a "continuous professional development and training program on AI" for science teachers in Chile. The program was implemented between 2022 and 2023 as part of a public policy initiative for curricular updates, involving science teachers from various regions across the country.

2 Related Work

2.1 Government Initiatives for Integrating Artificial Intelligence into K-12 Education

The new uses of AI are transforming people's lives and work, offering promising opportunities but also posing ethical challenges. This has made AI a topic of global interest for governments and public policies [44, 45]. This global relevance is also reflected in the attention it receives from the field of education [1, 2, 3, 4, 14, 46, 47], especially with the emergence of generative language processing AI [48, 49, 50, 51].

While AI is currently an emerging area of research in education, it is not a new field. The incursion of AI in education has roots dating back to 1971, when Papert and Solomon proposed the idea that children could begin developing algorithms related to AI through a programming language called LOGO [52]. This proposal was later expanded by Kahn, who confirmed the hypothesis put forth by Papert and Solomon in his papers on the LOGO natural language system and the interactions between AI and education [53].

Current research proposals address the integration of AI in teaching and learning, exploring both teachers' perceptions and the factors influencing the acceptance and use of AI-based educational tools. It is argued that AI in teachers' pedagogical practice can have multiple applications and benefits, such as providing tools and resources that enhance personalized learning, optimizing decision-making, automating administrative tasks, and facilitating the creation of educational content. However, it is essential for teachers to familiarize themselves with these technologies and understand how to integrate them effectively into their teaching. Pedagogical work has also emerged relevant to AI development, such as collaborative learning projects, problem-solving, or robotics [54]. AI is a new topic for students and schoolteachers, and it requires exploration in terms of understanding, acceptance, and effective application, especially due to the lack of empirical evidence [15, 47].

Currently, governmental initiatives worldwide aim to integrate AI into K-12 education systems. In Asia, countries like South Korea have been pioneers in this field, implementing educational policies since 2015 to integrate AI into the curriculum [55]. In the United States, the AI4K12 educational guide was launched in 2019 for school communities [56], along with various teaching resources and specific guidelines for teachers and school leaders [57]. In the United Kingdom, a national strategy for data literacy and AI understanding was established [58]. Meanwhile, the European Union has launched an online learning program on AI to improve citizens' basic competence [59]. In Australia, frameworks have been created for the ethical use of AI in education and society [60]. In Latin America, Uruguay has launched prominent "Computational Thinking and Artificial Intelligence" programs to update the training of teachers and students [61], while Brazil has opted to establish a Brazilian Artificial Intelligence Strategy to promote AI research and innovation, including in education [62].

In 2021, Chile enacted the "National Artificial Intelligence Policy", aimed at contributing to people's overall well-being by improving their quality of life, leveraging the benefits of AI, and addressing its risks and potential negative impacts, with an unwavering commitment to human rights [63]. However, teacher training initiatives began earlier. In 2019, the Chilean Ministry of Education (Mineduc) introduced the National Digital Languages Plan through its Innovation Center, offering programs, curricula, talks, workshops, and training sessions on AI and digital citizenship for teachers and students nationwide [64, 65].

Despite the efforts, the lack of adequate and impartial perspectives and evidence on the use of technology explains some of the difficulties in its current adoption [15, 17, 66]. Additionally, teachers need more preparation and confidence to teach with technology, a crucial aspect for students to face these future technological challenges [28].

This overview indicates that although international organizations and governments recognize the potential of AI for education, its integration and appropriation still face significant challenges for educational practice, especially in areas such as science education, where evidence is not as abundant.

2.3 Artificial Intelligence for K-12 Science Education

For the sciences, research has shown that AI plays a significant role, as it can facilitate complex scientific tasks such as hypothesis formulation, mathematical proof development, experiment design and monitoring, data collection and analysis, simulation, and inference [67]. Its application enables the addressing of major socio-environmental challenges, including climate change and the large-scale spread of diseases [68]. However, its potential has yet to be fully harnessed in school education, largely due to the lack of strategies and training programs that promote its use in multidisciplinary contexts and foster collaboration among specialists in fields such as education, sciences, and computer science [69, 70].

Recent literature reviews on the integration of AI into science education reveal a progressive increase in research on this topic over the past decade [71, 72, 73]. Previous reviews have also focused on examining trends in AI-driven automation of assessment processes [69], as well as on analyzing students' scientific reasoning and argumentation [67, 74] and exploring the use of motivational strategies combined with AI to support science teaching in schools [73].

According to trends identified by [69], the specific applications of AI for teaching sciences in primary and secondary education are primarily concentrated in subjects such as physics [75, 76, 77], geosciences [78], general science [79, 80], and to a lesser extent, biology [81, 82] and chemistry [83].

[69] also identified that the latest AI applications in science education focus mainly on the use of automated assessment and feedback systems [78, 84, 85], personalized learning systems [75, 83], adaptive learning systems [77, 86], and expert systems [80]. More recently, there has been an emerging interest in the use of unplugged computational thinking approaches [87, 88]. Other less-represented applications in current literature include chatbots, text classifiers, predictive models, and intelligent tutoring systems. Most of these applications are designed to support students directly by providing adaptive learning content and tailored responses to their questions. Additionally, they help teachers save time by automating tasks such as assessment and planning based on predictive models.

The use of AI applications in science education enables students to enhance their argumentation skills through continuous interaction and feedback [78, 85, 89]. Some experiences have also demonstrated their effectiveness in helping students achieve learning outcomes related to mechanical physics [90], electricity and magnetism [91], kinematics and dynamics [92], and changes in matter [79].

While some comparable experiences exist, significant research gaps remain in AI-driven school education, particularly in physics areas such as astronomy, fluid dynamics, and optics. Moreover, there is an almost complete absence of empirical studies addressing AI applications in the teaching of chemistry and biology.

3 Method

In this work, we adopted the Educational Design-Based Research methodology [93, 94, 95, 96] to develop, implement, and evaluate a series of 'school science teaching' activities that incorporate some basic processes of Supervised Machine Learning. This method is flexible and according to [97, 98, 99] allows the implementation of multiple cycles of evaluation and redesign [e.g. 99, 100]. To achieve our objective, we established four main strategic stages (see Fig. 1):

