Power to the Teachers: An Exploratory Review on Artificial Intelligence in Education

Lameras, P. & Arnab, S.

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Review

Power to the Teachers: An Exploratory Review on Artificial Intelligence in Education

Petros Lameras * **and Sylvester Arnab**

Centre of Post-Digital Cultures & School of Computing, Electronics and Mathematics, Coventry University, Coventry CV1 5FB, UK; aa8110@coventry.ac.uk
* Correspondence: ab3430@coventry.ac.uk

Abstract: This exploratory review attempted to gather evidence from the literature by shedding light on the emerging phenomenon of conceptualising the impact of artificial intelligence in education. The review utilised the PRISMA framework to review the analysis and synthesis process encompassing the search, screening, coding, and data analysis strategy of 141 items included in the corpus. Key findings extracted from the review incorporate a taxonomy of artificial intelligence applications with associated teaching and learning practice and a framework for helping teachers to develop and self-reflect on the skills and capabilities envisioned for employing artificial intelligence in education. Implications for ethical use and a set of propositions for enacting teaching and learning using artificial intelligence are demarcated. The findings of this review contribute to developing a better understanding of how artificial intelligence may enhance teachers' roles as catalysts in designing, visualising, and orchestrating AI-enabled teaching and learning, and this will, in turn, help to proliferate AI-systems that render computational representations based on meaningful data-driven inferences of the pedagogy, domain, and learner models.

Keywords: artificial intelligence in education; teachers; AIED tools and applications; AIED skills and competencies; AIED ethics

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1. Introduction

This exploratory review presents an analysis and synthesis of processes, practices, applications, and tools of Artificial Intelligence in Education (AIED). In particular, the paper attempts to contemplate on the question: "What do we mean by Artificial Intelligence in Education?". It considers key implications of AIED such as ethical concerns and digital competencies that teachers would need to develop for embracing and transforming discourse and rethinking their roles as teachers who position intelligent computational representations as sophisticated scaffolds that might help students to enhance their learning experience and intellectual capabilities. This amalgamation of teaching practice and AI support, used as a supplementary tool, may reinvigorate the way teaching and learning is designed, sequenced, orchestrated, and assessed in educational institutions.

Embracing teaching and learning with the use of AI is a complex and ill-defined decision that teachers would need to consider when reflecting on the overarching question: "What would it mean to teach and learn in the age of AI?". In fact, commentators such as Seldon and Abidoye [1] eloquently refer to education as being the 'Cinderella of the AI story', alluding to the underdeveloped and largely ignored phenomenon of using AI in teaching and learning contexts. Au contraire, Holmes et al. [2] perceived that it would be naïve to think that AI will not have an impact on teaching and learning, not only from a technological standpoint but also from pedagogical, ethical, and teacher competency development perspective.

The predominant difference of AIED with other educational technology applications is that it attempts to provide the opportunity to construct adaptive and personalised learning experiences for each student. In conjunction with this, AIED systems would ideally be positioned to make computational inferences that would help teachers to gain deep understandings of how students optimally learn and how such learning is influenced by prior knowledge, ways of teaching, and learning and physical contexts.

The review starts with reviewing the analysis and synthesis process, including search strategy, screening, coding, and data analysis. To situate the study into the context of AI, historical backgrounds and meanings were contemplated along with a categorisation of AI technology and its impact on innovative technology interventions. The review continues by articulating on adaptability and how it may be designed and computationally represented for discerning the impact of AIED applications and tools based on distinctive teaching and learning strategies. The review then articulates on AIED challenges, risks, and implications with a focus on ethics and teachers' AIED competencies. Propositions are made in terms of how teaching and learning could be enacted with AIED to support the design and orchestration of adaptive teaching and learning, how ethics could be embedded in the design and actual use of AIED, and the need for teachers to develop AIED-related competencies following dedicated competency frameworks that may empower teachers to develop, reflect, and self-assess AIED competencies and skills.

2. Materials and Methods

The purpose of this review was to answer the overarching question: "What do we mean by Artificial Intelligence in Education?". Based on a process of search, retrieval, appraisal, extraction, synthesis, and interpretation, the review attempted to show evidence from the literature and shed light to an emergent phenomenon through deconstructing and delimiting meanings, practices, and discourses of artificial intelligence in teaching and learning. A top-level schematic illuminating the methodology process is presented in Figure 1.

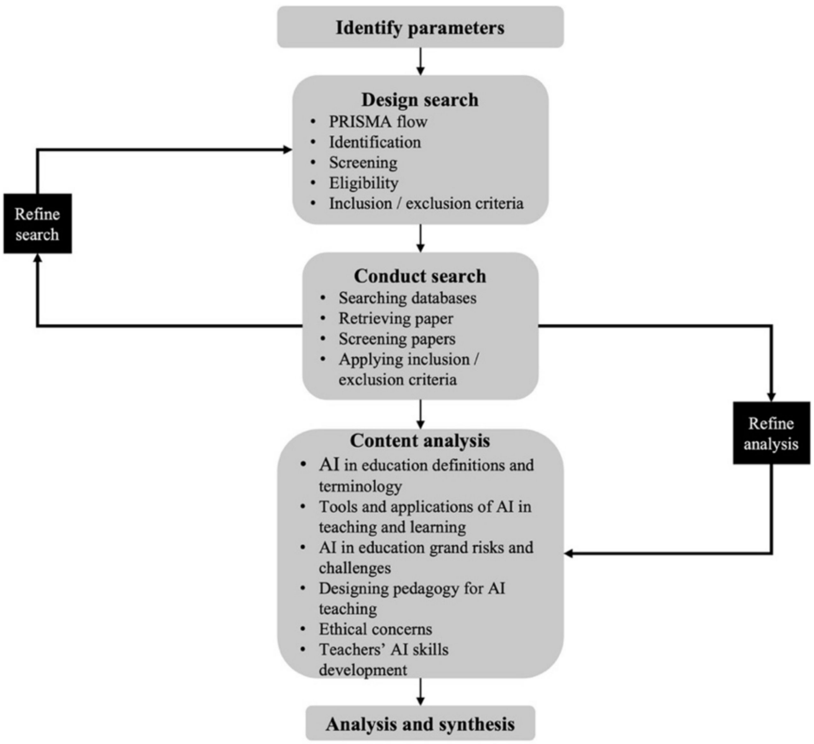

Figure 1. Schematic on thematic analysis and synthesis process.

The process commenced by identifying the parameters of the search strategy such as scope, search strings, databases, and ways of analysing and synthesising the review. Then, search and analysis processes were comprehensively contemplated, designed, and refined by adopting the PRISMA framework (e.g., Moher et al. [3]) for carrying out standard procedures of identifying and screening eligibility and inclusion criteria (see Figure 2). The search was then conducted through international databases for retrieving, screening, and adding items to the corpus. Content analysis prompted codings and themes that formulated and synthesised the review on AI in teaching and learning.

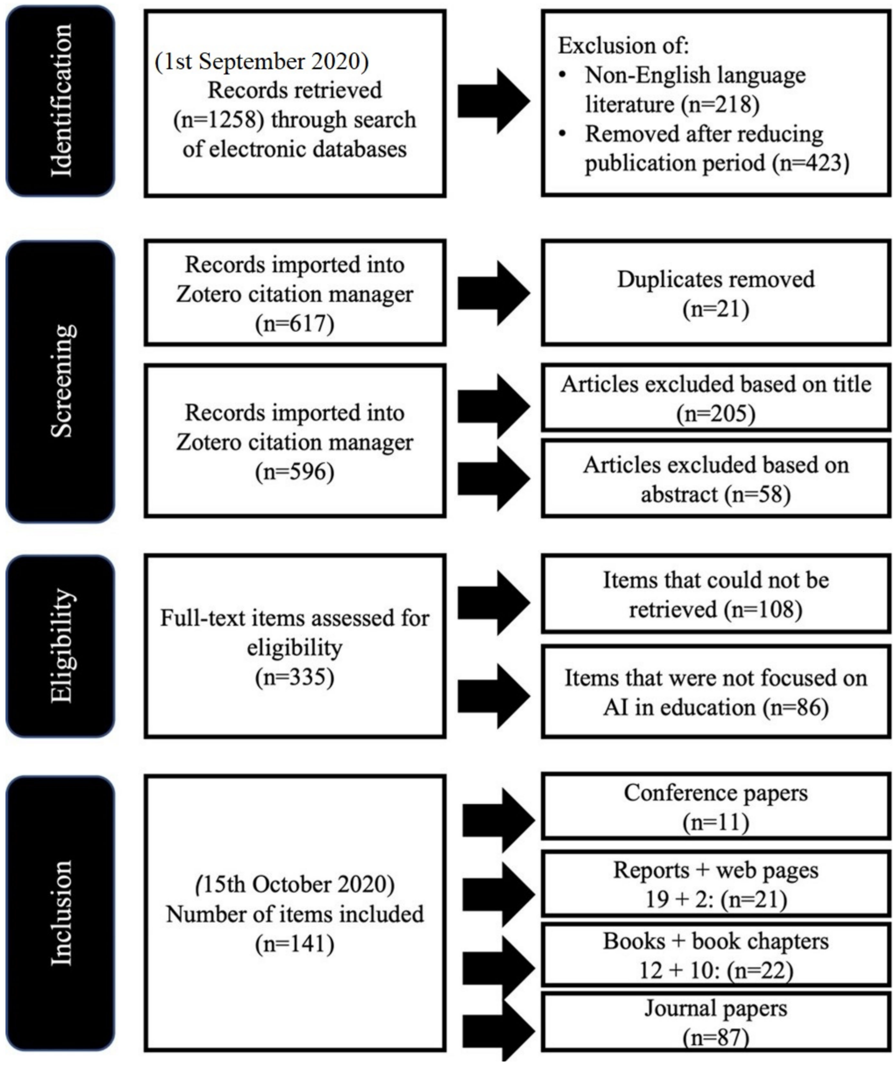

Figure 2. PRISMA diagram representing a sequential process for compiling the final corpus.

2.1. Search Strategy

The search strategy exemplified a sequential process of identification, screening, eligibility, and inclusion as means to comprise a final corpus of 141 items. The database searches commenced in September 2020, with an initial 1258 items identified.

The search was conducted by accessing three main bibliographic databases such as EBSCO, Web of Science, and Scopus. Searches were also carried out via Coventry University Locate subject database, which allowed global searches across databases encompassing semantic search in open access journals for accessing and retrieving 'deep web' sources often ignored to be indexed in international databases. Normally, using Boolean and Proximity search for scanning titles, abstracts, and keywords ensured that a wide and relevant array of references were retrieved, as seen in Table 1.

Although items related to AI in school education was the primary focus of this study, items that investigated applications and use of AI in higher education were also included to add depth and breadth in terms of the varied ways AI is used as an emerging technology that is sparingly adopted within and across different educational levels. Detailed technical descriptions of AI applications or AI techniques without any associations of use within an educational context at any scale were excluded (see Table 2).

Table 1. Search terms and strings used.

Topic	Search Terms
Artificial intelligence in education	"artificial intelligence in teaching" OR "artificial intelligence in learning" OR "artificial intelligence in teaching and learning" OR "definitions of AI in education" OR "definitions of AI" OR "AI terminology" OR "AI methods" OR "intelligence" "augmented intelligence" OR "machine learning" OR "neural networks" OR "deep learning" OR "data mining" "reinforcement learning" OR "algorithms" OR "data analytics"
AND Applications of AI in education	"Intelligent tutoring systems" OR "exploratory learning environments" OR "learning management systems" OR "virtual assistants" OR "virtual pedagogical assistants" OR "teacherbots" OR "chatbots" OR "assessment & feedback systems" OR "AI learning companions" OR "learning analytics" "AI teaching assistants" OR "AI classroom assistants" "games" OR "augmented and virtual reality" OR "dialogue-based tutoring systems" OR "Education Data Mining"
AND Pedagogy	"domain model" OR "pedagogy model" OR "learner model" OR "open learner model" OR "collaborative learning" OR "teacher-centred" OR "content-centred" OR "activity-centred" "role of teacher" OR "role of student" OR "role of AI" "feedback & assessment" OR "adaptive learning" OR "personalised learning" OR "self-regulating learning" OR "social learning" OR "emotional learning" "learning design"
AND Subject	"Science, Technology, Engineering and Mathematics" OR "physics" OR "mathematics" OR "computing" OR "computer science" OR "ICTs"
AND Ethics	"biases" OR "risks" OR "privacy" OR "dataset bias" OR "association bias" OR "automation bias" OR "interaction bias" "misuse" "ethical" OR "ethical frameworks" "transparency" "diversity" "reliability" OR "data security" OR "accessibility" OR "ethical approaches" OR "sensitive information"
AND Teacher skills	"competencies" OR "skills" OR "capabilities" OR "literacies" OR "support"
AND Education level	"secondary education" OR high school" OR "higher education"

It was decided that core terms such as 'AI in education' (e.g., AIED) 'AI in teaching and learning' or close synonyms such as 'augmented intelligence in teaching and learning' at the level of title and/or abstract were added in the corpus. It was also decided to limit items to those published between 2008–2020, as a means to add breadth and depth of the different constellations and meanings of how AI is used in teaching and learning. Key papers and selected items found before 2008 were included in the corpus. Peer-reviewed items in English encompassing primary and secondary research were included to ascertain rigour and trustworthiness across the items in the corpus.

Table 2. Final inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
The term Artificial Intelligence in education or close synonyms	No artificial intelligence in education
English language	Not in English language
School and higher education	Not school and higher education
Primary and secondary research	Not an academic paper (e.g., non-research article or review)
Indexed in Scopus, Science Direct, Web of Science, EBSCO, or via an institutional database system called Locate	Not indexed in Scopus, Science Direct, Web of Science, EBSCO, or via an institutional database system called Locate
Published between 2008–2020	Published before 2008

2.2. Screening

The first screening of 1258 items titles and abstracts was carried out with the premise to include rather than exclude items that had the use of AI in education as a predominant scope. Items were examined based on their inclusion criteria and, hence, items were included in, or excluded from, the corpus. Then, the remaining 617 items were checked for duplication. Then, 596 items were imported into the Zotero citation manager system and a third screening procedure was carried out for excluding items based on title and abstract relevancy, resulting in 335 items that were retrieved and screened. The final screening iteration on full text excluded items that could not be retrieved from the database or via direct contact with authors, as well as items that were not proliferating AI in educational contexts, resulting in 141 items remaining for synthesis.

The final corpus was diverse and ubiquitous in terms of the research methods employed for collecting and analysing results (see Table 3). In particular, the overarching approach to investigating AI in education was quantitative, with 47 items representing 33.3% of the corpus. The most prevailing quantitative method was quasi experimental, with 38 items that comprised 80.8% of the quantitative methods employed. Such studies attempted to estimate causal relationships without random assignment. Randomized Control Trials (RCTs) were utilised in nine studies, making just 19.2% of the total quantitative studies encompassing a random assignment to control or experiment group.

Table 3. Research methods used in corpus items.

Research Design	Number of Papers
Quantitative	47
Quasi-experimental	38
RCTs	9
Qualitative	18
Thematic analysis	17
Ethnography	1
Mixed studies	5
Literature reviews	71
Systematic	7
Evidence-based/exploratory	64

Qualitative studies as means to empirically understand perceptions, experiences, and approaches to using AI in teaching and learning were 18, making 12.7% of the corpus. Studies that used thematic analysis were 17, representing 94.4% of the qualitative studies and only one study employed ethnography, making just 5.6% of the qualitative studies. It seems that the adoption of qualitative methods for understanding ways teachers experience AI in teaching and learning is marginal and underutilised (see Figure 3). Possible reasons for this may be that AI in education is an emergent phenomenon that has not been embraced by teachers and institutions alike and, therefore, there is a vague or a blurred perception of how teachers experience and perceive the use of AI in teaching and learning.

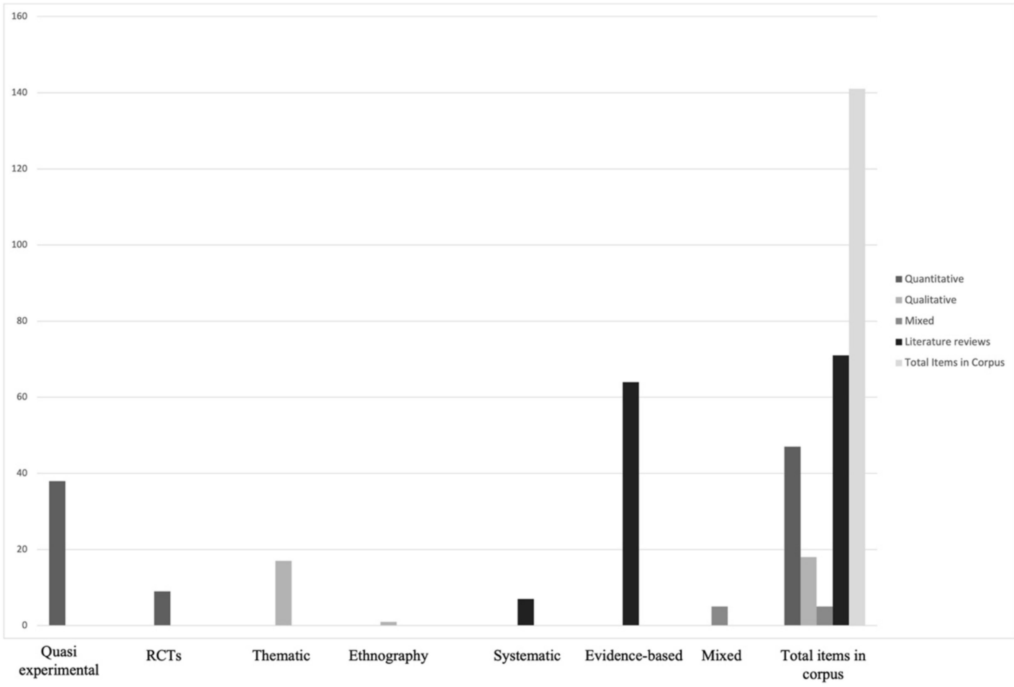

Figure 3. Number of different research methods employed in corpus items (n = 141).

