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Findings on Teaching Machine Learning in High School: A Ten-Year Systematic Literature Review

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Abstract. Machine Learning (ML) is becoming increasingly present in our lives. Thus, it is important to introduce ML already in High School, enabling young people to become conscious users and creators of intelligent solutions. Yet, as typically ML is taught only in higher education, there is still a lack of knowledge on how to properly teach younger students. Therefore, in this systematic literature review, we analyze findings on teaching ML in High School with regard to content, pedagogical strategy, and technology. Results show that High School students were able to understand and apply basic ML concepts, algorithms and tasks. Pedagogical strategies focusing on active problem/project-based hands-on approaches were successful in engaging students and demonstrated positive learning effects. Visual as well as text-based programming environments supported students to build ML models in an effective way. Yet, the review also identified the need for more rigorous evaluations on how to teach ML.

Keywords: machine learning, content, pedagogy, technology, High School, K-12.

1. Introduction

Machine Learning (ML), a subfield of Artificial Intelligence (AI), has evolved out of the need to teach computers how to automatically learn a solution to a problem (Essinger and Rosen, 2011). It plays an increasingly important role in our daily life as part of a wide variety of applications, such as speech recognition systems, intelligent assistants, self-driving cars, etc. Therefore, it is becoming a common understanding that students need to be prepared to thrive in the future with AI/ML already in school (Pedró *et al.,* 2019; Burgsteiner *et al.,* 2016; Estevez *et al.,* 2019). Yet, so far, most AI/ML courses are targeted at adult learners in higher education (Bennett, 2017; Kwan, 2014).

Recently some initiatives and projects have emerged to bring AI/ML to the High School level in diverse countries (Kim *et al.*, 2021; House of Lords, 2017), as High School students may have the ability to understand the core concepts of AI/ML (Huang *et al.*, 2021). At this age they begin to consolidate their hypothetical-deductive thinking ability, and their cognitive process is accelerated by problem-solving in different contexts using technologies (Santana *et al.*, 2018). In addition, developing AI/ML literacy may encourage more students to consider STEM careers and provide solid preparation for higher education and their future career (Marques *et al.*, 2020).

Yet, as teaching AI/ML at this educational stage is only emerging, the question of what to teach (content), how to teach (pedagogical strategies), and which technology support to use (technology) still remains open. And, although, some researchers have already reviewed this kind of knowledge with regard to teaching computational thinking in K-12 (e.g., Grove and Pea, 2013; Martins-Pacheco *et al.*, 2019; Lye and Koh, 2014; Garneli *et al.*, 2015), reviews on teaching AI and ML in K-12 are still scarce. Zhou *et al.* (2020), conducted an exploratory review of AI4K12 literature and tools regarding the development of AI learning experiences in K-12. Marques *et al.* (2020) and Tedre *et al.* (2021) conducted reviews of teaching ML in schools. Focusing on pedagogy, Sanusi and Oyelere (2020) examined how ML has been taught in the recent past and explored the ways and suitable approaches for the K-12 context. However, a more comprehensive review synthesizing the findings of studies analyzing the teaching of ML in High School is still not available. In general, there is a lack of literature proposing adequate ways to teach ML (Evangelista *et al.*, 2018), with only a few draft indications on how to adjust the content, pedagogy, and technologies to teach ML in High School (Mariescu-Istodor and Jormanainen, 2019).

Therefore, we review studies in order to analyze and synthesize their findings regarding content, pedagogical strategies, and technology for teaching ML in High School. The results of this review can be used to guide and facilitate the design and development of instructional units aimed at teaching-learning of ML in High School.

Section 2 of this article presents the definition and execution of the systematic literature review. In section 3 the findings are summarized with regard to content, pedagogy and technology. The conclusions are presented in Section 4.

2. Definition and Execution of the Systematic Literature Review

Observing the importance of ML competencies to be developed in High School, there is a need to understand the technology, pedagogy and content knowledge involved in teaching and learning ML. For that reason, the purpose of this article is to provide an analysis and synthesis of findings by conducting a systematic literature review, following the procedure defined by Petersen *et al.* (2008). According to this procedure, we defined the research question and analysis questions that reflect the study goals and delimit the research scope. We defined a review protocol containing the definition of the sources, search terms, and selection criteria (Kitchenham and Charters, 2007). Following the review protocol, we executed the searches and screened the results in accordance with the inclusion, exclusion, and quality criteria. Once the relevant articles were selected, we extracted information concerning the analysis questions following the defined extraction strategy. We analyzed the questions based on the extracted data, analyzing the encountered findings and discussing the results.

2.1. *Definition of the Review Protocol*

The research question is: Which are the main findings from teaching Machine Learning in High School with respect to content, pedagogical strategies, and technology? This research question is decomposed into analysis questions based on the dimensions of the Technology Pedagogical Content Knowledge (TPACK) model (Schmidt *et al.*, 2009):

- **AQ1**. **Content:** What are the findings related to the ML content taught in High School?
- **AQ2**. **Pedagogy:** What are the findings related to pedagogy adopted for teaching ML in High School?
- **AQ3. Technology:** What are the findings from technology used to teach ML in High School?