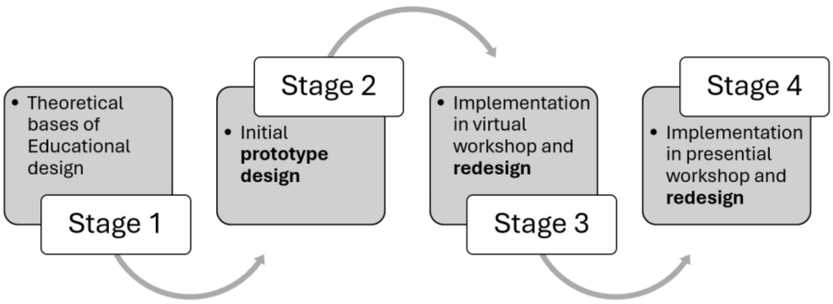


Figure 1: Stages for Educational Design Research model

1. In the first stage, we established conceptual foundations that allowed us to support and guide the design of educational activities. This step was essential to justify the initial design decisions. On one hand, this stage enabled us to identify and incorporate activity ideas from other similar studies in the field, based on their main 'lessons learned.' On the other hand, we were also able to identify and evaluate some digital resources such as Teachable Machine (https://teachablemachine.withgoogle.com/) and RAISE Playground (https://playground.raise.mit.edu/).
2. In the second stage, we developed initial prototypes of science teaching activities using Supervised Machine Learning. This first prototype was built based on an adaptation of [101, 102], where the task is to observe the morphological characteristics of a set of fish images to distinguish poisonous ones from non-poisonous ones. In this activity, we incorporated a play-based dynamic, which consists of building a "logical decision tree" (or flowchart) based on the physical characteristics of the fish (such as eyes, tail, fins, colors, etc.). Participants formulate "scientific hypotheses" based on the "decision tree" and share it with another participant who uses it to guess and avoid the possible bite of four new fish that could be poisonous. The winner is the one who gets bitten the least by poisonous fish. At the end of the activity, they use Teachable Machine to compare their own statistical prediction models with those of the digital machine.

3. The third stage took place in 2022 and consisted of the implementation and evaluation of a virtual workshop with 42 science teachers (physics, chemistry and biology), 22 women and 20 men, from different regions of Chile. Most of the science teachers had more than 5 years of experience teaching in primary or secondary schools. The implementation mode was virtual due to the COVID-19 pandemic lockdown. In this workshop, we incorporated the initial activity prototypes from the previous stage, along with an initial and closing activity where teachers share ideas for new school science projects that integrate Supervised Machine Learning and Artificial Intelligence into the Chilean school curriculum. After evaluating the workshop, we carried out the first redesign of the educational activities.
4. The fourth stage took place in 2023 and consisted of the implementation and evaluation of an in-person workshop with a group of 14 science teachers from different regions of Chile (9 women and 5 men). In this workshop, we used the redesign developed in the previous stage. Additionally, based on [103] and [87, 88] we included news activities involving computational thinking (unplugged or without the use of digital screens) and incorporated some activities based on ideas proposed by the science teachers in the previous workshop. Finally, we conducted an evaluation and redesign of all educational activities as a whole.

Throughout both workshops (virtual and in-person), we evaluated changes in the perception of science teachers using self-perception surveys on a 4-point Likert scale (see Table 1), following the Knowledge and Prior Study Inventory (KPSI) model [104].

Table 1: KPSI Questionnaire

Questions	1	2	3	4
Q1. Can I explain the concept of Machine Learning?				
Q2. Do I know ways to incorporate Machine Learning into my teaching practice?				
Q3. Can I establish criteria to identify and select appropriate Machine Learning resources for my teaching practice?				
Q4. Am I aware of the necessary processes to integrate Machine Learning resources into the curriculum?				
Q5. Do I know how to design activities that integrate Machine Learning technology and align with science learning objectives?				

Note. Where: 1 = Completely Agree, 2 = Agree, 3 = Disagree, 4 = Completely Disagree.

We applied the survey to gather evidence on possible attitudinal changes associated with self-perception in the use of Machine Learning in the teaching of sciences (physics, chemistry and biology). The surveys were administered in both workshops, at the beginning and end of the activities, following a pre-post test design. Content analysis of the responses and descriptive statistical analysis were performed to compare significant changes in the average scores of teachers' perception responses, contrasting initial results with final ones. Responses were coded according to their trend. In both cases, Wilcoxon non-parametric tests were used as they allow for comparing significant differences between initial and final mean scores of two related ordinal samples [105].

Lastly, throughout all stages, we adhered to ethical consent principles, respecting transparency, anonymity, confidentiality, voluntary withdrawal from the activity, among other principles."

4 Results

4.1 Initial Design “Virtual Science Education Workshop with Machine Learning”

The objective of this virtual workshop was to explore and evaluate some applications of Machine Learning for Science Education. The workshop was primarily aimed at in-service or pre-service science teachers of primary or secondary education (physics, chemistry, or biology), without excluding educators from lower levels (e.g., early childhood educators). To achieve the workshop's objective, teachers and educators created some classifiers and decision trees to support the development of a school scientific investigation and improve the understanding of the basic processes underlying Artificial Intelligence. Across the board, teachers created simple classifiers (using text, image, audio, or video) with Google's "Teachable Machine" software (https://teachablemachine.withgoogle.com/) and discussed their use on platforms like "RAISE Playground" (https://playground.raise.mit.edu/).

At the beginning of the workshop, teachers were presented with brief explanations of fundamental concepts of artificial intelligence and supervised machine learning, accompanied by examples illustrating their application in executing projects in the field of sciences. This introductory phase aimed to establish a common basic understanding and familiarize participants with the essential concepts of these technologies in the context of their discipline. This pedagogical strategy helped ensure that teachers had a solid initial understanding of artificial intelligence and machine learning, setting the stage for the workshop with a shared knowledge base.

In the core activities of the workshop, an activity involving the construction of decision trees and scientific hypotheses was conducted. To achieve this, science teachers first explored 'training' situations, similar to the training process in supervised machine learning. Based on [101, 102] activities, teachers worked with cartoon images of fish and were tasked with distinguishing between poisonous and non-poisonous fish based on their morphological physical characteristics (e.g., eyes, tail shape, fin shape, dorsal colors, etc.), as exemplified in Fig. 2. During this activity, teachers played an active role in creating decision rules, establishing criteria and guidelines for making distinctions through decision trees. Subsequently, they compared the rules in 'model tests' to evaluate their effectiveness. In this activity, teachers also proposed 'scientific research hypotheses' based on the characteristics described in their own decision trees. This experience not only allowed teachers to understand the basic principles of machine learning but also to apply them to the formulation of logical scientific hypotheses, enriching their understanding and didactic skills for the discipline.

