Emerging Technologies in K–12 Education: A Future HCI Research Agenda

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This systematic mapping review sheds light on how emerging technologies have been introduced and taught in various K–12 learning settings, particularly with regard to artificial intelligence (AI), machine learning (ML), the internet of things (IoT), augmented reality (AR), and virtual reality (VR). These technologies are rapidly being integrated into children's everyday lives, but their functions and implications are rarely understood due to their complex and distributed nature. The review provides a rigorous overview of the state of the art based on 107 records published across the fields of human-computer interaction, learning sciences, computing education, and child–computer interaction between 2010 and 2020. The findings show the urgent need on a global scale for inter- and transdisciplinary research that can integrate these dispersed contributions into a more coherent field of research and practice. The article presents nine discussion points for developing a shared agenda to mature the field. Based on the HCI community's expertise in human-centred approaches to technology and aspects of learning, we argue that the community is ideally positioned to take a leading role in the realisation of this future research agenda.

CCS Concepts: • **General and reference** → *Document types*; *Surveys and overviews* • **Social and professional topics** → *Computing education*; *K-12 education*;

Additional Key Words and Phrases: K–12 education, emerging technologies, computing education, computational literacy

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1 INTRODUCTION

This article provides an interdisciplinary account of how emerging technologies are being introduced and taught in K–12 settings, leading up to a future HCI research agenda. The use of emerging technologies such as **artificial intelligence** (**AI**), **machine learning** (**ML**), the **internet of things** (**IoT**), **augmented reality** (**AR**), and **virtual reality** (**VR**) has grown rapidly in children's everyday lives, but the general understanding of these technologies is still limited [84, 85]. This means that there is a significant imbalance between the far-reaching importance of emerging technologies and children's ability to comprehend these technologies and their consequences.

The urgent need on a global scale to educate K–12 students so they can critically and constructively engage in the digitisation of societies has brought with it an increased focus on K–12 teaching across a diverse range of research fields. In the past decade, **human-computer interaction** (**HCI**) research has produced novel technologies to support computing education [27, 55, 76], as well as overviews of the competences required for engaging with emerging technologies [85]. At the same time, the learning sciences are rapidly developing new didactics [123, 154], assessment practices [152], and specialised curricula [115, 136], which can support educators in introducing emerging technologies into K–12 teaching. Further, design research and especially **child–computer interaction** (**CCI**) research have studied children's perceptions of emerging technologies [143] and provided insightful design recommendations [82, 121, 164] as well as approaches to teaching about emerging technologies [2, 41].

Policymakers at national and international levels as well as non-governmental organisations have called for action to provide children with knowledge, skills, and competences in relation to digital technology, digitisation and, more recently, emerging technologies. Initiatives include, among others, the Digital Education Action Plan [47] and Informatics for All coalition [69] in Europe, and in the United States, the National Artificial Intelligence Initiative [140], with one of six strategic pillars focused on Training and Education. UNICEF (United Nations Children's Fund), in turn, has developed guidelines for "AI and child rights policy" together with a number of renowned international experts [139]. Their premise is that "the rights of children, as current users of AI-enabled systems and the future inhabitants of a more AI-saturated world, must be a critical consideration in AI development" [139]. It is argued that integrating the benefits of novel technologies, computational thinking, digital literacy, and maker education will enable children to actively participate in a society with increasing human-computer interaction [19–21, 101].

In response to these urgent calls and to identify progress to date across academic research, we conducted a systematic mapping review of the state of the art of emerging technologies in K–12 education, based on 107 records published between 2010 and 2020. The review covers the five central topics of (1) target groups and teacher roles (Section 4.2), (2) learning objectives and curricular implementation (Section 4.3), (3) educational frameworks and practices (Section 4.4), (4) technology and other learning tools (Section 4.5), and (5) empirical evaluation and student assessment (Section 4.6). It identifies trajectories in the current literature across fields, and provides a strong starting point for developing a shared research agenda in emerging technologies in K–12 education (Section 5).

The HCI community is ideally positioned both to take a leading role in the realisation of this inter- and transdisciplinary agenda and to act as a mediator between neighbouring and subfields for diverse reasons. Firstly, it has a proven track record of human-centred approaches and commitment to understanding people's entanglement with technology [11, 49]. For decades, HCI researchers have investigated how people learn to use and adapt technology tools, with "designing for learnability" as a key HCI design principle [160]. The HCI community's interest in aspects of learning has also been manifested in the design of educational technologies (ed–tech), providing a second reason for why the community has a pivotal role in the realisation of this agenda.

Designing for learning (e.g., MOOCs, intelligent tutoring systems, VR learning tools) has specific design and interaction issues that go beyond more generally applicable design knowledge, witnessed by the increased engagement of learning scientists with the HCI community. This has, in turn, led to the creation of the newly established Learning, Education and Families subcommittee with 179 articles submitted for CHI 2020 [160]. A third reason is the community's ongoing commitment for advancing UX and HCI education by addressing the changing needs of students and professionals in computing and interaction design [156]. This has brought forth several curricular innovations in the domain of technology education (tech-ed) such as the integrated studio approach for teaching HCI to undergraduates [153]. By drawing on this extensive expertise in human-centred approaches, ed–tech and tech-ed, and bringing in researchers from neighbouring fields, the HCI community can act as a catalyst for change and create a lasting impact on children's agency in an increasingly digitalised society – an impact that reaches beyond research into policy and education, as suggested by Bødker and Kyng [12].

The article is organised as follows. Section 2 defines the concept of emerging technology and discusses considerations for K–12 education. Section 3 describes the review method and explains in detail how the literature was collected, analysed, and synthesised. Section 4 presents the results, including a description of the dataset and findings for each of the five central topics of interest. Section 5 discusses the main findings, leading up to nine discussion points for developing a shared agenda for future research. Finally, Section 6 summarises the main conclusions of the systematic mapping review.

2 EMERGING TECHNOLOGIES: DEFINITIONS AND CONSIDERATIONS

Emerging technologies have only recently emerged as a topic in education [14, 19, 21, 25–27], and still receive only a fraction of the attention devoted to the digitisation and digital technology more generally [83]. In this section we discuss the unique characteristics of emerging technologies and argue why addressing these technologies – AI, ML, IoT, AR, and VR in particular – is critical for K–12 education.

Many definitions of emerging technology have been suggested [30, 31, 130, 131]. An early definition is provided by Martin [89], who emphasises its transformative impact as a key characteristic, describing it as "a technology the exploitation of which will yield benefits for a wide range of sectors of the economy and/or society" (p. 165). In addition to the potential impact and the transformative nature of emerging technologies, Day and Schoemaker [32] emphasise its origins in radical innovation and/or technology convergence. They describe an emerging technology as "a science-based innovation that has the potential to create a new industry or transform existing ones. It includes discontinuous innovations derived from radical innovations (...) as well as more evolutionary technologies formed by the convergence of previously separate research streams" (p. 30). Boon and Moons [13], in turn, emphasise a further characteristic, uncertainty, due to the fact that these technologies are still in the early development stage. This means that "several aspects, such as the characteristics of the technology and its context of use or the configuration of the actor network and their related roles are still uncertain and nonspecific" (p. 1915).

Building on this work, Rotolo et al. [114] foreground five characteristics of emerging technologies: their radical novelty, their relatively fast growth, a certain degree of coherence and momentum, their significant impact on specific domains or on society more broadly, and uncertainty and ambiguity about possible outcomes and uses. They define an emerging technology as

> a relatively fast-growing and radically novel technology characterised by a certain degree of coherence persisting over time and with the potential to exert a considerable impact on the socioeconomic domain(s) which is observed in terms of the

The internet of things (IoT) describes physical objects or 'things' that are embedded with sensors, processing ability, software, and other technologies that connect and exchange data with other devices and systems over the internet or other communications networks.

Artificial intelligence (AI) is intelligence demonstrated or simulated by technological means, as opposed to natural intelligence. It allows computers and robots to do tasks that are usually done by humans because they require human intelligence and discernment.

Machine learning (ML) is a type of AI that allows software applications to become more accurate at predicting outcomes without being explicitly programmed to do so. ML algorithms use historical data as input to detect patterns and predict new output values.

Virtual reality (VR) is a computer-generated environment with scenes and objects that appear to be real, making the user feel they are immersed in their surroundings. This environment is typically perceived through a device known as a VR headset or helmet.

Augmented reality (AR) is an interactive experience of a real-world environment where objects are enhanced by computer-generated perceptual information, sometimes across multiple sensory modalities. Unlike VR, which creates its own computer-generated environment, AR adds to the existing world as it is.

Fig. 1. Generic descriptions of the emerging technologies are under consideration in this article.

> composition of actors, institutions and the patterns of interactions among those, along with the associated knowledge production processes. Its most prominent impact, however, lies in the future and so the emergence phase is still somewhat uncertain and ambiguous. (p. 1,828)

This definition frames emerging technology as radically novel in using a different basic principle to fulfil a given function than what was previously used to achieve a similar purpose, thereby changing the status quo [114]. However, the attribute of novelty is, to a large extent, context-specific. A technology can be considered "old" and no longer emerging in one domain (e.g., the commercial or business sector) while still being considered emerging in another (e.g., the education sector) where the potential growth and socioeconomic impact of a technology are still largely untapped [94]. Moreover, what is considered an emerging technology may differ among actors, depending on how they conceive the expected growth and impact [114].

To be labelled as emerging, though, a novel technology requires a certain coherence compared to others that are still in flux and lacking in established momentum and/or a relatively fixed identity (lacking, e.g., an agreed-upon label and abbreviation) [114]. This does not mean that emerging technologies have yet reached technology maturity, as they tend to have incomplete specifications and nonuniform standards. Low technology maturity means that, especially at the beginning, only a few ethical and societal issues are observable. As time passes, however, and as an emerging technology is used in different applications, the number of new and unanticipated ethical and societal concerns it throws into relief gradually increases. At the same time, the technology matures, resulting in lowered costs and uncertainty levels as possible uses, outcomes, and associated meanings become apparent [64].

Emerging technology is a term that applies to a broad range of application domains, including but not limited to agriculture (e.g., cultured meat), medicine (e.g., RNA vaccine technology), construction (e.g., four-dimensional printing), finance (e.g., digital currency), robotics (e.g., powered exoskeletons), and materials science (e.g., bioplastic) [37, 38, 72]. In this article, we confine ourselves to the domain of IT and communication, and in particular to those emerging technologies that children are increasingly exposed to in their everyday lives in school, family, and leisure time. These include the IoT, VR, AR, AI, and ML (see Figure 1). Examples of such exposure are AR filters in Snapchat and TikTok, ML-powered recommendations in YouTube and Netflix, popular VR games such as AstroBot or Beat Saber, educational applications including Froggipedia and Mondly, smart home assistants like Alexa and Google Assistant, and the "Internet of Toys" – Hello Barbie, Little Bits R2D2, and other connected toys [90]. These technologies are rapidly becoming integrated into aspects of everyday life, but are rarely understood due to their complex and distributed nature, which allows little transparency into their functions and implications. Children's use of and exposure to these emerging technologies, often unknowingly, has increased in recent years, but the full impact of these technologies on children's lives is yet to be realised [6, 16, 127, 161]. It is therefore important that children move beyond passive consumption to develop the competences and critical understanding they will need to maximise the benefits and opportunities that these technologies offer, now and in the future, while limiting exposure to risks and potential harm [19, 24, 84].

Although the selected emerging technologies differ in their complexity and in their prevalence in children's lives, they are rapidly becoming ubiquitous and, to some degree, relate to topics of growing interest in K–12 computing education such as data literacy and cybersecurity. The selection furthermore captures the characteristics and potential impacts of emerging technologies that make them so challenging and ambiguous to integrate in learning processes for coming generations.

3 METHOD

The aim of this article is to provide a state-of-the-art review of emerging technologies – and of AI, ML, AR, VR, and IoT in particular – in K–12 education (see the typology of reviews by [62]). We conducted a critical analysis and synthesis of peer-reviewed archival and non-archival records published in English between 2010 and 2020 that focus on introducing or teaching emerging technologies in different educational settings. The main contribution of this state-of-the-art review is a well-grounded agenda for further research to improve the knowledge base and advance this emerging field [128, 135]. To this end, as suggested by [110], we used a systematic approach combining electronic and manual searching to identify and select relevant literature from a broad range of fields.