In light of this methodological incongruity, more qualitative studies may be needed to create a critical mass of studies that investigate the qualitative ways in which teachers experience the use of AI for designing and delivering teaching and learning. Mixed studies employing both quantitative and qualitative methods were five, comprising 3.5% of the corpus. All five mixed studies employed quantitative approaches as the core method complemented by qualitative approaches for further investigating subjective nuances on how individuals experienced the phenomenon in question. Literature reviews were the most frequent studies, with 71 items comprising 50.5% of the corpus. Systematic literature reviews were evidenced in seven studies, making 9.8% of the literature review items, while 64 studies employed evidenced-based reviews, encompassing 90.2% of the literature review items.

2.3. Coding and Data Analysis

A coding scheme, as seen in Table 4, was developed to code and extract data from the items in the corpus. The coding scheme discerned codes related to resource identifier (title, author, publication year), resource type (journal, conference), AI for teaching and learning in schools (vision, meanings, definitions, and background), designing and orchestrating teaching using AI (pedagogy and AI), applications and tools (AI-based digital learning environments), AI and teacher skills (competencies, digital literacies in teaching using AI), and ethical AI in education (ethics, opportunities, challenges, and risks). Thematic data analysis was carried out via utilising the data analysis software package Dedoose for associating and mapping corpus items to the coding scheme. Developing the codings and the overarching descriptions was a requirement of optimisation and inclusivity rather than a mere process of achieving linearity and completeness; hence, constant updates, refinements, and reiterations were performed to the coding scheme not only during the analysis phase but also during the final synthesis of the review.

Table 4. Coding scheme.

Code/Themes	Description
Resource identifier	Title, author, date of publication
Resource type	Journal article, conference paper, book, book chapter, policy report
AI meanings and techniques	AI understandings and meanings, AI definitions, techniques
AI for teaching and learning in schools	Vision and meanings of AI in teaching and learning; the development of AI in teaching and learning; impact and challenges of AI in teaching and learning;
Designing and orchestrating teaching with the use of AI	Pedagogy and AI; teachers' and students' perceptions of AI in teaching and learning; teaching models, frameworks, and approaches to using AI design of learning activities with the use of AI; design of feedback, assessment for AI; role of the teacher in using AI; role of the student in using AI; role of the AI in designing and delivering teaching and learning; personalisation of learning through AI; social, affective, and emotional learning
Applications of AI in teaching and learning	Intelligent Tutoring Systems; educational data mining; assessment and feedback systems; intelligent virtual agents; exploratory learning environments; game-based learning environments
AI and teacher competencies, capabilities, and skills	Pedagogical competencies, technical competencies, data literacy, ethics
Ethical AI in education	Ethical frameworks; opportunities, risks, principles, and recommendations; misuse of AIED and impact; privacy and autonomy; fairness and transparency; encouraging ethical use of AI in education

2.4. Limitations

While this review was undertaken as rigorously and consistently as possible, there are still certain limitations influenced by the chosen search strategy. For example, although the search strings used were driven by the overarching scope of the study, the items returned may not cover the entire spectrum of the evidence base. In congruence to this, the three main databases that were used to access and retrieve items may not have returned the entire gamut of items, including gray literature pieces that negotiate the use of AI in education in languages other than English or in other formats. Therefore, a caveat needs to be highlighted as some articles, conference papers, books, and reports may have been missed due to language and other search restrictions. Depending on the scope and scale of research, future studies may consider employing a wider set of databases and inclusion criteria with proffered multiple language search strings and varied databases to accommodate a more complete search strategy.

3. Results

In the following sections, the results of the review are presented by articulating on the themes that emerged from the analysis process. To situate the results into the context of using AIED in teaching and learning an attempt was made to provide background information on meanings and ways of understanding AI and how it may impact technology applications and practice.

3.1. Background, Meanings, and Impact of AI

It may be challenging to make explicit the different meanings and conceptualisations that underpin AI. Indeed, there are many competing understandings and meanings in common use of what constitutes AI. Max Tegmark [4], in the influential book Life 3.0, provided a simple definition of AI as "non-biological intelligence". Tegmark stressed the importance of conceptualising 'intelligence' as the ability to accomplish complex goals perpetuating intelligence as consisting of multiple types including acquiring and understanding concepts and ideas, problem solving, creativity, negotiating, planning, and social and emotional learning. To contemplate further on the notion of multiple intelligences, Baker et al. [5] probed the nature and meaning of intelligence by proposing a broad definition of AI as "computers which perform cognitive tasks, usually associated with human minds, particularly learning and problem solving".

To differentiate intelligence that is enacted by humans or by machines Seldon and Abidoye [1] referred to AI as Machine Intelligence (MI), denoting a digitally controlled mechanical process by a human-centred machine that perceives its environment and adapts to it for achieving its objectives. This meaning of AI pertains to a focus on machine intelligence in terms of being able to "mechanically calculate logical statements for achieving objectives". It seems, therefore, that such an aphorism may be problematic as the focus is placed on the machine's capability to intelligently think and adapt with a 'logical and linear structure', alluding to perceiving intelligence as the linear computation of data-driven facts and thereby raising assumptions about the philosophical foundations of AI. Instead of using AI or MI, the terms augmented intelligence (e.g., Lui and Lamb, 2018 [6]) or hybrid augmented intelligence (e.g., Zheng et al. [7]) were favoured by researchers as a means to develop a hybrid form of AI that emulates the human brain as the source of intelligence. The overarching assumption of augmented intelligence is that computers and intelligent software are incapable to perform tasks that require intuition, creativity, and decision making for solving open-ended and ill-defined tasks and, therefore, by introducing human-like cognitive models, it would be possible to enable human–computer collaboration or render cognitive models in the intelligent software.

Despite the continuing debates between augmented and artificial intelligence and the epistemological and ontological merits of 'intelligence', this study uses the term AI to refer to computer systems or intelligent agents that collect, analyse, and represent data and information in intelligent ways for achieving complex goals. As such, intelligent ways may be manifested as the ability to memorise and recall information (e.g., Chase et al. [8]), optimisation of procedures and parameters (e.g., Noothigattu et al. [9]), autonomy (e.g., Duan et al. [10]), and understanding of human natural language (Kaplan and Haenlein [11]). To this end, AI involves programming effort for writing the necessary steps and rules for a computer to complete a task. Machine learning, however, is a technique that is being used for computers to learn the steps and the rules necessary for predicting outcomes. This does not negate the necessity of programming but rather it reinforces the ability of a computer to learn the programming task and continue to develop it for predicting outcomes. An extension of machine learning is known as deep learning, which employs neural networks' algorithms and iterative clustering for identifying connections between similar objects through constant iteration until it recognises the object. Deep learning is the reference technique employed by AlphaGo.

To develop intelligent models or systems that require human interaction, researchers' efforts are engrossed towards studying and delineating behavioural theories of socially meaningful activities premised in cultural and social constructs. For example, Tuomi et al. [12] developed a conceptual model that frames three levels of human and machine intelligence pertaining to the theory of 'cultural-historical activity'. The behavioural, cognitive, and cultural levels are perceived as potential areas of AI impact on human activities. The impact of AI in social practices emerges in three distinct sub-levels: (1) at the level of *operations* augmenting, enhancing, and complementing the efficiency of doing existing operations performed by humans, (2) at the level of *acts* substituting or automating acts that were previously done by humans, and (3) at the level of *activity* transforming existing activities to more advanced activities that could not be conceived, designed, or implemented by humans.

The epitomised hierarchy and taxonomy of AI and how it impacts technological and social practices may be further delimited using the Substitution, Augmentation, Modification Redefinition (SAMR) model, developed by Puentedura [13] as a developmental ontological framework that demonstrates how AI will increasingly influence the dynamics of technology development as a means of entering a state of transformational activity underpinned by advanced forms of human intelligence (see Figure 4).

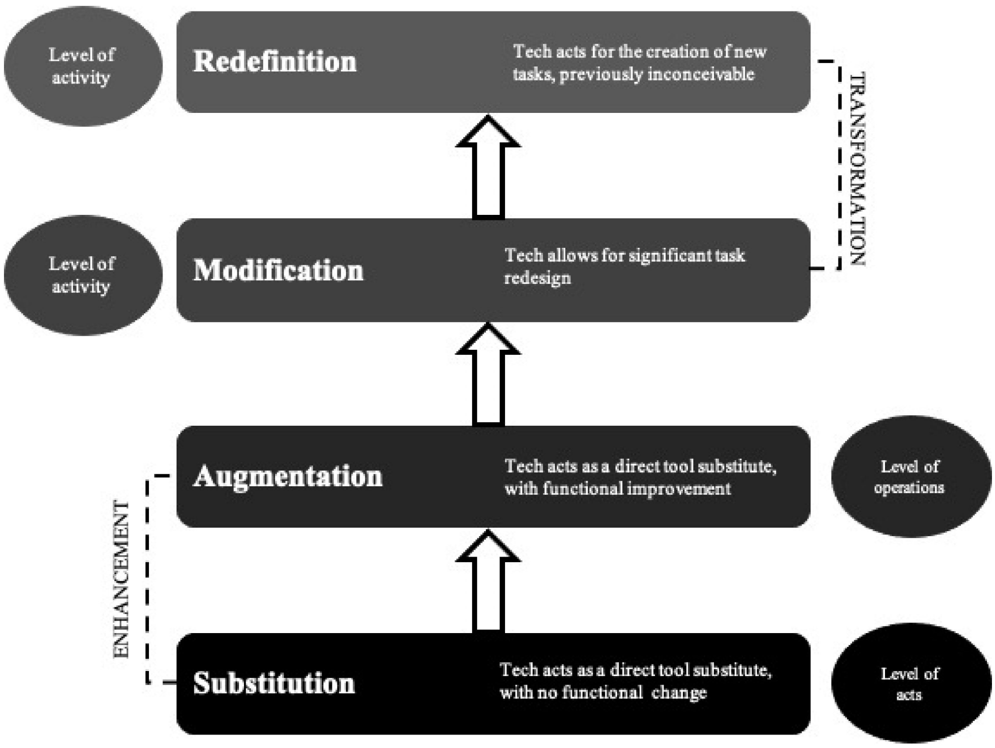

Figure 4. The SAMR model: a taxonomy of AI technology and impact on social practices.

The 'interdisciplinary' nature of AI in terms of emulating how the human mind processes information and knowledge from a cognitive and socio-cultural perspective has been embraced by Zanetti et al. [14] and Dodigovic [15] referring to AI as an interdisciplinary area of knowledge and research, whose aim is to understand how the human mind works and then emulate this understanding to AI technology design. Dodigovic argues that a fundamental factor for AI to accomplish such emulations is the knowledge of language. The term given to AI when it can perform broad intellectual human-level goals using natural language as well as having the ability to learn is Artificial General Intelligence (AGI), known also as 'strong AI' (e.g., [4]). In contrast, AI systems that tend to perform only specific goals such as playing board games or automatic analysis of medical images are known as narrow AI (e.g., Cameron [16]).

In the 1950s, the term AI was coined by John McCarthy during a workshop organised at Dartmouth College in the US. To understand and distinguish between human intelligence and machine intelligence, the computer scientist Alan Turing suggested the Turing Test to address the inquiry "Can Machines Think?". To answer this question, Turing suggested a simulated game with a simple goal for a human arbiter to communicate by typing messages to a human and to a computer with the purpose to distinguish between the two. The machine passes the Turing Test if no difference is noticed, from the human arbiter, in verbal communication. Since then, AI has grown exponentially and created an impact across sectors. For example, AI can accumulate and assimilate data for creating patterns and making predictions. The UK-based company DeepMind, acquired by Google, adopted AI-based techniques such as machine learning to demonstrate the power of AI for mastering complex board games. As part of DeepMind's approach to 'solve intelligence' a machine learning model was developed, wrapped in software called AlphaGo that can search and autonomously decide the best path to victory and, hence, demonstrating human-like potential by defeating the world's best players in chess as well as in Go. Recent advances in machine learning, defined as a subfield of AI that analyses data to identify patterns rendered into a model to predict data-driven inferences (for example, by identifying patterns in geospatial data, AI predicts future locations, e.g., Popenici and Kerr [17]), have made AI transformative and autonomous in a sense that it can be embedded and perpetuated from smart voice assistants and mobile applications to face recognition, household appliances, and autonomous vehicles. Other AI techniques such as neural networks, deep learning, and algorithms open new avenues of technological innovation via analysing large amounts of labelled (i.e., supervised learning) and unlabelled data (i.e., unsupervised learning) aiming to uncover hidden data patterns to make unpredicted and ill-defined decisions and thereby optimising the quality of certain data-intensive services and enabling AI-driven automation.

As AI solutions have the potential to collect, analyse, and interpret large amounts of data for perpetuating automation and, in some instances, simulate thinking and demonstrating rational behaviour, there are risks and challenges often narrated as part of dystopian scenarios. For example, Tegmark [4] formulated a range of AI scenarios where AI acts as a 'benevolent dictator' or as 'conquerors' and 'descendants' where an AI system takes control and runs society and ultimately replaces humans. Each scenario has properties that define human existence, intelligence, consciousness, and happiness. The underpinning question that remains to be answered is 'If AI progress continues, will machines be able to think, be creative, and develop consciousness that may trigger an intelligence explosion that will fundamentally change the way we live, learn, and interact with the world?'. It is unlikely that such an intelligence explosion will be infiltrated into a monolithic human-level AGI system in the short term but there are signs of intelligence enacted by machines and consensus that AI will eventually infer goals from human behaviour.

3.2. A Stimulus for AI in Education

Having proliferated an understanding of AI, this enables us to rationalise and delimit how AI may be conceptualised and realised in teaching and learning contexts. Often referred to as a research strand that studies the application of Artificial Intelligence in Education (AIED), it aims to investigate how teaching and learning may be enacted with the use of AI. In particular, AIED encompasses the design, application, and evaluation of tools, pedagogical models, instructional strategies and frameworks, ethical implications, and teacher competencies surrounding the use of AI in education that have been the focus of attention for about 30 years. Luckin et al. [18] perceived the goal of AI in teaching and learning as to transform and translate intrinsic educational, psychological, and social knowledge to computational language that AI can interpret and make explicit. The assumption is that the role of technology in general and the role of AIED in particular is to support, guide, and enhance human thinking by augmenting technological innovation with activity-based, adaptive, and student-oriented teaching strategies. This is aligned to the premise of experiencing AIED not only as a technological solution that is able to resolve current teaching and learning challenges but, most importantly, as a system that enables deeper and qualitatively deeper understandings of how learning happens, conjecturing to influences and relationships such as a student's prior knowledge, ways of learning, assessment, and feedback (e.g., Zhou et al. [19], Kukulska-Hulme et al. [20], Luckin et al. [18]).

The fast-approaching revolution of AI has already been acknowledged and there is consensus that AIED has the potential to address teaching- and learning-related challenges that schools and universities currently experience. For example, some authors [1] asserted that AIED may entail an integral part of the fourth education revolution as it may alleviate some of the challenges that the current educational mass model reinforces, especially in relation to the narrow segment of skills and capabilities that students develop, which largely remain inert. To understand how technology in education has developed and evolved to accommodate complex, adaptive, and personalised AI-based learning environments, a brief history of educational technology before the introduction of AIED is provided to situate AIED developments within a broader educational technology research base.

3.2.1. Educational Technology and Accompanied Learning Perspectives before AI

Since the 1990s, the advent of modern educational technologies including an amalgamation of using computers and the Web improved the way students accessed, retrieved, and made sense of multimodal learning experiences. From utilising multimedia to visualise information, e.g., to employing games with interactive storylines for increasing engagement and self-directed learning (e.g., Connolly et al. [21]), educational technology is increasingly situated as the driving force for transforming digital teaching and learning to more open, social, and personalised intervention (e.g., Dillenbourg [22]). The use of educational technology may be manifested during the design phase (authoring) and during the runtime or implementation phase (orchestration). Schools and universities have been experimenting with educational technology for designing learning and for orchestrating digital learning to create increasing opportunities to learn from anywhere anytime. A multitude of terms have been used to describe the use of computer technologies for teaching and learning, spanning from e-learning and distance learning to blended, flipped, and game-based learning, to demonstrate the impact of technologies of learning and teaching, roles and pedagogy, organisational structures, and associated strategy and policy.