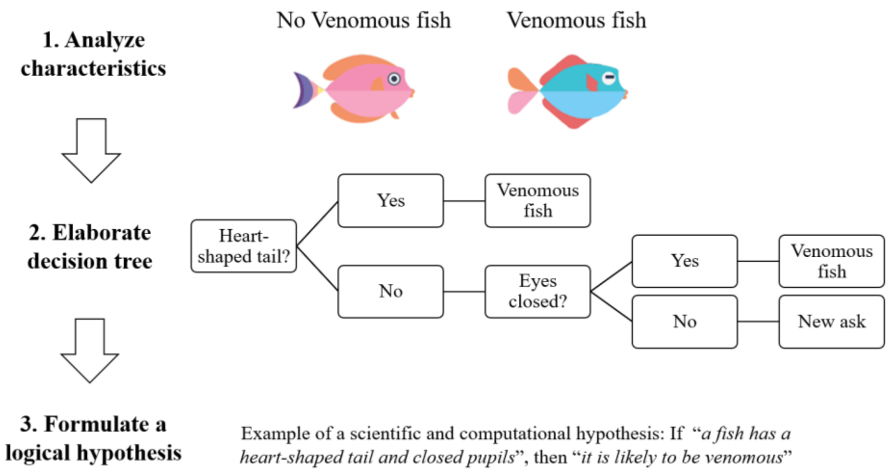


Figure 2: Fish classification activity example. Adapted from ReadyAI activities

At the end of the experience, the science teachers compared their models and hypotheses with those of Teachable Machine. They also shared project ideas and activities for applying Machine Learning to science education on a collaborative mural (see Fig. 3). The mural featured various ideas on the use of Supervised Machine Learning for classifying waste, identifying local flora and fauna, improving the efficiency of solar panels, classifying stars, and more.

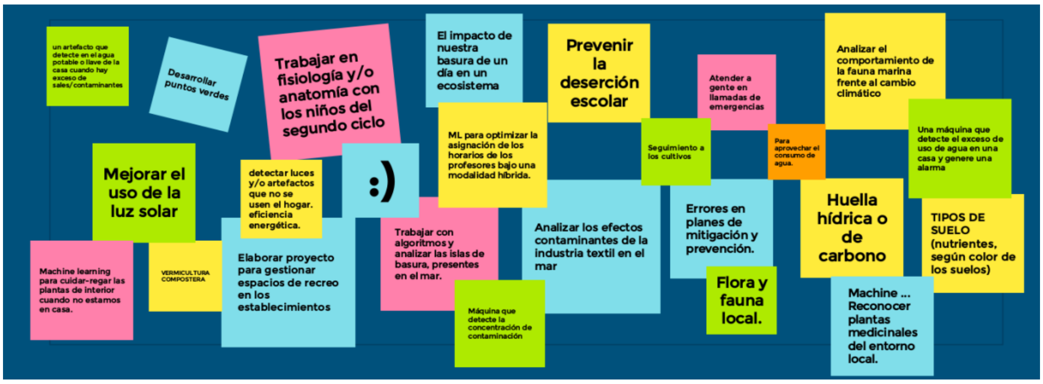


Figure 3: Activity closure with a brainstorming session on a collaborative mural

At the end of the workshop, we noticed in conversations that some science teachers had difficulties proposing new application ideas for disciplines such as physics and chemistry. This was partly because the only example developed during the workshop was the fish classification. Other teachers also expressed difficulties in differentiating the basic stages of Supervised Machine Learning, as it was a new topic for them. These findings were important for reorienting a new design of our educational activities, considering the incorporation of more and new discussions on the functioning of AI, with greater graduality, participation, and presenting more examples and resources to help improve their understanding.

4.2 Teachers' Self-Perception in Virtual Workshops

The results in Table 2 indicate changes in all average scores of the responses from science teachers. The trends show favourable changes, notably leaning towards the "Agree" or "Strongly Agree" options on the Likert scale. The greatest increase (i.e., the largest difference between post-test and pre-test) was observed in question 1 (Q1), with moderate Effect Size (ES) 'Cohen's d = 0.466'. This question pertains to perceptions about the ability to explain the concept of Machine Learning. On the other hand, the smallest increase was observed in question 4 (Q4), which refers to whether science teachers know the processes necessary to integrate Machine Learning resources into the curriculum (local curriculum in Chile).

Table 2: Descriptive statistics of teachers' self-perception questions in virtual workshop (N = 42)

Questions	Mean	Increment	SD	Cohen's d	ES Interpretation
KPSI Pre-test					
Q1	2,83	-	,621	-	-
Q2	3,14	-	,683	-	-
Q3	2,45	-	,889	-	-
Q4	2,52	-	,943	-	-
Q5	2,26	-	,828	-	-
KPSI Post-test					
Q1	1,64	-1,19	,656	0,466	Moderate
Q2	2,19	-0,95	,994	0,283	Small
Q3	1,86	-0,59	1,026	0,154	Trivial
Q4	1,98	-0,54	,869	0,149	Trivial
Q5	1,64	-0,62	,656	0,209	Small

Note. Where: 1 = Completely Agree, 2 = Agree, 3 = Disagree, 4 = Completely Disagree.

As evident in Table 3, when comparing responses in the pre-post KPSI test, significant changes were revealed (with an asymptotic bilateral significance $p < 0{,}001$) in indicators related to:

- The explanations they can provide for the concept of Machine Learning.
- The ways to incorporate Machine Learning into their own teaching practice.
- The identification of criteria and selection of Machine Learning resources.
- The perception of the necessary processes to integrate Machine Learning into the curriculum.
- The knowledge about designing activities that integrate Machine Learning technology and are consistent with science learning objectives.

Table 3: Wilcoxon test significance results (virtual workshop)

Questions	Z	Asymptotic Bilateral Significance
Q1	-5,529	<,001
Q2	-4,918	<,001
Q3	-5,000	<,001
Q4	-3,758	<,001
Q5	-4,564	<,001

The results suggest that, although there was a significant increase in all evaluated areas, the differences were more nuanced in aspects related to teachers' ability to establish criteria for identifying and selecting appropriate Machine Learning resources for their own teaching practice (Q3) and being aware of the processes necessary to integrate Machine Learning resources into the local curriculum (Q4). In other words, despite having explored Machine Learning resources during the virtual workshop and having created opportunities to discuss their relationship with the local curriculum, teachers still require more focused work on these aspects.

In general, these findings provide us with guidance on the areas that require more focused attention to address the perceived needs of teachers for the development of new educational resource redesigns.

4.3 First redesign "In-Person Science Education Workshop with Machine Learning"

The objective of the in-person workshop was the same as that of the virtual workshop and was aimed at in-service or trainee science teachers. However, unlike the virtual workshop, in this one, teachers developed classifiers, decision trees, and constructed scientific hypotheses through 'unplugged' computational thinking activities, using only paper and pencil without digital resources.

For the in-person workshop, we designed five computational thinking activities, though we only implemented three due to time constraints. These activities aimed to gradually introduce the basic characteristics of Supervised Machine Learning. Additionally, it allowed us to address specific topics in the teaching of Physics, Chemistry, and Biology. A distinctive feature of this workshop was the use of play-based strategies, incorporating roles, scores, lives, and competitions.

At the beginning of the workshop, we encouraged discussion with the teachers about their previous experiences with Artificial Intelligence in schools through a brainstorming session on Mentimeter. This generated a debate on fundamental issues when interacting with AI machines, such as trust in understanding processes, ethical issues associated with data use, and algorithm errors. We then presented fundamental concepts of AI and supervised machine learning, with examples and news applied to sciences and engineering, to establish a common understanding among participants.

