Integrating Machine Learning for the Continuing Education of Science Teachers

Jhon Alé[1]

[1] *University of Chile, Capitán Ignacio Carrera Pinto 1045, Santiago, Chile*

Abstract

This study investigates the perception of 42 science teachers in Chile after participating in a two-week workshop focused on the curricular integration of Machine Learning technology to enrich their teaching strategies in the Science course. Using KPSI-type Likert surveys, a pre and posttest was administered to assess changes in perception, followed by statistical analysis.

The results highlight significant improvements in teachers' perception in key areas, such as digital citizenship knowledge, digital resource selection to support their teaching, and more positive attitudes towards the integration of Machine Learning in the classroom. However, significant challenges were identified related to the conceptualization and application of Machine Learning in the educational environment.

This study underscores the need to provide additional support and specific training to overcome barriers to the successful adoption of these technologies in science education. These findings are relevant for the development of effective teacher training strategies and the promotion of successful integration of Machine Learning in educational settings.

Keywords

Continuing Education, ICT into the Curriculum, Machine Learning, Science Education, STEM Education.

1. Introduction

The potential of technology to strengthen educational systems and advance towards the achievement of the Sustainable Development Goals is internationally recognized [1]. These technologies are positioned as strategic factors that contribute to equitable growth and address the challenges of the 21st century [2]. Pedagogical practice is increasingly influenced by emerging technologies, such as Artificial Intelligence (AI), Machine Learning (ML), or Extended Realities (virtual, augmented, or mixed), which pose ethical challenges [3] and essential questions about how to interact with these technologies, select them, and harness their potential to support students' teaching and learning, as well as prepare them for the future [4].

Despite the widely accepted importance of teacher knowledge [5, 6] as the cornerstone to address students' digital competence [7, 8], the reality shows that technology is barely integrated into classrooms, and when it is, it often follows traditional teaching methods [9]. This situation is attributed, in part, to the lack of an educational focus in technology research [10], the absence of new theories, models, and methods for integration into pedagogical practice [11], and the lack of evidence, especially in the Latin America and the Caribbean region [12].

In this context, the present study focuses on contributing to this purpose and presents the results of the implementation of a remote workshop for science teachers throughout Chile. The aim of the workshop is to assess teachers' perceptions of the use of Machine Learning tools in their science classes.

CISETC 2023: International Congress on Education and Technology in Sciences, December 04–06, 2023, Zacatecas, Mexico
jhon.ale@ug.uchile.cl (J. Alé-Silva)
0000-0002-1999-4012 (J. Alé-Silva)

2. Method

The work is oriented towards research in educational design [13]. Workshops and educational resources are constructed, considering distance work and progressive activities that allow the curricular integration of Machine Learning technological resources to support the curricular learning of science.

The teachers participating in the workshop are 22 women and 20 men (n = 42). Moreover, the majority of them are teachers with more than 5 years of teaching experience in different cities in Chile.

A 4-point Likert self-assessment survey was used (see Table 1), following the model of the Knowledge and Prior Study Inventory (KPSI) [14].

Table 1
KPSI Questionnaire questions (Spanish version)

Questions	1	2	3	4
Q1. ¿Puedo explicar el concepto de Machine Learning?				
Q2. ¿Conozco formas de incorporar el Machine Learning en mi ejercicio docente?				
Q3. ¿Puedo establecer criterios para identificar y seleccionar recursos de Machine Learning apropiados para mi ejercicio docente?				
Q4. ¿Soy consciente de los procesos necesarios para integrar curricularmente recursos de Machine Learning?				
Q5. ¿Sé cómo diseñar actividades que integren tecnología de Machine Learning y sean coherentes con los objetivos de aprendizaje de ciencias?				