The review has five main focus areas. It examines (1) who is the target group of the learning activities, and what are the roles of teachers and other actors in preparing and facilitating these activities, (2) what is being taught about emerging technologies and for what reasons, (3) how it is being taught and what theoretical frameworks are relied on, (4) what technology and other tools are used to this end, and finally (5), how practices and tools are evaluated and students' learning assessed. In the following section we explain in detail how we collected, analysed, and synthesised literature, resulting in a substantial agenda for future research in emerging technologies in K–12 education.

3.1 Data Collection

To ensure transparency and to limit bias in the selection of literature, we followed the PRISMA-ScR guidelines and flow diagram (see Figure 3) [106, 138]. We first conducted an electronic search, then screened and assessed records for eligibility, and finally searched the included records for relevant citations.

3.1.1 Step 1: Electronic Search Query. An electronic search was conducted in the Scopus database (+80 million records), which integrates the ACM Digital Library, IEEE, and Elsevier databases, among others (see Figure 2). Only records with the exact or stemmed words of the inclusion criteria in either the title, abstract, or keywords were included. The inclusion criteria can be divided into three groups. The first of the three relates to the target group (including terms such as children, kids, youngsters, K–12, students, or pupils), the second to the educational context (terms such as education, learning, teaching, school, classroom, or literacy), and the third to the type of technology (terms such as emerging technology, AI, ML, AR, VR, or IoT). Our reasons for

(TITLE-ABS-KEY (K12* OR child* OR kid* OR teen* OR pupil* OR student* OR youngster*)
AND TITLE-ABS-KEY (learn* OR teach* OR educat* OR literacy OR literate OR school* OR classroom*)
AND TITLE-ABS-KEY ("emerging technolog*" OR "artificial intelligence" OR ai OR "machine learning" OR ml OR "augmented reality" OR ar OR "virtual reality" OR vr OR "internet of things" OR iot)) AND NOT (universit* OR college OR "higher education")
AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "ch") OR LIMIT-TO (DOCTYPE, "bk") OR LIMIT-TO (DOCTYPE, "re")) AND (EXCLUDE (SUBJAREA, "MEDI") OR EXCLUDE (SUBJAREA, "HEAL") OR EXCLUDE (SUBJAREA, "NEUR") OR EXCLUDE (SUBJAREA, "NURS") OR EXCLUDE (SUBJAREA, "PHAR") OR EXCLUDE (SUBJAREA, "IMMU") OR EXCLUDE (SUBJAREA, "DENT") OR EXCLUDE (SUBJAREA, "VETE")) AND (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) OR LIMIT-TO (PUBYEAR, 2010))

Fig. 2. Search query used to identify records in the Scopus database (incl. IEEE, ACM DL, and so on.).

compiling the search terms as above were twofold: first, so many children are encountering these technologies on a very frequent basis that it is critical that they learn about them and their potential impact from an early age; and second, we wanted to limit the corpus of included records to a manageable size.

To further limit the scope, only records published in English between 2010 and 2020, and in the form of peer-reviewed articles, conference proceedings, reviews, book chapters, and books were included. The search was limited in time because emerging technologies in K–12 education are a recent phenomenon, and the peer-review criteria were used to ensure a minimum academic quality for the included records. To focus on K–12 education, any records using the words "university," "college" or "higher education" in the title, abstract, or keywords were excluded.

3.1.2 Step 2: Screening and Assessing for Eligibility. Using this search query (see Figure 2), 1,873 records were retrieved from the Scopus database by April 4, 2021. Based on an initial screening of the title and abstract by the first author, 1,357 records were excluded because they were duplicates, were not published in English, or did not focus on education. The remaining 550 records were screened and assessed for eligibility by the first author and an additional researcher based on the title, abstract, and, if needed, the full text. The researchers worked independently and flagged any doubtful cases. The results were compared, followed by a discussion of all doubt cases and disagreements between the two coders (n = 120). For the majority of records, a final decision was reached this way (n = 75). In other cases, an additional check of the target group was required (n = 16), or the record had to be screened and assessed by a third researcher (n = 29). In this process, 476 records were excluded because either the target group did not correspond with the inclusion criteria (n = 104), the focus was on educational technology (e.g., using AR to teach geography) rather than technology education (n = 312), or the topic was considered irrelevant (e.g., no reference to emerging technologies, education mentioned but not the main focus) (n = 58). From the remaining 76 records, two could not be retrieved. This left a total of 74 records, which were downloaded and organised in folders per publication year.

3.1.3 Step 3: Citation Searching. All 74 included records were scanned for relevant citations by the first author, using the same inclusion and exclusion criteria as for the electronic search. This "snowballing" process resulted in 33 additional references, which (as in the preceding stage) were screened and assessed for eligibility by the first author and an additional researcher based on the title, abstract, and, if needed, the full text. One record was removed because the body text was not in English, but there were no further disagreements between the two researchers. The remaining 32 records were downloaded and sorted in the folders per publication year. This resulted in a total

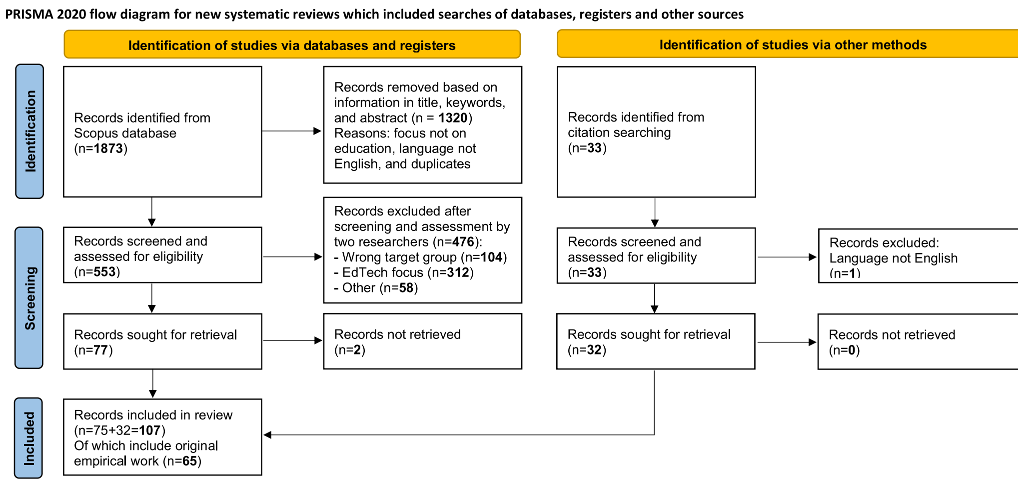

Fig. 3. Flow diagram based on the PRISMA-ScR guidelines [106, 138].

Table 1. Data Descriptors and Leading Questions were used to index all 107 Included Records

Data descriptor	Leading question
Publication year	When was the publication published?
Publication venue	Where is the publication published (name of the conference, journal, book series, and so on)?
Publication type	What type of publication is it (archival or non-archival conference proceeding, journal article, or book chapter)?
Geographical distribution	In which country is the first author's institute located?

of 107 records included for review. 65 of these records report original empirical data (for a detailed description of the dataset, see Section 4) (see Figure 3).

3.2 Data Analysis

3.2.1 Step 4: Deductive Analysis based on Predefined Categories. To analyse the records, a spreadsheet was created with separate columns for descriptive information including the title, author information, abstract, year of publication, publication venue, publication type, and geographical distribution (see Table 1). Additional columns were created for the deductive analysis categories, which were defined based on the **research question** (**RQ**):

> What is the state of the art of teaching emerging technologies in diverse K–12 learning settings, with particular regard to AI, ML, AR, VR, and the IoT?

The five deductive analysis categories are "target group, teacher roles and other actors," "learning objectives and implementation," "educational frameworks and practices," "technology and other tools for learning," and "evaluation and/or assessment" (see Table 2). A final set of columns was created to summarise the overall relevance of the record for the review, and to list any relevant references or other resources.

First, each record was read carefully by the first author and descriptive information was filled out in the spreadsheet. Then, relevant information for each of the five main categories was copied into the dedicated cells with reference to the page number. In some cases, this required several readings of the same record. Once this step was completed, a short summary was added for each main

Table 2. The five main Deductive Categories, the Leading Questions for each Category, and data-driven Child Codes

Main categories or parent codes	Leading question per category	Inductive child codes for each category
Target group, role of teachers and any other actors (section 4.2)	Who is the target group of the learning activities and tools, and what is the role of teachers and other actors (backstage and/or frontstage)?	Age-range target group Number of participants in study Role of researchers Role of teachers (backstage and/or frontstage): Role of other actors
Learning objectives and (curricular) implementation (section 4.3)	What are the learning objectives and to what extent are these implemented in or across (new) curricula?	Standalone activities or curricular integration Higher-order objective (career vs. literacy) Progressive objectives Learning objectives: – Technology concepts – Technology skills – Societal/ethical implications – Design knowledge/skills – Other knowledge/skills – Attitudes and mindsets Prior knowledge/skills requirements
Educational frameworks and practices (section 4.4)	How is children's learning supported, and to what extent are these practices grounded in the corpus of learning theory?	Theoretical learning framework Pedagogical strategies: – Hands-on – Collaborative – Theory-driven – Adaptability – Other strategies Format and duration of activities Formal, informal, or non-formal learning
Technology and other tools for learning (section 4.5)	Which technology and other (unplugged) learning tools are proposed/used in the activities?	Type of emerging technology: AI/ML, IoT, AR/VR Off-the-shelf technology tools New and new combinations of technology tools Unplugged tools Other characteristics of tools
Empirical evaluation and assessment of children's learning (section 4.6)	How are the learning activities and tools empirically evaluated, and/or children's learning assessed?	Evaluation of learning tool(s) Evaluation of learning activities Assessment of learning: – Summative assessment – Formative assessment – Constructive alignment Type of data collection Type of findings

category in these cells, as well as a note about the overall relevance of the record for the review. Finally, interesting references and other relevant resources were added to the last column of the spreadsheet. This process was repeated for all 107 records, after which a second coder skimmed each record and verified the deductive analysis conducted by the first author. Three co-authors took the role of second coder, thereby focusing on records matching their particular expertise in either AI and ML, AR and VR, or IoT. Any inaccuracies and disagreements were flagged and discussed in plenum until an agreement was reached.

3.2.2 Step 5: Inductive Analysis within and Across Categories. The next step involved an inductive analysis for each of the five main deductive categories (or parent codes) across all 107 records. First, we identified data-driven child codes by going through the tabular data per category. These child codes were interpreted from the data and once an initial set of codes was established for each of the five categories, we duplicated the respective columns in the spreadsheet and conducted a more fine-grained analysis by restructuring the tabular data in the duplicated columns according to each child code. This was a highly iterative process of going back and forth between different records, somewhat akin to "open coding" [132], which required a few child codes to be omitted or altered along the way. The final code scheme is presented in Table 2.

Once we had coded all the data extracted from the included records, we sought for possible patterns within and across child codes in a process akin to "axial coding" [132]. As with the previous step, these patterns were interpreted from the data. Examples of such patterns include the co-occurrence of pedagogical strategies coded as "hands-on" and "collaborative," and the strong link between the child codes "societal and ethical implications" and "AI/ML" (see Appendix).

Next, we summarised the findings per the main category in a separate document that was verified by the same researchers who had acted as second coder in the previous step. We then compared findings across categories, in a process akin to "selective coding" [132], and collaboratively identified major implications of the review and key topics for a future research agenda. Finally, we reported both the detailed findings, which we illustrated with examples from the reviewed records (see Section 4), and the agenda topics (see Section 5).