Data sources. We examined published English-language articles or material that are available on the Web via the prominent digital libraries and databases in the field of computing, including: ACM Digital Library, IEEE Xplore, arXiv, Scopus, SocArXiv, ERIC (U.S. Dept. of Education), ScienceDirect, SpringerLink, Web of Science and Wiley with access through the Capes Portal[1]. In addition, Google Scholar and Google searches were performed to complement the search, minimizing the risk of omission (Piasecki *et al.*, 2018). We further included publications from the MIT Media Lab repository due to their research in this specific knowledge area.

Inclusion/exclusion criteria. We considered any artifact that presents findings related to an instructional unit (course, workshop, hackathon, curricula) that covers ML concepts in High School and has been published during the last ten years (between 2011 and 2021). Table 1 details the criteria adopted for the selection of relevant artifacts.

Quality criteria. We considered only articles or material which provide substantial information regarding findings related to the teaching of ML, indicating, for example, lesson content, pedagogic strategies, instructional material, the technology used, etc.

Definition of the search string. The search string was based on contextualized keywords and composed of concepts related to the research question, including synonyms, as indicated in Table 2. The definition of the keywords has been calibrated based on several informal searches to minimize the risk of omission.

The term "data science" was used, as ML is closely related to the fields of statistics and data science (Royal Society, 2017). The term "MOOC" (Massive Open Online Courses), was used as an alternative mode of teaching to support AI (and ML) learning (Yu *et al.,* 2017).

We defined a generic search string, using wildcard characters to cover as many variations of the terms as possible, and adjusted the string in conformance with the specific syntax of each data source, as presented in Table 3:

[1] A web portal for access to scientific knowledge worldwide, managed by the Brazilian Ministry of Education for authorized institutions, including universities, government agencies and private companies (`www.periodicos.capes.gov.br`).

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("machine learning" OR "artificial intelligence" OR "deep learning"
OR "data science") AND ("high school" OR "k-12" OR teen* OR school*)
AND (teach* OR education OR course OR MOOC OR learn*).
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Table 1
Inclusion/exclusion criteria

	Inclusion	Exclusion
Focus	Teaching of ML.	Using ML as a technology to enhance learning systems (e.g., intelligent e-learning platforms, analysis of learning performance, AI/ML bots).
Content	Presentation of any kind of findings related to instructional units for teaching and learning ML to students.	No presentation of any kind of findings.
Educational stage	High School.	Other educational stages.
Publication language	English.	Other languages, e.g., Chinese, Portuguese, Spanish, etc.
Type of publication	Scientific articles in journals, conferences, online repositories, internet, as well as academic works, such as dissertations, theses, etc.	Blogs, videos, or tools without further description of an instructional unit.

Table 2
Search terms

Main concepts	Synonyms
Machine Learning	artificial intelligence, deep learning, data science
High School	K-12, teen, school
Instructional unit	teach, education, course, MOOC, learn

Table 3
Search string per data source

Source	Search string
ACM Digital Library	[[Abstract: "machine learning"] OR [Abstract: "artificial intelligence"] OR [Abstract: "deep learning"] OR [Abstract: "data science"]] AND [[Abstract: "high school"] OR [Abstract: "k-12"] OR [Abstract: teen*] OR [Abstract: school*]] AND [[Abstract: teach*] OR [Abstract: education] OR [Abstract: course] OR [Abstract: MOOC] OR [Abstract: learn*]] AND [Publication Date: (01/01/2011 TO 07/31/2021)]
arXiv	date_range: from 2011-01-01 to 2021-07-02; include_cross_list: True; terms: AND abstract="machine learning" OR "artificial intelligence" OR "deep learning" OR "data science"; AND abstract="high school" OR "k-12" OR teen* OR school*; AND abstract=teach* OR education OR course OR MOOC OR learn*
ERIC (U.S. Dept. of Education)	abstract: (("machine learning" OR "artificial intelligence" OR "deep learning" OR "data science") AND ("high school" OR "k-12" OR teen* OR school*) AND (teach* OR education OR course OR MOOC OR learn*)) naep pubyearmin:2011 pubyearmax:2021

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Table 3 – continued from previous page