During the workshop, we implemented plays 1, 2, and 5, and presented the main features of plays 3 and 4, although they were not fully developed. All the plays were designed to progressively build predictive models and were based on explanations of decision trees and scientific hypotheses. Similar to the activities of the virtual workshop, the teachers explored 'training' situations of supervised machine learning, first working with images and then with data tables. For each play, the teachers completed a guide sheet to collaborate and compete.

The first play, adapted from [103], involved observing the facial features of a set of animal images (monkeys) to distinguish those that bite from those that don't. The teachers took on roles as zookeepers with the task of feeding the monkeys without being bitten, introducing role-playing and contextualizing the activity (see Fig. 4).

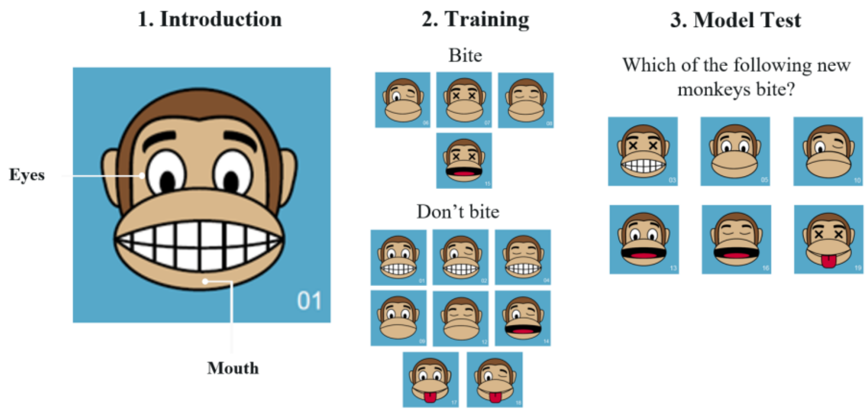


Figure 4: Play 1: Monkeys that Bite and Monkeys that Don't Bite

Teachers should freely record three common facial features of monkeys that bite and three of those that don't bite on an answer sheet (see Fig. 5), simulating unsupervised training. Subsequently, they observe new images of monkeys, different from those used during training, and must guess by hand which monkeys bite and which do not. For each correct guess, they earn points in the play.

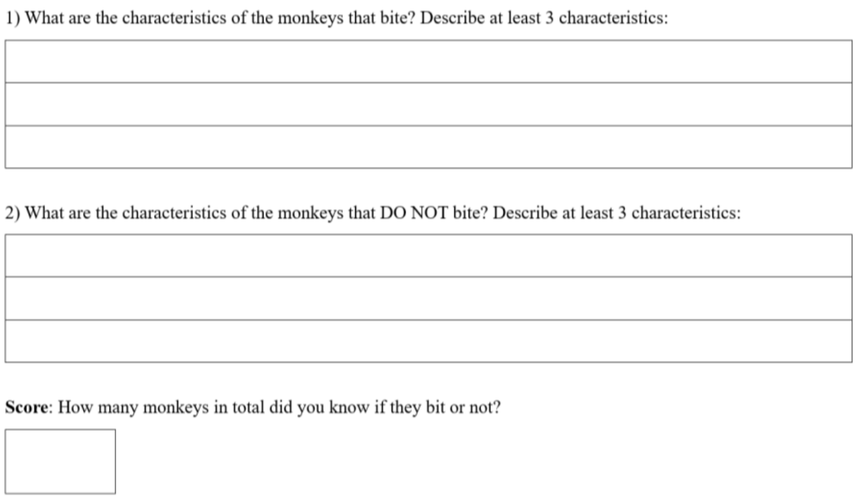


Figure 5: Answer Sheet for Play 1

The second play is an adaptation of activities used in the virtual workshop to differentiate between poisonous and non-poisonous fish. This activity is more complex than the previous one, as it involves the incorporation of more variables such as color, fin shape, pupils, gills, tail, among others (see Fig. 2). For this reason, it is presented as the second activity and not the first.

Teachers are presented with an introductory role-playing scenario in which they must assume they are jungle explorers with the mission of identifying and classifying poisonous and non-poisonous fish. Poisonous fish are very dangerous and easily mistaken for non-poisonous ones, so they must classify them with clear criteria that can be shared with other explorers to avoid poisonings. Unlike the virtual workshop, this activity incorporates a play dynamic that involves constructing decision trees in a guided manner on an answer sheet (see Fig. 6).

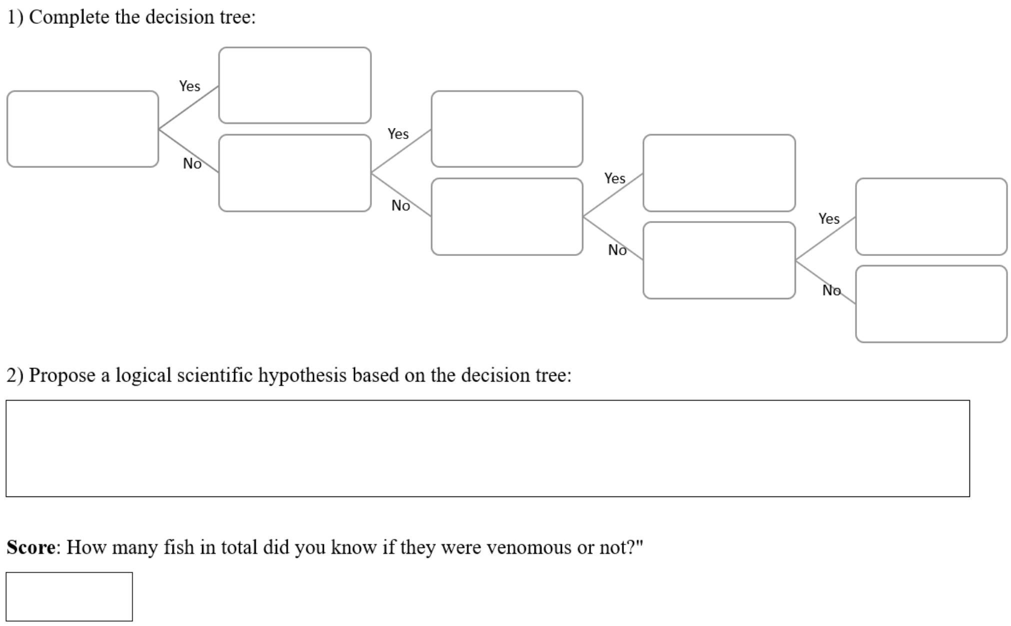


Figure 6: Answer Sheet for Play 2

Then, teachers hand their decision tree to another person, who must use it to guess and avoid being stung by poisonous fish (see Fig. 7). In this play dynamic, the winner is the one who manages to avoid the most poisonous fish stings, thereby accumulating the most points.