3.3 Limitations

As with any study, this review has a few limitations. First, we used only the Scopus database to identify and select relevant literature. Although Scopus integrates multiple relevant databases (e.g., Elsevier, ACM DL, IEEE), a crosscheck with Web of Science or other databases might have been productive. As an alternative, we combined electronic search with citation screening to identify any records that we might have missed. Another limitation is that we included both archival and non-archival records (but not grey literature). This was done to gain a good overview of current research on emerging technologies in K–12 education, while ensuring academic quality by including only peer-reviewed records. A third limitation is that we limited the scope of the review to the emerging technologies with which we believe children are already interacting on a frequent basis: that is, artificial intelligence and machine learning, augmented and virtual reality, and the internet of things. In future work, the review could be extended to include additional emerging technologies (e.g., humanoid and social robotics, e-textiles, holographic displays) and/or topics of growing interest in K–12 computing education (e.g., data literacy, cybersecurity, quantum computing) to provide an even more comprehensive overview. Related to this, the review does not include records published after 2020, although emerging technologies and research on education surrounding these topics have continued to expand rapidly. A fourth and final limitation is that, due to pragmatic considerations, the deductive and inductive analysis was conducted by one researcher (i.e., the first author) and only verified afterwards by three co-authors. This stands in contrast with the selection process, in which two researchers independently screened and assessed all records.

4 RESULTS

The results section is structured by the main deductive categories used to analyse the 107 included records. First, we describe the dataset, including the types of records, publication venues, publication year, geographical distribution, and the emerging technology focused on (Section 4.1). Next, we discuss the target groups mentioned in the records, as well as the role of teachers and other

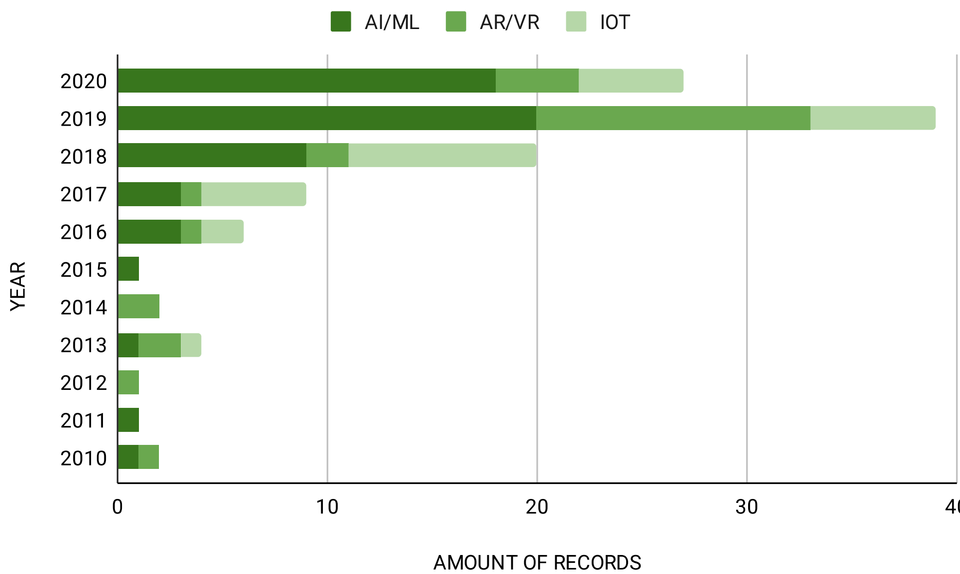

Fig. 4. Distribution of included records (n = 107) per technology and publication year.

actors involved in the preparation and/or facilitation of learning activities (Section 4.2). Then, we move on to discussing the learning objectives – both high- and low-level – and the ways in which learning objectives are integrated into existing or new curricula, if at all (Section 4.3). Following this, we dive into the theoretical learning frameworks and practices reported in the records. Here we also give an overview of preferred pedagogical strategies (Section 4.4). From there, we move on to discussing technology and other tools developed or used by researchers to support educational practices (Section 4.5). Finally, we look at how these practices and tools were evaluated, and if and how students' learning was assessed (Section 4.6). Important to note is that we grouped AI and ML as well as AR and VR in the presentation of the findings. In addition, we only distinguished between the three groups of emerging technologies when the analysis of the data revealed clear differences in the ways in which these technologies are taught in K–12 education.

4.1 Description of the Dataset

This section describes the dataset, starting with the distribution of records across publication year and type of emerging technology. As Figure 4 clearly shows, interest in teaching emerging technologies such as AI, ML, IoT, AR, and VR in K–12 education has increased. From the 107 records included in the review, 57 primarily focus on AI/ML, 28 on IoT, and 27 on AR/VR. Only five articles focus on more than one of these technologies, of which three combine IoT with AR/VR and two IoT with AI/ML. The vast majority of articles (82 out of 107) were published in the last three years, with 27 records in 2020, 36 in 2019, and 19 in 2018. Especially for records that focus on teaching AI and ML (57 in total), there has been a sharp increase in the past two years, with 18 records published in 2020 and 20 in 2019.

The 107 records were published in 78 different venues, including 58 conferences, 17 journals, and three books. Within this broad range of venues, the following groups can be distinguished: HCI and IxD venues (13 venues for 27 records), learning sciences (four venues for 26 records), computing and/or engineering education (19 venues for 26 records), learning technologies or EdTech (16 venues for 20 records), computing and/or engineering (14 venues for 14 records), intelligent systems (10 venues for 12 records) and miscellaneous (two venues for two records). Put differently,

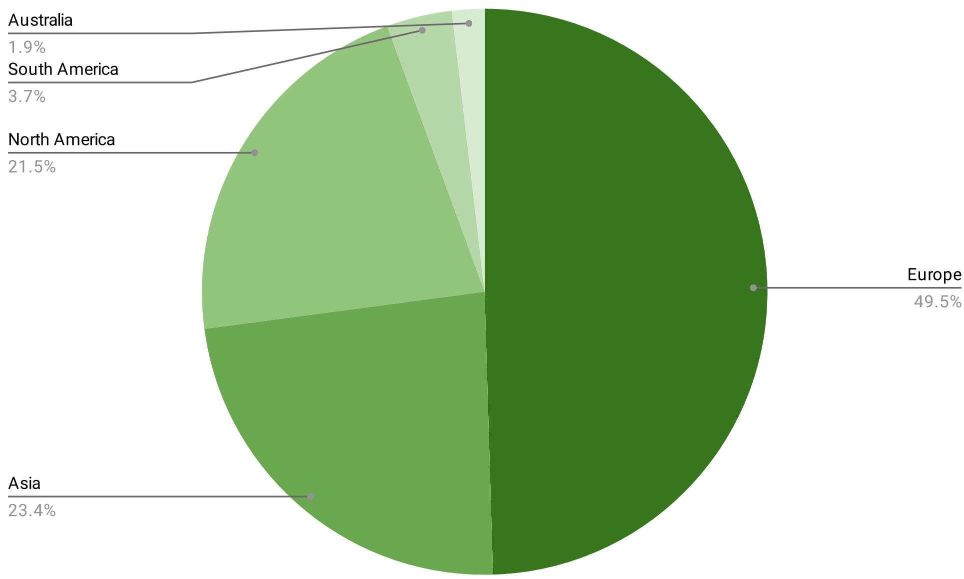

Fig. 5. Geographical distribution of included records across continents (n = 107).

24 venues have a predominantly technical focus, 23 venues focus on (technology) education, 16 on educational technology, and 13 on HCI and IxD.

Among individual venues, **Interaction Design & Children Conference** (**IDC**) is the most represented (9 records), followed by CHI (Conference on Human Factors in Computing Systems) (6 records), and **Innovation and Technology in Computer Science Education Conference**(**ITiCSE**) (4 records). Runners-up are **Frontiers in Education Conference** (**FIE**), **Global Engineering Education Conference** (**EDUCON**), **International Conference on Teaching, Assessment, and Learning for Engineering** (**TALE**), **European Conference on Technology Enhanced Learning** (**ECTEL**), and AAAI (Conference on Artificial Intelligence) (three records each), and the International Journal of Child–Computer Interaction, **Conference on Informatics in Schools: Situation, Evolution, and Perspectives** (**ISSEP**), **Symposium on Educational Advances in Artificial Intelligence** (**EAAI**), and T4E (International Conference on Technology for Education) (two records each). All other venues are represented once only. With regard to the publication type, the selection includes 56 (full) papers, 16 journal articles, three book chapters, and 32 non-archival publications (e.g., magazine article, work in progress, demo).

With regard to geographical distribution (i.e., the country in which the first author's home institute is located), 30 countries are represented in the selection. The United States is represented by approximately one-fifth of the records (21 in total), followed by Spain (11 records) and Greece (9 records). China, Germany, and India each have six records in the selection, Finland and Israel five, Portugal and the UK four, and Brazil and Italy three. The remaining countries are represented by either one or two records. As for distribution across continents, Europe is represented by half of the records (53 in total), Asia by 25, North America by 23, South America by 4, Australia by 2, and Africa by none (see Figure 5). Important to note here is that we selected only English records for this review (see Section 3 for more details about inclusion and exclusion criteria).

In sum, the vast majority of records included for review were published in the last three years, and records focused on AI and ML especially have sharply increased. When looking at the venues in which these records were published, we observe a large diversity of technical, educational,

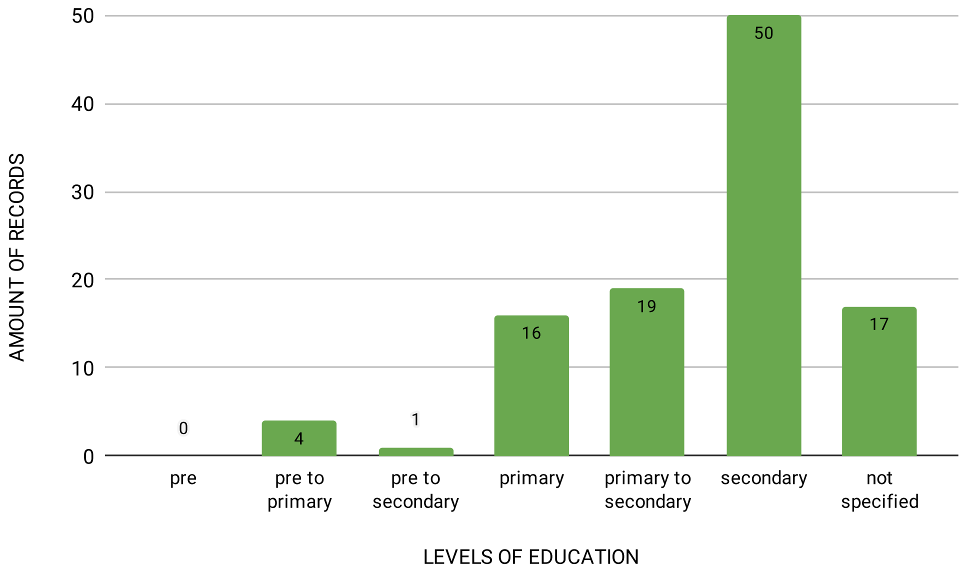

Fig. 6. Distribution of included records (n = 107) per aggregated level of education: preschool, primary education (grades 1–6) and/or secondary education (grades 7–12).

and HCI/IxD-oriented conferences and journals. Less diversity was found in the geographical distribution of the institutions of the first authors, showing a clear overrepresentation of Western countries.

4.2 Target Group and Roles for Teachers and other Actors

In this section, we look at the primary target groups for the learning activities, and at any other actors playing an active role in the development (i.e., backstage work) and facilitation of these activities, most notably researchers and teachers, as presented in the 107 reviewed records.

The most common target group for learning activities teaching about emerging technologies is students in secondary education, in particular, grades 8 to 10 (ages 13–16) (e.g., [57, 81, 163]). Lower primary education, and especially preschool, are less represented (e.g., [70, 75, 158]) (see Figure 6). Of the 107 included records, eight use generic terms such as "K12" or "secondary education," and 17 do not mention a specific grade or age range. All other records provide detailed information about the target group, which often covers several grades. Very few reports focus on specific groups of students, such as girls or other underrepresented groups in computing education [79]. On the other hand, gender balance seems to be an explicit aim in several studies when recruiting participants (e.g., [28, 54, 120, 163]).

Of the 107 included records, 65 reports original empirical work, with an average of 34 students and a mean value of 25 students per study. Thus, most studies seem to aim for "depth" with fewer students rather than "breadth" with many respondents. Notable exceptions include one study with 150 students [129] and another that impacted over 3,000 students by rolling out a STEM and IoT programme in 18 schools [79]. In contrast, two studies involved as few as three students [44, 58]. Important to note is that we refer to "a study" here also as a combination of multiple studies (e.g., a presurvey, pilot study, and main study) reported in a single article.

