A Vision of Teaching and Learning with AI

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***Abstract*— Rapid development of AI technologies with breakthroughs in algorithmic machine learning and autonomous decision making have generated unprecedented opportunities for technological innovation. There is consensus from policy report that in the next years AI could revolutionise the way teaching and learning is designed and delivered to students leading to seamless intelligent services that are more tailored to student's needs and interests. Current impetus on AI-based research in education has mainly focused on a knowledge-based approach inherently prevalent in Intelligent Tutoring Systems employed in specific domains. The aim of this paper is to proliferate a compendious framework that classifies teaching practice with a spectrum of AIED applications and tools. The framework acts as a point of departure for teachers that envisage to use AI for enhancing the way learning and teaching is manifested. It may also serve as a blueprint for AIED developers to design AIED systems that focus on specific teaching and learning instances.**

Keywords—artificial intelligence in education, AIED applications and tools, teaching models, Intelligent Tutoring Systems, teachers, adaptive teaching

I. Introduction

This paper presents evidence on the impact of Artificial Intelligence in Education (AIED). It contemplates on AIED applications and tools and attempts to develop a taxonomy of different teaching strategies and models with associated AIED-based systems. It is essential to develop a granularised instantiation of what AIED systems teachers may use for supporting specific instances of teaching and learning.

Embroiling AI-based systems for teaching and learning is still an undefined and mysterious process for teachers because there seems to be unfamiliarity and inexperience of how AIED could be utilised for enhancing the student's learning experience. In fact, Seldon and Abidoye [1] argue that AI in education has not been explored extensively. However, there is evidence (e.g. [2], [3], [4]) that AI already impacts education not only from a techno-pedagogical perspective but also from social, cultural, and ethical stances. Despite the slow uptake, school are gradually starting to use AI-based systems as part of a wider digital education policy typically realised through intelligent tutoring systems, pedagogical agents, chatbots, virtual assistants, as means to automate, to a certain extent the administrative side of the education process but also to enhance the learning experience. The promise of AIED is that it can enhance the way students learn through creating personalised learning instances to students. To achieve this, AIED would be ideally positioned to provide data-driven inferences for helping teachers understand student's prior experiences, misconceptions, ways of learning and emotional states as to design learning experiences that is tailored to them.

The paper starts by perpetuating on different meanings, understandings, and conceptualisations of AI as to set the context of the discussion. It then highlights the innovative aspect that AIED brings to the fore, especially in relation to the 'adaptive learning' element that makes AI inherently distinctive over other educational technology systems. Particularly interesting aspects of adaptive learning and teaching is in line with how learning and teaching may be designed and planned to provide personalised ways of learning. The paper then offers a conceptual framework for helping learning designers, teachers, and educators to better understand how different AIED technologies may be used based on practice. Some pertinent challenges, risks and implications are then discussed surrounding the use of AIED in education.

II. Understandings of AI

There are different meanings, understandings and conceptualisations of AI all of which have a common starting point that view AI as 'non-biological intelligence' [5]. The ability to accomplish complex goals through activities and tasks emulated by humans as the sine qua non principle that defines AI. Assimilating and accommodating data, understanding information, applying concepts to solve complex problems, and critically evaluating ideas were perceived by commentators as aspects of intelligence that could be characterised as multiple intelligences (e.g., [5] [6]). Other meanings of AI include digitally controlled mechanical processes by human-centred machines which perform objectives based on how they understand their environment. By calculating logical statements, the focus is placed on the capability of the machine to compute facts and linear data as means to make data-driven inferences. To shift the focus on a human-computer collaboration for making inferences and predictions for a specific computational outcome, [7] coined the term augmented intelligence to signify a fusion of intelligence connecting the human brain with the artificial brain. The term AI is used to refer to computer systems that use data and information in intelligent ways for achieving complex goals. The term AI was envisaged by John McCarthy at Dartmouth College in US to describe how computers could potentially make their own decisions based on data and information that could be processed and analysed by them. To understand machine intelligence especially in terms of its differences with human intelligence, the Turing Test was developed by Alan Turing for responding to the question 'Can Machines Think?" The goal was the understanding of any differences between messages typed by a human and a machine. If no difference in the messages was noticed, then the machine passes the test. Since then, AI has grown rapidly as means to 'solve intelligence' with research centres using machine learning models for finding similarities and patterns out of large amounts of data for solving complex problems. The key question that researchers aim to address is: 'how AI may be utilised to help humans to achieve goals that were inconceivable and will eventually contribute to an enriched social, cultural, and educational life?'