Indeed, educational technology had a profound impact on educational institutions as students were starting to make choices on how, where, and when learning would be realised, hence, becoming more empowered, resilient, and self-directed. Arguably, early applications of educational technology were characterised by the adoption of behaviourist learning principles following Skinner's [23] notion of programmed instruction and operant conditioning. The most important factor was on designing digital learning environments that were based on student–system interactions with foci on presenting chunks of information followed by questions and feedback that reinforced correct responses. Direct access to course content and instructional material as means to transmit information was a sine qua non through accessing an institutional web site or Virtual Learning Environment (VLE). Some of the habits of mind associated with these technologies were regarded by teachers as unhelpful, particularly the naïve and uncritical reliance on web-based information, but the use of emails was perceived as a more direct medium for students to ask queries and get asynchronous feedback from the teacher [1].

The dominant approach to using educational technology was premised on Instructional Systems Design (ISD) springing a recursive decomposition of knowledge and skills (e.g., Gagné [24]). The key principle of ISD is that learning is formed step by step from previous knowledge or cognitive schemata that constitute a new and more holistic learning structure. The main problem with this approach was that such systems did not enclose diagnostic, explanatory, or student support strategies to identify incorrect responses. The focus was on developing static online instructional learning repositories that emulated traditional instruction approaches for effectively transmitting information by teachers to be rote-learned by students. Another example of a content-driven, transmissive, and didactic orientation is evident in the development of standards such as the Advanced Distributed Learning Shareable Content Object Reference Model (SCORM) as means to track students' progress through the accessed content. There has also been criticism about commercial VLEs that foster content-driven learning and, therefore, inhibit conceptual understanding (e.g., Britain and Liber [25], Conole et al. [26]). The first-generation models of such web-based learning systems were monolithic and were not open at a service level. The SCORM approach, embedded in commercial first-generation digital learning environments, did not align with more student-centred and process-based learning designs; hence, teachers felt overwhelmed and demoralised to share learning content (e.g., [25]).

From 2004 onwards, there was a shift in understanding and developing educational technology from merely as 'software' and 'hardware' used for transferring information to 'technologies for learning' where priority is given to the cognitive account in terms of embedding multimodal and constructivist learning into designing technologies that are adaptive to a student's contextual behaviour (e.g., Öman and Sofkova-Hashemi [27], Jewitt [28]). Increasingly, educational technology was designed under the assumptions of constructivism that learning is gained through an active process of creating hypothesis and building new forms of understanding through activity. The influence of Jean Piaget and the theory of cognitive development in using learning technologies has been significant, particularly the assumption that conceptual development is triggered through intellectual activity rather than the mere transmission and absorption of information, which constituted Piaget's [29] constructivist theory of knowledge. The impetus was to create digital learning environments that will be modular and bespoke with content and communication standards' compliancy, ensuring interoperability appropriate to pedagogical purposes rather than as dictated by specific features and applications provided by a particular digital learning system. The SAKAI project was one of the first systematic efforts to provide a framework for offering a coherent, open, and integrated learning experience to the student. Another important integrated digital learning initiative was the E-learning framework (ELF), developed by JISC in the UK, a service-oriented architecture exploiting services to control discreet behaviours and increased unified functionality such as course management, assessment, course sequencing, and e-portfolios (Cook et al. [30]). These systems managed to provide an interoperable and integrated experience that encouraged students to construct learning but did not consider a more holistic role to constructing learning based on a student's needs. This was due to the pivotal institutional role in terms of facilitation of change and, therefore, a lack of adaptivity.

Vygotsky's [31] emphasis on the significance of social interactions for the development of complex cognitive functions influenced Duffy and Cunningham [32] to distinguish between cognitive constructivism (stemming from Piaget) and socio-cultural constructivism (stemming from Vygotsky). The socio-cultural perspective of learning has been highly associated with situated learning. Situated learning assumes that students will be subjected to influences from the cultural and social setting in which learning is manifested. As such, knowledge is viewed as distributed socially and embedded within communities of practice. Barab and Duffy [33] elaborated on two different aspects of situated learning. The first emphasises the importance of context-dependent learning encompassing the creation of constructivist learning activities perceived as authentic to the social context that the acquired knowledge and skills are applied and embedded. Examples of this may be inquiry-based and problem-based learning. The second aspect is the relationships that an individual student creates with a group of people rather than the relationship of an authentic activity to the wider social and cultural context. This dimension underlines the creation of community of practices as characterised by Lave and Wenger [34] in terms of enabling processes of participation in which less experienced students are in the periphery of the activities enacted by the community and gradually, as learning develops, their participation becomes more substantial and indispensable to the construction of knowledge within the community. Both perspectives on designing and delivering situated learning in classroom-based settings were enhanced through computer-mediated communication (CMC) and computer-aided instruction (CAI).

The notable difference in the hardware and software architecture as well as in the pedagogical design of CMC and CAI as opposed to other educational technology systems was the integration of a palette of interactive multimedia communication tools and applications that endorsed interactions, conversations, and dialogue. Such tools and applications were synchronous and asynchronous messaging, user forums, remote screen sharing, and games. Related concepts of relevance to learning from interactive multimedia are the notions of 'modalities' such as seeing, hearing, feeling, and tasting integrated into multimedia software-like games (e.g., Gee [35]) and 'multimodality' drawing on the process of creating meaning through connecting and combining teaching modes, multimedia, and technology (Lameras and Papageorgiou [36]). Such multimodal resources were coined as 'learning objects' (e.g., Conole [37]) representing simple, interoperable digital learning assets that are predisposed to reuse in multiple learning contexts. A range of standards were developed such as the IEEE Learning Objects Metadata and the IMS Learning Design specification as the core for implementing technical architectures that support interoperable digital learning assets.

3.2.2. AI Offering beyond Mainstream Educational Technology

The introduction of 21st century skills has advocated commentators to support the view that more general and high-level learning competencies and skills are needed to accommodate adaptive educational technologies (e.g., [2,5,38]). These learning skills are held to entangle a preference for creativity, problem solving, inquiry, and high levels of collaboration, resilience, and social interaction (e.g., [12,39]). Subsequently, it may be assumed that AI systems may be designed and developed in pedagogically rich ways that could scaffold students' efforts to acquire 21st century competencies and skills. There is a set of questions that are interesting to be highlighted to contemplate how AI could be designed and developed as means to help students to acquire skills and competencies for becoming active citizens (e.g., [40]). Such questions revolve around 'What should students be learning?' and 'How may such learning be designed, represented, and assessed through AI?'. Answers to these questions underpin much of the debate of what constitutes good learning (e.g., [41]) and how AI could become adaptive to the needs of individual students (e.g., [42]). Following Ellis and Goodyear [41], attention is drawn upon a top-level view of 'good learning' that perpetuates learning as a guided process of knowledge construction with the following characteristics: Learning is active, cumulative, individual, self-regulated, goal-oriented, situated, and, most importantly, an experience of the student. The importance of designing AI systems that can embrace the notion that the student is at the centre of the learning activity for developing understanding and not on technology per se would potentially contribute to much of the discourse around the use of AIED in terms of breaking out of a stable state of making deterministic use of technology and towards offering a comprehensive compound that contains methods of classifying desired attributes that are both meaningful and pedagogically coherent. In an ideal, technology enhanced learning situation AI would be capable of adapting to the needs and interests of individual students for helping them gain confidence and skill in managing their own learning.

3.3. Designing for Adaptive AIED Teaching and Learning

The context in which AIED is positioned is one in which it is part of a broader ecology of learning that involves the process of 'designing for adaptive teaching and learning'. Designing for adaptive learning involves an adaptive representation of the learning experience to which students are exposed. To understand the legitimate hypothesis that AIED could possibly provide a tailored learning experience, a relational assumption is made that teachers need to design adaptive learning activities that are informed by the context within which the activity occurs, the pedagogy, and the tasks undertaken for helping students to achieve intended learning outcomes. As such, adaptive learning activities involve the creation of interactions of student(s) with other student(s), employing tools and applications that can infer, process, and visualise a student's prior knowledge, needs, interests, and ways of learning.

From this perspective, designing an adaptive learning activity enacted via an AI system might encompass an AI-based and -initiated discussion around a topic that a student is mostly interested to learn, comparing, and evaluating arguments based on a student's understandings or solving problems that are tailored to a student's knowledge levels and skills. As such, designing for adaptive learning places the student at the forefront of the learning process and thereby assumes the advent of adaptive learning technologies (e.g., [43]), which aim to provide individualised and tailored learning content that is matched to a student's performance on set tasks. To design learning that is individualised and tailored to a student's needs, the learner and pedagogical models that underpin adaptive learning technologies may be necessary to computationally represent a student's (1) subject-specific experience, knowledge, and competence; (2) motives for learning and expectations of the learning situation; (3) prior experience of learning, including the specific mode (e.g., blended or online); (4) preferred approaches to learning; (5) social and interpersonal skills; and (6) confidence and competence in the use of adaptive learning systems [44].

Bartolomé et al. [45] found that there are two approaches to adaptive learning. The first approach emphasises the guidance provided by an adaptive learning system through inferring data on how a student learns. The second approach adheres to a more flexible learning orientation in which students make their own choices over aspects related to the material they will select to aid learning and the assessment methods deployed to assess learning. This learning flexibility is compounded as a variation of adaptive learning that was described in Luckin et al.'s [46], 'Ecology of Resources' framework utilised for the development of learning experiences supported by AI to enable students to adapt learning resources for supporting their learning needs. To this end, Luckin et al. [46] asserted that the role of AIED for enabling adaptive learning is to help with identifying ways in which resources are adapted to meet the needs of the student rather than as a tool that can adapt itself to the context and to the student. Contextualising activities to be orchestrated in schools or out-of-school contexts is a key design principle that fosters 'continuity' of activities when context is changing.

There are different ways for designing adaptive teaching and learning through using AIED. However, there are certain learning activities that stand out as being particularly suitable for AI-enabled teaching and learning: (1) adaptive, collaborative learning support and (2) learning through conversation and social and emotional learning.

3.3.1. Adaptive, Collaborative Learning Support

There is increasing research on Computer-Supported Collaborative Learning (CSCL) especially as a sub-research strand of AIED (e.g., [47–49]). CSCL emphasises how students learn and solve problems (e.g., [50]) by participating in collaborative learning activities and how such collaborative activities may be supported by technology. Tchounikine et al. [51] argued that an approach to support collaboration through technology is via macro-scripts for introducing structure that guides collaborative interactions between students. A CSCL script would be perceived as a guiding brief that describes the learning outcomes to be achieved, the subtasks that need to be addressed, how tasks will be executed and sequenced, the role of the students in the CSCL activity, and the tools that will be employed for students to be aware of how collaboration and interactions will be supported by technology. A key aspect of AIED research is to refine dynamic adaptations through shifting the focus from interface design to interaction design (e.g., [52]). It may also require modelling on how the AI system will adapt the provided support for making individual and collaborative interactions more meaningful. It would make sense, therefore, that design for adaptive learning would discern CSCL activities for small groups in which students are engaged in interactions with peers for pursuing an intended learning outcome through an adaptive and automated script. In such small group interactions, higher-skilled students may serve as more experienced peers and thereby help less experienced students. The AI system could potentially identify and model higher-skilled students and associate them to lower-skilled students as a means of scaffolding intelligent interactive assistance between students with different performance traits. Casamayor et al. [53] developed and tested a collaborative intelligent interface that provided a summary of student progress that indicated the level of knowledge that individual students exemplified and associated conflicts that were generated during the collaboration. Conflict detection accuracy seemed to improve processes of collaboration and interaction among students and contributed to a holistic development of a student's learning.

A CSCL strategy particularly pertinent and applicable to AIED systems is Adaptive, Collaborative Learning Support (ACLS). This approach focuses on providing feedback and support commensurable to a particular collaborative skill and the AI system would be able to validate that the student is improving collaborative skills. To facilitate the design of ACLS, Walker et al. [54] provided a set of design elements in the context of developing a system for improving the quality of collaborative student interaction. Three design principles for ACLS were identified in the context of using intelligent agents: (1) ACLS design for accountability (i.e., the intelligent system presents interaction feedback and praises the collaborative activity of the group), (2) ACLS design for efficacy that situates AI and teachers as collaborators in providing feedback to students on cognitive aspects as well as on collaboration and interaction dynamics, and (3) ACLS design for relevance as a means to motivate students to apply AI interaction support to their own interactions with other peers. To further study the effect of CSCL, Walker et al. [55] assessed an adaptive peer tutoring assistant with 122 students and discovered that ACLS is more effective when it is relevant to a student's behaviour and support was perceived as adaptive when students felt accountable for their actions. Kent and Cukurova [56] suggested a novel method for measuring the process of collaboration from a collective and adaptive prism, *Collaborative Learning as a Process*, which utilises social network analysis for balancing interactivity gains and coordination costs within communities of learners to gain better understanding on the collaborative process rather than its linear outcomes.

3.3.2. Learning through Conversation and Social and Emotional Learning

Closely aligned with CSCL is the activity of learning through conversation or through discussions recognised as a central part of the collaborative experience of learning. Discussions supported from educational technology may be text or audio-based and can be broadly divided into synchronous and asynchronous modes. Synchronous discussions support students to interact in real time and do not always leave a permanent record. Asynchronous discussions allow students to discuss learning aspects over an extended period by contributing to the discussion through posing, responding, and reflecting to questions at their own pace and time. However, the challenge in designing discussions through technology is to stimulate and promote engagement in social practice that in turn would lead to the formation of a community of practice (e.g., Lave and Wenger [34]) where students exchange ideas, information, and knowledge that drive the interests and needs of the community.

A central tenet of developing and nurturing communities of practice is that learning occurs through internalising dialogical activity (Vygotsky [31]). For example, students develop collaborative skills through internalising the necessary content and process of dialogical argumentation and negotiation of meaning in practice. This collaborative construction of meaning within an online learning community offers opportunities for group-centred rather than teacher-centred modes of learning. However, the levels of interactivity as a process of knowledge construction that emerge during online discussions are difficult to be delineated. Kent et al. [57] conducted a quasi-experimental study for exploring the relationship between the assessment of interactivity as a learning process and learning outcomes. An intelligent learning analytics' approach was proposed to measure interactivity in online discussions by establishing a relationship between interactivity and learning outcomes. Adamson et al. [49] developed a tutorial dialogue AI agent for improving interaction and interactive support within a synchronous collaborative intelligent environment. Conversational agents provide dynamic support through real-time analysis of the collaborative discussion, and interactive script integration allows for a natural flow in student–agent interactions. Dyke et al. [58] investigated the use of conversational agents to facilitate online collaborative learning discussions. The factorial design study revealed that students are scaffolded from the discussions with the agent to follow their own lines of reasoning and to refine ideas.

Despite the meaningful developments in adaptive conversations via AI-enabled agents that can trigger meaningful interactions in online collaborative learning activities, it is perceived that emotions, affection, and empathy play a key role in influencing what students learn and how learning occurs. Learning may be more effective when students are focusing on the social and emotional experiences especially when grounded in a collaborative learning setting. Social and Emotional Learning (SEL) may be broadly defined as the process of acquiring competencies and skills as a means to recognise and manage emotions, develop empathy for others, and establish positive relationships [59]. SEL serves as an umbrella term to convey active learning approaches for helping students to develop and practice skills that foster positive attitudes, behaviours, and thinking processes. This is in congruence with the need for students to form social and emotional connections for cognition and learning. Donnelly et al. [60] perceived SEL as a set of individual and functional skills that can be nurtured from the student. Such skills are divided into three categories: (1) cognitive skills such as reasoning and problem solving; (2) affective or emotional skills such as emotional awareness and managing feelings; and (3) behavioural competencies such as leadership skills. In the context of conceptualising SEL as a series of competencies, Chatterjee-Singh and Duraiappah [59] emphasised Social and Emotional Competence (SEC) as intrapersonal and interpersonal. Intrapersonal competencies are knowledge skills and attitudes directed towards oneself such as cultivating a growth mindset or self-efficacy, and interpersonal competencies are knowledge, skills, and attitudes directed towards other people such as showing empathy or the ability to collaborate with others for solving problems. Jones and Bouffard [61] asserted that the scope and focus of SEL vary as some focus on a set of skills while others are focusing on broader educational interventions such as conflict resolution. AIED systems may support students' social and emotional learning by identifying a student's affective states. For example, Mavrikis et al. [62] investigated how a student's emotional state can be detected using machine learning to develop patterns for diagnosing a student's affective states. Similarly, D'Mello and Graesser [63] designed and tested an intelligent system that automatically detects and responds to students' emotional states. Controlled experiments were carried out to show gains in domain knowledge increase, particularly for less assertive students. Burleson and Picard [64] developed a real-time affective agent for providing affective support to students. The system collected data from sensors about student's affective states, which were displayed by the engine. Findings from an analysis variance showed that students' meta-affective skills, mastery orientation, and overall emotional intelligence increased. Bosch et al. [65] used computer vision, learning analytics, and machine learning to detect a student's affective states such as boredom, confusion, delight, and concentration via a baseline affective state classification system. It was demonstrated that intelligent detection of affective states was possible in noisy class settings where student distractions were apparent. Grawemeyer et al. [66] designed an intelligent formative support that incorporates information about a student's affective state. A quasi-experimental evaluation in a classroom setting showed that emotional awareness support contributes to helping students to move from nominally negative affective states to nominally positive affective states. The type of feedback adaptation that influenced affect was the distinct feature of the investigation rather than adapting the feedback message as the subject of previous intelligent affective support research. McStay [67] enunciated some of the implications of adopting emotional AIED, especially around effectiveness, a student's well-being, and how it is exaggerated from mining aspects of subtle emotional situations, and the problematic application of using inferences of a students' emotions to train neural networks as a means of making predictions on a student's affective states.