Teachers are frequently referred to as important actors in learning activities. Teachers' roles, and the ways in which they collaborate with researchers, are specified in fewer than one-third of all records (33 in total). Although researchers take the lead in preparing learning activities (i.e., the backstage work), in 12 records teachers are actively involved in this stage, either by co-creating learning content and activities with researchers or simply by providing feedback on initial work prepared by researchers (e.g., [78, 97, 115, 134]). The co-creating option gives teachers the most impact on and ownership of the outcomes of this preparation stage. Teachers are also involved in the next stage, that is, facilitating learning activities in formal and non-formal learning settings. In 14 records, teachers either co-facilitate the activities with the leading researchers (e.g., [123, 126, 167]) or facilitate the activities alone while researchers attend the sessions passively, for instance, by taking notes and collecting research data (e.g., [14, 46, 58]).

Only in a few cases (five records) are teachers actively involved both in backstage work to prepare an intervention and in facilitating the resulting learning activities. Charlton and Avramides [23], for instance, actively involved teachers in constructing knowledge and experimenting with ideas on how an IoT system could be used for collaborative, problem-based, and multidisciplinary STEM education. Heinze et al. [65] in turn, report on a three-year-long collaboration between an AI researcher and two local teachers to develop a K–6 AI curriculum as part of the Scientists-in-Schools program in Australia. The learning objectives, content, and activities were developed collaboratively and tried out by the teachers across subjects and in multiple iterations.

In just two records, teachers do not partake in backstage work or facilitation of interventions, but instead participate in in-service and professional development programmes set up by researchers [79, 148]. The aim of these programmes is to train teachers to integrate emerging technologies in K–12 education, something that is deemed important for scaling and sustaining research-led initiatives on technology education. On that account, Vazhayil et al. [148] developed a course for teachers on how to introduce AI to middle and high school students. 34 teachers with different educational backgrounds and levels of experience participated in the course. They learned theoretical concepts of AI and the various stages of an AI project cycle, and afterwards applied this knowledge in CS subjects in their respective schools.

Besides K–12 students (i.e., the target group) and teachers, only a few records (10 in total) mention active involvement by other actors such as parents [146], additional researchers and/or industry partners [149], education experts [151] and policymakers [162]. The role of these actors is diverse, ranging from the co-facilitation of learning activities to providing input for the development of these activities.

In sum, the primary target group for learning activities for emerging technologies is students in secondary education, in particular grades 8 to 10. Very few records specifically address very young and underrepresented target groups. On average, 34 students participate in a single study, meaning that “depth” with fewer respondents is a preferred research strategy. Including a broader range of students from early years throughout secondary education, and complementing small with larger cohorts of student participants, would offer great potential in terms of outreach and diversity. As for teachers, we found their role in learning activities for emerging technologies to be fairly limited: fewer than a third of all records involved teachers in the development, facilitation, or evaluation of learning activities. A further limiting factor on long-term impact was the scarcity of in-service and professional development programmes, which are important for scaling and sustaining research-led initiatives. These findings are consistent across all three types of emerging technologies.

4.3 Learning Outcomes and (Curricular) Implementation

This section zooms in on the learning objectives associated with emerging technologies, the implementation of those objectives, and additional overlapping and interconnected aspects. In the analysis, we first looked for information about the higher-order objective for teaching emerging technologies in K–12 education. Next, we looked at the different types of concrete learning objectives: these formed a disparate list, ranging from technical understanding and skills, design skills, to societal and ethical implications, attitudes, and other objectives including developing STEM and transversal skills. We then analysed whether learning objectives were integrated with existing or new curricula, their level of detail or abstraction and whether they account for a range of progression levels, and lastly, the extent to which prior knowledge and skills are required to participate in the learning activities targeting these objectives.

A higher-order objective for the authors' belief that children should be taught about emerging technologies – AI, ML, AR, VR, and IoT in particular – is identified in fewer than half the records (48 out of 107). In the other half, such a higher-order objective is either missing or not explicitly communicated. For those that do mention a higher-order objective, a distinction can be made between records foregrounding a career perspective (20 records), often in STEM disciplines (e.g., [3, 60, 63]), and those that advocate a broad literacy perspective (28 records), most often with regard to AI and ML (e.g., [37, 72, 80, 88]).

In the literacy perspective, education about emerging technologies is considered relevant for all children, regardless of future career trajectories, as with the core subjects of maths, reading, and writing. In this perspective, developing a critical understanding of emerging technologies and the operational skills to work with them will in the near future be a precondition to full participation in society. A good example is provided by Druga et al. [42], whose aim is to develop children's AI literacy through physical tinkering and learning activities using smart toys and agents. The authors argue that it is important for children in contemporary society to understand how machines perceive and model the world as they grow up with these technologies. Tissenbaum et al. [133], in turn, argue that providing low-barrier means for all types of students to design and implement IoT solutions to problems that have personal relevance to them can help them develop computational identities or "the ability to create meaningful change using computing and recognising one's place in the large computing community," as well as their sense of digital empowerment or "opportunities to put that identity into action." These notions of identity and empowerment clearly point to a broad literacy perspective, even if the term itself is not used [133].

In addition to higher-order goals, we assessed whether learning activities were integrated in or across existing curricula, or presented as new curricula altogether. We found that almost half of the records (48 out of 107) lack such integration and present standalone learning activities (see Figure 7). This means that researchers are conducting activities in formal or non-formal learning contexts, during or after regular school hours, but without integrating the objectives they are introducing with established ones (e.g., [17, 73, 82, 86]).

If not presented as standalone activities, curricular integration is quite common in STEM (19 records, of which ten focus on IoT: e.g., [96, 119]) and **computer science** (**CS**) education (9 records: e.g., [75, 149]) (see Figure 7). Along these lines, Ota et al. [105] combined general STEM objectives, especially in relation to mathematics, with IoT-specific objectives. They developed a 15-hour STEM course with IoT learning materials and modules in which high school students create prototypes that solve real-world problems of their own choosing. Through this process, students learn how to collect and analyse sensor data with probability statistics (i.e., mathematics).

An alternative approach to integrating learning activities in a single school subject is a cross-curricular approach, pushing against traditional subject boundaries (10 records, of which seven focus on AI/ML: e.g., [23, 142]) (see Figure 7). A good but rare example of a cross-curricular approach is provided by Chow [26], who engaged high school students in a seven-month-long project that ran across different subjects. Students collaborated in small groups to create a VR model of their school campus. This required them to learn a range of skills, many of which were not covered in their regular school subjects. Among other things, students learned advanced programming, 3D modelling, project-management skills, synthesising literature, heritage science as applied to the history of their school campus, and graphic design.

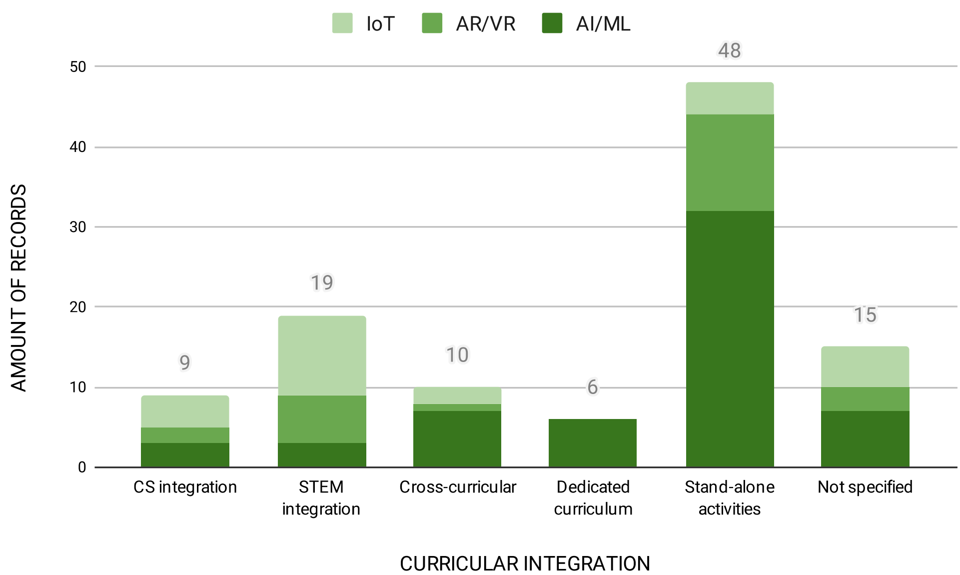

Fig. 7. Distribution of records (n = 107) per technology and integration of activities in/across curricula.

A further approach, taken by six records, is to propose a dedicated curriculum, covering one or multiple grades, for introducing emerging technologies in K–12 education (e.g., [115, 162]) (see Figure 7). All six of these records focus on AI/ML. Gong et al. [59] for instance, present an "AI education system" for primary and high school students including different cognitive and practice-based objectives, hardware and software tools, and concrete cases that can be used in a modular way depending on students' level and grade.

With regard to the degree of detail of the learning objectives, half of the records (57 in total) provide only high-level descriptions with little operational detail. In contrast, 12 records provide very detailed learning objectives (e.g., [48, 85]). Only a few records (9 in total) suggest progressive learning objectives, such as specifying objectives per grade for a dedicated technology curriculum (e.g., [33, 65]). Often cited in this regard is Touretzky et al. [137], who present five big ideas about AI and detail what students in different grades should be able to do and know in relation to each of them.

Although providing low barriers to entry seems to be the norm for learning activities about emerging technologies, in one-fifth of the reviewed records (22 in total) a certain degree of prior skills and knowledge is required to participate in the activities. Knowledge of fundamental concepts in computing, robotics or AI is most often required (e.g., [15, 155]), followed by experience with Scratch or other (block-based) programming languages (e.g., [17, 28]), followed in turn by having met the objectives of prior grades or modules (e.g., [75, 137]), and knowledge of mathematics in order to better understand ML and other algorithms (e.g., [104]).

Regarding the types of learning objectives, a distinction can be made between (1) technology understanding and skills, (2) ethical and societal technology implications, (3) design skills, (4) attitudes and mindsets, and (5) other forms of knowledge and skills (see Figure 8). These different types of objectives are combined in varying combinations in the reviewed records. They will be discussed in more detail in the remainder of this section.

Technology understanding and/or skills are mentioned as learning objectives in all but three records (i.e., [95, 97, 120]) (see Table 3). The term "understanding" (or knowledge) refers to familiarity with factual information and theoretical concepts, whereas the term "skills" refers to the

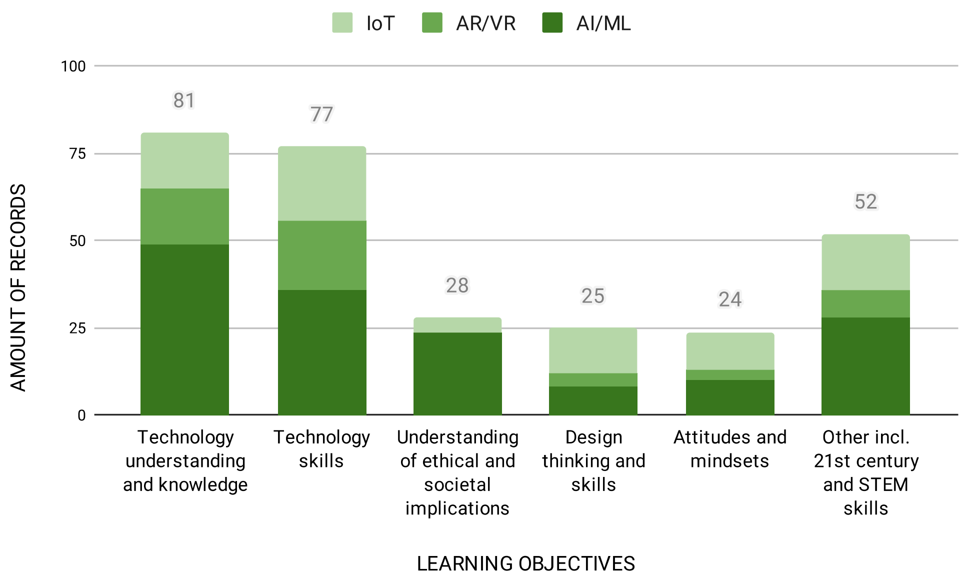

Fig. 8. Distribution of included records (n = 107) per technology and type of learning objective.