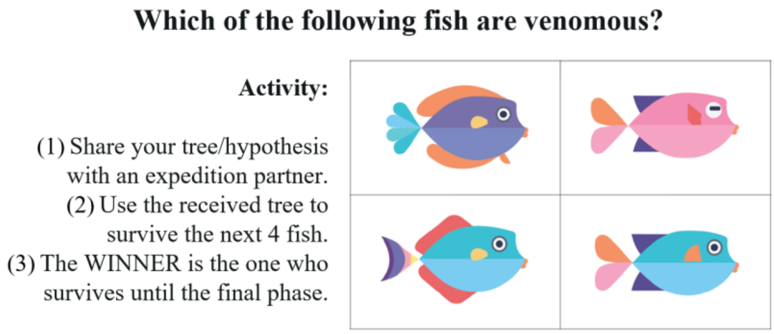


Figure 7: Team Activity for Play 2

The third play, which we developed ourselves, is integrated into Chile's primary education science curriculum for physics. Teachers are presented with an introductory role-playing scenario in which they must assume they are astronomers tasked with identifying and classifying galaxies. They are then assigned the task of observing the physical characteristics of a group of galaxy images and distinguishing them from another set of images that are not galaxies. Similar to plays 1 and 2, participants observe and try to guess based on their own models (see Fig. 8).

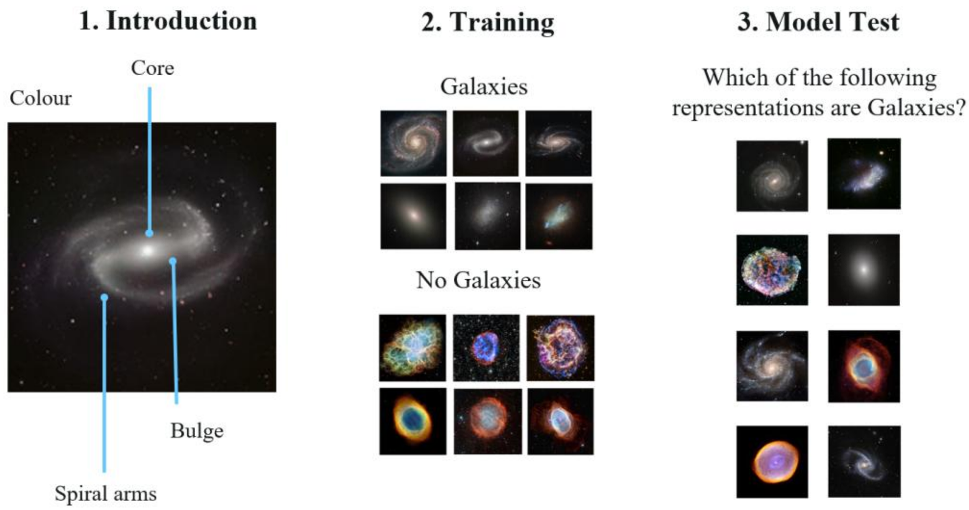


Figure 8: Play 3: Galaxy Classification

The fourth play, also of our own creation. This activity is integrated into Chile's secondary education science curriculum for physics and is more complex than the previous plays. Teachers are presented with an introductory role-playing scenario in which they must assume they are astrophysicists whose research area is the classification of stars based on their temperature and luminosity. They are then assigned the mission of observing a data set organized in a table to identify patterns in the colors and luminosities of the stars. Based on their observations, participants must place stars of high and low luminosity (where high is above average and low is below average) on a color line. They then identify two regions by comparing the grouping of stars and finally represent a "conclusion" in natural language, computational language, and through a decision tree (see Fig. 9).

Color	Luminosidades del Sol	Alta luminosidad (mayor a la media)
Azulado	10^4	1
Blanco azulado	10^5	1
Blanco	10	0
Blanco amarillento	10^4	1
Amarillento	1	0
Anaranjado amarillo	10^2	0
Anaranjado	10^4	1
Anaranjado rojizo	10^{-2}	0
Rojo anaranjado	10^5	1
Anaranjado	10^{-3}	0
Anaranjado	10^{-3}	0
Anaranjado amarillo	10^{-5}	0
Anaranjado amarillo	10^{-3}	0

$Average\ luminosity = \bar{x} = 10^3$

- **Circle**: High Luminosity.
- **Cross**: Low Luminosity.

Conclusion in Natural Language:
Regarding this database, the graph shows that the cooler stars (red, orange, and yellow) tend to have lower luminosity than the hotter stars (light blue and blue).

Conclusion in Computational Language:

If the star has a color ('Yellow White' or 'White' or 'Blue'…)

Then, it has high luminosity (greater than the average: $\bar{x} = 10^3$)

Else, it has low luminosity.

Figure 9: Play 4: Classification of stars based on their temperature and luminosity

The final play is also of our own creation and is integrated into Chile's secondary education science curriculum for physics. Teachers are presented with an introductory role-playing scenario in which they must assume they are Data Scientists, and their research area is the life and death of stars. Similar to the previous plays, participants have the task of analyzing a data set organized in tables to predict the behavior of stars based on the initial mass during their formation. Based on the data, they must place stars with high and low average life expectancy on a numerical line of Initial Solar Masses. They then identify two regions by comparing the grouping of stars and finally represent a solution in computational language and through a decision tree (see Fig. 10).

1) Complete the data table:

Star	Solar mass	Lifespan (million years)	Longer Life Than Average? (1 true, 0 false)
Blue Supergiant	25	25	
Orange Dwarf	0,75	30.000	
Blue Supergiant	30	20	
Yellow Dwarf	5	10.000	
Blue Giant	9	60	
Yellow Dwarf	2	9.000	
Blue Giant	12	50	
Yellow Dwarf	8	7.500	
Blue Giant	15	45	
Orange Dwarf	0,5	25.000	
Blue Supergiant	40	15	
		$\bar{x}$ = 7.428	

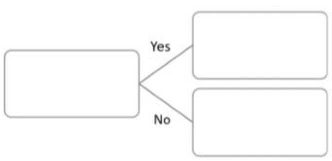
2) On the line, indicate with a circle the stars with a lifespan longer than the average and with a cross those with a shorter lifespan.

- Circle (1) = longer than average lifespan
- Cross (0) = shorter than average lifespan

3) Indicate the two main regions and divide them with a line.

4) If information on a new star is added to the database, with an initial solar mass of 8.6 units, in which region would it be? Represent the solution in a decision tree and in computational language:

Decision Tree



Computational Language

IF………………………………………………..

THEN…………………………………

ELSE…………………………………………

Figure 10: Answer Sheet for Play 5

At the end of the workshop, the teachers reflected and shared about the applications to their own areas and specific contexts. Other examples reported in the literature where Machine Learning models are used to solve real-world problems were also analyzed.