Source	Search string
Google	*Due to limitations of the Google search engine a reduced search string has been used:* "Machine Learning" "high school" teaching course "k-12"
Google Scholar	("machine learning" OR "artificial intelligence" OR "deep learning" OR "data science") AND ("high school" OR "k-12" OR teen* OR school*) AND (teach* OR education OR course OR MOOC OR learn*)
IEEE Xplore	(("Abstract":"machine learning") OR ("Abstract":"artificial intelligence") OR ("Abstract":"deep learning") OR ("Abstract":"data science")) AND (("Abstract":"high school") OR ("Abstract":"k-12") OR ("Abstract":teen*) OR ("Abstract":school*)) AND (("Abstract":teach*) OR ("Abstract":education) OR ("Abstract":course) OR ("Abstract":MOOC) OR ("Abstract":learn*)) Filters Applied: 2011– 2021
MIT media lab	*No search string has been applied, all publications listed have been considered.*
ScienceDirect (Elsevier)	("machine learning" OR "artificial intelligence") AND ("high school" OR "k-12" OR school) AND (teach OR education OR course OR learn) Filter: Year: 2011-2021
Scopus	TITLE-ABS-KEY (("machine learning" OR "artificial intelligence" OR "deep learning" OR "data science") AND ("high school" OR "k-12" OR teen* OR school*) AND (teach* OR education OR course OR MOOC OR learn*)) AND (LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014) OR LIMIT-TO (PUBYEAR , 2013) OR LIMIT-TO (PUBYEAR , 2012) OR LIMIT-TO (PUBYEAR , 2011)) AND (LIMIT-TO (SUBJAREA , "COMP"))
SocArXiv	("machine learning" OR "artificial intelligence" OR "deep learning" OR "data science") AND ("high school" OR "k-12" OR teen* OR school*) AND (teach* OR education OR course OR MOOC OR learn*)
SpringerLink	("machine learning" OR "artificial intelligence" OR "deep learning" OR "data science") AND ("high school" OR "k-12" OR teen* OR school*) AND (teach* OR education OR course OR MOOC OR learn*) Filter: Computer Science Filter: within 2011–2021
Web of Science	("machine learning" OR "artificial intelligence" OR "deep learning" OR "data science") AND ("high school" OR "k-12" OR teen* OR school*) AND (teach* OR education OR course OR MOOC OR learn*) Filter used: 2011–2021
Wiley Online Library	("machine learning" OR "artificial intelligence" OR "deep learning" OR "data science") AND ("high school" OR "k-12" OR teen* OR school*) AND (teach* OR education OR course OR MOOC OR learn*) Filter used: 2011–2021

Where possible, we limited the search focusing on either the title, abstract and keywords. In addition, we filtered the search results at SpringerLink to the field of computer science. We have also filtered the search results from 2011 until 2021.

2.2. *Search Execution*

The search was realized in January 2022 by the first author and revised by the co-author. The initial search returned 715,176 artifacts. Several searches returned a large number of results even after a calibration of the search string. This is due to the fact that articles describing how to use ML/AI techniques for education, e.g., for personalized learning platforms, correspond to the same search terms. In the first analysis step, we reviewed titles, abstracts and keywords to identify articles that adhere to the exclusion criteria in 2920 results, resulting in 208 potentially relevant artifacts (Table 4).

Table 4
Number of identified articles per repository and selection stage

Source	No. of search results	No. of analyzed results	No. of potentially relevant results	No. of relevant results (without duplicates)
ACM Digital Library	229	229	43	10
IEEE Xplore	665	300	38	3
arXiv	131	131	4	0
Scopus	2,067	300	21	2
MIT media lab	86	86	13	7
SocArXiv	6	6	4	0
ERIC	5,585	300	12	0
ScienceDirect	68	68	2	0
SpringerLink	35,050	300	12	0
Web of Science	63,550	300	3	0
Wiley Online Library	2,839	300	1	0
Google	588,000	300	29	1
Google Scholar	16,900	300	26	1
Snowballing				
Backward snowballing	3			
Forward snowballing	3			
Total number of relevant results without duplicates	30			

In the next step, we analyzed the full texts and excluded irrelevant ones following the inclusion/exclusion and quality criteria. We also excluded articles describing instructional units targeting undergraduate and graduate/college level (Yu and Poger, 2020; Bennett, 2017; Kwan, 2014), other K-12 levels such as pre-school and elementary school (Tedre *et al.,* 2020), or teachers' preparation programs (Mike and Rosenberg-Kima, 2021; Lin and Van Brummelen, 2021). We also excluded articles focusing on teaching data science targeting K-12 but not covering any ML concepts (Harvey and Kumar, 2019).

Applying the quality criteria we also excluded artifacts not providing substantial information with regard to our analysis questions (Digh, 2021; Evangelista *et al.*, 2018; Heinemann *et al.*, 2018), for presenting only a "lightning talk" (McBride *et al.*, 2021), special session (Judd, 2020), poster (Posner *et al.*, 2018) or abstract only (Haqqi *et al.*, 2018; Young and Ringenberg, 2019). Furthermore, some potentially relevant articles not accessible via Portal Capes were also not considered (Joshua, 2021; Micheuz, 2020).

In order to further reduce the risk of omission, we also conducted a snowballing procedure (backward and forward)(Wohlin, 2014). As a result, 6 relevant articles were encountered.

We then excluded duplicates and articles referring to the same instructional unit were unified. As a result, a total of 30 articles presenting findings with regard to the research question were identified (Table 5). Some of these articles present instructional units focusing exclusively on ML, while some contemplate ML in courses covering data science, programming, information technology and/or as a subfield of AI curricula.

