

Unplugged vs. Plugged Classification Activities in Lower Secondary AI Education

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Abstract

Artificial Intelligence (AI) literacy is emerging as a key competency for young learners, yet many AI concepts remain difficult to teach in lower secondary classrooms. In particular, classification—how AI systems label new data based on features—is a foundational but underrepresented topic. This paper presents a study design comparing two pedagogical approaches for teaching classification to 10–14-year-old students in Austria’s digital literacy curriculum. One group uses an unplugged decision-tree game (AI Unplugged), while the other uses a plugged digital tool (Teachable Machine). We outline research questions, study methodology, assessment strategy (AI Concept Inventory), and anticipated challenges. We further integrate findings from computing education literature comparing unplugged and plugged instruction. Our goal is to evaluate how modality influences conceptual understanding, engagement, and misconceptions, providing insights for future AI literacy interventions.

Keywords

AI education, AI literacy, unplugged activities, Teachable Machine, classification, secondary school

1. Introduction

Artificial Intelligence (AI) is increasingly integrated into everyday technologies. To prepare young people for a world shaped by intelligent systems, many national curricula now call for foundational AI literacy. One central AI concept is *classification*—how systems map input data to output labels using learned patterns.

Despite its importance, classification is often taught only implicitly, without dedicated classroom strategies or tools that match the cognitive level of lower secondary students (ages 10–14). Moreover, there is limited empirical research on *how* different pedagogical methods influence students’ understanding of classification.

Recent frameworks, such as the AI4K12 guidelines [1], outline core concepts and progressions for teaching AI in schools. Other foundational initiatives emphasize the importance of both unplugged and plugged activities for inclusive access to AI concepts [2, 3].

This study investigates whether *modality*—plugged (digital) vs. unplugged (analog) learning—affects how students grasp classification. Specifically, we compare a physical card-sorting game based on decision trees (from AI Unplugged) with a guided use of the online Teachable Machine image classifier. We design parallel lessons, aligned with curriculum goals, and assess their impact using the AI Concept Inventory (AI-CI).

We aim to address two research questions:

- **RQ1:** Does the learning modality (plugged vs. unplugged) influence students’ conceptual understanding of classification?
- **RQ2:** How do motivation, engagement, and misconceptions differ across modalities?

The results will inform AI literacy initiatives and support teachers in selecting developmentally appropriate methods for introducing AI in the lower secondary classroom.

2nd Workshop on Education for Artificial Intelligence (edu4AI 2025, <https://edu4ai.di.unito.it/>), Co-located with ECAI 2025, the 28th European Conference on Artificial Intelligence which will take place on October 26, 2025 in Bologna, Italy

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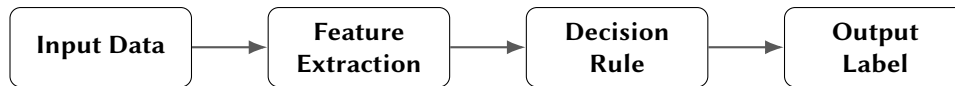


Figure 1: Conceptual model of classification: data flows from raw inputs, through feature extraction and decision rules, to output labels.

2. Related Work

Research on AI literacy has expanded rapidly in recent years [1, 2, 3]. Initiatives such as AI4K12 provide guidelines for what all students should know about AI, underlining the inclusion of core concepts like classification and ethical awareness in K–12 education. Research on computing education shows that both unplugged and plugged approaches can effectively teach computational thinking (CT) and programming.

2.1. Unplugged Methods

Unplugged activities—like sorting games, kinesthetic simulations, and logic puzzles—can make abstract computing concepts accessible, especially for young or novice learners. Brackmann et al. [4] showed that unplugged CT activities improved 10–12-year-olds’ understanding significantly. Delal and Öner [5] reported similar gains with sixth graders.

Meta-analyses confirm that unplugged methods play a positive role in K–12 CT development [6]. Such activities reduce cognitive load, support inclusive access, and promote collaborative learning.

2.2. Plugged Methods

Plugged tools—such as Scratch, programmable robots, and ML platforms—offer interactivity, immediate feedback, and data-rich environments. Sigayret et al. [7] found that primary students using Scratch outperformed unplugged peers in CT assessments. Similarly, Zhang et al. [8] observed stronger learning and executive function development in preschoolers using robot programming.

Block-based tools like Machine Learning for Kids, Teachable Machine, and open online platforms have lowered the barrier for engaging with real AI models in schools [3]. However, such tools often hide algorithmic mechanisms, potentially weakening conceptual depth without structured reflection.

Teachable machine [9] provided by Google is a learning environment with focus on machine learning classification. Based on this idea the GenAI Teachable Machine [10] was developed, at the University of Eastern Finland, using the design science research methodology, where learners can “easily navigate the complete ML workflow—from data collection to app deployment—without any programming skills”.