Table 3. Different Objectives for technology Understanding and Skills Found in the Reviewed Records

Type	Technology	Learning Objectives	Examples
Understanding	Computing	COMPUTATIONAL THINKING AND CS CONCEPTS/PROCESSES	[50, 70, 82]
Skills	Computing	BLOCK-BASED AND MORE ADVANCED PROGRAMMING	[25, 27, 46]
Understanding	AI/ML	AI AND ML CONCEPTS/PROCESSES AND APPLICATIONS	
		– General understanding of AI and different types of ML	[111, 146]
		– Nuanced understanding of how ML works incl. data analytics and different algorithms	[45, 165]
Skills	AI/ML	BUILDING, TRAINING AND TESTING ML MODELS	
		– GUI; without programming	[18, 66]
		– Incl. block-based programming	[73, 166]
		– Incl. more advanced programming	[88, 113]
Understanding	IoT	IoT CONCEPTS/PROCESSES AND APPLICATIONS	[60, 93, 123]
Skills	IoT	EXPLORING, DESIGNING AND PROTOTYPING IoT	
		– Exploring and designing IoT applications	[56, 96]
		– Prototyping IoT applications (incl. electronics and programming)	[99, 129]
Understanding	AR/VR	AR/VR CONCEPTS/PROCESSES AND APPLICATIONS	[26, 63]
Skills	AR/VR	USING & CREATING AR/VR ENVIRONMENTS	
		– Using AR authoring tools	[78, 82]
		– Creating AR/VR environments (incl. 3D modelling and programming)	[26, 63]

ability to perform a certain task or role and requires the application of knowledge to specific situations. Technology understanding is formulated both in fundamental CS concepts (e.g., [70, 82]) and in terms of the way emerging technologies such as AI/ML (e.g., [111, 165]), AR/VR (e.g., [26]) and IoT (e.g., [93, 123]) work and what their application domains are. Technology skills, in turn, are diverse. They include block-based and more advanced programming (e.g., [25, 27, 46]), building, training and testing ML models (e.g., [88, 166]), prototyping IoT applications, including electronics (e.g., [56, 99]) and creating AR and VR environments (e.g., [26, 78]). Developing these skills often goes hand in hand with deepening the understanding and knowledge of emerging technologies

– and vice versa. Moreover, many researchers do not make a clear distinction between technology "understanding" or "knowledge" on the one hand and the development of practical technical "skills" on the other, approaching these two objectives as one and the same. An example can be found in Williams et al. [158] who introduced the AI concepts of knowledge-based systems, supervised machine learning, and generative AI to young children (ages four to six) by letting them explore and tinker with real examples using the block-based programming platform PopBots.

Remarkably, half of the records that focus on AR and VR (14 out of 27) use the technology as an instructional aid in teaching programming skills, rather than a learning objective in itself. This means that the objective in these records is not to develop students' understanding of how AR and VR work and what their functional strengths and limitations are (e.g., [27, 34, 87]). These records were nevertheless included in the review because their focused objective is technology education, which aligns with the inclusion criteria.

About one-quarter of the records (28 in total) include the ethical and societal implications of emerging technologies as learning objectives. Most of these (24 out of 28) focus on AI/ML. However, this focus on ethical and societal implications is often merely an afterthought, with most attention given to developing students' technology understanding and skills. A few reports refer very broadly to ethical and societal implications without further specification [159]. Others focus on concrete issues such as bias [35], fairness [18], data privacy [129], security [33], accuracy [134], accountability [4], transparency (e.g., [48], and how the technology should or should not be used [85]. Complex issues related to power and democracy are rarely touched upon. One of the few records that foregrounds ethics is Bilstrup et al. [9], who engaged high school students in the design of a supervised ML application that addresses a real-world need in their lives, while simultaneously exploring the ethical implications of the proposed design. During the process, students become aware of how difficult it is to avoid ethical issues, even with the best intentions.

Almost one-quarter of the articles (25 in total) combine technology understanding and/or skills with one or more design skills as learning objectives. "Ideation" is the design skill that is most often mentioned (e.g., [54, 120]), followed by "designing IoT applications" (e.g., [5, 133]), "presenting and providing arguments for design concepts" (e.g., [9, 93]), and "design and creative thinking" (e.g., [17, 123]). "Iterative testing of design concepts" (e.g., [105]) and "game design" (e.g.,[82]) are mentioned a few times. Not all records that refer to design skills as learning objectives attribute the same importance to them. Noteworthy is that design skills always co-occur with other learning objectives, especially with technology understanding and/or skills. In many cases, practising design and technical skills go hand in hand, both contributing to students' technology understanding. A good example is provided by Toivonen et al. [134], who developed a two-week program to introduce students to the core theoretical concepts of ML (i.e., training set, prediction accuracy, class label) as well as the practical skills involved in training an ML model to solve a predefined problem. The program includes ideation, user-interface design, iterative testing, and pitching design concepts [134].

Attitudes and mindsets are referred to in almost one-quarter of the records (24 in total) as study objectives in the context of emerging technologies. A recurrent objective in this regard is for students to develop a positive attitude towards and interest in STEM (10 records) (e.g., [57, 141]), AI (e.g., [159]), or digital technology more broadly (e.g., [117]) (8 records). Other, less frequently mentioned attitudes include "active and engaged citizenship" (e.g., [133]), "resourcefulness" (e.g., [148]), and "confidence in one's own abilities" (e.g., [73]). Just as with the presentation of ethical and societal implications and design skills, these attitudes are presented in conjunction with technology-related learning objectives.

This is also the case for other learning objectives (52 records) – for instance, in relation to STEM subjects such as physics and maths (e.g., [51, 119]), or transversal "twenty-first century" skills applicable in a wide variety of contexts including collaboration (e.g., [23, 104]), critical thinking and reflection (e.g., [22, 142]) and problem-solving (e.g., [5, 151]). Roughly half of the records (52 in total) refer to learning objectives like these in addition to technology understanding and/or skills. A good example is an educational scenario developed by Spyropoulou et al. [129]. This aims at familiarising students aged 14–16 with IoT technologies through a cross-curricular STEM approach including learning objectives related to science (i.e., ultrasonic physics), technology (i.e., Arduino programming and the use of sensors), engineering (i.e., developing and testing IoT applications), and maths (i.e., volume and distance calculation).

In sum, initial steps have been taken towards defining learning objectives with regard to emerging technologies, sometimes in the form of dedicated curricula or cross-curricular approaches. Although learning objectives tend to lack operational detail and multiple progression levels, it is encouraging that technology-specific objectives are often combined with a range of other objectives. This is the case for all three emerging technologies, although clear differences could be discerned in terms of emphasis (see Figure 8 and Table 3). Objectives include the ethical and societal implications of emerging technologies, design thinking, positive changes in student attitudes, a broad range of the twenty-first century or transversal skills such as critical thinking and collaboration, and STEM objectives beyond technology, such as maths and physics. But despite this combination of different types of objectives, a humanities perspective foregrounding the implications and design aspects of emerging technologies is generally either lacking or treated as an afterthought in the learning activities. More holistic approaches need to be developed, which balance technology-specific objectives with a humanities perspective to promote more comprehensive understandings and skillsets. Related to this, the urgency of "why" students need to attain these learning objectives needs to be explicitly addressed by researchers. In more than half of the records, this is currently not the case. An almost similar proportion of the records present standalone activities that are not, or are insufficiently, integrated in school environments and curricula. These findings are indicative of a rather narrow focus of research on emerging technologies in K–12 education.

4.4 Educational Frameworks and Practices

This section looks into the theoretical learning frameworks and educational practices adopted or proposed for introducing emerging technologies to K–12 students. Educational practices include the format and duration of suggested activities (within a larger setting of formal, non-formal, or informal learning), as well as the pedagogical strategies used to attain the learning objectives explicitly or implicitly referred to in the reviewed records.

The majority of records do not present a solid theoretical learning framework for introducing emerging technologies. Records that integrate learning theory (24 in total, of which 15 relate to AI/ML and nine to IoT) rely on one or more of the following theories: constructionism (e.g., [25, 158]), socio-constructivism [97], actor-network theory [51], participatory and collaborative learning theories [5], situated and experiential learning [93], universal design for learning [111], and design-oriented pedagogy [147].

Of these articles, the majority (13 in total, of which ten relate to AI/ML and three to IoT) rely on constructionism as the underlying theoretical framework, but typically without providing much explanation, using it as a synonym for hands-on activities or learning-by-making (e.g., [73]). In short, constructionism holds that learning happens most effectively when children engage in making tangible objects in the real-world, thereby creating mental models to understand the world around them and using what they already know to acquire more knowledge [107, 108]. Constructionism advocates student-centred discovery learning, whereby students make connections between different ideas and areas of knowledge, facilitated by the teacher through coaching rather than lectures or step-by-step guidance [108].

Among the reviewed records, Dhariwal and Dhariwal [35] illustrate clearly how they implemented constructionism by scaffolding an open-ended creative learning process with a custom-developed extension for Scratch. Students aged 14 to 17 used the tool called "Let's Chance" to create their own data, models, and possibilities, allowing them to explore powerful ideas of probabilistic thinking and modelling, which in turn helped them to understand how AI technologies make predictions based on training data [35]. Another example is provided by Kandlhofer et al. [75], who state that they developed teaching modules to introduce AI and ML to high school students largely based on principles of constructionism, comprising a wide range of hands-on activities, tools, and platforms as well as different pedagogical strategies including project-based teamwork, storytelling, and peer tutoring [75].

Regarding the format and duration of the suggested learning activities, about one-quarter of all records (24 in total) report on a single workshop or session of one or a few hours (e.g., [43, 44, 167]). A similar number (28 in total) report on a limited number of short sessions, typically three to six sessions of a few hours each (e.g., [78, 92, 118]). Notable exceptions include a small number of records (nine in total) reporting interventions that ran on a regular basis for several months (e.g., [58, 63]) up to a whole year, for instance in the form of a dedicated AI course (e.g., [65, 115, 126]). Three additional records propose AI and ML curricula covering multiple grades, but without having conducted any activities yet [85, 137, 162]. For the remaining records, the format and duration were unclear or not relevant.

Not surprisingly, formal education in primary or high schools is the predominant context for learning activities about emerging technologies (66 records) (e.g., [42, 116, 118]), followed by non-formal education (17 records) such as after-school robotics clubs [29] or workshops [67], science fairs [3], makerspaces [112], and summer schools [155]. Only a few records (five in total) target both formal and non-formal education (e.g., [18, 50]). Two records focus on informal education in a home context, facilitated by parents (e.g., [122, 146]). As discussed in the section on learning objectives, however, the preference for the formal education context does not necessarily mean that the learning activities conceived by researchers are integrated in existing school curricula. Oftentimes, researchers move rapidly in and out of schools to iteratively evaluate learning activities and tools and collect empirical data. A strength, on the other hand, is that most studies are conceived as interventions in the real-world and cover a variety of learning contexts. These findings are consistent across all three emerging technologies under consideration.

Finally in this section, we look into pedagogical strategies used or suggested by researchers. We use the term pedagogical strategies to refer to the ways in which learning content and materials are created and presented to learners – in this case, K–12 students. Detailed information about pedagogical strategies was found in approximately one-fifth of the records (20 in total, of which 12 focus on AI/ML, seven on IoT and one on AR/VR) (e.g., [60, 79, 147]). One-third (34 in total) disclose no information about such strategies, or the code was not applicable; however, some information about pedagogical strategies could be derived indirectly, for instance, by looking at whether learning activities were hands-on or collaborative.

Based on this explicit and implicit information in the reviewed records, 15 distinct pedagogical strategies could be discerned (see Table 4), of which three are predominant: active and engaged teaching, as opposed to passive listening (e.g., [52, 100, 125]), small group work and peer learning (e.g., [1, 68, 88]), and technology-mediated teaching by letting students use, modify, and/or construct technology artefacts. This last strategy includes block-based and more advanced programming activities (e.g., [34, 87]), developing IoT applications (e.g., [56, 99]), building or modifying and testing ML models (e.g., [88, 166]), and creating AR games [78] and VR environments [26].