Table 5

Number of identified instructional units per repository and per selection stage

Reference	Name of the instructional units	Brief description
(Bhatia, 2020)	Using Transfer Learning, Spectrogram Audio Classification, and MIT App Inventor to Facilitate Machine Learning Understanding.	A workshop applying transfer learning and spectrogram audio classification methods to teach basic ML concepts to High School students.
(Bilstrup *et al.*, 2020)	Machine Learning Ethics Workshop.	A workshop that allows students to reflect on ethical dilemmas by designing their own ML applications.
(Burgsteiner *et al.*, 2016a) (Burgsteiner, 2016b)	IRobot: Teaching the Basics of Artificial Intelligence in High Schools.	An educational project teaching fundamental concepts of AI (problem-solving, search, planning, graphs, data structures, automata, agent systems, ML) at the High School level.
(Chua *et al.*, 2019)	Budding Data Scientists Hackathon.	Pilot program to bring data science into a High School's curriculum in Singapore.
(Estevez *et al.*, 2019)	Introduction to Artificial Intelligence for High-School Students Using Scratch.	A workshop to introduce High School students to the fundamentals and operation of the most popular AI algorithms.
(Grillenberger and Romeike, 2019)	Introducing Secondary School Students to Aspects of Data Mining.	A course to teach concepts focusing on data analysis and prediction.
(Huang *et al.,* 2021)	Medical Artificial Intelligence Course.	A medical AI course to provide High School students an overview of deep learning applications in medical image analysis, and inspire them to pursue careers in the field of medical AI.
(Kandlhofer *et al.*, 2016)	AI Literacy.	A course for different educational levels (including High School) to teach fundamental AI/computer science topics (automatas, intelligent agents, graphs and data structure, problem-solving and ML).
(Kandlhofer *et al.*, 2019)	Enabling the Creation of Intelligent Things: Bringing Artificial Intelligence and Robotics to Schools.	An educational project aiming at the development and implementation of a professional, standardized, internationally accepted system for training and certifying educators and young people in AI (including ML) and Robotics.
(Kaspersen *et al.*, 2021)	The Machine Learning Machine: a tangible user interface for teaching Machine Learning.	A tool in order to teach students about ML and in this way contribute towards a more widespread understanding of ML.
(Lao, 2020)	Machine Learning Education Framework.	A workshop using the ML Education Framework to transform ML consumers to be ML contributors.
(Mariescu-Istodor and Jormanainen, 2019)	Machine Learning method.	Workshop teaching ML for object recognition that can be implemented using the knowledge that High School students attain during their normal math and IT classes.
(Mike *et al.*, 2020)	Data Science and Machine Learning program.	Course to adapt a data science course to computer science High School pupils that incorporates both a broad view on data science and data workflow, as well as a deep understanding of data processing algorithms and specifically, ML.
(Mobasher *et al.*, 2019)	Data Science Summer Academy for Chicago Public School Students.	Summer camp to increase awareness about data science among High School students, also exploring ML and AI.

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Reference	Name of the instructional units	Brief description
(Neumann, 2019)	A First Introduction to Modeling and Learning using the Data Science Workflow.	An introductory AI/ML course on the early undergraduate level (or even High School) to expose students to AI/ML problems and introduce basic techniques to solve them without relying on the computational and mathematical prerequisite knowledge.
(Norouzi *et al.*, 2020)	ML/NLP cluster for High School students.	A course to teach ML and NLP topics to High School students.
(Rodríguez-Garcia *et al.*, 2021)	LearningML: online workshop to teach Artificial Intelligence to 10–16-year old students.	Online workshop on AI/ML techniques, and programming projects using the LearningML platform with 10–16 year old students.
(Rodríguez-Garcia, *et al.*, 2019)	Developing Computational Thinking at School with Machine Learning.	Practical activity to teach concepts underlying modern AI-based on ML.
(Santana *et al.*, 2018)	Deep learning practice for High School student engagement in STEM careers.	A course with a practical activity using deep learning (didactical implementation methodology) for High School students to engage in STEM careers.
(Sperling and Lickerman, 2012)	Software Engineering Curriculum in Israeli High School.	Proposal of a software engineering curriculum for High School students that includes AI and ML subjects.
(Tang *et al.*, 2019) (Tang, 2019)	PIC: A Personal Image Classification Webtool for High School Students.	A workshop that teaches core ML concepts with image classification, using the Personal Image Classification Tool (PIC), a companion extension for MIT App Inventor aiming at the development of intelligent apps.
(Vachovsky *et al.*, 2016)	SAILORS: Stanford Artificial Intelligence Laboratory's Outreach Summer.	A summer camp to increase interest in AI, contextualize technically rigorous AI concepts through societal impact, and address barriers that could discourage 10th-grade girls from pursuing computer science. It covers computer vision, control systems, NLP, and computational biomedical concepts.
(Van Brummelen, 2019) (Van Brummelen, *et al.*, 2020)	Tools to Create and Democratize Conversational Artificial Intelligence.	A High School workshop to democratize AI technology, and empower technology consumers to become technology developers. Enabling anyone to create complex conversational AI applications.
	AI Literacy Workshop Curriculum Design.	A workshop aligned with the K-12 AI curriculum from (Van Brummelen 2019), in which students develop conversational agents using an interface in MIT App Inventor.
(Voulgari *et al.*, 2021)	ArtBot: a game-based approach for teaching Machine Learning to primary and secondary education students.	A game-based learning environment for supporting AI literacy skills of students.
(Wan *et al.*, 2020)	SmileyCluster: supporting accessible machine learning in K-12 scientific discovery.	An environment that explores data visualization, hands-on activity, and collaborative learning to assist learning ML concepts, methods and sense-making of patterns.
(Zhu, 2019)	An Educational Approach to Machine Learning with Mobile Applications.	A course to introduce students to what ML can do and to allow them to build powerful applications (through extensions for MIT App Inventor).
(Zimmermann-Niefield *et al.*, 2019)	AlpacaML: Youth yearning Machine Learning through building models of athletic moves.	A workshop to introduce youth to making ML models within the context of their athletic interests.