2.3. Comparative Studies

Open-source resources such as AI Unplugged [11] offer high-quality unplugged activities for foundational AI concepts. Empirical studies suggest that blending unplugged and digital modalities can foster more equitable access and conceptual understanding [2, 3]. Studies comparing modalities show mixed results. While plugged methods often yield higher performance [7], unplugged methods may better support foundational understanding in early stages [12]. Hybrid models—starting unplugged and transitioning to plugged—may offer the most balanced pathway [13].

3. Study Design

3.1. Participants and Context

The study will involve two classes ($N \approx 20$ each) of 10–14-year-old students in Austrian *Digitale Grundbildung* courses. One class will use the unplugged method; the other the plugged method (as shown in Figure 2). Both lessons are 45 minutes long.

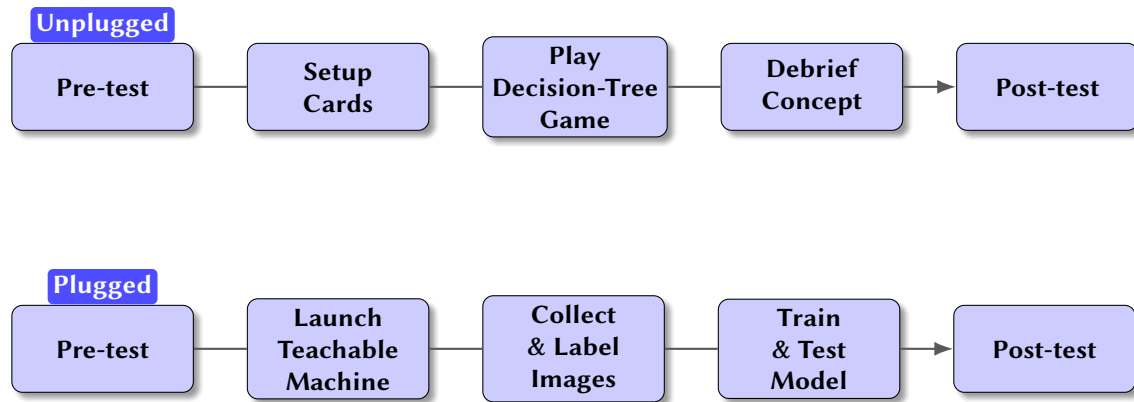
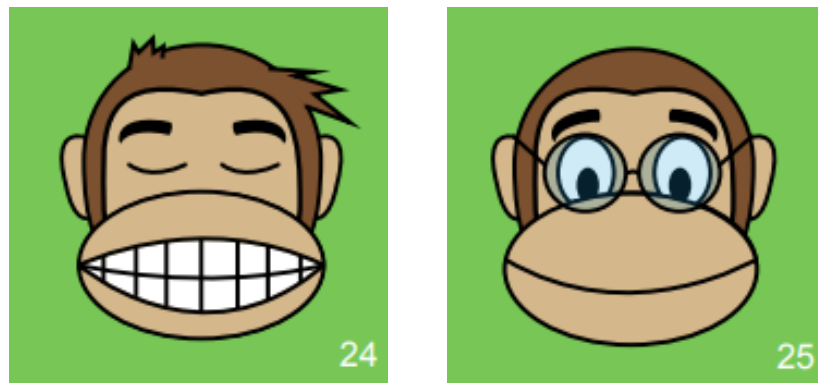


Figure 2: Parallel workflows: (top) Unplugged decision-tree game, (bottom) Plugged Teachable Machine activity.



(a) First example of a play card from the aiunplugged classification game

(b) Second example with different characteristics

Figure 3: Two unplugged activity graphics from aiunplugged.org; (CC BY Annabel Lindner & Stefan Seegerer).

3.2. Intervention Overview

Unplugged: A paper-based decision-tree classification game from <https://www.aiunplugged.org/>. Students collaboratively build and use a decision tree to classify image cards (as shown in Figure 3) based on observable features to tell if the monkey bites or doesn't bite.

Plugged: The GenAI Teachable Machine activity at <https://tm.gen-ai.fi/>, where students train a binary image classifier using uploaded (adapted) variations of the aiunplugged image cards. The GenAI teachable machine was chosen to ensure GDPR compliance. A worksheet guides them through data collection, labeling, training, and testing.

1. Pre-test: 6 AI-CI items focused on classification.
2. Lesson: Method A (unplugged) or B (plugged).
3. Post-test: 6 parallel AI-CI items.
4. Survey: Likert-scale questions on confidence, enjoyment, and perceived difficulty.
5. Observation: Teacher logs of engagement, technical issues, and timing.