Among other pedagogical strategies used in varying combinations are: low-entry barriers to student participation in activities (e.g., [48, 117]), inquiry- and project-based approaches in which

Table 4. Frequently used Pedagogical Strategies Embedded in Learning Activities about Emerging Technologies Across Age Cohorts in K–12

Pedagogical strategy	Description	Examples
Active and engaged learning	Students are active and engage in hands-on activities, as opposed to passive listening	[52, 100, 125]
Technology-mediated	Learning is facilitated through the use, modification, and/or construction of technology artefacts	[87, 99, 166]
Collaboration and peer learning	Students collaborate, often in small teams, and facilitate each other's learning or act as tutors for peers	[1, 68, 88]
Low-entry barriers	Students with little prior knowledge or experience are enabled to participate in learning activities	[36, 48, 117]
Inquiry or project-based	Projects or inquiries with multiple pathways towards a solution drive students' engagement and learning	[56, 60, 129]
Design-process driven	Students are guided through a design cycle incl. field study, problem (re)framing, ideation, prototyping, testing, and so on.	[5, 109, 133]
Tinkering and creative exploration	Free exploration and tinkering with creative materials and learning contents	[35, 40, 158]
Reflective practice	Students discuss and critically reflect on their learning trajectory, practices, and/or technology artefacts	[9, 22, 120]
Authenticity and closeness	Real-world and personally meaningful problems are used as a starting point for learning activities	[79, 133, 147]
Learner-centred or self-guided	Students direct their own learning and can pursue their own interests in relation to the topic	[26, 58, 71]
Knowledge-driven	New topics or concepts are introduced through (short) lectures, often complemented with hands-on activities later	[104, 119, 149]
Unplugged approach	A range of non-digital activities and tools are used to learn about digital technologies	[48, 81, 103]
Embodied learning	Students are enabled to use their bodies, via actions and gestures, to construct new knowledge	[109, 126, 167]
Crossdisciplinary	Students are introduced to topics from different disciplinary perspectives and across school subjects	[43, 54, 142]
Modular and adaptive	Learning content is broken into different parts that can be taught independently and adapted to students' current level	[59, 65, 75]

students engage with open or wicked problems (e.g., [56, 60]), design-process driven activities (e.g., [109, 133]), creative exploration and tinkering with learning materials and content (e.g., [35, 158]), reflective practices (e.g., [9, 120]), an emphasis on authenticity and closeness by structuring activities around real-world and personally meaningful challenges (e.g., [79, 133]), self-guided or student-centred learning (e.g., [26, 71], knowledge-driven approaches introducing new concepts with (short) lectures, often complemented with hands-on activities later to apply this new knowledge (e.g., [119, 149]), unplugged activities in which the use of digital technology is deliberately avoided (e.g., [48, 81, 103]), embodied learning or using one's body via actions and gestures to create new knowledge (e.g., [126, 167]), crossdisciplinary perspectives that are not confined to traditional subject boundaries (e.g., [43, 142]), and modular and adaptive activities (e.g., [59, 65]) (see Table 4 for an overview). Although these pedagogical strategies are used across the three types of emerging technologies, no distinct patterns could be discerned. The reviewed records also provide little information about the suitability of these strategies for particular age cohorts, although generally speaking less emphasis is placed on cognition (see strategies "knowledge driven" and "reflective practice") and self-efficacy (see "self-guided" and "inquiry or project based" learning) when younger pupils are targeted in lower primary school.

An excellent example in which multiple pedagogical strategies are integrated is provided by Byrne et al. [17]. The authors frame their research on teaching IoT to high school students within a social constructivist framework: more specifically, the Bridge 21 model for collaborative, student-centred, technology-mediated, hands-on, and project-based learning, which aims at supporting an innovative, twenty-first-century learning environment within schools. With these pedagogical strategies in mind, they developed a four-day hackathon event in which students expand their domain and technical knowledge, investigate a design challenge and IoT possibilities, come up with ideas, and develop a working prototype, realise a digital media campaign to promote their concept, and finally, pitch and critically reflect on their work. In this approach, the development of technical and twenty-first-century skills such as problem solving, communication, and teamwork are integrated [17]. Rattadilok et al. [111], in turn, proposed an active and engaged approach to introduce basic ML concepts to students with little interest in technology. To motivate students, they used the pedagogical strategy of "closeness" by using a well-known and popular mobile game, Clash of Clans, among students as an object of study and experimentation. Students collaborated in small teams to develop game strategies on a worksheet, and fed these to a game bot called "iGaME" (In Class Gamified ML Environment) that used the input a predefined number of times, after which it created an output file about its success rate. Students iteratively improved their strategies and competed with other teams to find who had developed the most successful strategy. The session concludes with a class discussion on lessons learned [111].

In sum, the format and duration of learning activities typically ranges from a single workshop to a few sessions of one or more hours. The preferred setting for these activities is formal education, followed by non-formal education, including after-school robotics clubs, science fairs, maker spaces, and summer schools. To scaffold students' learning in these settings, a wide range of pedagogical strategies are suggested in the literature, among which three are predominant: active and engaged learning, collaboration, and technology-mediated teaching by letting students use, modify, or construct technology artefacts. These are complemented with a range of other pedagogical strategies in varying combinations such as learner-centred and inquiry-based teaching, authenticity and closeness, tinkering, and reflective practice. These findings are more or less consistent across all three types of emerging technologies. Remarkably, only one-fifth of the records – none of which focus on AR/VR – connect these strategies to the existing corpus of learning theory, and often in an ad hoc manner. This lack of clear and well-developed theoretical trajectories hampers the advancement of this new research field.

4.5 Technology (and Other) Tools for Learning

This section looks into technology and other tools developed or used by researchers to support learning activities about emerging technologies. Here we distinguish between unplugged tools, tools that incorporate emerging technologies, and any other digital technology tools. The section first looks into tools used to teach or introduce AI and ML, followed by IoT, and finally AR and VR.

Only 16 records do not present or refer to new or existing technology tools – no surprise, as the topic of interest is technology education. From the 57 reports that focus on AI or ML education, 42 present technology tools, often in the form of ML-powered tools specifically designed to teach ML and referred to in this section as "ML tools." What these ML tools have in common is that they allow students to develop, train, and test models, be it with different types of input data including, among others, images (e.g., [88, 122, 155]), sounds (e.g., [86]), and gestures (e.g., [67]). A good example of a custom-developed ML tool is the iOS application AlpacaML, which facilitates the construction and use of ML gesture models based on data from wearable sensors [166, 167]. With this tool, students create, improve, and test models of their own sports-related gestures and get real-time feedback (e.g., about a bad or good soccer pass). By using students' sport expertise and identity as a point of departure, the authors hope to foster curiosity about ML [166].

Another characteristic of ML tools is that they expose or glass-box some ML concepts or processes while black-boxing others, often to lower the barrier for novice learners. This is, for instance, the case with the gesture-based supervised ML tool developed by Hitron et al. [66]. The ML tool aims at familiarising students with data-labelling aspects (i.e., sample size, sample versatility, and negative examples) and model evaluation, while deliberately black-boxing other aspects such as feature extraction, model selection, and validation to reduce students' cognitive load [66].

ML tools differ in their degree of complexity in operation and, related to this, the possibilities they offer to explore and learn about ML. A distinction can be made between ML tools using **graphical user interfaces** (**GUIs**), low-code, or block-based coding environments, and more advanced programming environments. GUIs provide the lowest entry level as they require no coding to train, test, and execute predefined ML models (e.g., [111, 117, 147]). An example of an easy-to-use GUI is **Google Teachable Machine** (**GTM**). Vartiainen et al. [146] used GTM to introduce young children (ages 3–6) with no programming experience to ML. GTM is a web-based ML system powered by classification algorithms such as convolutional neural networks. It allows people to quickly train their own ML models, without programming, using images, gestures, and sounds as predictive modes. Children used GTM to create models for three different facial expressions, then explored the relationship between input (facial expressions) and output (sounds and images) [146].

ML tools that adopt block-based programming environments are more challenging to operate, but offer more possibilities in return. These ML tools utilise a visual drag-and-drop learning environment whereby students use coding instruction "blocks" to develop simple ML applications. Most often used are extensions for Scratch (e.g., [1, 35, 113, 157]), Snap! [73], and App Inventor [112]. García et al. [52], for instance, developed an educational resource to teach ML in schools with ML4K (Machine Learning for Kids), a web platform for children to build ML models that can be exported to Scratch or App Inventor to develop ML-powered applications [52].

In a few records, students use more advanced programming environments such as Python, C++, and/or Java to develop ML-powered applications (e.g., [43, 88]) or autonomous robots and vehicles (e.g., [58, 68]). Since these tools are technically complex, prior knowledge of computing is usually required. To extend the possibilities, block-based and more advanced programming environments are sometimes combined with general ML platforms and open-source libraries such as ExpliClas [4], WatsonAI [148], Tensorflow [100], and AzureML Studio [159].

In addition to ML tools, a range of complementary digital tools are used to support K–12 students' learning about AI and ML, including Lego WeDo 2.0 [158], Microsoft Excel [46], and video communication and cloud computing tools [68]. A few reports (six in total) deliberately use unplugged tools to provide alternative pathways to develop an interest in and understanding of AI and ML. These studies often target students with little motivation for or expertise in technology-related subjects. Examples include a card-based design game to introduce AI ethics [9], a man-machine simulation game [103], and a Turing roleplaying activity [81].

Of the 28 records that focus on IoT education, 27 present or refer to the use of technology tools. The characteristic of these tools is that they combine existing with custom-made components and modules, often in the form of open-source IoT toolkits. IoT toolkits usually include a range of tangible components, especially compared to ML tools that are often primarily web-based. Typical components are microcontrollers, programmable sensors and actuators, software, and coding environments including brands such as Arduino, Udoo, Raspberry Pi, ThingsBoard, Micro: bit, CloudBits, Bee-Bots, Lego Mindstorms NXT, and Cubelets (e.g., [5, 25, 33, 56, 99]). Important to note is that some authors use the term IoT interchangeably with 'physical computing,' thereby disregarding the cloud component (e.g., [54]).

Educational Lab Kit is an example of such an IoT toolkit [98]. It is an open-source platform that combines widely available and custom-made hardware electronics that are Arduino- or Raspberry Pi-compatible with web-based tools, gamification elements, and activity guides. With the toolkit's sensing devices and cloud infrastructure, students can collect real-time data from their school buildings and use it in maker-like STEM activities in a context of energy awareness and sustainability [98]. Another example is the UMI-Sci-Ed toolkit that consists of an Udoo-Edu hardware kit with an accompanying online programming environment and different educational scenarios [57]. The Udoo-Edu hardware kit is packed in a suitcase and includes an Udoo Neo Board with USB, ethernet, and Wi-Fi, a 1 GB RAM processor, and multiple sensors and actuators. The educational scenarios provide teachers with all the necessary components to facilitate students in exploring and developing IoT applications, including design challenges (e.g., smart recycling), learning objectives, activities and materials [60].

Overall, IoT toolkits require prior knowledge of electronics and programming to operate, both for students and facilitators. Substantial efforts have nevertheless been made to provide low barriers to entry for novice learners, not least through the development of easy-to-use GUIs and software platforms to program IoT components (e.g., [77, 150]). Setiawan et al. [124], for instance, developed a visual mobile programming tool for IoT applications with Raspberry Pi, which students with no programming knowledge or skills should be able to use. Along the same lines, Vakaloudis et al. [141] introduced a new software platform that enables teachers with no experience to integrate IoT in STEM education, and Rizzo et al. [112] developed an extension for the App Inventor (UAPPI) that transforms it into a GUI to program physical objects. Arora et al. [5], in turn, developed a physical and digital toolkit called DIO that consists of custom-made dome-shaped modules with an embedded assortment of input and output functionalities. The modules can be easily programmed through an AR-based application leveraging 3D identification patterns present on each module. This way, DIO facilitates children to develop multiuser wearables and environmental interaction designs [5].

Only one record relies exclusively on unplugged learning tools for IoT education. The Tiles IoT Inventor Toolkit, developed by Mavroudi et al. [93], enables children to generate ideas for IoT ecologies within a specific domain and without the use of technology. In other records, IoT toolkits are sometimes combined with unplugged tools, such as educational scenarios and/or activity guides (e.g., [56, 98, 129]), but these tools merely have a supporting role.

All 27 records focusing on AR and VR present technology tools. Five of these are VR tools, 22 AR tools. AR and VR tools are typically custom-made with technologies such as Unity 3D, Vuforia Engine, TopCode, EasyAR, and Google ARcore. They can be grouped into tools that aim at developing students' computational thinking and programming skills (18 records), or alternatively, authoring tools to create AR and VR (game) environments (seven records).