Besides articles focusing specifically on High School level, some courses are designed for a wider scope of educational stages, such as elementary or middle school to High School (Zimmermann-Niefield *et al.*, 2019; Kandlhofer *et al.* 2016; Rodríguez-Garcia *et al.*, 2021; Voulgari *et al.*, 2021). We also observed that some instructional units are specifically targeting girls aiming at the inclusion of minorities (Vachovsky *et al.*, 2016). Most of the instructional units are aimed at ML novices (71.4%), while, some courses require prior knowledge on mathematical concepts (Estevez *et al.*, 2019) or programming (Mariescu-Istodor and Jormanainen, 2019; Tang *et al.*, 2019). Very few instructional units (10.7%) are aimed at advanced levels for students with prior experiences on a variety of AI knowledge or experience, e.g., robotics and programming (Wan *et al.*, 2020; Zhu, 2019). Half of the instructional units are designed as non-formal education, generally in the form of courses and workshops, with short duration and/or low intensity (e.g., Mariescu-Istodor and Jormanainen, 2019). On the other hand, about a third of the courses (35.7%) are adopted in formal education in an institutionalized, intentional way following defined curricula. Only a very small number (14.3%) of informal initiatives have been encountered as intentional learning activities, but in a less organized and less structured way.

3. Analysis of the Results

Based on the information extracted we analyze findings with regard to content, pedagogies, and technologies. A complete description of the findings reported in the relevant articles is documented in a technical report (Martins and Gresse von Wangenheim, 2022).

Taking into consideration the increasing importance of popularizing AI/ML knowledge already in High School, several instructional units are being proposed, usually designed as non-formal education targeting novices. As part of this systematic literature review we encountered 30 studies reporting findings on the content, pedagogical strategies, and technologies adopted for teaching ML (Table 5). These findings are mostly based on qualitative and quantitative evaluations of the courses and/or the student's learning assessments or other factors such as motivation. Most evaluations were conducted as case studies, showing also a need for more rigorous studies including experiments in order to explore this research question in more detail.

3.1. *Content: What are the Findings Related to ML Content Taught in High School?*

Most findings related to ML content taught in High School, reported a gain in students' knowledge of basic ML concepts, algorithms, and neural networks, observing them to become confident and able to explain and discuss how an ML system works, as well as to recognize critical issues (Table 6). On the other hand, some topics may be more difficult for High School students to understand, including statistics and some AI techniques, such as agents architectures and propositional logic. The learning of topics related to

Table 6

Overview on findings on the students learning with regard to ML concepts

	References
Positive findings	
Students demonstrated a gain in understanding of what ML is, basic concepts and how ML works, enabling them to understand, discuss and explain how ML systems work.	(Bhatia 2020; Chua *et al.,* 2019; Zhu, 2019; Lao, 2020; Voulgari *et al.,* 2021; Wan *et al.*, 2020; Burgsteiner *et al.*, 2016)
Students were enabled to design an ML system as a result of some courses .	(Chua *et al.*, 2019; Bilstrup *et al.*, 2020)
Students understood the importance of data for ML especially through courses that cover data science to support the teaching of AI/ML.	(Bhatia, 2020)
Increase in students' interest in AI or data science careers in the future.	(Huang *et al.*, 2021; Vachovsky *et al.*, 2016; Mobasher *et al.*, 2019)
Difficulties	
The topic on statistical tests has shown to be challenging for students to grasp.	(Chua *et al.*, 2019)
Students did not understand well some sub-topics of AI, such as agents architectures and propositional logic.	(Kandlhofer *et al.*, 2016)
Ethical dilemmas turned out to be challenging to address, and students, who were able to have qualified and interesting discussions about ML ethics, found it difficult to come up with good solutions to the issues.	(Bilstrup *et al.*, 2020; Van Brummelen, 2019)