4.4 Teachers' Self-Perception in In-Person Workshops

The results in Table 3 indicate changes in all the average scores of the science teachers' responses. The trends show favorable shifts, notably leaning towards the options of 'Agree' or 'Strongly Agree' on the Likert Scale.

Table 4: Descriptive statistics of teachers' self-perception questions in-person workshop (N = 14)

Questions	Mean	Increment	SD	Cohen's d	ES Interpretation
KPSI Pre-test					
Q1	3,86	-	,535	-	-
Q2	3,93	-	,267	-	-
Q3	3,86	-	,363	-	-
Q4	3,93	-	,267	-	-
Q5	3,93	-	,267	-	-
KPSI Post-test					
Q1	1,93	-1,93	,475	0,96	Large
Q2	1,86	-2,07	,535	1,29	Very large
Q3	1,79	-2,07	,699	0,97	Large
Q4	1,64	-2,29	,633	1,27	Very large
Q5	1,86	-2,07	,633	1,15	Large

Note. Where: 1 = Completely Agree, 2 = Agree, 3 = Disagree, 4 = Completely Disagree.

As seen in Table 3, all post-test responses had high or very high effect sizes. The largest increases were observed in questions 2 (P2) and 4 (P4), with 'Cohen's d = 1.29 and 1.27' respectively. P2 refers to teachers' perceptions of how to incorporate Machine Learning into their practice, for example, diversifying its use across various scientific disciplines through different examples and resources. P4 pertains to teachers' perceptions of their ability to identify the necessary processes to integrate machine learning resources into the curriculum. Conversely, the smallest change was observed in question 1 (P1), which relates to teachers' perceptions of their ability to explain the concept of machine learning.

Furthermore, as shown in Table 5, comparing the pre- and post-test responses also revealed significant changes with improvements in self-perception in all questions ($p < 0.001$). This indicates an increase in teachers' confidence in aspects such as:

- Their explanations of the concept of Machine Learning.
- The ways to incorporate Machine Learning into their own teaching practice.
- The identification of criteria and selection of Machine Learning resources.
- The perception of the processes necessary to integrate Machine Learning into the curriculum.
- The knowledge of designing activities that integrate Machine Learning technology and align with science learning objectives.

Table 5: Wilcoxon test significance results (in-person workshop)

Questions	Z	Asymptotic Bilateral Significance
Q1	-3,354	<,001
Q2	-3,402	<,001
Q3	-3,402	<,001
Q4	-3,384	<,001
Q5	-3,402	<,001

These results suggest that, although there was a significant increase in all evaluated areas, the differences were nuanced in the theoretical aspects related to the explanations given for the concept of Machine Learning. In other words, despite having generated discussion about the concept with formative explanations during the workshops, teachers' ability to communicate and understand this specific concept still requires more focused work to improve comprehension. This finding has important implications for teacher training in the context of science education.

Despite the growing relevance of artificial intelligence and Machine Learning in education, it seems that teachers do not feel fully prepared to discuss the topic or explain basic concepts about how it works.

Similarly, the responses to questions 2 and 5 (Q2 and Q5) had significant values, but the changes were more nuanced. This would suggest that difficulties persist in the ways of incorporating Machine Learning into their teaching practice and in their knowledge of designing activities that integrate Machine Learning technology and align with science learning objectives. This is despite the opportunity given to teachers to explore the integration of Machine Learning in their teaching. These results also suggest the need to pay more specific attention to teacher training regarding the understanding of this technology and its integration into the sciences curriculum.

Overall, it should be assumed that these results are not yet generalizable, as the workshop was conducted with a small number of participants and with a short implementation duration. This implies that the observed results might not be sufficient to achieve substantial changes in these areas of teaching competence, as they require deeper and more specialized attention.

4.2.1 Answer Sheet: Written Responses During In-Person Workshop

Regarding the written results, the science teachers were able to complete all the proposed activities within the estimated time. However, after analyzing the responses in the documents they submitted, some difficulties were identified.

One of the most frequently observed problems in responses was in constructing the initial decision trees. Teachers struggled with maintaining continuity in the decision tree nodes. Many of them identified an initial question to answer with the options 'yes (true) or no (false)' (see Fig. 11) but had difficulties formulating a new question when following the False alternative.

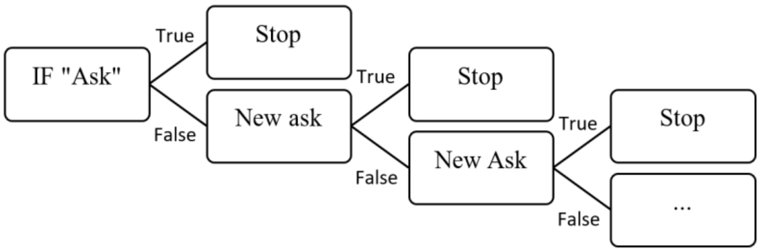


Figure 11: Example of Decision Tree Diagram Used by Science Teachers

For example, in play 2, which involved classifying fish based on their morphological characteristics, teachers tended to place 'poisonous' under the 'True' option and 'non-poisonous' under the 'False' option. Instead of opening the False option with a new question about another morphological characteristic (see example in Fig. 12).

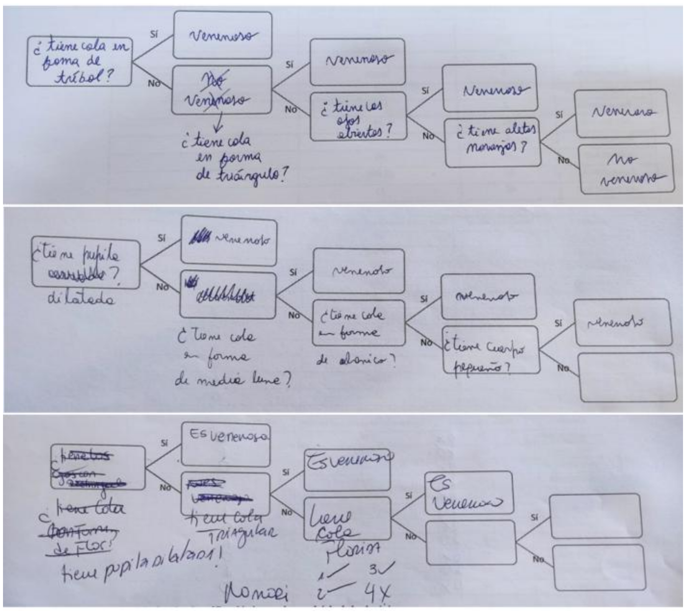


Figure 12: Difficulties in the Construction of Decision Trees by Science Teachers

Another aspect that posed a challenge for some teachers during the implementation of the activities was identifying the regions of data clusters on the numerical line. Some initially indicated a dividing line in the middle and then corrected it by drawing another line (see Fig. 13).