3.3. Assessment Design

We use the AI Concept Inventory (AI-CI) [8] to measure students' conceptual understanding of classification. The AI-CI consists of multiple-choice items that probe key aspects of how AI systems represent features, make branching decisions, and assign labels. To avoid simple memorization effects, we select

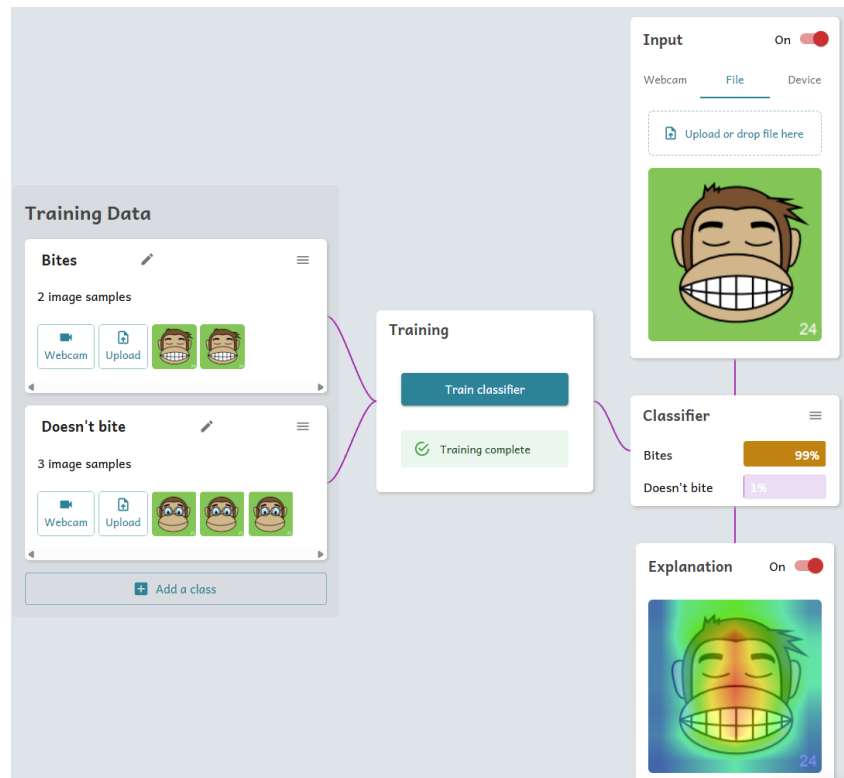


Figure 4: Teachable machine classification, (graphics from aiunplugged.org; CC BY Annabel Lindner & Stefan Seegerer)

three items for the pre-test and three parallel items for the post-test, focusing on decision-tree classification. One such example can be seen in Figure 5 with the prompt “Computers make use of decision trees to classify data. Below is a decision tree. Imagine you categorize a blueberry using this tree. In which category will it end up?”.

In addition to the AI-CI multiple choice items, we include:

- **Transfer Task:** A set of novel fruit or object examples that students classify using the same decision logic they learned, administered as a short worksheet.
- **Open-Response Question:** “How does the AI know which label to choose for a new item?” This invites students to describe in their own words how data features and decision rules result in classification.
- **Misconception Probe:** “Which of these statements about decision-tree classification is incorrect? Explain why.” This item surfaces common misunderstandings such as treating AI decisions as guesses or attributing human-like reasoning to the system.

4. Challenges and Potential Disruptive Factors

When comparing methods, several confounding variables must be controlled or at least monitored:

1. **Teacher/Instructor Differences:** If different teachers conduct each method, their familiarity with AI and teaching style could affect results. Ideally, the same instructor (or equally trained instructors) should teach both methods. Provide training or detailed guides to ensure consistent delivery.
2. **Student Prior Knowledge and Interest:** Students may vary in their familiarity or attitudes toward AI or computers. Random assignment to conditions helps, and pre-testing for baseline knowledge can control for these differences.

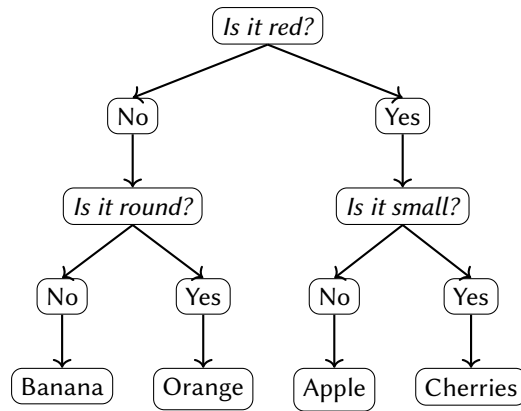


Figure 5: Example item from AI-CI on decision tree

3. **Group vs. Individual Work:** Whether an activity is completed in teams or individually can change engagement and learning outcomes. Group structure should be kept consistent across conditions.
4. **Time and Resources:** Ensure each method receives the same amount of instruction and practice time. If technology is required for one method, technical issues (e.g., internet outages, slow devices) are a risk. Pilot-testing can help identify such practical issues.
5. **Novelty and Engagement:** A brand-new game or flashy software may temporarily increase engagement (novelty effect). Observers should note if one method appears more exciting solely due to its novelty or difference.
6. **Assessment Interaction:** The act of assessment (tests or quizzes) should not favor one method. For example, if a test is administered on computers, students from the unplugged condition might be disadvantaged simply due to format familiarity. A balanced assessment design is essential.