III. AI in Education

Gaining a basic awareness of AI would provide the basis for articulating the integration of AI in teaching and learning.

The research area that investigates the design and implementation of AIED may be placed under the umbrella of a wider research strand that explores the use of educational technology for improving teaching and learning. Luckin et al. [8] argued that the goal of AIED is to make explicit educational models, strategies, processes, and knowledge to computational representations that can be interpreted from intelligent systems as means to make predictions on 'what' and 'how' students learn. This indicates that research, development and employment of AIED should not only be manifested from a technical and data-driven perspective, but it should be manifolded towards more huma-centred design elements including models, processes, frameworks and contexts that would entail the most essential features to understand how AIED may be employed in different learning scenarios and educational settings (e.g. [9], [10]). The fast-approaching uprising of AI is underway and there is agreement that AIED may provide viable solutions to enhancing learning and teaching especially in terms of identifying skills and competencies as well as misconceptions that students have which deters them to increase their knowledge and understandings

The introduction of 21st century skills underlined the importance of social-based and 'soft' competencies and skills that students would need to learn such as creativity, collaboration, leadership, problem solving and critical thinking. AIED could provide a leap in learning innovation by helping students to develop 21st century skills through personalising the learning experience towards specific needs and interests (e.g., [11]; [12]). Consequently, there may be an assumption that AIED systems could be underpinned by sound pedagogical principles that would allow for an automated and adapted support based on students specific needs. A starting point to contemplate on how AIED could help students to amplify knowledge and skills could be through conceptualising a set of questions around: 'What skills and knowledge is mostly relevant to a particular student?' 'How such skills and knowledge will be collected, analysed, and represented from AI?' Answers to these questions underpin what constitutes adaptive learning [13] and how AI will realise this adaptivity through collecting, analysing, and predicting student learning behaviour. In this sense, AIED systems may be designed from a student-centred perspective where the student is at the centre of the learning process and can determine how learning could be designed around past learning experiences, contextual differences, misconceptions and learning expectations. This could potentially lead to a better appreciation of how individual students learn and then providing directions on what do they need to do in order to adjust current learning mechanisms that would lead to a renewed model of learning. This would be the ultimate offering of AIED in terms of analysing a student's learning situation and then providing alternative instances of learning support through learning how a student learns. This would entail the collection and analysis of data for delineating how a student learns as means of recommending rich-pedagogical instances and subject content that would be well-suited for a particular student. The analysis of a student's profile would entail data and inferences from past learning as well as from present learning events for the AIED system to have a complete and coherent set of data that would help the system to make tailored interventions of how this learning should be designed as to be deemed personalised and meaningful for the student.

IV. Adaptivity and AIED

To propagate an assumption that an AI system could potentially guide and support students to learn in ways that make sense to them, then the AIED data provider, whether it is a teacher or an instructional designer, need to devise a model that will support the design of learning activities based on student's ways of learning, the context of learning and the pedagogical interventions that are going to be enacted by the AIED system. These learning activities could be aimed for creating interactions between peers and between the teacher and thereby capturing the processes of learning, the feedback received and the learning outcomes by the student. There are a plethora of instances that this could be instantiated as for example, having an AI-based agent suggesting subject content for the student to access and then initiating questions to see how the student comprehended the content. Then the AI could adjust and tailor the content provided to the student by analysing and inferring student responses to subject material that would be more closely aligned to students needs. A new iteration of subject content provision could then be provided by the AI with more relevant nuances as to meet in more accurate ways the student's needs and performance [14]. However, to be able to develop this level of adaptation and personalisation, associated models, such as the learner and the pedagogical, often found in Intelligent Tutoring Systems, would need to represent students subject-focus cognitive knowledge; understandings of learning context; learning instantiations in previous learning settings and emotional skills that will aid in the conceptualisation and use of AIED tools [15].