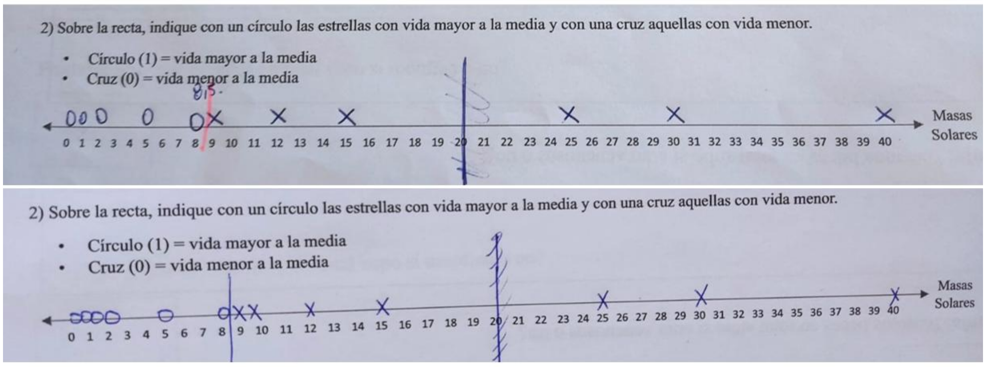
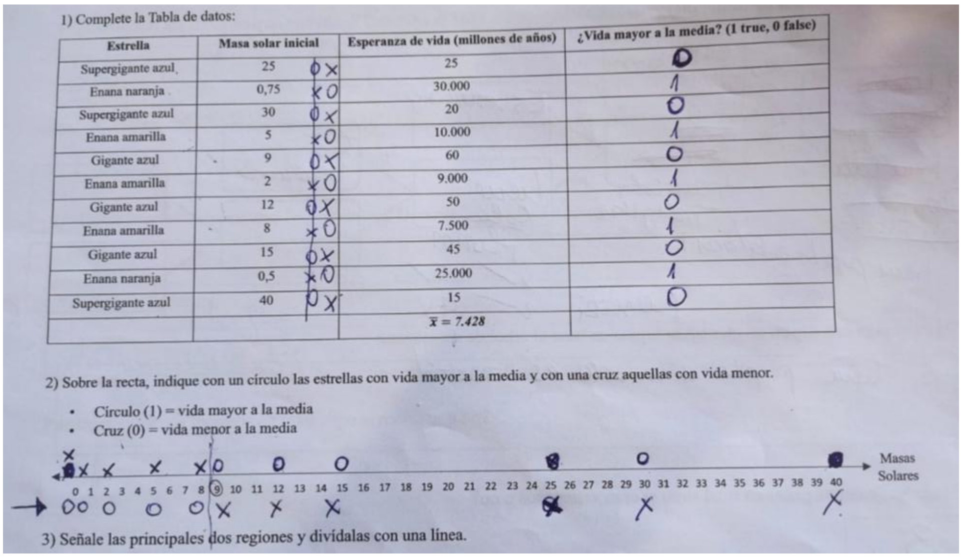


Figure 13: Regions and Data Clusters Identified by Teachers (and Corrected)

Additionally, some teachers had difficulties when assigning '0' and '1' to the values of the new column they incorporated into the data table. Some teachers even confused '0' with '1', which led to the construction of a numerical line with incorrectly mixed crosses and circles (see Fig. 14)."


1) Complete la Tabla de datos:

Estrella	Masa solar inicial	Esperanza de vida (millones de años)	¿Vida mayor a la media? (1 true, 0 false)
Supergigante azul	25	25	0
Enana naranja	0,75	30.000	1
Supergigante azul	30	20	0
Enana amarilla	5	10.000	1
Gigante azul	9	60	0
Enana amarilla	2	9.000	1
Gigante azul	12	50	0
Enana amarilla	8	7.500	1
Gigante azul	15	45	0
Enana naranja	0,5	25.000	1
Supergigante azul	40	15	0
		$\bar{x}$ = 7.428	

2) Sobre la recta, indique con un círculo las estrellas con vida mayor a la media y con una cruz aquellas con vida menor.

- Círculo (1) = vida mayor a la media
- Cruz (0) = vida menor a la media

Masas Solares

3) Señale las principales dos regiones y divídalas con una línea.

Figure 14: Data Tables with Alternating 0 (X) and 1 (O) Values

4.3 Final modifications

For the final version of the workshop, we kept all the activities from the redesign but incorporated new information to address some of the observed difficulties and guide the curricular implementation for science teachers.

First, we established clearer curricular links with the skills and scientific investigation processes prescribed in Chile's curriculum:

- For example, we linked the scientific skills of 'Observation of nature' and 'Asking questions based on observations of the environment' with the observations of the morphological characteristics of monkeys (play 1), fish (play 2), or the physical characteristics of galaxies (play 3).
- We also linked the scientific skills of 'Creating, using, and adjusting simple models' and 'Formulating hypotheses' with the development of decision tree models (plays 2, 4, and 5) and scientific hypotheses (plays 2, 4, and 5).
- The scientific skills related to 'Communicating and comparing ideas with others' and 'Evaluating models' were linked to the collaborative activities of play 2.

- Finally, the scientific skills related to 'Processing and analyzing evidence,' 'Organizing data in graphs,' and 'Examining results to formulate inferences and conclusions' were linked to the final activities of plays 4 and 5, where teachers had to use tabulated information to create graphs and formulate inferences and conclusions based on the evidence.

We also incorporated new, brief, and simple examples to show that constructing decision trees is not only based on physical or morphological characteristics but can also be based on actions, sounds, or any type of data. For example, classifying animals as swimmers, fliers, crawlers, jumpers, etc., or classifying sounds from different species based on characteristics like frequency, amplitude, duration, etc.

Based on the difficulties observed in constructing the decision tree in plays 2, we added supporting information below the boxes to help teachers know where to place the new questions. We also improved some instructions in play 5 that may have caused confusion during the data cluster identification processes on the numerical line.

We also decided to reintroduce the possible uses of the 'Teachable Machine' and 'RAISE Playground' software, which were part of the first virtual workshop. This was mainly due to the positive reception from teachers during this stage. However, considering that using both software requires computers and internet access, we did not incorporate them as part of the core activities but rather as part of the projections for future activities and projects that science teachers could undertake.

Finally, at the end of the workshop activities, we added a conceptual formalization stage to connect the stages of the plays with the stages of the 'Concrete Pictorial Abstract (CPA)' approach. To do this, we added a brief explanation accompanied by an example based on one of the galaxy observation plays (concrete), whose characteristics were transformed into a decision tree (pictorial) and finally could be expressed in computational language (abstract).