Documenting these factors (e.g., through teacher logs, technical checklists, and possibly questionnaires about student experience) will help interpret any observed differences between methods.

5. Outlook and Next Steps

The comparative study will be piloted in Winter Semester 2025. Based on outcomes, we will refine materials, assessment tools, and teacher support. A larger-scale rollout with additional classrooms is planned for 2026.

Our goal is to build an evidence base on modality effects in AI literacy and to co-develop curriculum-aligned resources for Austrian educators.

Acknowledgments

This research was done as part of the "FutureDEAL - Future of Digital Education and Learning" initiative within the doctoral program "Bildungsinnovation braucht Bildungsforschung", which is supported and partially funded by the Austrian Federal Ministry of Education, Science, and Research.

Declaration on Generative AI

During the preparation of this work, the author(s) used Chat-GPT-4 and Perplexity.ai in order to: Draft content, Generate Latex Code, Paraphrase, Improve writing style and Plagiarism detection. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

References

- [1] D. Touretzky, C. Gardner-McCune, F. Martin, D. Seehorn, Envisioning ai for k-12: What should every child know about ai?, in: *Proceedings of the AAAI conference on artificial intelligence*, volume 33, 2019, pp. 9795–9799.
- [2] D. Long, B. Magerko, What is ai literacy? competencies and design considerations, in: *Proceedings of the 2020 CHI conference on human factors in computing systems*, 2020, pp. 1–16.
- [3] D. T. K. Ng, J. Su, J. K. L. Leung, S. K. W. Chu, Artificial intelligence (ai) literacy education in secondary schools: a review, *Interactive Learning Environments* 32 (2024) 6204–6224.
- [4] C. P. Brackmann, M. Román-González, G. Robles, J. Moreno-León, A. Casali, D. Barone, Development of computational thinking skills through unplugged activities in primary school, in: *Proceedings of the 12th workshop on primary and secondary computing education*, 2017, pp. 65–72.
- [5] H. Delal, D. Oner, Developing middle school students' computational thinking skills using unplugged computing activities, *Informatics in Education* 19 (2020) 1–13.
- [6] P. Chen, D. Yang, A. H. S. Metwally, J. Lavonen, X. Wang, Fostering computational thinking through unplugged activities: A systematic literature review and meta-analysis, *International Journal of STEM Education* 10 (2023) 47.
- [7] K. Sigayret, A. Tricot, N. Blanc, Unplugged or plugged-in programming learning: A comparative experimental study, *Computers & Education* 184 (2022) 104505.
- [8] H. Zhang, A. Perry, I. Lee, Developing and validating the artificial intelligence literacy concept inventory: An instrument to assess artificial intelligence literacy among middle school students, *International Journal of Artificial Intelligence in Education* 35 (2025) 398–438.
- [9] M. Carney, B. Webster, I. Alvarado, K. Phillips, N. Howell, J. Griffith, J. Jongejan, A. Pitaru, A. Chen, Teachable machine: Approachable web-based tool for exploring machine learning classification, in: *Extended abstracts of the 2020 CHI conference on human factors in computing systems*, 2020, pp. 1–8.
- [10] N. Pope, H. Vartiainen, J. Kahila, J. Laru, M. Tedre, A no-code ai education tool for learning ai in k-12 by making machine learning-driven apps, in: *2024 IEEE international conference on advanced learning technologies (ICALT)*, IEEE, 2024, pp. 105–109.
- [11] A. Lindner, S. Seegerer, R. Romeike, Unplugged activities in the context of ai, in: *International conference on informatics in schools: Situation, evolution, and perspectives*, Springer, 2019, pp. 123–135.
- [12] L. Sun, J. Liu, Y. Liu, Comparative experiment of the effects of unplugged and plugged-in programming on computational thinking in primary school students: A perspective of multiple influential factors, *Thinking Skills and Creativity* 52 (2024) 101542. URL: <https://www.sciencedirect.com/science/article/pii/S1871187124000804>. doi:<https://doi.org/10.1016/j.tsc.2024.101542>.
- [13] J. del Olmo-Muñoz, R. Cózar-Gutiérrez, J. A. González-Calero, Computational thinking through unplugged activities in early years of primary education, *Computers & Education* 150 (2020) 103832.