Designing for personalised and adaptive ways of learning and teaching with AIED could be instantiated in different ways with the most notable ones being (a) adaptive collaborative learning support and (b) learning through conversation and social and emotional learning

A. Adaptive Collaborative Learning

Computer Supported Collaborative Learning (CSCL) is perceived as an associated research field of AIED (e.g., [16]; [17]). CSCL places emphasis on student's learning by employing collaborative processes for solving learning problems (e.g., [18]) and how these problems are solved collaboratively through using technology. [19] supported that collaboration through technology can be initiated through micro-scripts that provide structure and sequence in the way that collaborative interactions are manifested. A CSCL script is an outline that describes the learning activities, tasks, objectives and learning goals along with instruction of how students will collaborate in solving the exercises and the coursework. Essentially it provides the tools, processes, and methods that student will deploy for realising collaborative activities. It also outlines the roles, dynamics and scaffolding mechanisms that will define the collaborative endeavours practiced by the students. This is particularly relevant for AIED research as it investigates the dynamic relationships that occur not only from an interface design perspective but most importantly from an interaction design angle (e.g., [20]). This assists the AI algorithm to make the interactions of collaboration more meaningful by analysing the nature of the interactions made and how such interactions would suit to a particular learning instance. This differentiation between actual learning and interactions of collaboration may lead to more insightful inferences of how students develop and nurture interactions with peers and teachers impact learning and performance. It would be key therefore to design CSCL activities with scripting elements for pinpointing interactive learner support with personalised learning processes offered by the AIED system. It could also track and recognise the traits of high-skilled students with associated interaction levels and low-skilled students with different interaction traits as to differentiate aspects of interactivity that high-skilled students adopt with aspects of interactivity that low-skilled students adopt and then attempt to adapt interactivity support included in the micro-scripts for alleviating performance difficulties often observed in groups that involve students with mixed skills and performances.

B. AIED for Adaptive Conversations and Social and Emotional Learning

Communities of practice is a significant aspect of situated and collaborative learning, and it begins by constructing knowledge and experiences in participatory way with people that share common interests and aspirations [21]. For example, students develop their understanding on a particular topic through externalising their knowledge and experiences for the community to approve, refine or extend initial knowledge and conceptualisations. This shared process of creating meaning with the community of practice facilitates students to streamline misconceptions from the community and have more structured and situated examples of the problem in question. However, the contribution levels and the nuances that resulted to a clearer interpretation of the problem, especially from online community learning, is challenging to contemplate. [22] carried out a study for investigating interactivity as something that can be learned and learning outcomes. The authors proposed an approach to measure interactivity in terms of coupling it with intended learning outcomes through an intelligent analytics approach. [17] complemented the importance of perceiving interactivity as something that can be learned through developing an AI agent that could identify ineteraction processes between students and coupling them with learnng goals. These agents are called conversational agents and provide gudance and support to students dynamically though real time analysis of the interactions that are taking place in the online environment thus providing continious support of the interaction levels noticed in online discussions and students comprehension of the scripting mechanism [23]. The results revealed that students are systematically aware of their inetaction levels woth the rest of group and thereby they can adjust their interaction strategy for imroving learning outcomes.

Research innovation in adaptive support through AI agents can indeed optimise interactions in online learning communities. However, there are certain variables that may influence how such interactions in online communities are created and sustained. Emotions, empathy and affection can influence both the quantity and the quality of learning. For example content accomodation and assimilation may be more effetive when the student is feeling positive and persevere. On a similar note, the processes of learning that a student employs may be more developmental when a studen feels more empathic and more asisistive in helping others to learn in more collaboritive manners. To this end, Social and Emotional Learning (SEL) is conceived as the way students develop emotions, feelings and empathy as to create and manage a constrictive learning experience [24].

Student-centred and activity-based learning are the vehicles for facilating students to develop positive nehaviours and attitues towards learning. Forming connections that are underpinned from an emotional and social system can indeed foster increased learning outcomes and boosted student perfomance. [25] argued that SEL can be identified and nurtured by students gradually as they gain experience of the learning process and as they become familiarised with the context, the actors and the technologies that they have in place for instigating learning. In order for students to build on their SEL capacity they need to develop skills such as reoasning and problem solving, managing feelings and becoming emotionally aware and leadership skills for learning to make decisions that are informed by evidence and emotions.