Table 7

Overview on findings on the students learning with regard to ML algorithms

Positive findings	References
Supervised learning applied to classification tasks through decision trees is understood by the large majority (90%) (n=12) of the students.	(Mobasher *et al.*, 2019)
Students understood neural networks, including the evaluation of their performance and the impact of training parameters.	(Santana *et al.*, 2018; Estevez *et al.*,2019)
Regarding unsupervised learning through k-means, students understood different concepts of centroid, selection of the appropriate k cluster number, cluster analysis and were able to interpret patterns of the clustering result as well as to decide when clustering should be used.	(Wan *et al.*, 2020; Mobasher *et al.*, 2019)
More than 90% (n=12) of students understood the algorithms behind k-nearest neighbors.	(Mobasher *et al.*, 2019)
Teaching a variety of ML techniques also seems to allow students to acquire the ability to contemplate the similarity between two quite different situations formulated as prediction problems.	(Estevez *et al.*, 2019)

the social implications and ethical issues of ML also seems to be more challenging, indicating a research opportunity on how to design instructional units on these topics to facilitate learning. However, teaching ML concepts in High School seems to increase the students' interest in pursuing careers related to AI and data science, including also girls.

Table 8

Overview on findings on the students learning with regard to the ML process

Positive contributions	References
Students were very interested in the data collection process, which also helped students to recognize the importance of data for ML.	(Santana *et al.*, 2018; Bhatia, 2020)
Teaching model training using appropriate technological support, enables students to train different ML models and also allows them to observe as well as to describe the process by which models use data to create representations and learn from patterns.	(Kaspersen *et al.*, 2021; Bhatia, 2020)

Regarding ML algorithms, the vast majority of the courses currently teach supervised learning algorithms in which a desired model predicts the label for yet-unseen data. A few instructional units (n = 5) also cover unsupervised learning, a process that seeks to learn in the absence of a previously identified output. Both, supervised and unsupervised learning algorithms were reported to be understood by the students, applying them mostly to image classification and/or natural language processing tasks (Table 7).

Students also seem to be able to understand and apply the ML process from data management to the evaluation of model performance, and in some courses even to build their own ML models (Table 8).

3.2. *Pedagogy: What are the Findings Related to Pedagogy Adopted for Teaching ML in High School?*

Findings related to the pedagogical strategies point out the predominant adoption of constructivist approaches sometimes in combination with objectivist principles. Such a combination is also proposed by the “Use-Modify-Create” cycle (Lee, 2011; Lytle, 2019) commonly used for the progression of learning computing concepts and practices, which can also be adopted for ML education. Following this cycle, students first learn basic concepts “using” and analyzing a given ML artifact, then “remixing/modifying” an existing one, until eventually “creating” their own ML models. This progression allows a smooth transition from reusing a predefined artifact to learner-generated creative construction, in order to go beyond coding or using ML applications following predefined tutorials and provide the opportunity for a deeper understanding and creativity (Bellettini, 2014). Findings also emphasize the importance of active learning with hands-on activities being not only favored but even eagerly awaited by the students. The effectiveness of problem/project-based learning has also been reported, especially for engaging and motivating students to solve real-world problems (Table 9).

Together with the tendency to more “student-centered” approaches with peer-to-peer learning, cooperative and collaborative learning strategies are commonly adopted in which students work in groups on learning activities. Yet, on the other hand some studies

Table 9

Overview on findings with regard to learning strategies

	References
Positive contributions	
The use of interactive and active learning strategies with accessible technology actively engaged students in exploring, understanding, and thinking about ML and gave them more confidence to discuss ML concepts and to solve a problem. An interactive strategy also seems to offer a fertile space for young people to begin to develop intuitions, curiosities, and theories about ML.	(Bhatia, 2020; Kaspersen *et al.,* 2021; Sperling and Lickerman, 2012; Van Brummelen *et al.*, 2020; Santana *et al.*, 2018; Wan *et al.*, 2020; Zimmermann-Niefield *et al.*, 2019)
High-order thinking tasks help in engaging students with technology.	(Voulgari *et al.*, 2021)
Students enjoyed project-based learning, building AI systems and had positive feelings about their projects.	(Huang *et al.*, 2021; Van Brummelen, 2019)
Applying problem-based learning, successfully allowed students to work on powerful, purposeful real-world applications in their communities, engaging students to recognize constraints in the real world and the inexistence of one perfect solution to problems. Students especially enjoyed exploring and building their own ML applications. Furthermore, problem-based learning resulted in positive results regarding behavioral, emotional and cognitive dimensions applied to context, problem, data collection and data analysis, as the students' feedback reflected the engagement, motivation and happiness in learning.	(Bhatia, 2020; Chua *et al.,* 2019; Vachovsky *et al.*, 2016; Van Brummelen, 2019; Huang *et al.,* 2021; Santana *et al.*, 2018; Van Brummelen, 2019)
Inquiry-based learning stimulated students to define hypotheses and theories making sense and drawing conclusions from the analysis of the ML models.	(Wan *et al.*, 2020; Zimmermann-Niefield *et al.*, 2019; Tang *et al.*, 2019)
Students enjoyed game-based learning and 73% (n = 95) of the students (indicated that the game helped them to understand ML principles and processes.	(Voulgari *et al.*, 2021)
Difficulties	
The effectiveness of project-based learning depends on students to have sufficient time to develop their projects and learn the concepts.	(Van Brummelen, 2019; Zhu, 2019; Burgsteiner, 2016b)
Coming up with ML project ideas turned out not to be a trivial step for the students, requiring several discussions and iterations.	(Mike *et al.*, 2020)
Regarding the game ArtBot, some students found the game as either too monotonous, boring, easy, and slow, or too complicated and time-consuming at times.	(Voulgari *et al.*,2021)