3.4. The Impact of AIED Applications on Teaching and Learning

Developing AI tools and applications to support student learning has been the focus of research and discourse for more than 30 years (Kukulska-Hulme et al. [20]). However, only recently there was an assumption that AIED tools could serve different cognitive purposes and learning needs related to learning, teaching, and institutional functions (e.g., Zawacki-Richter [68]). Baker et al. [5] identified three broad categories of AIED applications: (1) learner-facing, (2) teacher-facing, and (3) system-facing. AI-powered *learner-facing tools* focus on adapting the student's learning experience by providing and curating personalised learning content, engaging into intelligent dialogical processes for diagnosing misconceptions, providing intelligent feedback, and facilitating collaboration. Examples of such software are Intelligent Tutoring Systems (ITS) or adaptive learning platforms. *Teacher-facing tools* are facilitating teachers' efforts to design, sequence, and represent adaptive learning activities, assessment, and feedback in adaptive and personalised ways (e.g., Laurillard et al. [69]). Such software can help teachers to understand how students learn by gaining insights on a student's performance and on how much time is necessary for students to be engaged in a learning activity. *System-facing tools* provide administrative support spanning from managing attendance and timetabling to recording and predicting average student grades for quality assurance purposes. Zawacki-Richter [68] carried out a systematic review on AIED applications and identified four different areas of AIED applications: (1) profiling and prediction, (2) assessment and evaluation, (3) adaptive systems and personalisation, and (4) intelligent tutoring systems. Roll and Wylie [38] emphasised the role of interactive learning environments as applications with distinct affordances that can support learning and teaching in more diverse and omnipresent ways across tasks, contexts, and roles.

To design AIED applications that can capture, analyse, and represent data for providing adaptive support and feedback, a set of computational representations are required to infer information and knowledge related to real teaching and learning instances. Holmes et al. [2] argued that this knowledge about real-world teaching and learning may be represented through models that are normally featured in ITS. Typically, learning models, teaching strategies, learning outcomes, assessment, and feedback are represented in the *pedagogical model*. Knowledge of the subject being learned, for example, how to add two fractions or learning about the greenhouse effect, is represented in the *domain model*. Knowledge of the student's prior knowledge and learning experiences, interests, needs, and affective state is represented in the *learner model*. Some AIED systems incorporate a fourth model known as the *open learner model* (e.g., Conati et al. [70]) that visualises and makes explicit the outcomes of the teaching and learning processes carried out by the system. The open learner model data presented to the student and to the teacher can be accessed through a dashboard or a visual representation and may be used for students to reflect on their learning journey and for teachers to understand how students better learn in order to adapt future learning to students' needs and interests. The pedagogy, domain, learner, and open learner models may be used to determine the level of adaptation that is necessary for aligning the intended learning outcomes while revealing connections between what students do when they learn, their learning characteristics, the teaching strategies employed, and the subject content to be learned. Figure 5 shows how the pedagogy, domain, and learner models may be augmented to provide an adaptive and personalised learning activity.

This iterative cycle of extracting and discerning knowledge from the domain, pedagogy, learner, and open learner models would help AI algorithms to process the data for inferring adaptive content and personalised learning activities. Essentially, this cycle may partially enable the ITS system to understand the student's experience of teaching and learning. This dependence of learning on experience constitutes a relationship between the student and the phenomenon of teaching and learning. The ITS establishes a relationship between the student and a particular teaching and learning experience that allows the formulation of the '*what*' (via the domain model) of the experience, '*how*' (via the pedagogy model) the experience will be structured, and the characteristics of '*who*' (via the learner model) is doing the experience. This relational perspective of processing computational models is still in its infancy, but it can prove valuable in terms of stepping outside of a deterministic line of thought that deems AIED as a replacement of established ways of teaching and learning to one that is more relational in terms of integrating the student's experience in its totality. To enable this relationality at its full scale, it would be essential for the domain, pedagogy, and learner models to be decomposed to lower sub-model levels as a means to establish more meaningful and integrated relationships.

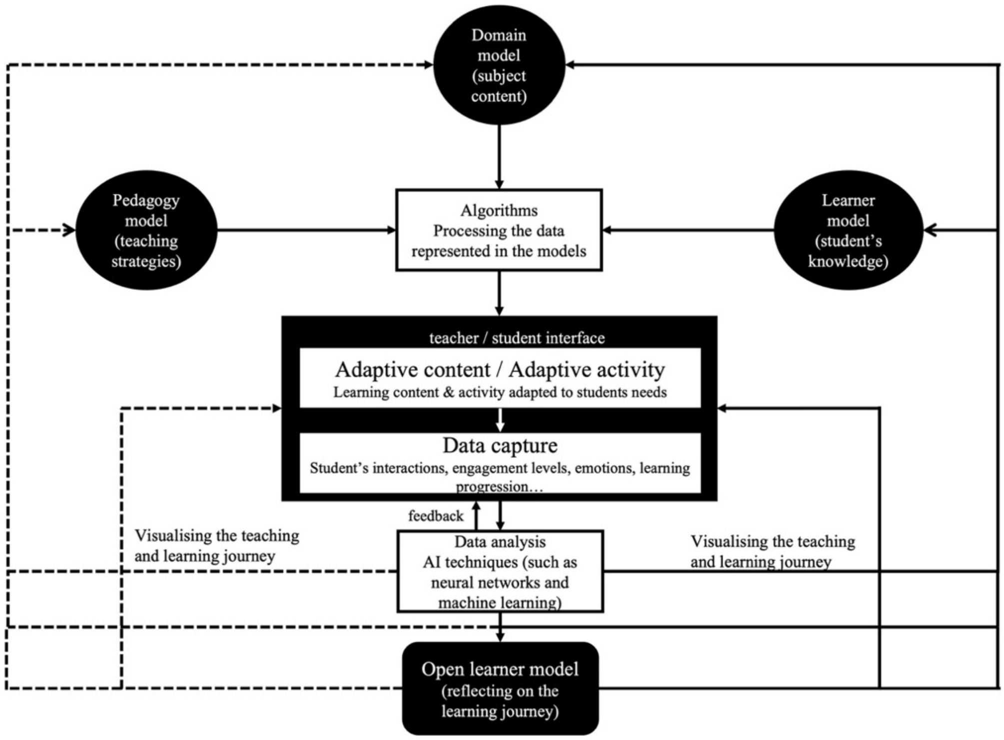

Figure 5. The interaction between the domain, pedagogy, learner, and open-learner models for providing adaptive support through an ITS (adapted from [18]).

This relational perspective may help the design of AIED systems to support the personalisation of learning through making explicit or visible (1) the centrality of the learning experience (what learning situations students experience and how; how they interpret such learning situations; and what learning strategies they adopt); (2) the importance of what is in the AI system in terms of content, processes, and features; and (3) designing and developing AIED applications and systems that are becoming an integral part of provision for learning and teaching. This relational thinking approach to understanding the impact of AIED as a broader ecology of learning and teaching has been exemplified by [1], which considers five broad aspects of teaching and learning and how AIED may support them in tandem. The predominant focus of this study was on teachers' experiences of AIED; therefore, Seldon and Abidoye's five aspects of teaching and learning were adapted to consider the role of the teacher in supporting the student with adaptive and personalised learning by employing AIED applications and tools (see Figure 6). AIED applications and tools are mapped against different aspects of teaching and learning to offer a distinctive account of 'what' and 'how' AIED applications may be used based on an overarching framework of teaching and learning with the use of AI-based systems.

3.4.1. AIED for Preparing and Transmitting Learning Content

Learning content can be variously perceived, but, in this context, it may be understood in conjunction with print-based artefacts such as books or digital content-based artefacts that use representational media such as text, images, and sound. It is perceived that the tool or the medium used may have a profound impact on personalising learning content. ITSs may be used to help teachers and students to find, access, and retrieve adaptive content. ITSs utilise AI techniques and prediction mechanisms to adapt and scaffold the experience of the individual student for improving the quality of learning as well as minimising the learning time (du Boulay [71]). Linear representation of information, progress tracking, and transferring information were some of the early features that defined ITSs. Drawing on the domain, pedagogy, and learner models, an ITS may determine optimal learning resources and types of content that may address a student's learning queries and misconceptions (e.g., Erümit and Çetin [72]). As the student addresses misconceptions from recommended content, the system constantly tests the student's knowledge, identifies mistakes, tracks misconceptions, and guides him/her towards finding and retrieving learning content. Baylari and Montazer [73] developed an ITS that discovers a student's learning difficulties by using a neural network approach for recommending adaptive learning content to the student. A key feature in matching a student's learning with the difficulty level of the recommended content is content sequencing. Chen et al. [74] developed an intelligent system to match a student's ability with the recommended learning content. The assumption was that traditional digital and non-digital artefacts such as web-based learning resources and textbooks typically follow a fixed sequence to different topics and sections with no consideration of harmonising a student's prior knowledge and skills with recommended content. Personalised content sequencing may provide learning paths that accommodate adaptive provision of learning materials by predicting a student's capabilities for preventing a student's disorientation through filtering out unsuitable material, reducing cognitive load, and ensuring concept continuity.

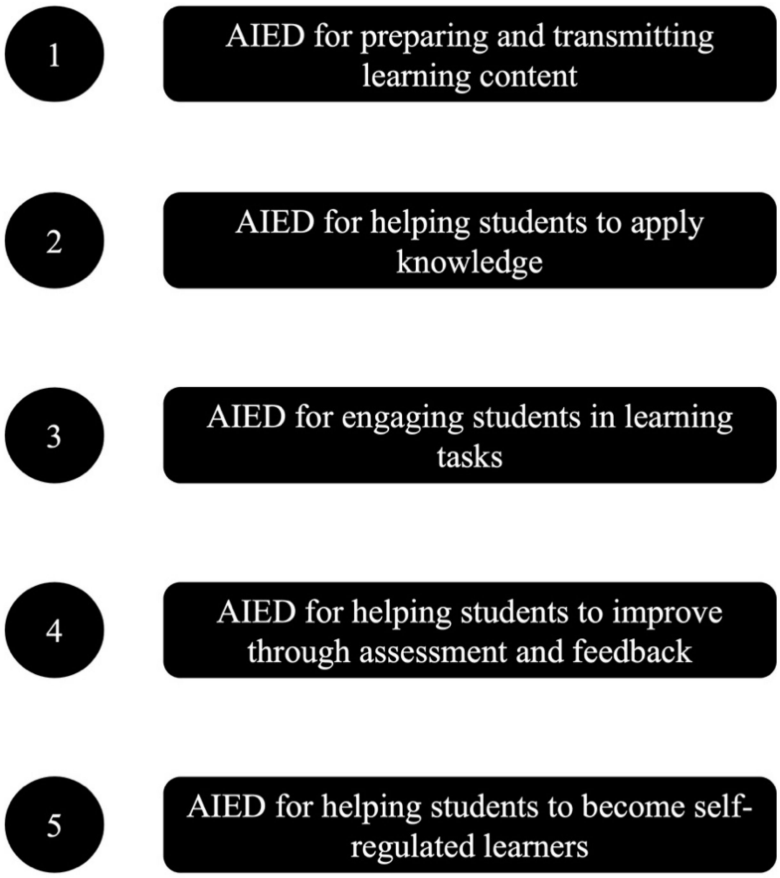

Figure 6. The five aspects of teaching and learning (adapted from [1]).

To facilitate ITS with implementing content sequencing, teachers may provision the preparation of content creation by conglomerating content with a student's perceived skills and abilities. Thalmann [75] proposed a classification of adaptation needs to which adaptive arrangements to content may be undertaken by teachers with less technical expertise. A set of 10 adaptation criteria was proposed for alleviating ill-prepared content, which seems to be an obstacle for designing and sequencing adaptive content. The criteria spanned from content preferences, didactical approach, and knowledge structure to preferences for media types, previous knowledge, user history, and user status. A key driver to adaptive content and sequencing is the degree to which a student can retrieve content personalised to individual learning properties and contexts. Steichen et al. [76] referred to personalised information retrieval as a way of addressing the information overload problem that students are facing when they search for learning content over the Web. For example, a simple query adaptation may be improved by using Boolean operators (i.e., AND, OR, NOT) to delimit a new personalised query. A typical approach to overcoming information overload is through grouping, sequencing, and presenting information in a structured manner. Statistical analysis on historical usage of learning content could create a pattern of a student's information interests, which may be used for recommending future personalised but also contextualised learning content.

3.4.2. AIED for Helping Students to Apply Knowledge

Adaptive learning content is key for students to gradually acquire knowledge that is proportional to skills, capabilities, and competencies. However, for enhancing understanding, AIED systems may support students to learn through examples, experiments, and scenarios designed to encounter the needs, interests, and knowledge of the student. ITS research has asserted that intelligent systems are able to provide personalised support for problem solving in a variety of domains (e.g., chemistry, physics, programming, and mathematics) based on analysing the domain knowledge and predicting a student's cognitive processes for understanding how the problem may be solved. For example, Conati and Kardan [42] presented a user-modelling framework that can be embedded into a learner model for analysing a student's interaction with a problem-solving task. The model contains a log with a student's self-explanation tendencies of how a particular problem could be solved. This enables the ITS system to generate interventions that explicitly target problem-solving skills. Drawing on du Boulay's [77] four examples of AIED systems that are employed to help students to understand basic scientific concepts through problem-based situations, the assumption is made that such systems should go beyond focusing on knowledge outcomes by analysing inferences and relationships that would encourage the student to persist on solving the problem.

VanLehn [78] analysed studies for different types of tutoring systems that are designed particularly for scaffolding a student's efforts to improve understanding. Five types of tutoring mechanisms were compared: (1) no tutoring (e.g., learning with just a textbook), (2) answer-based tutoring (i.e., providing answers to student's questions), (3) step-based tutoring (i.e., deconstructing problem in steps and giving feedback on each step); and (4) substep-based tutoring (i.e., scaffolding on a more detailed level). Van Lehn [78] concluded that ITS systems particularly used for understanding concepts in STEM were just as effective as one-to-one human tutoring. It was also argued that an ITS may be used to supplement human tutor support and also to replace the whole learning experience. Ma et al. [79] conducted a meta-analysis that compared the outcomes on ITSs that were assimilated by students for developing subject domain understandings to those from non-ITS learning environments. There was no significant difference between enhancing understandings from ITS and learning from human tutoring. The role of the ITS did not influence the impact on improving a student's understanding in terms of whether it was used as an aid to homework, as a predominant means of instruction, or as a supplement or an integral component of teacher-led instruction.

Attempts to utilise ITSs' capabilities to enhance a student's understanding have led researchers and AIED practitioners to investigate applications such as pedagogical agents. A pedagogical agent may be defined as a conversational virtual character employed in ITSs or in other educational technology such as serious games and augmented and virtual reality that uses rules and agent technologies to guide a virtual character's reasoning to support learning and instruction (Richards and Dignum [80], Veletsianos and Miller [81]). Pedagogical agents may span from simple static characters that respond through text-based input to three-dimensional animated avatars that can provide audio, visual, and haptic feedback. Schroeder et al. [82] carried out a meta-analysis of using pedagogical agents for helping students to enhance learning and understanding through knowledge application. The findings indicated that students gained better understanding when they attempted to apply knowledge with the aid of the pedagogical agent than a system without a pedagogical agent. It could be inferred from this that the participants felt more confident to apply the acquired knowledge as the pedagogical agent would intervene in case an error was made. However, more research is needed to investigate the interventions introduced by a pedagogical agent that facilitates a student's understanding. Kim et al. [83] investigated how students perceived AI agents or teaching assistants in higher education via an online survey. Perceived ease of communication, perceived usefulness, and teacher training are key factors for incorporating non-human agents while pertinent research questions emerged in terms of the role of 'machine teachers' in designing, orchestrating, and assessing teaching and learning.

3.4.3. AIED for Engaging Students in Adaptive Learning Tasks

In thinking about helping students to understand and apply knowledge, it is essential for AIED applications and systems to take a view that focuses on supporting deeper learning processes to be embedded in intelligent adaptive tasks. Aleven et al. [84] presented three broad categories in which AIED-based teaching and learning tasks may be adapted based on students' similarities and differences: (1) design-loop adaptivity involving the design of data-driven learning tasks made by teachers and updated based on student learning and also based on similarities among students; (2) task-loop adaptivity involving data-driven learning tasks made by the system where the teaching strategy changes per activity or task; and (3) step-loop adaptivity involving data-driven learning tasks that the system makes in relation to a student's individual actions and characteristics during a learning task. A key feature for these task adaptation methods to work efficiently is to improve ways of assessing prior knowledge and knowledge development and then select the task adaption method required for enhancing the desired learning outcomes.

Pareto [85] designed and tested an agent tutoring task to foster conceptual understanding and reasoning in mathematics among school students. The intelligent learning environment provided a game-based intervention through having students to play a game and getting them engaged to in-game tasks. The agent is providing the task to the student through a question to instigate dialogue as a means to challenge a student's mathematical thinking and to transfer knowledge gained from the in-game task to applying mathematics in live learning situations. A quasi-experimental study was conducted to investigate students' perceptions and performances of the agent in-game task. It was revealed that the in-game agent task engaged students in mathematical thinking in school education and helped to achieve deeper learning that may be transferred beyond the game contexts.