By perceiving SEL as a set of skills and capalities, [24] coined the term Social and Emotional Competence (SEC) with two dimensions covering inteprersonal and intrapersonal constiuents with certain properties. For example, intrapersonal are atributes, capacities and capabilities that are concern personal development such as making efforts to learn how to control feelings and attitudes or how to manage behaviour in challenging circumstances. Interpersonal are more directed towards delveoping capacities to improve relsationships with others such as having increaed negotation skills for passing meanings in more effective ways or the ability to explain and reflect on meanings for people to grasp ideas in more nuanced and clear ways. Indeed SEL can have multiple practices and contexts ranging from skills and capacities to interventions that are used most likely to resolve conflicts and arguments [26]. In the context of AI, a conversational agent may be used to reinforce students affective states for developing patterns that categorise different emotional states of students [e.g. 27]. Intelligent systems that can detect and leverage students affective states have neen reported in the literature through controlled expetiments that showed content knowledge can be increased on more calm students. Another example is an affective agent that provided emotional support to students [29]. Sensors were used to collect data on emotions which where then visualised on a display which showed that students skills on devleoping emotions have increased.

Machine learning, computer vision and learning analytics have been deployed as techniques by researchers to detect students' emotional and affective levels associated with concentration, boredom, confusion and engagament predominatly acting as metrics in a classification system. Student distractions were prevalent in noisy classrom environments where the detection of affection could be compate and consolidated into classification system [30]. A formative support system was designed that contained data and information about the different emotional states that students exerted during a lesson [31]. Another study showed that emotional awareness scaffolds are key for helping students to changing negative affective states to emotions that are positive and optimistic as means to increase learning and engagement. The methods of feedback being employed had a positive influence on the negative affective state as oposed to modifying the feedback element which was an area of research on previous studies. Implications of enacting emotional processes with AI highlighted concerns of quality and the relationship between well-being and emotional change [32]. More research needs to be conducted in ternms of how neural networks may be trained for making granuralised inferences on affection, emotion and empathy.

V. Tools and applications for AIED teaching and learning

Research activity around the use of AI for learning and teaching has been carried out for more than thirty years [4]. The predominant challenge however that AI researchers are working to solve is how AI could be used to identify and couple cognition with student needs and learning outcomes (e.g., [33]. AIED applications can be divided into three categories for capturing the way students learn. The first is learner-facing, the second is teacher-facing and the third is system-facing [6]. The learner-facing tools are in line with assisting students to learn through optimising learning activities, feedback, learning outcomes and assessment. Learner-facing tools can range from virtual learning environments to chatbots, pedagogical agents and Intelligent Tutoring Systems (ITS). On the other hand, teacher-facing tools are pertinent to teachers in terms of supporting learning design processes and finetuning how activities, topics and subjects are sequenced and orchestrated. In parallel, teacher-facing tools can provide data, metrics, and evidence on how students learn and make predictions on performance levels (e.g., [34]). System-facing tools are focused more on administrative processes for helping institutions and teachers to monitor and manage quality assurance.

To enable AIED systems to make meaningful inferences of how students learn, they need data wrapped in models. Such models are called computational representations that capture how teaching and learning is permeated in conventional and online classroom settings. A pedagogical model is a representation that captures all the strategies, frameworks and strategies employed in a particular instance for enacting learning and teaching. For example, how to formulate evidence or how to acquire information or any collaborative processes can be part of the pedagogical model. The learner model is a representation contains information of the student. For example, data on prior learning experiences, ways of learning, misconceptions, progression models and learning advantages. The domain knowledge representation stores the subject-content elements in terms of the processes being used to assimilate content. For example, how the Foucault Pendulum is working or what are the calculation steps for equations. There is also another representation – the open learner model (e.g., [35]) that attempt to provide visual scaffolds of the predictions of the AIED system by using the data stored to the pedagogy, learner, and domain models. The inferences generated from the open learner model are viewed via a user interface embedded in the AIED system and can contain visual outputs concomitant to teacher's roles and to student's roles. In essence all the representation models can be used to help teachers and students to gain an informed understanding of the teaching and learning journey and the goals or outcomes that have been achieved. By having an interface like this, alignment of teaching strategies and learning needs of students may be achieved by comparing, contrasting, and modifying elements, practices, and strategies.