also indicate issues related to group work, which may be caused by a non-homogeneous composition of groups of students with different levels of preexisting knowledge and, therefore, different learning paces. It was also reported that female students feel more comfortable and confident when working in groups with other girls (Table 10).

To complement learning strategies, motivation strategies are defined by factors related to interest and excitement in learning, and are directly linked to skill development (Mariescu-Istodor and Jormanainen, 2019). Burgsteiner (2016b) and Santana *et al.* (2018) observed high self-motivation with students executing tasks voluntarily beyond the expected, demonstrating a process of autonomy and self-discipline especially as part of data collection activities.

Table 10

Overview on findings with regard to cooperative and collaborative learning

	References
Positive contributions	
Collaborative learning suits High School students, who are capable of coming up with new and unexpected ideas. It allows students to perceive contradictions, inconsistencies and limitations of their understanding during the interaction with peers. Working in groups was one of the favorite activities of the students and they expressed great interest in each other's projects.	(Mariescu-Istodor and Jormanainen, 2019; Sperling and Lickerman, 2012; Van Brummelen *et al.* ,2019; Wan *et al.* ,2020)
Peer-to-peer learning, by having students teaching other students, encourages a more in depth understanding of the concepts.	(Chua *et al.*, 2019; Rodríguez-Garcia *et al.*, 2019; Sperling and Lickerman, 2012; Vachovsky *et al.*, 2016; Van Brummelen *et al.*, 2020)
Difficulties	
Students forming non-homogenous groups in terms of prior knowledge coming from different school years can complicate the work in groups.	Burgsteiner (2016b)
While some students liked to work in groups, others preferred to learn on their own, as group work may result in a slower or faster pace given the students' working style, group composition, and amount of group discussions.	Neumann (2019)
Female students felt more confident, comfortable and encouraged by working with other students of the same gender.	(Vachovsky *et al.*, 2016; Norouzi *et al.*, 2020)

Diverse instructional methods were adopted in the courses, with a predominance of hands-on activities guiding students to gain knowledge by experience (Table 11).

Several studies also point out the importance of providing information at the pace of the students' learning (Wan *et al.*, 2020). This may also include the provision of advanced material to faster learning students for self-study, while the students with a slower pace receive additional help from the instructors (Chua *et al.*, 2019). Burgsteiner *et al.* (2016a) also warned of too extensive homework, which may demotivate students.

Table 11

Overview on findings on instructional methods

	References
Positive contributions	
Especially hands-on activities for developing ML models in groups were essential for the effectiveness of learning, as students demonstrated less difficulty to maintain focus than, e.g., in lectures.	(Huang *et al.,* 2021; Van Brummelen *et al.*, 2020)
In general most students participated actively in discussions, which was observed as even unusual in particular for one of the classes.	(Grillenberger and Romeike, 2019)
Unplugged computer science material or card-based material turned out to be effective for students to describe ML systems.	(Kandlhofer *et al.*, 2019; Kandlhofer *et al.*, 2016; Bilstrup *et al.*, 2020)

Continued on next page

Table 11 – continued from previous page

	References
Students agreed that course material in the form of code, multimedia, and real-world examples helped in their learning.	(Chua *et al.,* 2019)
Difficulties	
Certain instructional materials/tools need to be adapted to reduce the complexity and extent of certain contents in order to present AI topics in a target group-specific manner.	(Kandlhofer *et al.*, 2019)
Information in text form may take students a long time to read and understand, indicating a need for the adoption of other formats.	(Wan *et al.*, 2020)
Longer lectures are challenging to maintain students' focus, requiring more breaks or breaking up the lecture with more hands-on activities.	(Mobasher *et al.*, 2019)
Time spent on a topic needs to be related to the interest of the students in order to prevent them from losing interest.	(Grillenberger and Romeike, 2019)

3.3. *Technology: What are the Findings from Technology Used to Teach ML in High School?*

The adoption of technology aims to facilitate the teaching and learning of ML in High School. One of the main decisions of using technology is related to the environments for developing ML models. For teaching more classical ML algorithms, like decision trees and artificial neural networks, the use of the Python language is predominant (Chua *et al.,* 2019; Huang *et al.,* 2021; Norouzi *et al.,* 2020) (Table 12).