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

The survey was conducted using a pre-post test to assess changes in the perception of the 42 science teachers. A descriptive statistical analysis was performed to compare significant changes in the average scores of the teachers' perceptions by comparing the initial results with the final ones. The responses were coded according to their tendency, with 1 = " Completely Agree or Agree" and 0 = "Disagree or Completely Disagree”. Non-parametric chi-squared tests and the McNemar Test for paired samples were utilized in the analysis [15].

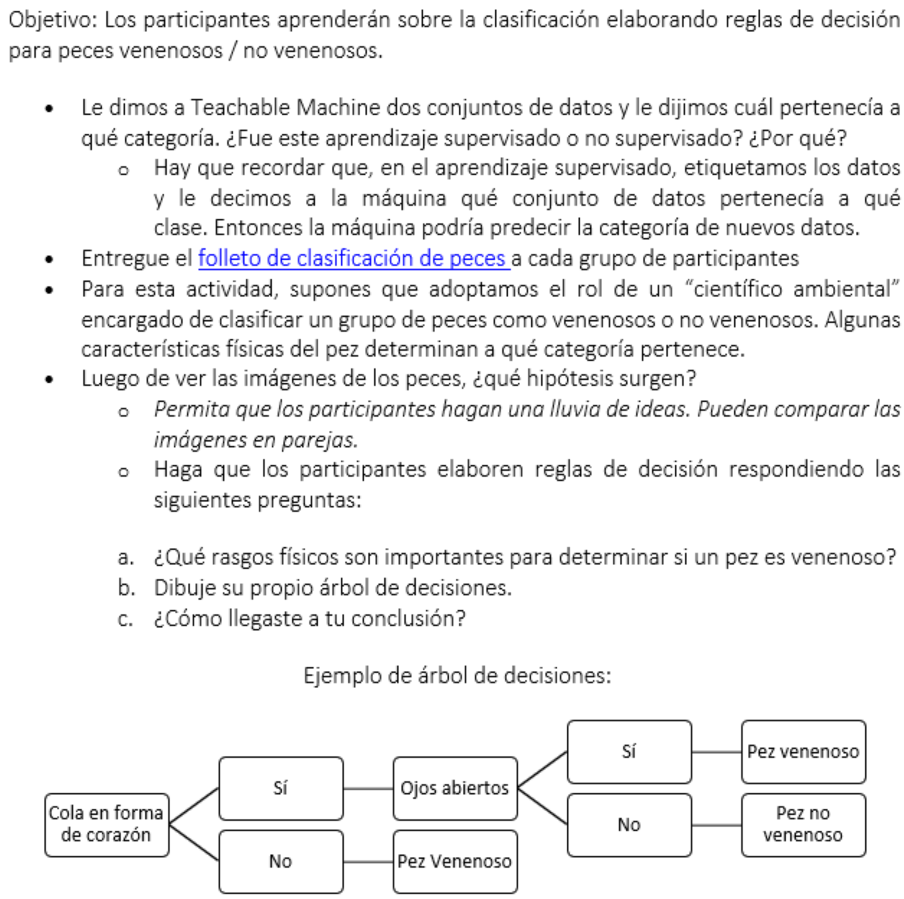
2.1. Science Workshop with Machine Learning

The objective of the workshop is to explore and evaluate some applications of Machine Learning for Science Education, through the creation of various classifiers and decision trees that support the development of school scientific research and the understanding of the basic processes underlying Artificial Intelligence. The workshop is primarily aimed at in-service or pre-service Natural Science teachers in primary or secondary education (Physics, Chemistry, or Biology), without excluding educators from lower levels. At the end of the workshop, teachers and educators create simple classifiers (with text, image, audio, or video) using Google's "teachable machine" software. Teachers use decision trees to test scientific research hypotheses in various areas and to support the resolution of socio-scientific problems.

At the beginning of the workshop, teachers were given explanations of fundamental concepts of artificial intelligence and machine learning, accompanied by examples illustrating their application in the execution of projects in the field of natural sciences. This introductory phase aimed to establish a common 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 foundation.