AIED applications can certainly incorporate the pedagogy, domain, learner and open learner models widely but more systematically as to combine and chain the data gained from each model for optimising the learning experience of the student in terms of 'how' it being experienced, they strategies students employ and why they are employed (i.e. centrality). To comprehend the internal structure of the AI application in terms of how it stores, predicts and make decisions based on data and computational representations that would, ultimately propagate AIED as systems that can determine particular learning instances tailored to students' needs, emotions and ways of learning. In what follows the aspects of teaching and learning are presented along with AIED applications that can afford the instantiation of distinct teaching learning strategies.

A. *AIED content and information*

Content and information may be used in different ways in terms of optimising the way a student acquires, accommodates and assimilates information for getting a solid knowledge-base of the topic. Information can be usually obtained from books, notes and other printed text or from digital resources that the teacher provides during the lesson. The challenge with this approach is that the content inside the medium does not reflect student's needs and interests. As such it cannot adapt itself to meet the needs of the student by presenting the content in the order, structure, or arrangement that the student prefers. Most essentially it does not learn from what the student is doing while interacting with the content and thereby it does not provide a tailored and personalised experience for the student. AIED applications that are focused on learning how the student selects, reads, and interacts with information and content may have a profound impact on transforming learning and teaching into an adaptive experience. AIED applications such as chatbots or ITS may employ data from representation models to train on how a student absorbs, captures, and process the information gained found in printed and electronic resources. This could help students to understand better the processes and strategies they use for memorising content, refine and apply them for augmenting the information acquisition learning process [36]. The automation of transmitting and transferring content and information to students was one of the early features of ITS applications but the actual processing of how a student learns from the content for finding patterns of learning remains a challenge. By drawing on representations stored in the domain knowledge, predictions and valid inferences can be made as to recommend content and information that is associated with student's content-based learning methods and pattern (e.g., [37]).

The process of providing recommended comment to the student has certain benefits: (1) The student can easily track and identify problems, mistakes or misconceptions made and can easily refine them; (2) the AIED can redevelop a pattern of the new learning schema developed by the student and then recommend content that best suit student's learning needs; (3) the student can be more aware of how to search and retrieve information that is more relevant and structured to own needs and learning arrangements. Learning difficulties that students are experiencing were investigated by using a neural network that trained itself to understand students' content learning methods for recommending information and content that would make sense [38]. In this sense, content sequencing is central to associate learning from content with difficulties experienced in understanding content [39]. The rigidness and inflexibility that current analogue and digital resources have to adjust the sections and topics in a way that would make sense to students is a deterring factor for students to focus on aspects of learning without compromising understanding. Sequencing information and content based on student's learning paths could impact the process of content-based learning but also how much of this content is being absorbed by the student.

B. AIED and knowledge application

Personalised and sequenced learning content could provide help for students to monitor and develop the way information is processed, retained and recalled. Applying knowledge gained from content is another interesting aspect that may be facilitated from AI. Having students to learn through experiments, discussions, creativity, prototyping and reflection may be the next stage of development for AIED. For example, there have been instances where intelligent systems can scaffold problem identification and problem solving in different domains and disciples based on structuring the nuances of the disciplinary knowledge and how it is practically being applied encompassing the pedagogies, techniques and methods for providing the means for students to solve the problem in question. For example, user-modelling frameworks were augmented into representational models for discerning how students identify and solve problems [40]. The model stores data on problem-solving attempts and self-explanations on the steps taken to solve the problem. The intelligent agent then parses the data and builds a problem-solving model. Based on the model constructed, suggestions and hints are provided for refining and improving the problem-solving pattern. It is however logical to expect that the agent should not only focus on the problem-solving outcomes, that is as to the problem-solving strategy was optimal to solve the problem but most importantly to provide the mechanisms and operations that would encourage the student to persist in finding a solution to the problem [41].

Pedagogical agents are used to provide practical suggestions on how students can solve problems. A pedagogical agent adopts conversational and dialogical techniques to help students apply knowledge and skills. Pedagogical agents can be embedded in games, simulations, virtual learning environments and ITSs that use textual and voice dialogical properties for guiding students towards a solution [42]. Pedagogical agents can have different modalities from avatars and non-player-characters to text-based input prompt and sound messages that can get involved into discussion or through a question-and-answer session. Pedagogical agents have been researched for understanding the problems and challenges students are facing when they apply knowledge [43] and how agents can propagate a system of trial and error for mitigating the challenges of knowledge application.