5 Discussions

Artificial Intelligence (AI) has become a globally relevant topic in the field of education [1, 2, 3, 4, 5]. Although its significance has increased in recent years, its integration into K-12 education systems has been slow [10]. Several factors contribute to this situation, including the lack of theories, models, strategies, and evidence regarding its curricular integration, as well as insufficient teacher preparation in AI-related topics.

Previous research has consistently highlighted that teacher preparation is one of the most critical factors for fostering the adoption of AI in educational practices [26, 27, 29, 34, 35]. Moreover, studies indicate that a significant research gap remains unaddressed, particularly regarding teachers' professional development and continuous training in AI integration [43]. In response, public policies have promoted the implementation of teacher training and professional development programs, which include activities and workshops designed to encourage the appropriation and curricular integration of AI.

The workshops presented in this study are part of ongoing efforts by various universities and teacher development centers in Chile to contribute to continuous professional development and to bridge research gaps in regions such as Latin America and Chile. In summarizing the findings of this study, several key discussion points emerge:

First, after completing the first workshop, teachers showed significant ($p < .001$), though small or trivial, improvements in their self-perception ($0.1 < ES < 0.5$) regarding their knowledge and skills in integrating AI subfields into science education (physics, chemistry, and biology). Following the second workshop, the improvements were also significant ($p < .001$), with large effect sizes in teachers' self-perception ($0.95 < ES < 1.3$). Although research on teachers' perceptions of AI use in education remains scarce [21, 22, 23, 24, 25], these findings align with several ongoing discussions in the field. For instance, [106] examined the benefits and concerns regarding the use of generative AI tools in school curricula and found that as teachers became more comfortable with AI, their perception of its value as a pedagogical tool improved. Similarly, [107] reported that improving teachers' self-perception enhances their willingness to adopt AI, boosts confidence, and reduces apprehension. Findings from [108] suggest that strengthening teachers' digital competencies positively influences their attitude toward AI and their readiness to use it in teaching.

Second, the increase in teachers' self-perception after the second workshop suggests two key insights. On the one hand, the adjustments made based on the challenges identified in the first workshop were effective. These included introducing more gradual teaching strategies for learning computational concepts, starting at earlier ages, and establishing more explicit connections with Chile's science curriculum. These findings align with those of [87, 88, 103, 109, 110], which highlight advancements in the design of educational experiences that address fundamental AI concepts in primary and secondary science education. On the other hand, the increase in self-perception also indicates that the inclusion of new teaching activities based on unplugged Computational Thinking was well received and highly valued by teachers. This is likely due to their variety, ease of understanding, affordability, and accessibility, which make them adaptable to nearly any teaching context. Computational Thinking activities for learning AI have gained popularity in recent years and are incorporated into the ISTE standards [12, 57] in the U.S., as well as in frameworks proposed by [5, 6]. These resources are considered valuable tools that could eventually help reduce digital divides and social inequalities.

Third, the results from both workshops indicate that science teachers were able to successfully use software tools such as "Teachable Machine" and “RAISE Playground” and effectively carry out Computational Thinking activities. Teachers managed to build simple classifiers, decision trees, and data-driven hypotheses to support scientific inquiry in schools, which slightly improved their understanding of the basic processes underlying AI. However, after the first workshop, teachers expressed concerns and challenges. They highlighted the need for more examples demonstrating how AI resources could be integrated into the science curriculum and raised questions about how to use these tools with younger students and in subjects such as Physics and Chemistry.

Finally, while the results presented here provide an initial framework for designing better teacher training workshops and professional development programs, it is important to recognize that this is only a preliminary step. More extensive training programs with longer durations, greater internal and curricular coherence, and stronger support for teachers in AI curricular integration are still needed.

6 Conclusions

6.1 Achievement of the Aim

The results obtained from the science education workshops with supervised machine learning demonstrate achievements in meeting the objective set in this study, which was to design a sequence of learning activities that facilitate teachers in Chile in understanding and applying basic AI processes in science teaching. Below are the main ideas supporting this statement:

6.1.1 Design of Educational Activities

The results of the activity implementations were integrated through a combination of statistical techniques and content analysis, resulting in a refined version of the educational activities. The design of educational activities, both in virtual and in-person workshops, proved effective in facilitating the understanding of basic AI processes among science teachers. The results showed that teachers could create classifiers and decision trees, improving their understanding of how supervised machine learning works. These activities also allowed teachers to link some school scientific research activities with computational thinking (e.g., model building, scientific hypothesis formulation, data analysis, and graph construction), enriching their didactic skills.

6.1.2 High Self-Perception Among Science Teachers

The results of the self-perception surveys indicate a significant positive change in teachers' confidence regarding their ability to explain the concept of machine learning, incorporate this technology into their teaching practice, and select and use machine learning resources. The highest differences were observed after implementing the in-person workshop, particularly in teachers' ability to explain the concept of machine learning and their knowledge of designing activities that integrate this technology. While the results of the in-person workshop were higher than in the virtual workshop, they should not be compared as equivalent workshops, as the implementations in both workshops were different, and the participants were also different.

6.1.3 Curricular Integration of Artificial Intelligence

Despite the progress made, teachers still face challenges in effectively integrating machine learning resources into Chile's curriculum. This was reflected in the survey responses, highlighting areas that require more attention, such as formulating criteria for selecting appropriate resources and understanding the necessary processes for their integration into the curriculum. All of this led us to formulate a proposal linking activities and play with some scientific research skills proposed in the local science curriculum. These challenges underscore the need for more specific and integrated initial training on technology use and more up-to-date continuous training so teachers can adopt this technology in their practice considering their teaching experiences.

Although the curricular appropriation and integration is a global challenge that has not been resolved with the rise of emerging technologies, the achievements of this study could point in this direction. The incorporation of play-based strategies and unplugged computational thinking activities proved to be a useful and motivating tool for teachers. Gradual implementation and providing more practical and situated examples to the different disciplines comprising sciences also better addressed teachers' needs and levels of understanding.

In conclusion, the iterative design, enriched by feedback from experts and participants, has created an accessible, contextualized, and engaging educational resource that integrates supervised machine learning concepts without the need for digital technology.

6.2 Limitations and Future Work

During this research, we faced limitations that influenced the implementation and evaluation of educational activities. However, these challenges also suggest some opportunities for future research.

Firstly, the participant sample was not fully representative of the diversity of socioeconomic and cultural contexts in Chile, limiting the generalizability of the results. Future research should consider implementing educational resources for a broader and more diverse sample, as well as replicating activities in different regions and contexts. It would also be beneficial to explore other strategies and additional resources to improve understanding of AI concepts with science teachers in areas such as chemistry and biology, where there is currently less research. Additionally, future research should focus on evaluating the effects on student learning outcomes, considering the curricular incorporation of machine learning. This could be based on some of the activity ideas developed in this research.

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