During the workshop, an activity involving the construction of decision trees took place. In this phase, science teachers explored 'training' situations, similar to the machine learning training process. In these situations, teachers worked with images and undertook the task of distinguishing between poisonous and non-poisonous animals based on their physical characteristics, as exemplified in Figure 1. This activity aims for teachers to train and build their own machine learning model based on a dataset with pre-defined categories, specifically using a supervised learning model.

During this activity, teachers played an active role in creating decision rules, establishing criteria and guidelines for making these distinctions. Subsequently, they compared these rules in 'model tests' to evaluate their effectiveness, and they also propose scientific research hypotheses based on the characteristics described in their decision tree models. This hands-on experience not only allowed teachers to understand the principles underlying machine learning but also to apply them concretely and interactively in the classification of animals, enriching their understanding and skills in the subject.


Objetivo: Los participantes aprenderán sobre la clasificación elaborando reglas de decisión para peces venenosos / no venenosos.

- Le dimos a Teachable Machine dos conjuntos de datos y le dijimos cuál pertenecía a qué categoría. ¿Fue este aprendizaje supervisado o no supervisado? ¿Por qué?
    - Hay que recordar que, en el aprendizaje supervisado, etiquetamos los datos y le decimos a la máquina qué conjunto de datos pertenecía a qué clase. Entonces la máquina podría predecir la categoría de nuevos datos.
- Entregue el folleto de clasificación de peces a cada grupo de participantes
- Para esta actividad, supones que adoptamos el rol de un "científico ambiental" encargado de clasificar un grupo de peces como venenosos o no venenosos. Algunas características físicas del pez determinan a qué categoría pertenece.
- Luego de ver las imágenes de los peces, ¿qué hipótesis surgen?
    - *Permita que los participantes hagan una lluvia de ideas. Pueden comparar las imágenes en parejas.*
    - Haga que los participantes elaboren reglas de decisión respondiendo las siguientes preguntas:

a. ¿Qué rasgos físicos son importantes para determinar si un pez es venenoso?
b. Dibuje su propio árbol de decisiones.
c. ¿Cómo llegaste a tu conclusión?

Ejemplo de árbol de decisiones:

Figure 1: Activity of Classifying Poisonous Animals (in Spanish). Based on ReadyAI activities

At the end of the experience, teachers share ideas for school scientific projects that integrate Machine Learning and Artificial Intelligence into the curriculum to support teaching, as shown in Figure 2.

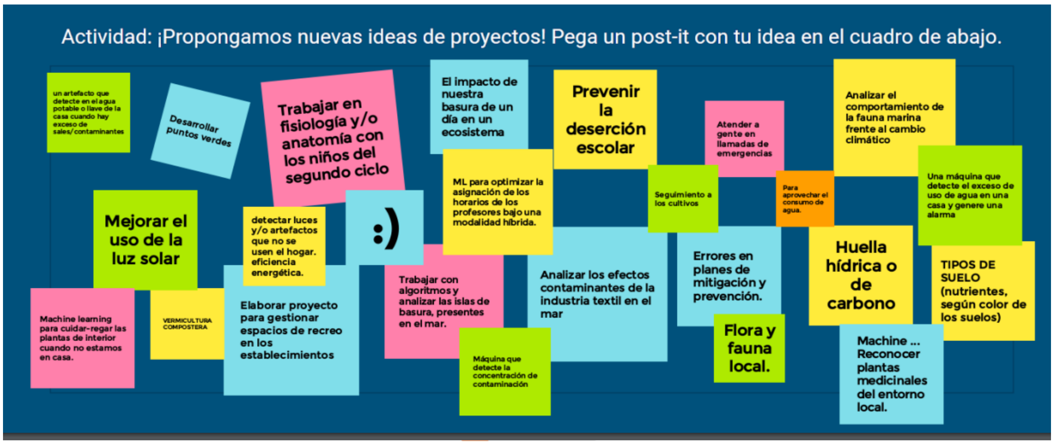


Figure 2: Brainstorming on Machine Learning in Science Education (Spanish version)

3. Results

The results from Table 2 indicate changes across all average scores of science teachers' responses. Trends show favorable shifts, notably leaning towards "Agree" or "Strongly Agree" options on the Likert Scale. The most significant change was observed in question 1 (Q1) concerning perceptions regarding the ability to explain the concept of Machine Learning.