C. AIED and adaptive tasks

Reflecting on and connecting with the process of having an AIED agent for knowledge application, there is a need to design adaptive tasks that tailor the challenge and the difficultly of the task according to student's performance. Adapted learning tasks have been researched in the context of analysing students' similarities and differences observed when they are engaged in online tasks. For example, [44] presented three adaptive learning task designs: (1) Design-loop adaptivity that triggers data-driven tasks provided by teachers' experiences on how students perform in tasks and the similarities identified amongst students when they have carried out a task. (2) Task-loop adaptivity that accommodate the use of data-driven inferenced provided by the system to the point of changing the strategy of teaching. (3) Step-loop adaptivity rendering data-driven tasks made by the system in conjunction to how the student approaches the task from start until completion. It is important to note that for the task designs to work effectively, data fetched from the four computational models that need to be processed and inferred for perpetuating the adapted task design to the learning context.

Task-based chatbots are employed for helping students to complete tasks and activities through dialogues and discussions. A chatbot uses natural language processing for recognising students response from text or audio. Different types of chatbots serve varied ways of interacting with students. There are chatbots for handling administration and chatbots for helping students to complete complex tasks. They can facilitate a task through providing step-by-step instructions or through briefing a student in terms of what the task requires [45]. For example a scratch-based chatbot was used to facilitate students effort on learning to code through providing mini dialogue-based tasks for students to complete coding goals [46]. Another example is the BookBuddy chatbot that helped students to comprehend book material through interactive tasks for learning basic English [47].

D. AIED and adaptive assessment

The way that feedback is designed and communicated is key driver for learning progression. Assessment can validate how much learning tool place and feedback can help students to revise misconceptions and the process they need to follow to improve. Summative assessment is useful for having a quantitative understanding of progress via grades and formative assessment is helpful for helping students to identify areas of improvement and plan for future learning. There is also diagnostic assessment for helping teachers to extract information on student's background from previous learning experiences or to diagnose aspects of learning either at a specific interval during the learning session or at the end of the learning period. Adaptive assessment through AI would be able to determine complexity levels based on student's performance and adjust assessment based on content, application and tasks completed by the students [48].

Adaptive formative feedback is an innovation that AIED could bring to teaching and learning for helping students to conceptualise deeper their learning routines, provide adaptive support based on emotion, engagement and empathy levels detected in the student and also based on students preferences of how feedback needs to be delivered. There are examples of implementing adaptive formative feedback through Exploratory Learning Environments (ELEs) that are able computationally analyse and provide formative feedback on open-ended tasks. Such systems are more focused on flexible and open-ended tasks and are designed to provide more structured deep learning support on the process of learning (i.e., how the student learns) rather than on learning content (i.e. what the student learns). The focus however is on complexity through ill-defined tasks that encourage students to demonstrate resilience, self-direction and deep learning. Factors that can impact how formative adaptive feedback is enacted in an ELE may be in line with feedback-related characteristics such as declarative or procedural feedback or student traits such as gender, prior knowledge, and ways of learning [49]. By consolidating feedback-related and student-related characteristics as sub-categories within the pedagogical and learner models we may be able to discern a fine-grained structure that will embrace more precise and complete patterns of adaptive summative and formative feedback provision in intelligent systems such as ELEs.

E. *AIED and self-regulation*

Adaptive tasks may lead to becoming more self-directed and establishing ownership in how learning is manifested. Self-direction therefore could be explained as a habit of mind that enable student to be more autonomous and strategic in setting up a viable plan of how learning will be aligned to personal interests and needs. By actively controlling how learning is enacted students may have the opportunity to becoming more aware of learning needs and involve teachers and peers into the learning journey [50]. Seeking feedback therefore is an active process initiated by the student for actively seeking alternative ways for mitigating misconceptions and refining learning strategies and tracking progress indicators. Self-assessment may be characterised as an attribute of self-regulated learning with traits such as peer progress assessment and cognitive strategies that help students to take control over their learning. An example of an AIED system that promotes self-regulated learning is Betty's Brain. It evokes a learning-by-teaching approach where students learn about a science topic through teaching Betty hence sharing their understanding with others promoting shared responsibility [51]. Other conceptual models for self-regulated learning include metacognitive process that promote reflection and strategic planning and constellations of deep learning through dialogue and conversation with an AI agent [52].