Task-oriented chatbots are particularly used for engaging students into a dialogue or conversation-based task. A chatbot is an intelligent system with natural language processing capabilities that enables a text- or audio-based conversation with a student. Pérez et al. [86] carried out a systematic review on the different types of chatbots used in educational settings: from chatbots employed to provide administrative information to chatbots that orient students towards undertaking a learning task. Kukulska-Hulme et al. [87] perceived that the optimal use of a chatbot is through identifying its role spanning from task facilitator, problem analyser, or guidance provider. Katchapakirin and Anutariya [88] developed a Scratch-based tutorial chatbot to assist school students to learn how to code through the Scratch block-based programming platform. The chatbot provided dialogue-based tasks or 'missions' for students to develop computational thinking skills. Ruan et al. [89] piloted the BookBuddy chatbot for transforming reading materials into interactive, conversational-based tasks for learning English. A small-scale preliminary interview study showed that students learned basic English through conversations with the chatbot and through assigning short language learning tasks. Smutny and Schreiberova [90] examined different types of educational chatbots embedded in social platforms such as Facebook Messenger. There was variation on the tasks rendered from recommending learning content and setting learning goals to monitoring learning progress against assigned tasks. To optimise the automation of collaborative learning tasks, Neto and Fernandes [91] developed a chatbot for helping student groups to collaborate and interact through networked conversations. The chatbot was able to provide support in group formation, group cohesion, and group activity implementation.

3.4.4. AIED for Helping Students to Improve through Assessment and Feedback

Assessment and feedback are the key drivers for learning. Assessment enables certification of learning and feedback, as information provided by an agent (e.g., teacher, AIED system, self) empowers students to refine, reflect, and transfer knowledge and understanding. A distinction is drawn between summative assessment (administered for grading purposes, thus resembling a linear and quantifiable representation of student's knowledge) and formative assessment (providing oral and textual feedback that assists students to gain a deeper understanding of the learning process). Other categorisations embody diagnostic assessment used by teachers to identify students' prior knowledge and final/continuous assessment (at the end of the course or throughout the course only). The design of adaptive assessment through an intelligent system would be able to determine the type of assessment and feedback aligned to a student's needs. An adaptive feedback system or a computerised adaptive test system (e.g., Grivokostopoulou et al. [92]; Barker [93]) may offer improved functionality to ascertain a student's level of knowledge, thereby adjusting assessment and feedback to delineate controllable levels of complexity. For example, Whitelock et al. [94] reported on findings from OpenEssayist, an intelligent, web-based feedback system for summative assessment tasks. The system provided feedback to students for improving essays before submission through clustering keywords, phrases, and sentences. The visual representations of the system encouraged students to investigate the distribution of key words and whether essays addressed the assignment's purpose. However, an adaptive feedback intervention that is optimised for structured tasks may not be helpful for more open and ill-defined tasks (e.g., Goldin et al. [95]).

Adaptive formative feedback is a key element of AIED systems that focus on helping students to construct their own learning by detecting errors, solving complex problems, and embracing uncertainty. AIED systems that automate open-task-dependent adaptive feedback are known as Exploratory Learning Environments (ELEs). Compared to ITSs that are focused on more structured and linear set of tasks, ELEs are designed to accommodate open-ended tasks that are focused on the process of learning rather than the acquisition of declarative or subject content knowledge (e.g., Gutierrez-Santos et al. [96]; Mavrikis et al. [97]). There is consensus that ELEs enable formative adaptive feedback as a means to scaffold students' efforts to learn and consolidate knowledge from ill-defined tasks and open-ended activities (e.g., Grawemeyer et al. [66]; Holstein et al. [98]). Narciss et al. [99] explored factors that may influence the effectiveness of formative adaptive feedback within an ELE. Two related factors were pinpointed: (1) feedback-related characteristics (such as procedural or conceptual feedback and the level of feedback elaboration) and (2) learner-related characteristics (such as prior knowledge, gender, and motivational states). These factors were assessed with students using the ActiveMath ELE. Results revealed that feedback strategies had an impact on the number of tasks students attempted to solve and prior knowledge had a significant impact on the number of tasks students solved correctly.

Holmes et al. [100] proposed six formative feedback purposes and four feedback levels in the context of using the Fractions Lab ELE for open-ended tasks. Fractions Lab helps students in schools to learn about fractions by providing intelligent formative feedback associated to the task that the student is undertaking (e.g., task-loop or task-dependent support). The six feedback purposes ranged from understanding the problem, suggesting the next-step, and support problem solving to opportunities for higher-level work, acknowledging success, and encouraging metacognition. Levels of feedback are designed as intelligent components to address different levels of learning needs. The four levels of feedback started from Socratic (finding solutions through dialogue), guidance (reminds domain rules), didactic-conceptual (suggests a possible next step for understanding a concept), and didactic-procedural (specifies the next step that needs to be commenced for achieving the intended learning outcome). The purposes and levels of feedback are triggered by a student's response and, when a particular response is repeated, the next level of feedback is triggered. Wiese and Koedinger [101] suggested grounded feedback to help students make sense of novel scientific representations in STEM subjects. Grounded feedback may allow students to make informed decisions about the level of correct responses referred to the ELE. The assumption is that grounded feedback provided via ELEs can help students to identify correct answers intertwined to open-ended tasks. Essentially, grounded feedback supports students' self-assessment processes by offering feedback that is intrinsic to the domain and reflects students' understanding linked with an external representation. Grounded feedback representations infer data from the learner model for rendering a student's prior knowledge and from the domain model as a means of associating feedback with learning outcomes.

To further demonstrate the value of intelligent adaptive formative feedback for open-ended tasks, Basu et al. [102] developed an adaptive scaffolding framework for students to receive adaptive feedback for computational thinking. The assumption made was that in an open-ended ELE it is challenging to interpret a student's actions and, therefore, the design and provision of meaningful AI-generated feedback that improves a student's understanding is regressive. A scaffold modelling scheme was defined to mitigate this challenge by using: (1) a hierarchical task model, (2) a set of strategies that support effective learning modelling, and (3) measures that help teachers to evaluate and assess a student's proficiency in undertaking different tasks and strategies. The effectiveness of the scheme was assessed with students who received scaffolding and showed an enhanced understanding of computational thinking concepts in comparison to students who did not receive scaffolding and did not demonstrate effective modelling strategies.

3.4.5. AIED for Helping Students to Become Self-Regulated Learners

Developing as a self-regulated learner involves an interplay of autonomy, self-direction, and resilience towards achieving the intended learning outcomes. Self-regulated learning is a term used to describe students who actively control their own learning through guidance and support (Schunk and Zimmerman [103]). Self-regulated learning is, therefore, an adaptive and deliberate process in which feedback is an inherent catalyst for optimising strategic, metacognitive, and motivational components within a particular domain (Butler and Winne [104]). Self-assessment is also perceived as a self-regulatory feature that encourages students to assess progress, level of effort, and their own ways of learning in relation to personal learning goals and expectations (e.g., Hattie and Timperley [105]). An effective self-regulatory attribute that helps students to assess skills, knowledge states, and cognitive strategies is through the learning by teaching paradigm.

A widely known AIED system that manifolded possibilities for self-regulation through learning by teaching is Betty's Brain. The learning-by-teaching paradigm, perpetuated as a self-regulatory strategy in Betty's Brain, probes students to read about a science topic (river ecosystem) for developing understanding through a sharing representation (a visual map) applied to problem-solving processes. Biswas et al. [106] contemplated that this shared representation promoted a shared responsibility because the student attempts to teach Betty (AI teachable agent) and then in turn Betty learns how to respond to questions based on the student's shared representations. In essence, students are supported to teach Betty and then to query Betty as a means to test acquired knowledge. The mechanisms and models that were employed for designing Betty as a learning-by-teaching system are connected with self-regulated strategies and tasks that are used in conventional teaching and learning contexts: teaching through visual representations for organising content and structures, developing an agent that learns autonomously and independently and provides feedback on what it has been taught, and building on interactions that promote self-regulating learning activities (asking questions, monitoring of and reflecting on performance). The most recent evaluation of Betty's Brain, as reported in Biswas et al. [106], showed that students were making progress in becoming self-regulated learners, especially students characterised as engaged and efficient. Kay and Kammerfield [107] introduced a conceptual model for helping students with metacognitive processes of self-monitoring, reflection, and planning through designing learning data that provide students with control and meaning beyond data access and mechanistic predictions.

To enhance automated and intelligent self-regulated learning, Lenat and Durlach [108] developed BELLA, a learning-by-teaching system that plays the role of a tutee. BELLA is employed by school students to learn mathematics and utilises a symbolic model knowledge of the student. All tasks and learning activities are perpetuated in a game-based learning environment that incorporates different game mechanics, dynamics, and aesthetics to represent the learning process in more contextualised, engaging, and connected ways. At each task, BELLA formulates several possible choices for what the student would possibly respond to the tutee. Then BELLA decides which of these choices are best for revealing aspects of the student's mental model used for helping the student to correct a misconception of the tutee. A similar learning-by-teaching strategy in a game-based learning environment for optimising self-regulation was adopted by Matsuda et al. [109] as a means of helping school students to solve algebraic equations by teaching an intelligent peer agent, called SimStudent. The results showed that students improved proficiency in regulating their learning especially in terms of augmented regulation of subsequent cognitive engagement in solving problems and increased extrinsic (e.g., engagement in tutoring) and intrinsic (higher desire and commitment to solve equations for winning the game) motivations.

Sabourin et al. [110] investigated self-regulated learning and metacognitive behaviours in an AI-driven, game-based learning environment called Crystal Island. Goal setting and monitoring behaviours were explored through text-based responses on queries, problems, and misconceptions that students posed on an in-game social chatroom. To make explicit self-regulatory behaviour, students were prompted to reflect on learning aspects, feelings, and emotions used to classify students into low, medium, and high self-regulated learning behaviour. Machine learning models were then trained for predicting students' self-regulated learning classifications offering possibilities for interventions in terms of leveraging student's self-regulated learning behaviour during gameplay. To infer data-driven evidence on a student's self-regulated behaviour, Winne [111] proposed an open-learner model that tacitly supported students to regulate learning. Open-learner model data inform self-regulated learners about adaptations to learning processes already familiar to them by creating a symbiotic relationship with learner models to trigger deep self-regulated learning. Hou et al. [112] assessed the effects of open learner models for self-regulated learning through a game named Decimal Point. The game teaches decimal numbers and operations to school students who played two different versions of the game. The first version encouraged learning through an open learner model that made inferences on self-regulated learning strategies while the second version encouraged playing for enjoyment only. Students' interactions with the open learner model game version showed a desire to re-practice and reflect on the in-game learning process as well as an increase in test performance. Käser and Schwartz [113] explored automated and intelligent self-regulated learning from an inquiry-based learning perspective. An ELE game was employed, named TugLet, through which students had to engage in game inquiry principles such as to explore and to challenge. TugLet resembles a simulation tug-of-war game in which students configured their teams and then simulated the tug-of-war result. The results of the evaluation showed that students' inquiry strategies influenced learning outcomes and were predictive for overall learning achievement.

3.5. Mapping Experiences of Teaching to AIED Applications and Tools

Drawing on the five aspects of teaching and learning with AIED, an attempt is made to cluster each aspect of teaching and learning with associated AIED technologies and applications (see Table 5). The assumption is that teachers may feel overwhelmed with the different types of AIED tools and applications permeated to support and guide different aspects of practice. One way to mitigate this complexity is by deconstructing and organising aspects of learning with AIED applications and technologies that may support teachers to employ AIED for contextualised and situated purposes as understood by teachers. Naturally, there is a non-exhaustive list of different instances and constellations between aspects and technologies to be coupled and augmented; however, an overarching mapping and representation is offered to set the stage for teachers to gain an awareness of how AIED applications may support varied and inter-related aspects of learning and teaching.

Table 5. Representation and mapping of teaching and learning aspects with AIED applications and SAMR model.

Teaching and Learning Aspect	AIED Applications and Technologies	SAMR Model
AIED for preparing and transmitting learning content	• ITSs for content transfer • content recommender system • personalised content sequencing • personalised information retrieval	**Substitution** (AIED as a substitute with no functional change)
AIED for helping students to apply knowledge	• ITSs for problem solving • answer-based ITS • step-based ITS • substep-based ITS • pedagogical/conversational agents	**Augmentation** (AIED as a substitute with functional improvement)
AIED for engaging students to adaptive learning tasks	• task-based ITS (design-loop, task-loop, step-loop) • task-focused games • task-oriented chatbots	**Modification** (AIED for task redesign)
AIED for helping students to improve through assessment and feedback	• adaptive feedback applications for open-ended tasks • web-based intelligent feedback systems • computerised adaptive test systems • ELEs for adaptive, formative feedback	**Modification** (AIED for task redesign)
AIED for helping students to become self-regulated learners	• ELEs for self-regulated learning via learning-by-teaching • games that promote intelligent self-regulation via learning-by-teaching • open-learner applications • intelligent inquiry-based learning through games	**Redefinition** (AIED for the creation of new tasks)

A pattern is observed when the SAMR model is mapped in each teaching and learning aspect and its associated AIED application and technology. For example, in the 'AIED for preparing and transmitting content' aspect, AIED applications and technologies are mainly

ITS for content transfer, recommendations, and information retrieval. An assumption can be made in terms of employing AI for substituting conventional teaching and learning already enacted in the classroom by enabling an AI agent to provide and suggest learning content and material. This would normally be facilitated by the teacher in the classroom considering that adequate information on a student's subject content needs is available for the teacher to make informed decisions on the learning content that a student requires for acquiring the necessary subject-content knowledge. In the 'AIED for helping students to acquire knowledge' aspect, the predominant tools and application being used are ITS for problem solving and pedagogical agents that offer step and sub-step guidance and support. It may be assumed, therefore, that the AIED tool augments conventional teaching and learning with functional improvements in a sense that AIED discerns and delineates adaptation through scaffolding and guiding students via question and answers and problem-solving scenarios in a step-by-step model intelligently automated by an ITS and/or a pedagogical agent. In 'AIED for engaging students to adaptive learning tasks', a significant task modification is relayed for employing task-based ITS and chatbots with prime focus on adaptive task redesign. Similarly, in 'AIED for helping students to improve through assessment and feedback', modification processes in adaptive feedback applications with a focus on open-ended tasks and ELEs are delimited for optimising adaptive and automated formative feedback. In the last learning aspect, 'AIED for helping students to become self-regulated learners', it seems that AIED tools such as ELEs and games redefine the creation of new tasks and processes for enabling automated and intelligent self-regulated learning through shared representations, intelligent learning-by-teaching, and adaptive inquiry-based learning.

3.6. Challenges, Risks, and Implications of AIED

There is an assumption that AIED has the potential to enhance the design and orchestration of teaching and learning, especially in terms of permeating adaptive and automated subject-content provision, tailored support for knowledge application, personalised tasks, meaningful and competency-based assessment, and constructive, formative feedback (e.g., Long and Aleven [114]; Kulik and Fletcher [115]). AIED seems also to empower teachers to collect, access, and extrapolate rich data and information on students' prior knowledge, affective states, ways of learning, and possible perceived misconceptions that would assist teachers to design learning, teaching, and assessment in personalised ways. However, AIED's impact on teachers and students, as the key stakeholders of exploiting AIED, has not been fully investigated. There is an array of related risks, challenges, and implications that emanates from the use of AI in educational contexts such as ethics, privacy, fairness, and what capabilities, capacities, and skills teachers may need to acquire for enhancing teaching and learning using AIED. The varied undertakings of AI have raised ethical challenges around bias (AIED systems may be biased to student's skills and performance) and privacy. For example, there are certain concerns about students' personal data that are being stored to AIED systems, how such data are being used, and possibilities of data misuse from third parties.

There is no doubt that teachers are catalysts in the pervasive use of AI for designing, orchestrating, and sequencing teaching and learning, and, therefore, the process of helping teachers to develop competencies, skills, and capacities for using AIED is essential. More than this, teachers' conceptions of and approaches to teaching along with associated skills and dexterities should be deconstructed and employed as part of the design of AIED applications. This will pave the way towards developing a system of reciprocity between AIED technologists and teachers fused by the collective that empowers the development of AIED-based solutions inherently following an informed approach to designing AIED interventions that are based on teachers' needs and skillsets. However, there are increasing presuppositions that the augmented utilisation of AIED tools may transform the role of the teacher (e.g., Luckin et al. [18]; Dillenbourg [22]; Luckin and Cukurova [116]) mainly by taking away some of the administrative workload that would allow teachers to focus on the actual teaching and learning process. To cope with this transformation there is a need for teachers to develop their understanding and digital competencies for AIED-based teaching and learning that will endow the ability to innovate, experiment, and enact different methods of teaching, thereby increasing teachers' confidence for the effective use of AIED.