Characteristic of the largest group, here referred to as AR and VR programming tools, is that these tools do not scaffold learning about AR and VR, but rather, use AR and VR as instructional aids to provide real-time visual feedback during programming and related tasks (e.g., [34, 44]). A good example is the mobile visual programming environment for the Thymio II robot, which runs on Android and iOS [87]. Students use the environment to solve increasingly challenging tasks, while learning robot programming and event handling. Another example is the AR game CodeCubes, which combines physical programming with simultaneous visualisation to promote an interactive and engaging learning experience [28, 29]). Similar approaches are used for tools such as AR maze [70], CodAR [125], CodeBits [61], HyperCubes [50], and ARQuest [53].

The second group, authoring tools, enable students to build their own AR games (e.g., [109]) or VR environments (e.g., [63]). Examples of AR authoring tools include TaleBlazer, an AR platform to make geolocation games [109], and the interactive storytelling platform ARIS, which consists of a web-based editor and a client-based app to develop AR games with physical objects in a specific location [82]. Examples of VR authoring tools include [63], who developed a low-cost VR-driving simulator and graphical programming interface, among others (e.g., [26, 91, 92, 95]).

In sum, a wealth of digital learning tools to introduce emerging technologies to K–12 students have been developed. ML tools are typically designed to glass-box some aspects of the technology while black-boxing others, and they differ in degree of complexity and possibilities. GUIs and block-based coding environments are most often used to enable students to develop, train, and test simple ML models, but in a few cases, students engage in more advanced programming to develop ML-powered applications. IoT toolkits are often open-source and combine existing with custom-made components and modules to enable students to design and develop IoT solutions. As with ML tools, IoT toolkits do not glass-box all processes in order to manage complexity. Although IoT toolkits require some prior knowledge in programming and electronics, easy-to-use GUIs and software platforms have been developed over the years to make programming IoT components more accessible. AR and VR tools, finally, are predominantly programming tools that do not necessarily enable students to learn about AR and VR, with an additional small group of authoring tools to create AR and VR (game) environments. The development of learning tools for AR and VR, their characteristics, and their implications provide opportunities for future research. Another interesting line of research, found in only a few records, is the use of unplugged tools to engage students with little interest and few prior skills in digital technology in learning activities.

4.6 Empirical Evaluation and Student Assessment

This last section presenting our results looks into the ways in which technology tools and teaching approaches are empirically evaluated, whether and how students' learning is assessed either formatively and/or summatively, and the degree of constructive alignment between learning objectives, activities, and student assessment. This section furthermore provides insight into the methods used to collect empirical evidence, and it provides examples of typical findings reported in the included records.

Of the 107 reviewed records, 65 present original empirical data, of which 30 focus on AI/ML, 18 on IoT and 17 on AR/VR. The majority of these include studies evaluating learning activities (55 records) and tools (50 records) (see Figure 9). Activities and tools are often evaluated in tandem (38 records), and these constitute the main focus of the record (e.g., [52, 96, 100]). This is especially the case with records that introduce tools for learning about emerging technologies. Examples include Glaroudis et al. [57], who evaluated a new open-source learning environment deployed in an inquiry-based and collaborative learning approach to introduce IoT, as well as Lindner et al. [81], who evaluated whether unplugged tools and hands-on activities are suited for teaching AI in a comprehensive way to high school students.

From an in-depth inspection of the quality criteria used to evaluate technology tools, three main criteria surface: usability (e.g., [25, 34, 124]), students' perception of tools (e.g., [29, 42]), and the ways in which they interact with said tools (e.g., [50, 146]). However, less studied are the particular aspects and mechanisms of technology tools (e.g., balancing the glass- and black-boxing of features) and how they contribute to students' learning.

For learning activities, the quality criteria are more diverse. They include students' engagement (e.g., [54, 74]) and collaboration with team members (e.g., [23, 53]), students' learning experiences, for instance in relation to factors such as "satisfaction" and "enjoyment" (e.g., [56, 166]) or with regard to how they perceive the activities and content (e.g., [15, 88]), and finally, possible shifts

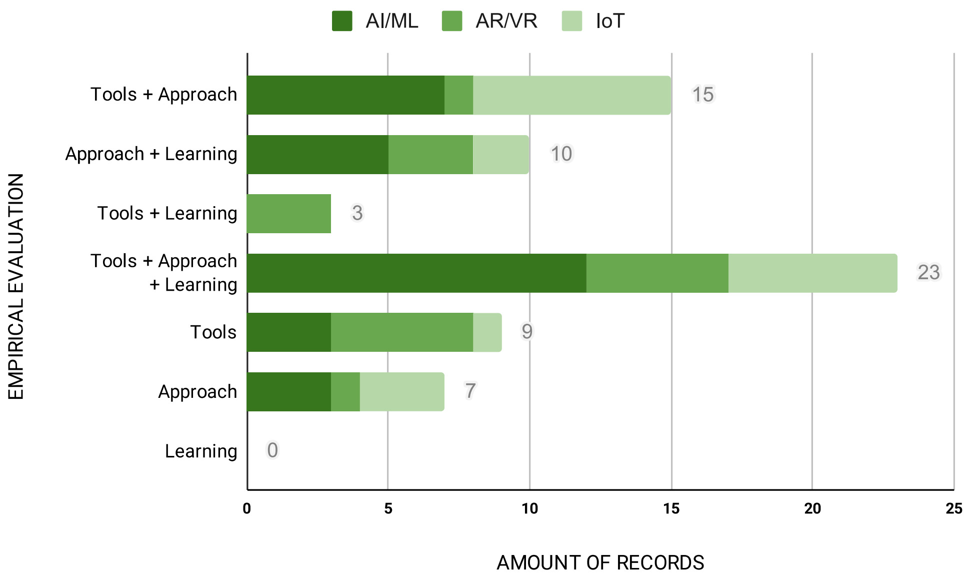

Fig. 9. Distribution of records presenting original empirical data (n = 65) per technology, based on empirical evaluation of learning tools, approach, and/or students' learning.

in students' interests and attitudes that can be attributed to the activities (e.g., [60, 126]). These quality criteria for evaluating learning activities are sometimes combined in a single study, as in Schneider et al. [123], who used observation notes to study students' engagement during the activities and a post-questionnaire to collect information about their experiences. This resulted in nuanced findings about students' learning process, the perceived workload, and how the activities unfolded [123].

This example furthermore shows how different qualitative data collection methods are combined to evaluate learning activities and tools. The most frequently used techniques are open and closed questionnaires (e.g., [117, 118]), semi-structured exit interviews (e.g., [23, 28]), and participant observation (e.g., [53, 115]). Mixed-methods studies, in which qualitative and quantitative data are triangulated, are rare (e.g., [129]).

From the 65 records presenting original empirical data, slightly more than half (36 records) include some form of assessment of students' learning (e.g., [15, 67, 105]) (see Figure 9). Assessment of students' learning is never the sole focus, and always takes place in conjunction with an evaluation of learning activities and/or tools. Furthermore, assessment is typically summative in nature, which means that students' learning is evaluated at the end of an instructional unit by comparing it against a standard or benchmark (e.g., with a pre- and post-test). Summative assessment serves the purpose of accountability, ranking or certifying competence [10]. This contrasts with formative assessment, which summarises students' development at a particular point, and primarily aims at promoting students' learning [10]. Surprisingly, though, no records could be identified that focus on formative assessment or, related to that, feedback and feed-forward practices to improve students' learning. This does not mean that such practices did not occur during the learning activities, either spontaneously or deliberately, but a formative assessment was not an explicit research objective in these studies.

In the reviewed records, summative assessment is directed towards students' knowledge and understanding of technology concepts and processes (e.g., [5, 67, 74]), and to a lesser extent, students' skill development, including technical skills (e.g., [34, 82]), design skills (e.g., [54, 134]), and problem-solving skills (e.g., [75, 93]). Pre- and post-tests are most often used to assess students' knowledge acquisition (e.g., [67, 105, 118])), whereas artefacts (i.e., worksheets, models, prototypes) and students' complementary explanations of these artefacts are used to gain insight into students' skill development and the ways in which they applied and further developed new knowledge by engaging with practical problems (e.g., [5, 117]). Students' self-perceived learning, in turn, is typically captured with open-ended questionnaires and semi-structured exit interviews (e.g., [15, 98]).

A related finding is that approximately half of the 36 records that include student assessment showcase constructive alignment. Constructive alignment is a principle devised by Biggs [7, 8] which refers to developing learning activities and assessment tasks that directly address the intended learning objectives. In the reviewed records, alignment often breaks down because assessment criteria do not or only partly align with pre-set learning objectives (e.g., [46, 82, 105]). Even with constructive alignment established, learning objectives may be described in high-level or vague terms, making it hard to judge whether these objectives are indeed aligned with the proposed learning activities and assessment tasks (e.g., [54, 91, 167]). There are, however, a few good examples of how constructive alignment can be established when introducing emerging technologies to K–12 students (e.g., [117, 149]).

One such example is provided by Hitron et al. [66] who showcase how they assessed students' understanding of three data-labelling aspects (i.e., sample size, negative examples, and versatility) in relation to classification problems in supervised ML. These learning objectives were set in advance and taught in three different activities, one for each main objective. The assessment procedure consisted of a pre-test before the learning activities, a short interview with students in which they explained the process they went through, a post-test in which they were given two ML examples (one similar to the learning experience and one different) and had to explain the underlying data-labelling processes, and two open follow-up questions to gauge whether students could relate the learning content to their own lives. This straightforward, yet effective procedure shows constructive alignment in practice.

Although providing a qualitative meta-analysis of empirical findings is not the focus of this review, it is apparent that most of the records present positive findings. Only seven records were identified as providing greater nuance by including unexpected or negative findings, for example in terms of students' learning, unforeseen obstacles (e.g., costs, public support, teacher motivation), or activities and tools that did not lead to desired outcomes (e.g., [42, 56, 123]). As for the majority of records, it is unclear whether there were indeed no unexpected or negative findings to report, or whether such findings were simply disregarded. Typical examples of positive findings include increased motivation among students to learn abstract concepts [92], design guidelines to build tools for learning about emerging technologies [82], positive attitudes towards (careers in) STEM [129], students being capable to build, train, and evaluate simple supervised ML models [167], good usability and acceptance of new technology tools [119], high effectiveness of a proposed curriculum and teaching platform [158], and so on.

In sum, of the 65 records that present original empirical data, the majority evaluate learning tools and activities, often together. An obvious strength of current research is the use of a range of qualitative methods to study different aspects of students' learning experiences in real-world settings. However, the results mainly provide a good news show with only a few records reporting unexpected or negative outcomes – a feature indicative of the lack of maturity of this nascent field. Quality criteria to evaluate tools are directed towards usability and students' perception of and interaction with these tools, but less towards the underlying mechanisms of these tools and how these contribute to students' learning. For learning activities, quality criteria include students' engagement and collaboration, their learning experiences, and possible shifts in attitudes. A remarkable finding is that only half of these 65 records include summative assessment of students' learning. Summative assessment is narrowly directed towards students' technology skills and understanding, leaving out the ethical and societal implications of emerging technologies as well as other aspects. Other remarkable findings are the lack of constructive alignment between learning objectives, activities, and assessment tasks, and the fact that no research on formative assessment could be identified in the literature.

To recap, the results of this systematic mapping review were structured along the five central topics of interest, preceded by a description of the dataset. The findings show a sharp increase in interest in teaching emerging technologies in K–12 education, especially in recent years, but many challenges remain unaddressed. The next section discusses our main findings, leading to our presentation of a future HCI research agenda to advance and mature the field.

5 DISCUSSION

In the past decade, research addressing the need to teach children about digital technology, digitalisation and, more recently, emerging technologies has increased on a global scale (e.g., [102, 129, 136, 137]). But teaching about emerging technologies has only now begun to appear beyond academia as a topic for education, and it makes up a very small share compared to digital technology and digitisation. Although the emerging technologies under consideration in this article (AI, ML, IoT, AR and VR) have reached a certain degree of coherence and momentum, as witnessed in increased technology maturity and growing numbers of applications, their full impact on society and on children's future lives is still uncertain and ambiguous [64, 114]. This poses unique challenges for K–12 education, as these technologies are hard to comprehend due to their complex and distributed nature, which allows little transparency into their functions and implications. It is, however, critical that children move beyond passive consumption, and acquire the competences to maximise the opportunities associated with emerging technologies while limiting exposure to harm and risk [19, 24, 84]. This may, in turn, contribute to children's computational empowerment [39] and the development of an *emerging technology literacy* – which will give them a say in a society with increased human-computer interaction [144, 145].