Table 2
KPSI descriptive statistical results

Questions	Mean	SD
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	,656
Q2	2,19	,994
Q3	1,86	1,026
Q4	1,98	,869
Q5	1,64	,656

As evident in Table 3, when comparing responses in the pre-post KPSI test, significant changes were revealed (with an asymptotic bilateral significance of $p < 0.05$) in indicators related to:

- Acquiring knowledge about the integration of Machine Learning in my teaching practice.
- Establishing criteria to identify and select appropriate Machine Learning resources for my teaching.
- Recognizing the necessary processes for the curricular integration of Machine Learning resources.

Table 3
Pre-post test significance results

Questions	Value	gl	Asymptotic Bilateral Significance
Q2	28,273	5	<,001
Q3	25,000	3	<,001
Q4	17,000	4	,004

In the context of this research, it is essential to highlight that the self-assessment of the ability to 'explain the concept of Machine Learning' did not reveal significant changes in science teachers' perceptions after completing the workshop. This suggests that, despite having formative explanations on the topic during the workshops, teachers' ability to communicate and understand this specific concept requires more focused work to enhance their 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 equipped to discuss the subject or explain basic concepts of how it works.

Similarly, the self-assessment of the ability to design activities that integrate Machine Learning technology coherently with the curricular objectives of natural sciences did not show significant differences in teachers' perceptions. This indicates that, although they were given the opportunity to explore the integration of Machine Learning into their teaching, teachers' ability to align these activities with the specific objectives of the natural sciences curriculum did not experience noticeable improvements. These results also suggest the need for more specific attention in teacher training regarding understanding and the ability to use Machine Learning technology effectively, as well as the integration of this technology into the natural sciences curriculum.

In general, it can be inferred that the two-week workshop might not be sufficient to achieve substantial changes in these areas of teaching competence, as they require more in-depth attention. These findings emphasize the importance of having more training activities in the future to develop learning that allows teachers to delve into the understanding and application of Machine Learning to support education.

4. Conclusion

This research focused on evaluating the perception of 42 science teachers in Chile after participating in a workshop designed to explore and assess the application of Machine Learning tools in their science classes. Despite international recognition of the potential of technology in education, there has been a lack of effective integration of these tools in the classroom. The research results indicate that, although the workshop provided teachers with an initial understanding of Machine Learning applications in science, no significant changes were observed in teachers' ability to explain the concept of Machine Learning or their ability to design activities that integrate this technology coherently with the curricular objectives of natural sciences. These findings underscore the need for more comprehensive and long-term training in the field of emerging technologies in science education.

The workshop proved to be a valuable experience for teachers by allowing them to apply Machine Learning concepts in practical situations, such as the construction of decision trees. However, the complexity of understanding and conveying these concepts, as well as effective integration into the curriculum, requires a deeper and ongoing approach.

Ultimately, this research highlights the importance of continuing to develop training opportunities for teachers to gain a more solid understanding of artificial intelligence and Machine Learning, allowing them to fully leverage its potential in science education. Future work should focus on addressing these shortcomings and enriching teacher training in this critical field for 21st-century education. To achieve this goal, teachers require more focused and detailed initial training on the concept of Machine Learning through specific pedagogical strategies. It is crucial to advance the effective integration of Machine Learning into the curriculum, enabling teachers to design activities that align with subjects and connect with real-world situations such as disease diagnosis prediction or machine diagnostics using Machine Learning [16, 17]. This involves developing didactic resources and teaching strategies that link technology with curriculum content. Furthermore, for the future, it is proposed to implement and evaluate extended training courses for teachers, focusing on the use and integration of Artificial Intelligence in scientific education, tailored to their specific needs and contexts.