An alternative to text-based programming languages are visual environments that are also used for teaching ML in High School (Gresse von Wangenheim *et al.*, 2021). In this context typically workflow-based environments are used for the development of ML models, which are then deployed through block-based programming environments as in-

Table 12

Overview on findings on the usage of Python as programming language

	References
Advantages	
Students understand basic Python commands to handle data, implement and apply simple learning models, as well as to visualize and interpret their results even without prior computational and mathematical knowledge.	(Neumann, 2019)
97% of students liked the introduction to Python.	(Neumann, 2019)
Disadvantages	
Students with limited programming skills demonstrated more difficulties in projects.	(Huang *et al.,* 2021)
Using a text-based programming environment requires spending more time teaching general Python programming concepts.	(Chua *et al.*, 2019)
Different levels of programming skills may result in differences with regard to the time it takes students to complete the activities with Python.	(Neumann, 2019)

Table 13

Overview on findings on the usage of visual development environments

	References
Advantages	
Visual tools allow students to focus on and understand the ML process and basic concepts and to efficiently build impactful ML models without programming knowledge.	(Bhatia, 2020; Lao, 2020; Tang, 2019; Tang *et al.*, 2019; Rodriguez-Garcia *et al.*, 2021)
The tools were perceived as easy and fun to use and being intuitive for beginners with no prior ML experience.	(Lao, 2020)
Block-based environments such as App Inventor and Scratch enable even beginners to deploy ML models and to create intelligent apps or games. 38% (n = 14) of the students cited the deployment of the trained models in MIT App inventor apps as their favorite part of the workshop. 84.4% (n=114) of the students perceived the LearningML tool for the deployment of ML models in Scratch as a useful application to learn about AI.	(Rodriguez-Garcia *et al.*, 2021; Van Brummelen *et al.,* 2020)
SmileyCluster, a web-based collaborative learning environment that supports learning basic ML concepts and methods of k-means clustering, demonstrated to be effective in enhancing the understanding and can positively support learning of k-means clustering.	(Wan *et al.*, 2020)
The tangible ML machine (MLM), a learning tool that enables K-12 students to iteratively work on ML models for binary classifications of doodles they draw using pen and paper, was found easy and engaging to use allowing students also to quickly find workarounds for any issues preventing any frustration.	(Kaspersen *et al.*, 2021)
Disadvantages	
Students struggled with understanding what the model artifact represented and what its functionality was in the tangible Machine Learning Machine.	(Kaspersen *et al.,* 2021)
Some students did not fully grasp basic conversational AI programming principles (like some blocks for AlexaSkill and the MIT App inventor conversational AI interface), therefore, simpler activity may be required, such as "Hello World" when deploying on the Alexa device.	(Van Brummelen, 2019)

telligent games or apps. Visual environments used in some courses for the development of ML models include Google Teachable Machine (Google Teachable Machine, 2021) as well as PIC (Lao, 2020; Tang, 2019; Tang *et al.*, 2019), PAC (Bhatia, 2020; Lao, 2020) and LearningML (Rodriguez-Garcia *et al.*, 2021) (Table 13).

Findings indicate that these tools have been successful in their overall goal of supporting young people to create their own ML models. Yet, we also identified still a lack of a wider scope of technology support for such courses covering in a more diverse way other ML tasks (e.g., object detection) and/or ML techniques.

Threats to validity. With the intent to minimize threats to the validity of the results of this study, we identified potential threats and applied mitigation strategies. Systematic reviews may suffer from the risk of omission of relevant studies. To mitigate this issue, we carefully defined the search string by considering not only key concepts, but also relevant synonyms. Moreover, we included not only scientific articles but also scholarly papers, such as theses and dissertations, to avoid the risk of excluding existing instructional units. We also searched several repositories related to the objective of the review as well as conducted snowballing in order to further minimize the risk of omission. The threats to the selection of relevant instructional units were mitigated by detailing inclusion/exclusion criteria, and quality criteria and applying these criteria carefully during the selection. Data extraction was hindered in some cases as relevant information was not explicitly presented. In these cases it was inferred according to context and available information. Data extraction was carefully done by both authors until consensus was achieved.

4. Conclusion

In this article we analyze and synthesize findings regarding the content, pedagogical strategy, and technology to teach Machine Learning in High School. We have encountered 30 studies published in the last 10 years, primarily focused on teaching novices through extracurricular courses or workshops. The results of our review indicate that High School students are able to understand and apply basic ML concepts, algorithms and processes applying predominantly active/hands-on learning strategies. In combination with problem/project-based learning in a collaborative way, students were able to learn ML concepts and even to build their own ML models in some courses. These learning strategies also helped to keep students engaged in reflecting, exploring, discussing and analyzing results about their projects and experiences. Findings also indicate that these learning strategies enabled High School students to be more confident, motivated, and interested in learning ML. Although the adoption of text-based programming languages, such as python, was considered beneficial in some studies, others reported issues depending on the prior programming skill level of the students. In this regard, courses that used visual environments for the development and deployment of ML models reported very positive results enabling even beginners to build their own intelligent applications.

As a result of the review we also identified several research opportunities, including the need for more and more rigorous evaluations on how to teach ML on larger scales, besides the improvement of instructional units and supporting technology based on the findings.

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