Research on emerging technologies in K–12 education stems from a diverse range of research fields – from novel technologies (human-computer interaction) to technology education and learning (computing education and learning sciences) and design for children (child–computer interaction). This systematic literature review has provided an overview of the state of the art across these fields, including 107 records published between 2010 and 2020. The literature was analysed covering central topics of (1) target groups and teacher roles, (2) learning objectives and curricular implementation, (3) educational frameworks and practices, (4) technology and other learning tools, and (5) empirical evaluation and assessment of students' learning. The findings show the urgent need on the global scale for inter- and transdisciplinary work that integrates such aspects into a more coherent and developed field of research and practice. In this section, therefore, we first provide a concise summary of the most important findings per central topic, followed by nine propositions for developing a shared agenda for future research (see Section 5.2 and a summary in Table 5).

5.1 State of the art of Emerging Technologies in K–12 Education

The findings of this systematic mapping show a rapid increase in interest in emerging technologies in K–12 education on a global scale in the past few years, across a broad range of venues, especially for AI and ML (see Section 4.1 – Figure 4). However, the vast majority of the 107 records retrieved from Scopus and through citation searching originate from Europe and North America, showing a limited and unequal geographical distribution (see Figure 5).

Table 5. Overview of the Nine Trajectories for a Future HCI Research Agenda, Cross-referenced with the Results Sections

No	Recommended research agenda	Cross-reference results
1.	Explicitly state the importance of teaching about emerging technology in K–12 and provide detailed and progressive learning objectives	Section 4.3. Learning objectives
2.	Foreground ethical and societal implications to offer a more comprehensive understanding of emerging technologies	Section 4.3. Learning objectives (Figure 7)
3.	Identify underlying mechanisms of both digital and unplugged learning tools, and develop tools to learn about and design with AR/VR	Section 4.5. Technology and other learning tools
4.	Target a more diverse range of K–12 students, leading to more inclusive approaches to introduce emerging technologies	Section 4.2. Target group (Figure 5)
5.	Actively engage teachers in both backstage work and facilitation, and coordinate professional development programmes	Section 4.2. Teacher roles
6.	Integrate learning activities in formal school environments and develop cross-curricular approaches beyond STEM subjects	Section 4.3. Curricular implementation (Figure 6)
7.	Provide an explicit focus on pedagogical strategies grounded in existing (and new) learning theories	Section 4.4. Educational frameworks and practices (Table 4)
8.	Consider formative assessment strategies and how these can inform feedback and feed-forward practices	Section 4.6. Student assessment
9.	Conduct long-term empirical studies to generate nuanced findings about emerging technologies in K–12 education	Section 4.6. Empirical evaluation (Figure 8)

Learning objectives (see Section 4.3) in the reviewed records prioritise technology skills and the understanding of core concepts and processes (see Table 3). Most of the studies require little or no prior experience from students. Technology-related objectives are usually combined with other STEM objectives, while a humanities perspective incorporating design aspects and ethical and societal implications of emerging technologies is largely missing (see Figure 8). The same goes for the higher-order objectives that motivate why children should develop technology and other competencies (e.g., preparation for STEM careers, a broad literacy perspective). In more than half of the records, these could not be identified. Nearly half of the records present standalone learning activities, without integration in or across existing (and new) curricula (see Figure 7). These two characteristics – the high ratio of standalone activities prioritising technology-specific learning objectives, and the lack of curricular integration and different learning progression levels – limit the depth and impact of the research.

When looking at practices to scaffold children's learning towards pre-set objectives (see Section 4.4), it is apparent that few studies ground learning activities in established learning theories, or that they do so in a rather superficial manner, especially in relation to constructionism. The format and duration of activities typically ranges from a single workshop to a few sessions in formal or non-formal learning settings, with grades 8 to 10 as the most common target group (see Section 4.2 – Figure 6). Further, even in the studies conducted in a school context, teachers are given a marginal role to play in developing, facilitating, and evaluating learning activities, with researchers retaining a firm grip on what should be taught and how. Teachers' limited involvement, and the fact that most interventions are short-term and include a rather narrow range of children, offers potential for future research.

A variety of pedagogical strategies have been used to engage and motivate students in learning activities. Hands-on, collaborative, and technology-mediated teaching are frequently used strategies (see Section 4.4 – Table 4). The characteristic of technology tools to support learning (see Section 4.5) is the way in which they are designed to glass-box some aspects of emerging technologies while deliberately black-boxing other aspects to reduce complexity. Another characteristic is the diversity of easy-to-use GUIs and block-based coding environments: for instance, for developing, training, and testing supervised ML models or programming IoT components. These tools, combined with a wide range of pedagogical strategies, have successfully lowered the barrier for novice learners to engage with emerging technologies. However, despite the available variety of pedagogical strategies and digital learning tools, the literature shows limited integration in the existing corpus of learning theory.

Of the 107 included records, 65 present original empirical data (see Section 4.6). This is typically qualitative in nature, stemming from 34 students on average per study. The majority of these studies focus on evaluating learning tools and activities based on diverse quality criteria, usually a combination of user experience and learner engagement (see Figure 9). Students' learning is assessed, in a summative way, in fewer than half of these 65 records. Only a few studies show clear constructive alignment between learning objectives, activities, and assessment tasks. This one-sided focus on evaluating learning tools and activities, often at the expense of assessing students' learning, indicates a lack of maturity of this nascent field of research.

5.2 Nine Trajectories for a Future HCI Research Agenda

Based on our extensive mapping of the literature, it is evident that education about emerging technologies in K–12 is not yet an established research agenda. Rather, the mapping reveals dispersed discussions across different research fields. Our literature review points to a range of potentials and discussion points that need to be addressed in order for this important research field to consolidate and mature. The HCI community is ideally positioned to take a leading role in this endeavour and to act as a mediator between neighbouring fields due to its expertise in human-centred approaches to technology and aspects of learning (both ed-tech and tech-ed). Based on the findings, we propose the following global research agenda (see Table 5 for an overview):

(1) Explicitly state the importance of teaching about emerging technologies and their characteristics and implications in K–12 education. This would clarify researchers' objectives, whether in preparing students for a career in STEM or in achieving the broad literacy considered to be important for all students, whatever their career prospects may be. Connecting this high-level objective or big 'why' question to concrete learning objectives with multiple progression levels would furthermore address the lack of a developmental perspective to learning found in the literature.
(2) Foreground the ethical and societal implications of emerging technologies, including complex issues related to power and democracy, and including the fact that the design of technology is never value-neutral. This would equip students with a more comprehensive and holistic understanding of emerging technologies, inclusive of how new and unanticipated ethical and societal concerns increase over time, while the uncertainty with regards to possible uses, outcomes, and meanings associated with an emerging technology decrease.
(3) Identify which underlying mechanisms of digital tools contribute to students' learning about emerging technologies, generating intermediate–level knowledge that transcends the design and evaluation of a particular tool. This would lead to a more nuanced understandings of digital tools and how they can be successfully integrated in learning activities and curricula, addressing a current gap in research. Other research opportunities are the development of learning tools for AR/VR and unplugged tools that lower the barrier for students with little interest in understanding technologies.
(4) Include a broader range of students beyond lower secondary education (i.e., grades 8 to 10) towards all levels of K–12 education, and with a special focus on underrepresented target groups such as girls, students of diverse socioeconomic and cultural backgrounds, and special education students. This would lead to a more inclusive approach, allowing for

diversity across age, gender, and interests to be represented in the literature. Introducing emerging technologies from an early age could furthermore promote a developmental perspective to learning.

(5) Actively engage teachers in the development, planning, and facilitation of learning activities so as to install a process of mutual learning between researchers and teachers in line with human-centred and participatory design approaches. Related to this, set up professional development programmes for teachers to scale-up and sustain research-led initiatives. Although initial steps have been taken in this regard, considerable effort is needed to increase the overall impact of research on emerging technologies in K–12 education.
(6) Carefully integrate learning activities and tools in school environments, as well as in existing and new curricula. Moreover, let K–12 students engage with different emerging technologies across subjects, also outside traditional STEM subjects such as maths and physics. This would not only provide a richer learning context for different types of students, but also avoid the frequently encountered pitfall of standalone learning activities that are insufficiently adapted to the specific characteristics of formal and non-formal learning environments.
(7) Include the development of different pedagogical strategies in research efforts (see Table 4 for an overview), ground them in the existing corpus of learning theory and, if possible, contribute to the development of (new) learning frameworks in relation to emerging technologies. A wide variety of pedagogical strategies are currently used in changing combinations, often loosely connected to constructionism, but they fail to provide a deeper understanding of how these particular strategies relate to theory and scaffold students' learning.
(8) Consider not only summative but also formative assessment strategies that prioritise students' individual progress as an integral part of learning activities about emerging technologies. The current literature focuses predominantly on summative assessment, evaluating students' learning at the end of an instructional unit rather than promoting learning through feedback and feed-forward practices based on continuous formative assessment. Providing teachers with formative assessment strategies could furthermore accelerate the integration of emerging technologies in K–12 education.
(9) Conduct long-term studies and provide nuanced empirical findings about the deployment of learning activities and tools in different educational settings and the ways in which these scaffold students' learning about emerging technologies. Most of the current research consists of short-term qualitative studies, often with a one-sided focus on user experience and student engagement. Moreover, studies that focus on constructive alignment of learning objectives, practices, and tools to scaffold K–12 students' learning are rare.

Bødker and Kyng [12] argued that the HCI community needs to take responsibility in the large contemporary issues and pursue social and political agendas beyond the technological. They point specifically to the need for research on children's engagement with technology, arguing that developing children's future skills in the digital domain is a useful way of opening up democratic debates precisely because technology is often considered an expert domain for the few, with children as easy targets for manipulation [12]. The proposed trajectories for a future research agenda are a response to this and similar calls. This research agenda, if realised over time on a global scale, would build the foundations for a mature inter- and transdisciplinary research field of emerging technologies in K–12 education. We encourage the HCI community to act as a catalyst in the realisation of this agenda. One way forward is to expand its methodological toolbox and initiate action-research-like programmes in collaboration with learning scientists, media studies scholars, child–computer interaction researchers, as well as other stakeholders. In this way, the HCI community would create a profound impact on children's agency in a digitalised society that reaches beyond academia into policy and education.

6 CONCLUSION

There is an urgent need on a global scale for research on approaches that address how to teach children about digital technology, digitisation, and, more recently, emerging technologies such as AI, ML, IoT, AR, and VR, to which children are increasingly exposed. Calls for action have been raised across policy, within STEM and informatics education, and in academia more generally to integrate and advance the benefits of computational thinking, digital literacy, and maker education for the coming generations.

The findings of the systematic mapping review presented in this article show a sharp increase in interest in education about emerging technologies in K–12, especially in recent years. Meaningful research has been conducted, generating a wide variety of digital learning tools, activities, and pedagogical strategies which have been empirically evaluated in both formal and non-formal learning environments. Initial steps have also been taken towards developing dedicated curricula and cross-curricular approaches that engage proactively with emerging technologies and their characteristics across school subjects. However, many challenges remain unaddressed. Among other things, there is a need for more inclusive approaches and active involvement of teachers, detailed learning objectives distinguishing between different progression levels in connection to school curricula, contextualised approaches that foreground ethical and societal implications of emerging technologies, better integration of pedagogical strategies with the existing corpus of learning theory, and long-term studies that move beyond a focus on technology tools. Based on our findings – and on the gaps in the current literature – we have proposed nine trajectories for a future research agenda (see Table 5). Inter- and transdisciplinary work will be required to realise this agenda on a global scale and to advance and mature this nascent research field. We have argued that the HCI community should take a leading role and act as a mediator with neighbouring fields in the realisation of this agenda. This would create a profound and lasting impact on children's agency in a society with increasing human-computer interaction.

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