3.6.1. AIED and Ethics

While certain aspects of AIED seem to generate increased research and development attention such as an extended focus on pedagogical design and on different types of AIED-based systems, there is less contemplation on the ethical dimensions of AIED and how they may impact the design and enactment of teaching and learning through using AIED systems. (e.g., [2,117]). A straightforward meaning of ethics would entail moral principles that define an individual's behaviour or the way that a particular activity is carried out. AIED ethics raise a fundamental question of how the educational technology community including developers, designers, policy makers, and educators should act ethically for mitigating or inhibiting ethical detriments that may impact the student's learning experience through employing AI. It is widely acknowledged within the community that important ethical aspects of using AIED encompass pedagogical designs permeated in an AI system, assessment, and feedback generated by the system, principles of fairness, transparency, autonomy, and privacy. There have been attempts to develop frameworks and principles that guide the ethical use of AI to raise awareness of designing and orchestrating AIED systems. For example, one of the earliest ethical principles of using AIED systems was introduced by Aiken and Epstein [118] and focused predominantly on rudiments of design that would encourage a more ethical use of AIED. Certainly, these overarching AIED principles could be characterised as ethical dimensions underpinned by human principles corresponding to a system design that encourages student involvement and the development of positive character traits to systems that do not attempt to replace the user and respect cultural imperialism.

The ethics of AI in general have been researched extensively for developing a plethora of ethical AI principles focusing predominantly on the processes of data collection and analysis. To consolidate and provide access to the wide array of AI ethical frameworks, a digital repository of AI ethics models has been developed mapped in a global AI ethics inventory (e.g., Algorithm Watch 9 [119]) for accessing and retrieving different AI frameworks and principles that may pertain to the ethical use of AI. Floridi [120] asserted that the plethora of different AI frameworks that have been proposed over the years have created confusion and inconsistency among the AI community in terms of the complexity and intricacy of adhering to specific AI ethical situations and contexts. To assist on mitigating such convoluted ethical requirements, Jobin et al. [121] conducted a study that investigated what constitutes ethical AI surrounding principles and best practices. Five ethical principles were identified, transparency, justice and fairness, non-maleficence, responsibility, and privacy, which would entail the ethical pillars for constituting a global AI ethics' agenda. A central challenge, however, towards the development of a standardised ethical agenda for AI is a balanced consideration of cultural and social diversity. An attempt to balance technical with cultural and social ethical aspects for AI was the Montréal declaration for responsible development of artificial intelligence (Université de Montreal [122]), providing a framework for identifying ethical principles and values that serve as the foundations for concerted cultivation of social and cultural trust towards using AI systems. Ten principles were proposed embracing well-being, respect for autonomy, protection of privacy and intimacy, solidarity, democratic participation, equity, diversity and inclusion, prudence, responsibility, and sustainable development. Winfield and Jirotka [123] explored the phenomenon of ethical governance in AI and robotics as a more holistic and agile governance of AI from an institutional perspective as a means to gain public trust. Five pillars of ethical governance were proposed such as the publication of an ethical code, provision of ethics and responsible innovation training, practicing responsible innovation, transparency of ethical governance process, and valuing ethical governance.

Such ethical frameworks, policies, regulations, and declarations particularly applied to AIED have not been developed or communicated to the wider AIED community for offering a comprehensive approach to investigating ethical concerns and dimensions permeated from the pedagogical and data-driven utilisation of AI systems in education (e.g., [2]). It seems, however, that the AIED ethics' landscape is starting to materialise with UNESCO's [124] recommendations on the ethics of artificial intelligence. The recommendations pertain to attention to ethical implications of AI systems in relation to education, science, culture, communication, and information. The recommendations involve values and principles as motivating ideals for inspiring desired behaviours and actions. Essential values are grounded on respect, protection and promotion of human dignity, human rights and fundamental freedoms, diversity, and inclusiveness. Principles are driven by proportionality and to do no harm, safety and security, fairness and non-discrimination, sustainability, privacy, transparency, responsibility and accountability, awareness, and literacy. To this line, UNESCO [125] highlighted the ethical implications of AI from a societal perspective and especially challenging the role of education in employing AI-based systems. Issues such as freedom of expression, ownership of data, information misuse, and bias and trust in science have been particularly relevant to the use of AI in educational contexts.

UNICEF [126] offered a deeper reflection on ethical aspects, particularly when involving children on the use of AI embracing convergence between how AI impacts children and preparing them through creating learning environments that support the use of AI in digital teaching and learning. Although the focus is not on education per se, nine requirements for child-centred AI were proposed that could act as an onset for triggering the development of an AIED framework with a central focus on students and teachers. The nine requirements that are proposed to be incorporated with AI-based systems, policies, and strategies are supporting children's development and well-being, ensure inclusion of and for children, prioritise fairness and non-discrimination for children, protect children's data and privacy, ensure safety, provide transparency, 'explainability' and accountability, empower government and businesses with knowledge of AI and children's rights, and prepare children for present and future developments in AI and create an enabling learning environment.

The ethics of AIED are, indeed, more diverse and multidisciplinary from principles that are merely focused on data biases stemming from risk of collection, processing, and sharing of data mainly exacerbated via the use of learning analytics (Zanetti et al. [127]; Kitto and Knight [128]) and big data in the form of dataset, association, interaction, confirmation and automation bias, teacher feedback, grades, student tracking, attendance monitoring, and integrated communications captured in student profiles that may lead to discrimination, stigmatisation, and exclusion (e.g., Chou, Murillo and Ibars [129]; Berendt et al. [130]). AIED ethics' frameworks and principles would need to embroider the ethics of the learning science (e.g., [117]), incorporating ways of designing, orchestrating, and assessing AIED in pedagogically rich ways and in conjunction with teachers' and students' perceptions of and approaches to the ethical use of AIED. This may help to discern more relational and informed ethical knowledge on the assumptions and implications of making a shift towards an automated and human-centred AIED. To assist towards this direction, Holmes et al. [117] attempted to develop an AIED framework that is predominantly focused on educational ethics' considerations with daisy-chaining general AI ethics. Three overarching themes were identified: (1) algorithms and computation (data and privacy), (2) big data (learning analytics ethics), and (3) education (ethics of designing, delivering, representing, and supporting AIED teaching and learning). Debating on the necessity of more developed and decomposed ethical AIED interpretations and frameworks is critical for teachers to better understand and employ ethics as a human-centred design element to be considered when planning and enacting teaching and learning with AIED.

3.6.2. AIED and Teacher Skills

To develop awareness, competencies and skills of teaching using AIED in pedagogically rich and ethical ways, teachers would need to acquire certain digital skills and capabilities that would be central to their role as catalysts in sequencing and orchestrating AI-based teaching and learning. Luckin et al. [18] contemplated the particular skills that teachers would need to develop in terms of (1) developing awareness and understanding of the properties and features of AIED systems to enable them to make informed decisions about how to select, use, and evaluate AIED tools; (2) developing research skills to enable teachers to collect, analyse, and interpret the data provided by the system to guide students on how to develop their learning following a data-driven approach; and (3) teamwork and management skills to enable teachers to create ethical relationships with AI teaching assistants as means to complement human teaching assistants (e.g., Eicher et al. [131]). AIED does not insinuate the dominance of artificial intelligence in the classroom by constituting teachers as obsolete, but rather it reinforces and transforms the role of the teacher as the designer and decision maker in terms of making informed decisions on how AI will be leveraged to offer personalised and memorable learning experiences. As such, teachers retain their primary teaching role in managing classrooms premised on the principle that creative and leadership activities are endowed by teachers while AIED is facilitating more data-driven tasks (e.g., Pedro et al. [132]).

The practical implementation of AIED by teachers requires an increasingly detailed and sophisticated list of skills that combine design for teaching and learning including pedagogy, research, and collaboration skills. The overarching assumption to empowering teachers to develop digital competencies for designing and orchestrating AI-based teaching and learning is that it will help to optimise students' experiences of personalised learning and will pave the way for teachers to have an informed and up-to-date mechanism and planner that will assist in obtaining reliable and valid indicators for reflecting and consciously practicing approaches, tools, and processes that are most effective to their own teaching context.

The core strand of research, which is bootstrapped with AIED-related skills, is digital competency development and may be understood as an inter-connected set of skills or competencies for enabling the design and orchestration of teaching with the use of digital technology (e.g., List [133]). The purposes of acquiring digital competencies are eminent in two types of competencies: (1) for helping students to use digital technologies in the classroom and (2) for designing rich, mediated, digitally enabled learning environments (e.g., Tondeur et al. [134]). A third type of competence, complementing the two, is competencies that promote inclusive, creative, meaningful, and personalised teaching and learning that may enable tracking a student's progress through meaningful and formative feedback.

Indeed, there have been efforts to formulate digital competency frameworks with a holistic approach to highlighting a gamut of digital competencies from data and information to pedagogy, ethics, and inclusion (e.g., JISC [135]; UNESCO [136]; Law et al. [137]; Valencia-Molina et al. [138]). One of the most important digital competency frameworks is the European Union's DigiCompEdu (Redecker and Punie [139]) designed to offer a frame for teachers to identify, develop, and assess digital competencies pertinent to using digital technologies in informed, creative, collaborative, and critical ways.

DigiCompEdu presented six competency themes that encompass key subthemes such as information and media literacy, content creation, self-regulated learning, collaborative learning, assessment strategies, feedback and planning, differentiation, and personalisation among others comprising 22 competencies in total. Lameras et al. [140] discerned a set of six overarching digital competencies for helping teachers to develop capabilities in technology-enhanced teaching and learning, thereby adapting to competencies for teaching and learning with AIED (See Table 6). These AIED competencies are perceived as holistic in the sense that they do not focus only on technical skills' development but rather they offer a human-centred account to developing AIED skills encompassing pedagogy, empathy, and ethics. This alludes to the premise that digital competency development and, subsequently, AIED competency growth should not only focus on data and algorithmic and system-based skillsets but most importantly on learning science skills particularly related to a rich, mediated pedagogy, meaningful feedback, and student empowerment (e.g., [141]).

Table 6. The AIED Comp: Teachers' digital competencies of teaching and learning using AIED.

AIED Competencies' Themes and Subthemes
A: Designing, developing, and delivering digital content
A.1 Designing digital content
A.2 Developing digital content
A.3 Representing digital content
B: Acquiring data, information, and data ethics' skills
B.1 Understanding and tracking a student's progress through gathering and analysing data
B.2 Finding, accessing, using, and sharing information
B.3 Using student data ethically
C: Developing skills in employing digitally and activity-led pedagogies
C.1 Collaborative learning and collaborative problem solving
C.2 Inquiry-based and research-based learning
C.3 Activity- and digitally led assessment
C.4 Utilising multiple modes of feedback
C.5 Reflection
D: Becoming proficient in AIED applications, tools, and software
D.1 Use of AIED software and hardware for tracking, recording, and visualising progress and performance
D.2 Applying knowledge to solve simple technical problems with AIED software and hardware
D.3 Identifying, selecting, and appraising AIED software and hardware based on educational and technical requirements
D.4 Basic understanding of big data, algorithms, AI techniques (e.g., machine learning), and systems' thinking
E: Developing digital creativity skills, empathy, and a do-it-yourself culture
E.1 Ideating, brainstorming, and designing AIED-based learning activities
E.2 Personalising, sharing, and remixing AIED learning activities
E.3 Making explicit students' affective states for integrating emotions in AIED activities
E.4 Designing and creating AIED that connects digital material with physical objects
F. Fostering student digital inclusion, social responsibility, and data compliance
F.1 Embracing equal learning opportunities into the design of AIED systems
F.2 Producing digital learning resources that are unbiased, inclusive, and diversified
F.3 Designing and visualising digital learning resources that are related to students' past learning experiences, feelings, culture, and code of ethics

4. Propositions for Enacting Teaching and Learning Using AIED

From the findings of this review, several propositions are demarcated for helping teachers to understand, plan, and reflect on processes, strategies, tools, and frameworks that would facilitate the use of AI in teaching and learning. The propositions delimit aspects related to (1) proposing a meaning of AIED that may be used to develop a broader understanding of what do we mean by AIED in teaching and learning; (2) propositions of human-centred aspects that may help to design for adaptive AIED-based teaching; and (3) AIED applications and tools aligned with teaching strategies, models, and approaches. Finally, to mitigate some of the implications caused by AIED, propositions are offered to scaffold and highlight the ethics of AIED and teachers' related AIED skills that deserve more detailed attention to determine an appropriate intervention to consciously think about the ethics of AIED and the competencies teachers need as to act as catalysts in the application of AI in educational contexts.

4.1. A Meaning of AIED

- It is proposed that AIED refers to educational technology systems that teachers and institutions may employ for designing, orchestrating, and assessing adaptive teaching and learning in intelligent and automated ways tailored to student's knowledge, skills, interests, and ways of learning.

4.2. Designing for Adaptive Teaching and Learning Using AIED

- It is proposed that AIED is employed to support teachers to design and orchestrate adaptive learning content and individualised learning activities aligned to a student's knowledge levels and skills.
- It is proposed that AIED is employed to support teachers to design and orchestrate adaptive collaborative learning support that situates teachers and AI agents as collaborators in offering cognitive feedback as well as in stipulating feedback on collaboration and interaction dynamics.
- It is proposed that AIED is employed to support teachers to design emotional awareness support and to diagnose social and emotional learning for developing partners of a student's affective states.
- It is proposed that AIED is employed to support teachers to design intelligent, formative feedback focusing on the process of learning aligned to students' needs.

4.3. AIED Applications and Tools

- Employing intelligent tutoring systems for helping students to find, access, and retrieve adaptive learning content.
- Employing intelligent tutoring systems and pedagogical agents for scaffolding a student's efforts to apply knowledge.
- Employing task-oriented chatbots for engaging students in dialogues or conversation-based tasks.
- Employing conversational agents for improving dialogical processes and interaction support in synchronous collaborative learning environments.
- Employing exploratory learning environments for providing adaptive, formative feedback for helping students to learn and consolidate knowledge from open-ended tasks.
- Employing open learner applications that bootstrap learning-by-teaching with self-regulated learning for optimising autonomy, self-direction, and resilience.

4.4. AIED Ethics

- It is proposed that more focused research is needed to delineate and demarcate what constitutes ethics in AIED and what are teachers' experiences of the ethical use of AIED.
- It is proposed that an ethics-by-design approach is perpetuated into the design, production, and actual use of AIED systems for allowing cross-fertilisation and practical implementation of ethics in AIED.
- It is proposed that a comprehensive AIED ethics' framework needs to be developed pertaining to ethical concerns and dimensions from learning sciences (including pedagogy, goals, social and emotional learning, and inclusivity) and data-focused indicators driven by human-centred designs.

4.5. AIED Teacher Skills

- It is proposed that teachers would need to acquire AIED teaching-related competencies and skills (e.g., data, pedagogical, ethical, and technical skillsets) that are central to their role as catalysts in promoting and enhancing AI-based teaching and learning.
- It is proposed that teachers' skills and competencies may be guided and supported by AIED digital competency frameworks for designing, developing, implementing, and assessing a set of learning goals and outcomes to be achieved with the use of AI.
- It is proposed that a self-progression AIED competency model is employed for teachers to self-assess and reflect on existing and new competencies for AIED teaching and learning.

5. Conclusions and Future Research

An exploratory review was conducted to address the question "What do we mean by Artificial Intelligence in Education?". The process of thematic analysis and synthesis was undertaken, and then different meanings of AI were discussed along with AI practices in education to situate the study in the wider context of educational technology research. Adaptivity and personalisation are the innovation that AIED is expected to bring to the fore as means to help students to learn and develop skills that are mostly relevant to their own needs and experiences. As such, AIED is viewed as part of a broader ecology of learning that involves adaptive representations and models that describe the associated pedagogy, the subject content, and how students learn including prior learning experiences, misconceptions, and ways of learning. An AIED system or agent will then process the data from the model to infer an adapted learning activity around topics that students are interested to learn. The student is at the forefront of the personalised learning process via receiving automated guidance and support provided by the AIED system while making his/her own decisions for contextualising learning and fostering continuity and transfer. This automated design for adaptation is compounded to activity-based and process-oriented strategies such as adaptive, collaborative learning support and social and emotional learning that may be detected by AI to provide affective support.

There are indeed discrepancies and nebulous conceptualisations among teachers of how to design and orchestrate teaching and learning instances using AIED tools and applications. To alleviate much of these overwhelming design decisions that teachers need to make for embracing AIED, an ontology is proposed for mapping particular teaching and learning instances with AIED applications and technologies and how such instances may be considered either as replications of traditional teaching or as innovations and redefinitions of practice that can be invigorated via the use of AIED.

Deconstructing the ethics of AIED is key for experiencing the rapid use of AIED and for allowing a better understanding between 'doing ethical things' and 'doing things ethically' (e.g., [117]). The development of AIED ethics' frameworks that are based on actual practice of ethics in real classroom settings is key, exerting focus on data biases, on pedagogy, and on the learning science in its totality. Helping teachers to develop necessary digital competencies and skills for using AIED applications and tools in ethical and informed ways is central to enhancing the student learning experience and attainment of learning outcomes. Human-centred and learning-focused AIED competency frameworks are needed to help teachers to plan, self-assess, and reflect on existing and new skills for empowering the evolution of the teacher's role in terms of facilitating students to acquire creative mindsets, becoming empathic, and transfer learning to other contexts through learning what makes sense to them.