Acknowledgements

This work has been developed with the support of the University of Chile.

References

[1] M. Fengchun, H. Wayne, Guidance for generative AI in education and research, UNESCO (2023). https://unesdoc.unesco.org/ark:/48223/pf0000386693
[2] UNESCO, The International Science and Evidence based Education (ISEE) Assessment: 2.6 Education Technology, UNESCO (2023). https://mgiep.unesco.org/iseeareport
[3] S. Giannini, Generative AI and the future of education, UNESCO (2023). https://unesdoc.unesco.org/ark:/48223/pf0000385877
[4] K. Zhang, A. Begum Aslan, AI technologies for education: Recent research & future directions, Computers and Education: Artificial Intelligence 2, (2021). https://doi.org/10.1016/j.caeai.2021.100025
[5] P. Mishra, M.J. Koehler, Technological Pedagogical Content Knowledge: A Framework for Teacher Knowledge. Teachers College Record (2006), 1017–1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x
[6] UNESCO, UNESCO ICT Competency Framework for Teachers, UNESCO (2018), https://unesdoc.unesco.org/ark:/48223/pf0000265721
[7] L. Cuban, H. Kirkpatrick, C. Peck, High Access and Low Use of Technologies in High School Classrooms: Explaining an Apparent Paradox. American Educational Research Journal, (2001), 813-834. https://doi.org/10.3102/00028312038004813
[8] OECD, OECD FUTURE OF EDUCATION AND SKILLS 2030 OECD Learning Compass 2030 A SERIES OF CONCEPT NOTES, OECD (2020). https://www.oecd.org/education/2030-project/teaching-and-learning/learning/learning-compass-2030/OECD_Learning_Compass_2030_Concept_Note_Series.pdf
[9] L. Ilomäki, M. Lakkala, Digital technology and practices for school improvement: innovative digital school model. RPTEL 13, 25 (2018). https://doi.org/10.1186/s41039-018-0094-8
[10] X. Chen, H. Xie, D. Zou, G.J. Hwang Application and theory gaps during the rise of artificial intelligence in education Computers and Education: Artificial Intelligence, 1 (2020), p. 100002. https://doi.org/10.1016/j.caeai.2020.100002
[11] K.Y. Tang, C.Y. Chang, G.J. Hwang Trends in artificial intelligence-supported e-learning: A systematic review and co-citation network analysis (1998–2019) Interactive learning environments (2021), 1-19. https://doi.org/10.1080/10494820.2021.1875001
[12] UNESCO, Global education monitoring report, 2023: technology in education: a tool on whose terms?, UNESCO. https://doi.org/10.54676/UZQV8501
[13] T. Plomp, N. Nieveen, An Introduction to Educational Design Research. Proceedings of the seminar conducted at the East China Normal University, (2007). https://ris.utwente.nl/ws/portalfiles/portal/14472302/Introduction_20to_20education_20design_20research.pdf
[14] D. Young, P. Tamir, Finding out what Students know. The Science Teacher, 44, 27- 28 (1977).

[15] JB du Prel, B Röhrig, G Hommel, M Blettner. Choosing statistical tests: part 12 of a series on evaluation of scientific publications. Dtsch Arztebl Int. (2010), 8.
[16] R. Araya, M. Isoda, J. van der Molen Moris. Developing Computational Thinking Teaching Strategies to Model Pandemics and Containment Measures. Int J Environ Res Public Health, 18 (2021), 12520. https://doi.org/10.3390/ijerph182312520
[17] R. Araya. What and How to Teach Mathematics for the Future?. Association of Mathematics Educators (2023), 84-108. https://ame.org.sg/2023/09/06/tme2023-vol-4-no-2-pp-84-108/