On reflection, inevitably research efforts need to focus on teachers' and students' experiences, understandings, and conceptualisations of how AIED is enacted in real classroom settings from a human-centred design prism. Such research endeavours will delineate rich data on how teachers and students perceive teaching and learning via using AIED and its associated impact on ethics and AIED skills' development. To demarcate further, investigations on processes, strategies, and approaches to using AIED for teaching encompassing subject-content, learning activities, feedback, and assessment as well as the impact of social and emotional adaptive learning would discern meaningful hermeneutics with regards to the role of the teacher, the role of AIED, and the role of the student in designing, representing, and enacting teaching and learning with AIED. This will, in turn, pave the way to exploit such findings for inducing rich, mediated data in the pedagogy, domain, learner, and open-learner models to render and update computational representations for optimising data processing and predictions on subject-content, effective approaches to teaching, and students' ways of learning.

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References

1. Seldon, A.; Abidoye, O. *The Fourth Education Revolution: Will Artificial Intelligence Liberate or Infantilise Humanity*; The University of Buckingham Press: Buckingham, UK, 2018.
2. Holmes, W.; Bialik, M.; Fadel, C. *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*; Center for Curriculum Redesign: Boston, MA, USA, 2019.
3. Moher, D.; Liberati, A.; Tetzlaff, J.; Altman, D.G. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *BMJ* **2009**, *339*, b2535. [CrossRef] [PubMed]
4. Tegmark, M. *Life 3.0: Being Human in the Age of Artificial Intelligence*; Allen Lane: London, UK, 2017.
5. Baker, T.; Smith, L.; Anissa, N. Educ-AI-Tion Rebooted? Nesta. 2019. Available online: https://media.nesta.org.uk/documents/Future_of_AI_and_education_v5_WEB.pdf (accessed on 18 November 2021).
6. Lui, A.; Lamb, G.W. Artificial Intelligence and Augmented Intelligence Collaboration: Regaining Trust and Confidence in the Financial Sector. *Inf. Commun. Technol. Law* **2018**, *27*, 267–283. [CrossRef]
7. Zheng, N.; Liu, Z.; Ren, P.; Ma, Y.; Chen, S.; Yu, S.; Xue, J.; Chen, B.; Wang, F. Hybrid-Augmented Intelligence: Collaboration and Cognition. *Front. Inf. Technol. Electron. Eng.* **2017**, *18*, 153–179. [CrossRef]
8. Chase, C.C.; Connolly, H.; Lamnina, M.; Aleven, V. Problematizing Helps! A Classroom Study of Computer-Based Guidance for Invention Activities. *Int. J. Artif. Intell. Educ.* **2019**, *29*, 283–316. [CrossRef]
9. Noothigattu, R.; Bouneffouf, D.; Mattei, N.; Chandra, R.; Madan, P.; Varshney, K.R.; Campbell, M.; Singh, M.; Rossi, F. Teaching AI Agents Ethical Values Using Reinforcement Learning and Policy Orchestration. *IBM J. Res. Dev.* **2019**, *63*, 2:1–2:9. [CrossRef]
10. Duan, Y.; Edwards, J.S.; Dwivedi, Y.K. Artificial Intelligence for Decision Making in the Era of Big Data—Evolution, Challenges and Research Agenda. *Int. J. Inf. Manag.* **2019**, *48*, 63–71. [CrossRef]
11. Kaplan, A.; Haenlein, M. Siri, Siri, in My Hand: Who's the Fairest in the Land? On the Interpretations, Illustrations, and Implications of Artificial Intelligence. *Bus. Horiz.* **2019**, *62*, 15–25. [CrossRef]
12. Tuomi, I.; Cabrera, M.; Vuorikari, R.; Punie, Y.; European Commission; Joint Research Centre. *The Impact of Artificial Intelligence on Learning, Teaching, and Education: Policies for the Future*; Publications Office of the European Union: Luxembourg, 2018.
13. Puentedura, R. SAMR: Moving from Enhancement to Transformation. In Proceedings of the 2013 AIS ICT Management and Leadership Conference, Canberra, Australia, 29 May 2013.
14. Zanetti, M.; Iseppi, G.; Cassese, F.P. A "Psychopathic" Artificial Intelligence: The Possible Risks of a Deviating AI in Education. *Res. Educ. Media* **2019**, *11*, 93–99. [CrossRef]
15. Dodigovic, M. Artificial Intelligence and Second Language Learning: An Efficient Approach to Error Remediation. *Lang. Aware.* **2007**, *16*, 99–113. [CrossRef]
16. Cameron, R.M. *A.I.—101: A Primer on Using Artifical Intelligence in Education*; Exceedly Press: Dubai, United Arab Emirates, 2019.
17. Popenici, S.A.D.; Kerr, S. Exploring the Impact of Artificial Intelligence on Teaching and Learning in Higher Education. *Res. Pract. Technol. Enhanc. Learn.* **2017**, *12*, 22. [CrossRef] [PubMed]
18. Luckin, R.; Holmes, W.; Griffiths, M.; Corcier, L.B.; Pearson (Firm); University College, L. Intelligence Unleashed: An Argument for AI in Education. 2016. Available online: https://discovery.ucl.ac.uk/id/eprint/1475756/ (accessed on 18 November 2021).
19. Zhou, X.; Van Brummelen, J.; Lin, P. Designing AI Learning Experiences for K-12: Emerging Works, Future Opportunities and a Design Framework. *arXiv* **2020**, arXiv:2009.10228.
20. Kukulska-Hulme, A.; Beirne, E.; Conole, G.; Costello, E.; Coughlan, T.; Ferguson, R.; FitzGerald, G.; Gaved, M.; Herodotou, C.; Holmes, W.; et al. *Innovating Pedagogy 2020: Open University Innovation Report 8*; The Open University: Milton Keynes, UK, 2020.
21. Connolly, T.M.; Boyle, E.A.; MacArthur, E.; Hainey, T.; Boyle, J.M. A Systematic Literature Review of Empirical Evidence on Computer Games and Serious Games. *Comput. Educ.* **2012**, *59*, 661–686. [CrossRef]
22. Dillenbourg, P. The Evolution of Research on Digital Education. *Int. J. Artif. Intell. Educ.* **2016**, *26*, 544–560. [CrossRef]
23. Skinner, B.F. *Are Theories of Learning Necessary*; Black Curtain Press: Auckland, New Zealand, 1954.
24. Gagné, R.M. *The Conditions of Learning and Theory of Instruction*, 4th ed.; Holt, Rinehart and Winston: New York, NY, USA, 1985.
25. Britain, S.; Liber, O. *A Framework for Pedagogical Evaluation of Virtual Learning Environments*; HAL: Lyon, France, 2012.

26. Conole, G.; Dyke, M.; Oliver, M.; Seale, J. Mapping Pedagogy and Tools for Effective Learning Design. *Comput. Educ.* **2004**, *43*, 17–33. [CrossRef]
27. Öman, A.; Sofkova Hashemi, S. Design and Redesign of a Multimodal Classroom Task—Implications for Teaching and Learning. *JITE Res.* **2015**, *14*, 139–159. [CrossRef]
28. Jewitt, C. Multimodality and Literacy in School Classrooms. *Rev. Res. Educ.* **2008**, *32*, 241–267. [CrossRef]
29. Piaget, J. *Science of Education and the Psychology of the Child*; Orion Press: New York, NY, USA, 1970.
30. Cook, J.; White, S.; Sharples, M.; Sclatter, N.; Davis, H. The Design of Learning Technologies. In *Contemporary Perspectives in e-Learning Research: Themes, Methods and Impact on Practice*; Conole, G., Oliver, M., Eds.; Routledge: Oxon, UK, 2007; pp. 55–68.
31. Vygotsky, L.S.; Cole, M. *Mind in Society: The Development of Higher Psychological Processes*; Harvard University Press: Cambridge, MA, USA, 1978.
32. Duffy, T.M.; Cunningham, D.J. Constructivism: Implications for the Design and Delivery of Instruction. In *Handbook of Research for Educational Communications and Technology*; Macmillan Library Reference USA: New York, NY, USA, 1996.
33. Barab, S.A.; Duffy, T.M. From Practice Fields to Communities of Practice. In *Theoretical Foundations of Learning Environments*; Lawrence Erlbaum Associates Publishers: Mahwah, NJ, USA, 2000; pp. 25–55.
34. Lave, J.; Wenger, E. *Situated Learning: Legitimate Peripheral Participation*; Cambridge University Press: Cambridge, UK; New York, NY, USA, 1991.
35. Gee, J.P. *What Video Games Have to Teach. Us about Learning and Literacy*, 1st ed.; Palgrave Macmillan: New York, NY, USA, 2004.
36. Lameras, P.; Papageorgiou, V. Experiences of Multimodal Teaching Through a Serious Game: Meanings, Practices and Discourses. In *Technology Supported Innovations in School Education*; Isaias, P., Sampson, D.G., Ifenthaler, D., Eds.; Cognition and Exploratory Learning in the Digital Age; Springer International Publishing: Cham, Switzerland, 2020; pp. 175–193. [CrossRef]
37. Conole, G. Describing Learning Activities: Tools and Resources to Guide Practice. In *Rethinking Pedagogy for a Digital Age: Designing and Delivering e-Learning*; Beetham, H., Sharpe, R., Eds.; Routledge: Oxon, UK, 2007; pp. 81–91.
38. Roll, I.; Wylie, R. Evolution and Revolution in Artificial Intelligence in Education. *Int. J. Artif. Intell. Educ.* **2016**, *26*, 582–599. [CrossRef]
39. Timms, M.J. Letting Artificial Intelligence in Education Out of the Box: Educational Cobots and Smart Classrooms. *Int. J. Artif. Intell. Educ.* **2016**, *26*, 701–712. [CrossRef]
40. Baker, F.S. Responding to the Challenges of Active Citizenship through the Revised UK Early Years Foundation Stage Curriculum. *Early Child. Dev. Care* **2013**, *183*, 1115–1132. [CrossRef]
41. Ellis, R.A.; Goodyear, P. *Students' Experiences of e-Learning in Higher Education: The Ecology of Sustainable Innovation*; Open and Flexible Learning Series; Routledge: New York, NY, USA, 2010.
42. Conati, C.; Kardan, S. Student Modeling: Supporting Personalized Instruction, from Problem Solving to Exploratory Open Ended Activities. *AI Mag.* **2013**, *34*, 13–26. [CrossRef]
43. Pinkwart, N. Another 25 Years of AIED? Challenges and Opportunities for Intelligent Educational Technologies of the Future. *Int. J. Artif. Intell. Educ.* **2016**, *26*, 771–783. [CrossRef]
44. Beetham, H. An Approach to Learning Activity Design. In *Rethinking Pedagogy for a Digital Age: Designing and Delivering e-Learning*; Beetham, H., Sharpe, R., Eds.; Routledge: Oxon, UK, 2007; pp. 26–40.
45. Bartolomé, A.; Castañeda, L.; Adell, J. Personalisation in Educational Technology: The Absence of Underlying Pedagogies. *Int. J. Educ. Technol. High. Educ.* **2018**, *15*, 14. [CrossRef]
46. Luckin, R.; Du Boulay, B.; Smith, H.; Underwood, J.; Fitzpatrick, G.; Holmberg, J.; Kerawalla, L.; Tunley, H.; Brewster, D.; Pearce, D. Using Mobile Technology to Create Flexible Learning Contexts. *J. Interact. Media Educ.* **2005**, *2005*. [CrossRef]
47. Rienties, B.; Køhler Simonsen, H.; Herodotou, C. Defining the Boundaries Between Artificial Intelligence in Education, Computer-Supported Collaborative Learning, Educational Data Mining, and Learning Analytics: A Need for Coherence. *Front. Educ.* **2020**, *5*, 128. [CrossRef]
48. Kowch, E.G.; Liu, J.C. Principles for Teaching, Leading, and Participatory Learning with a New Participant: AI. In Proceedings of the 2018 International Joint Conference on Information, Media and Engineering (ICIME), Osaka, Japan, 12–14 December 2018; pp. 320–325. [CrossRef]
49. Adamson, D.; Dyke, G.; Jang, H.; Rosé, C.P. Towards an Agile Approach to Adapting Dynamic Collaboration Support to Student Needs. *Int. J. Artif. Intell. Educ.* **2014**, *24*, 92–124. [CrossRef]
50. Cukurova, M.; Luckin, R.; Millán, E.; Mavrikis, M. The NISPI Framework: Analysing Collaborative Problem-Solving from Students' Physical Interactions. *Comput. Educ.* **2018**, *116*, 93–109. [CrossRef]
51. Tchounikine, P.; Rummel, N.; Mclaren, B. Computer Supported Collaborative Learning and Intelligent Tutoring Systems. In *Studies in Computational Intelligence*; Springer: Berlin/Heidelberg, Germany, 2010; Volume 308, pp. 447–463. [CrossRef]
52. Jones, C. Designing for Practice: Practicing Design in the Social Sciences. In *Rethinking Pedagogy for a Digital Age*; Beetham, H., Sharpe, R., Eds.; Routledge: Oxon, UK, 2007; pp. 166–179.
53. Casamayor, A.; Amandi, A.; Campo, M. Intelligent Assistance for Teachers in Collaborative E-Learning Environments. *Comput. Educ.* **2009**, *53*, 1147–1154. [CrossRef]
54. Walker, E.; Rummel, N.; Koedinger, K. Designing Automated Adaptive Support to Improve Student Helping Behaviors in a Peer Tutoring Activity. *Int. J. Comput.-Supported Collab. Learn.* **2011**, *6*, 279–306. [CrossRef]

55. Walker, E.; Rummel, N.; Koedinger, K. *Adaptive Support for CSCL: Is It Feedback Relevance or Increased Student Accountability That Matters?* International Society of the Learning Sciences: Hong Kong, China, 2011; Volume 1, pp. 334–341.
56. Kent, C.; Cukurova, M. Investigating Collaboration as a Process with Theory-Driven Learning Analytics. *Learn. Anal.* **2020**, *7*, 59–71. [CrossRef]
57. Kent, C.; Laslo, E.; Rafaeli, S. Interactivity in Online Discussions and Learning Outcomes. *Comput. Educ.* **2016**, *97*, 116–128. [CrossRef]
58. Dyke, G.; Adamson, D.; Howley, I.; Rose, C.P. Enhancing Scientific Reasoning and Discussion with Conversational Agents. *Learn. Technol. IEEE Trans.* **2013**, *6*, 240–247. [CrossRef]
59. Chatterjee Singh, N.; Duraiappah, A.K. *Rethinking Learning: A Review of Social and Emotional Learning Frameworks for Education Systems*; UNESCO MGIEP: New Delhi, India, 2020.
60. Donnelly, M.; Brown, C.; Batlle, I.C.; Sandoval-Hernández, A. *Social and Emotional Skills: Education Policy and Practice in the UK Home Nations*; Nesta & University of Bath: London, UK, 2020.
61. Jones, S.M.; Bouffard, S.M. Social and Emotional Learning in Schools: From Programs to Strategies and Commentaries. *Soc. Policy Rep.* **2012**, *26*, 1–33. [CrossRef]
62. Mavrikis, M.; Maciocia, A.; Lee, J. Towards Predictive Modelling of Student Affect from Web-Based Interactions. In Proceedings of the 2007 Conference on Artificial Intelligence in Education: Building Technology Rich Learning Contexts That Work; IOS Press: Amsterdam, The Netherlands, 2007; pp. 169–176.
63. D'mello, S.; Graesser, A. AutoTutor and Affective Autotutor: Learning by Talking with Cognitively and Emotionally Intelligent Computers That Talk Back. *ACM Trans. Interact. Intell. Syst.* **2013**, *2*, 1–39. [CrossRef]
64. Burleson, W.; Picard, R.W. Gender-Specific Approaches to Developing Emotionally Intelligent Learning Companions. *IEEE Intell. Syst.* **2007**, *22*, 62–69. [CrossRef]
65. Bosch, N.; D'Mello, S.K.; Baker, R.S.; Ocumpaugh, J.; Shute, V.; Ventura, M.; Wang, L.; Zhao, W. Detecting Student Emotions in Computer-Enabled Classrooms. In Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence, IJCAI'16, New York, NY, USA, 9–15 July 2016; pp. 4125–4129.
66. Grawemeyer, B.; Mavrikis, M.; Holmes, W.; Gutiérrez-Santos, S.; Wiedmann, M.; Rummel, N. Affective Learning: Improving Engagement and Enhancing Learning with Affect-Aware Feedback. *User Model. User-Adapt. Interact.* **2017**, *27*, 119–158. [CrossRef]
67. McStay, A. Emotional AI and EdTech: Serving the Public Good? *Learn. Media Technol.* **2020**, *45*, 270–283. [CrossRef]
68. Zawacki-Richter, O.; Marín, V.I.; Bond, M.; Gouverneur, F. Systematic Review of Research on Artificial Intelligence Applications in Higher Education—Where Are the Educators? *Int. J. Educ. Technol. High. Educ.* **2019**, *16*, 39. [CrossRef]
69. Laurillard, D.; Kennedy, E.; Charlton, P.; Wild, J.; Dimakopoulos, D. Using Technology to Develop Teachers as Designers of TEL: Evaluating the Learning Designer. *Br. J. Educ. Technol.* **2018**, *49*, 1044–1058. [CrossRef]
70. Conati, C.; Porayska-Pomsta, K.; Mavrikis, M. AI in Education Needs Interpretable Machine Learning: Lessons from Open Learner Modelling. *arXiv* **2018**, arXiv:1807.00154.
71. Du Boulay, B. Escape from the Skinner Box: The Case for Contemporary Intelligent Learning Environments. *Br. J. Educ. Technol.* **2019**, *50*, 2902–2919. [CrossRef]
72. Erümit, A.K.; Çetin, İ. Design Framework of Adaptive Intelligent Tutoring Systems. *Educ. Inf. Technol.* **2020**, *25*, 4477–4500. [CrossRef]
73. Baylari, A.; Montazer, G.A. Design a Personalized E-Learning System Based on Item Response Theory and Artificial Neural Network Approach. *Expert Syst. Appl.* **2009**, *36*, 8013–8021. [CrossRef]
74. Chen, C.-M.; Liu, C.-Y.; Chang, M.-H. Personalized Curriculum Sequencing Utilizing Modified Item Response Theory for Web-Based Instruction. *Expert Syst. Appl.* **2006**, *30*, 378–396. [CrossRef]
75. Thalmann, S. Adaptation Criteria for the Personalised Delivery of Learning Materials: A Multi-Stage Empirical Investigation. *Australas. J. Educ. Technol.* **2014**, *30*. [CrossRef]
76. Steichen, B.; Ashman, H.; Wade, V. A Comparative Survey of Personalised Information Retrieval and Adaptive Hypermedia Techniques. *Inf. Process. Manag.* **2012**, *48*, 698–724. [CrossRef]
77. Du Boulay, B. Artificial Intelligence as an Effective Classroom Assistant. *IEEE Intell. Syst.* **2016**, *31*, 76–81. [CrossRef]
78. VanLehn, K. The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems. *Educ. Psychol.* **2011**, *46*, 197–221. [CrossRef]
79. Ma, W.; Adesope, O.O.; Nesbit, J.C.; Liu, Q. Intelligent Tutoring Systems and Learning Outcomes: A Meta-Analysis. *J. Educ. Psychol.* **2014**, *106*, 901–918. [CrossRef]
80. Richards, D.; Dignum, V. Supporting and Challenging Learners through Pedagogical Agents: Addressing Ethical Issues through Designing for Values. *Br. J. Educ. Technol.* **2019**, *50*, 2885–2901. [CrossRef]
81. Veletsianos, G.; Miller, C. Conversing with Pedagogical Agents: A Phenomenological Exploration of Interacting with Digital Entities. *Br. J. Educ. Technol.* **2008**, *39*, 969–986. [CrossRef]
82. Schroeder, N.L.; Adesope, O.O.; Gilbert, R.B. How Effective Are Pedagogical Agents for Learning? A Meta-Analytic Review. *J. Educ. Comput. Res.* **2013**, *49*, 1–39. [CrossRef]
83. Kim, J.; Jr, K.M.; Xu, K.; Sellnow, D.D. My Teacher Is a Machine: Understanding Students' Perceptions of AI Teaching Assistants in Online Education. *Int. J. Hum.-Comput. Interact.* **2020**, *36*, 1902–1911. [CrossRef]

84. Aleven, V.; McLaughlin, E.A.; Glenn, R.A.; Koedinger, K.R. Instruction Based on Adaptive Learning Technologies. In *Handbook of Research on Learning and Instruction*; Mayer, R.E., Alexander, P., Eds.; Routledge Handbooks Online: New York, NY, USA, 2016; pp. 522–560. [CrossRef]
85. Pareto, L. A Teachable Agent Game Engaging Primary School Children to Learn Arithmetic Concepts and Reasoning. *Int. J. Artif. Intell. Educ.* **2014**, *24*, 251–283. [CrossRef]
86. Pérez, J.Q.; Daradoumis, T.; Puig, J.M.M. Rediscovering the Use of Chatbots in Education: A Systematic Literature Review. *Comput. Appl. Eng. Educ.* **2020**, *28*, 1549–1565. [CrossRef]
87. Kukulska-Hulme, A.; Bossu, C.; Coughlan, T.; Ferguson, R.; FitzGerald, E.; Gaved, M.; Herodotou, C.; Rienties, B.; Sargent, J.; Scanlon, E.; et al. *Innovating Pedagogy 2021: Open University Innovation Report 9*; The Open University: Milton Keynes, UK, 2021.
88. Katchapakirin, K.; Anutariya, C. An Architectural Design of ScratchThAI: A Conversational Agent for Computational Thinking Development Using Scratch. In Proceedings of the 10th International Conference on Advances in Information Technology (IAIT 2018), Bangkok, Thailand, 10–13 December 2018; Association for Computing Machinery: New York, NY, USA, 2018; pp. 1–7. [CrossRef]
89. Ruan, S.; Willis, A.; Xu, Q.; Davis, G.M.; Jiang, L.; Brunskill, E.; Landay, J.A. BookBuddy: Turning Digital Materials Into Interactive Foreign Language Lessons Through a Voice Chatbot. In Proceedings of the Sixth (2019) ACM Conference on Learning @ Scale, L@S'19, Chicago, IL, USA, 24–25 June 2019; Association for Computing Machinery: New York, NY, USA, 2019; pp. 1–4. [CrossRef]
90. Smutny, P.; Schreiberova, P. Chatbots for Learning: A Review of Educational Chatbots for the Facebook Messenger. *Comput. Educ.* **2020**, *151*, 103862. [CrossRef]
91. Neto, A.J.M.; Fernandes, M.A. Chatbot and Conversational Analysis to Promote Collaborative Learning in Distance Education. In Proceedings of the 2019 IEEE 19th International Conference on Advanced Learning Technologies (ICALT), Maceió, Brazil, 15–18 July 2019; Volume 2161, pp. 324–326. [CrossRef]
92. Grivokostopoulou, F.; Perikos, I.; Hatzilygeroudis, I. An Educational System for Learning Search Algorithms and Automatically Assessing Student Performance. *Int. J. Artif. Intell. Educ.* **2017**, *27*, 207–240. [CrossRef]
93. Barker, T. An Automated Feedback System Based on Adaptive Testing: Extending the Model. *Int. J. Emerg. Technol. Learn. (IJET)* **2010**, *5*, 11–14. [CrossRef]
94. Whitelock, D.; Van Labeke, N.; Field, D.; Pulman, S.; Richardson, J. *OpenEssayist: An Automated Feedback System That Supports University Students as They Write Summative Essays*; The Arab Open University: Kuwait City, Kuwait, 2013.
95. Goldin, I.; Narciss, S.; Foltz, P.; Bauer, M. New Directions in Formative Feedback in Interactive Learning Environments. *Int. J. Artif. Intell. Educ.* **2017**, *27*, 385–392. [CrossRef]
96. Gutierrez-Santos, S.; Mavrikis, M.; Magoulas, G.D. A Separation of Concerns for Engineering Intelligent Support for Exploratory Learning Environments. *J. Res. Pract. Inf. Technol.* **2012**, *44*, 347.
97. Mavrikis, M.; Geraniou, E.; Santos, S.G.; Poulovassilis, A. Intelligent Analysis and Data Visualisation for Teacher Assistance Tools: The Case of Exploratory Learning. *Br. J. Educ. Technol.* **2019**, *50*, 2920–2942. [CrossRef]
98. Holstein, K.; McLaren, B.M.; Aleven, V. Student Learning Benefits of a Mixed-Reality Teacher Awareness Tool in AI-Enhanced Classrooms. In *Artificial Intelligence in Education*; Penstein Rosé, C., Martínez-Maldonado, R., Hoppe, H.U., Luckin, R., Mavrikis, M., Porayska-Pomsta, K., McLaren, B., du Boulay, B., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2018; pp. 154–168. [CrossRef]
99. Narciss, S.; Sosnovsky, S.; Schnaubert, L.; Andrès, E.; Eichelmann, A.; Goguadze, G.; Melis, E. Exploring Feedback and Student Characteristics Relevant for Personalizing Feedback Strategies. *Comput. Educ.* **2014**, *71*, 56–76. [CrossRef]
100. Holmes, W.; Mavrikis, M.; Hansen, A.; Grawemeyer, B. Purpose and Level of Feedback in an Exploratory Learning Environment for Fractions. In *Artificial Intelligence in Education*; Conati, C., Heffernan, N., Mitrovic, A., Verdejo, M.F., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2015; pp. 620–623. [CrossRef]
101. Wiese, E.S.; Koedinger, K.R. Designing Grounded Feedback: Criteria for Using Linked Representations to Support Learning of Abstract Symbols. *Int. J. Artif. Intell. Educ.* **2017**, *27*, 448–474. [CrossRef]
102. Basu, S.; Biswas, G.; Kinnebrew, J.S. Learner Modeling for Adaptive Scaffolding in a Computational Thinking-Based Science Learning Environment. *User Model. User-Adapt. Interact.* **2017**, *27*, 5–53. [CrossRef]
103. Schunk, D.H.; Zimmerman, B.J. Self-Regulation and Learning. In *Handbook of Psychology*; American Cancer Society: Atlanta, GA, USA, 2003; pp. 59–78. [CrossRef]
104. Butler, D.L.; Winne, P.H. Feedback and Self-Regulated Learning: A Theoretical Synthesis. *Rev. Educ. Res.* **1995**, *65*, 245–281. [CrossRef]
105. Hattie, J.; Timperley, H. The Power of Feedback. *Rev. Educ. Res.* **2016**, *77*, 81–112. [CrossRef]
106. Biswas, G.; Segedy, J.R.; Bunchongchit, K. From Design to Implementation to Practice a Learning by Teaching System: Betty's Brain. *Int. J. Artif. Intell. Educ.* **2016**, *26*, 350–364. [CrossRef]
107. Kay, J.; Kummerfeld, B. From Data to Personal User Models for Life-Long, Life-Wide Learners. *Br. J. Educ. Technol.* **2019**, *50*, 2871–2884. [CrossRef]
108. Lenat, D.B.; Durlach, P.J. Reinforcing Math Knowledge by Immersing Students in a Simulated Learning-By-Teaching Experience. *Int. J. Artif. Intell. Educ.* **2014**, *24*, 216–250. [CrossRef]
109. Matsuda, N.; Yarzebinski, E.; Keiser, V.; Raizada, R.; Stylianides, G.J.; Koedinger, K.R. Studying the Effect of a Competitive Game Show in a Learning by Teaching Environment. *Int. J. Artif. Intell. Educ.* **2013**, *23*, 1–21. [CrossRef]

110. Sabourin, J.L.; Shores, L.R.; Mott, B.W.; Lester, J.C. Understanding and Predicting Student Self-Regulated Learning Strategies in Game-Based Learning Environments. *Int. J. Artif. Intell. Educ.* **2013**, *23*, 94–114. [CrossRef]
111. Winne, P.H. Open Learner Models Working in Symbiosis With Self-Regulating Learners: A Research Agenda. *Int. J. Artif. Intell. Educ.* **2020**, *31*, 446–459. [CrossRef]
112. Hou, X.; Nguyen, H.A.; Richey, J.E.; Harpstead, E.; Hammer, J.; McLaren, B.M. Assessing the Effects of Open Models of Learning and Enjoyment in a Digital Learning Game. *Int. J. Artif. Intell. Educ.* **2021**, 1–31. [CrossRef]
113. Käser, T.; Schwartz, D.L. Modeling and Analyzing Inquiry Strategies in Open-Ended Learning Environments. *Int. J. Artif. Intell. Educ.* **2020**, *30*, 504–535. [CrossRef]
114. Long, Y.; Aleven, V. Enhancing Learning Outcomes through Self-Regulated Learning Support with an Open Learner Model. *User Model. User-Adapt. Interact.* **2017**, *27*, 55–88. [CrossRef]
115. Kulik, J.A.; Fletcher, J.D. Effectiveness of Intelligent Tutoring Systems: A Meta-Analytic Review. *Rev. Educ. Res.* **2016**, *86*, 42–78. [CrossRef]
116. Luckin, R.; Cukurova, M. Designing Educational Technologies in the Age of AI: A Learning Sciences-Driven Approach. *Br. J. Educ. Technol.* **2019**, *50*, 2824–2838. [CrossRef]
117. Holmes, W.; Porayska-Pomsta, K.; Holstein, K.; Sutherland, E.; Baker, T.; Shum, S.B.; Santos, O.C.; Rodrigo, M.T.; Cukurova, M.; Bittencourt, I.I.; et al. Ethics of AI in Education: Towards a Community-Wide Framework. *Int. J. Artif. Intell. Educ.* **2021**, 1–23. [CrossRef]
118. Aiken, R.; Epstein, R. Ethical Guidelines for AI in Education: Starting a Conversation. *Int. J. Artif. Intell. Educ.* **2000**, *11*, 163–176.
119. Algorithm Watch. The AI Ethics Guidelines Global Inventory. Available online: https://algorithmwatch.org/en/ai-ethics-guidelines-global-inventory/ (accessed on 23 April 2021).
120. Floridi, L. Translating Principles into Practices of Digital Ethics: Five Risks of Being Unethical. *Philos. Technol.* **2019**, *32*, 185–193. [CrossRef]
121. Jobin, A.; Ienca, M.; Vayena, E. The Global Landscape of AI Ethics Guidelines. *Nat. Mach. Intell.* **2019**, *1*, 389–399. [CrossRef]
122. Université de Montréal. *Montréal Declaration for the Responsible Development of AI*; Université de Montréal: Montreal, QC, Canada, 2018.
123. Winfield, A.F.T.; Jirotka, M. Ethical Governance Is Essential to Building Trust in Robotics and Artificial Intelligence Systems. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* **2018**, *376*, 20180085. [CrossRef]
124. UNESCO. *First Draft of the Recommendation on the Ethics of Artificial Intelligence*; The United Nations Educational, Scientific and Cultural Organization: London, UK, 2020.
125. UNESCO. *Preliminary Study on the Ethics of Artificial Intelligence*; The United Nations Educational, Scientific and Cultural Organization: London, UK, 2019.
126. UNICEF. *Policy Guidance on AI for Children*; The United Nations Educational, Scientific and Cultural Organization: London, UK, 2020.
127. Zanetti, M.; Rendina, S.; Piceci, L.; Peluso Cassese, F. Potential Risks of Artificial Intelligence in Education. *Form@ re-Open Journal per la Formazione in Rete* **2020**, *20*, 368–378. [CrossRef]
128. Kitto, K.; Knight, S. Practical Ethics for Building Learning Analytics. *Br. J. Educ. Technol.* **2019**, *50*, 2855–2870. [CrossRef]
129. Chou, J.; Murillo, O.; Ibars, R. How to Recognize Exclusion in AI. Available online: https://medium.com/microsoft-design/how-to-recognize-exclusion-in-ai-ec2d6d89f850 (accessed on 21 September 2020).
130. Berendt, B.; Littlejohn, A.; Kern, P.; Mitros, P.; Shacklock, X.; Blakemore, M. *Big Data for Monitoring Educational Systems*; Publications Office of the European Union: Luxembourg, 2017.
131. Eicher, B.; Polepeddi, L.; Goel, A. Jill Watson Doesn't Care If You're Pregnant: Grounding AI Ethics in Empirical Studies. In Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society, AIES'18, Orleans, LA, USA, 2–3 February 2018; Association for Computing Machinery: New York, NY, USA, 2018; pp. 88–94. [CrossRef]
132. Pedro, F.; Subosa, M.; Rivas, A.; Valverde, P. *Artificial Intelligence in Education: Challenges and Opportunities for Sustainable Development*; Ministerio de Educación: Lima, Peru, 2019.
133. List, A. Defining Digital Literacy Development: An Examination of Pre-Service Teachers' Beliefs. *Comput. Educ.* **2019**, *138*, 146–158. [CrossRef]
134. Tondeur, J.; Aesaert, K.; Prestridge, S.; Consuegra, E. A Multilevel Analysis of What Matters in the Training of Pre-Service Teacher's ICT Competencies. *Comput. Educ.* **2018**, *122*, 32–42. [CrossRef]
135. JISC. *Building Digital Capabilities: The Six Elements Defined*; JISC: Bristol, UK, 2017.
136. UNESCO. *ICT Competency Framework for Teachers*; The United Nations Educational, Scientific and Cultural Organization: London, UK, 2011.
137. Law, N.; Woo, D.; de la Torre, J.; Wong, G. *A Global Framework of Reference on Digital Literacy Skills for Indicator 4.4.2*; UNESCO-UIS: Quebec, QC, Canada, 2018; pp. 3–142.
138. Valencia-Molina, T.; Serna-Collazos, A.; Ochoa-Angrino, S.; Caicedo-Tamayo, A.M.; Montes-González, J.A.; Chávez-Vescance, J.D. *ICT Standards and Competencies from the Pedagogical Dimension: A Perspective from Levels of ICT Adoption in Teachers' Education Practice*; Pontificia Universidad Javeriana and UNESCO: Bogota, Colombia, 2016; pp. 7–30.
139. Redecker, C.; Punie, Y. *European Framework for the Digital Competence of Educators: DigCompEdu*; Publications Office of the European Union: Luxembourg, 2017.

140. Lameras, P.; Moumoutzis, N. Towards the Development of a Digital Competency Framework for Digital Teaching and Learning. In Proceedings of the 2021 IEEE Global Engineering Education Conference (EDUCON), Tunis, Tunisia, 28–31 March 2022; IEEE Education Society: Vienna, Austria, 2021.
141. Laurillard, D. *Rethinking University Teaching: A Conversational Framework for the Effective Use of Learning Technologies*, 2nd ed.; Routledge: London, UK; New York, NY, USA, 2001.