VI. A FRAMEWORK FOR AIED TEACHING

Contemplating on the teaching and learning aspects, the depiction in Table 1 classifies and twins the learning aspects with AIED applications and tools that would most likely support the practice of the teaching.

TABLE I. A FRAMEWORK FOR ASSOCIATING AIED WITH TEACHING ASPECTS

Teaching and learning aspect	AIED applications and technologies
Content and information	• ITSs for information transmission • Recommending content and information • Sequencing information • Retrieving, recalling, and assimilating information
AIED and knowledge application	• Problem identification via agents • Dialogue based chatbots • ITS that provide step-based guidance • ITS that provide sub-step guidance • AI agents that encourage Q&As
AIED and adaptive tasks	• Chatbots for task-based learning • ITS for design-loop tasks • Games for step-loop tasks
AIED and adaptive assessment	• Adaptive formative assessment via ITS • Formative feedback via chatbots • Adaptive formative assessment via games • Open-based formative feedback via ELEs
AIED and self-regulation	• Ownership and learning control via ELEs • Sharing responsibility via ELEs • Self-assessment via agents

Table 1 may be used as an overarching framework and guide for teachers to start making sense of how AIED applications and tools can be coupled with associated teaching strategies that they employ in practice. It is indeed challenging for educators and practitioners alike to conceptualise and associate their teaching conceptions (i.e., beliefs of teaching) and approaches to teaching (i.e., actions of teaching) with new technologies and digital applications of learning. This seems to be the norm when new technologies are introduced, and teachers are expected to gain a learning curve for accommodating current and most likely conventional teaching practices to new technology. In the case of AIED, the overarching paradigms, epistemologies and ontologies that define teaching practices are in flux hence teachers are in limbo in terms of conceptualising and practically employ AIED.

It is of central importance therefore to delineate models and frameworks that provide a primary demarcation and categorisation of main teaching practices with tools and applications that can support a teaching instance. For example in 'content and information' aspect an ITS system could be used as an AIED tool for supporting teachers to provide personalised and tailored support for helping students to enhance the way they search, retrieve, recall and retain content and information. It is not an exclusive and exhaustive way of using ITS, but it rather provides a primer for initiating discourse and informed thinking on AIED application and tools that could be added into teachers' repertoire of AI-driven interventions for their teaching practice. Similarly in the 'knowledge and application' category there is a proposition being made that AIED could provide assistance and support in design (teacher-facing tools) and orchestration level (learner-facing tools) for designing and delivering a particular topic.

Chatbots, pedagogical agents and ITS could be employed for adapting application of knowledge and problem-based activities acting as an ecology of AI tools for problem-based applications. This complements the proliferation of the 'adaptive tasks' category that can encourage and support task-based learning for solving complex problems via chatbots, ITS or games. Adaptive tasks can embrace summative and formative assessment methods tailored to students' progress and needs. The 'adaptive assessment' category embraces the use of ITS, chatbots and ELEs as *systems of assessment adaptation* that can support computerised test for summative evaluation and formative feedback for open-ended tasks. This may require more autonomy and self-direction from the student-perspective as to exemplify autonomy, ownership, and strategical thinking not only in terms of enhancing the learning experience but also in terms of employing a more efficient learning management strategy. The 'self-regulation' category taps on the process of using AIED for encouraging students to be self-regulated through employing for example the learning-by-teaching paradigm as means to gain shared responsibility through exchanging knowledge reciprocally between an intelligent system and a student and thereby teaching the system how to teach the student based on the dedicated intricacies and nuances that define an individualised learning process. In learning situations there are internal and external factors that influence how learning and teaching is enacted. The role of the teacher is inextricably linked with identifying these factors and guide AIED to support an ecology of learning stipulated by the teacher.

VII. LIMITATIONS AND FUTURE RESEARCH

There are certain limitations that could be delineated from the way that the AIED framework has been designed. Firstly, it not based on a systematic process of identifying and analysing theory and thereby utilising a rigorous method for depicting a proffered rationalisation of how educators may choose and employ AIED applications and systems based on how they design instances of teaching and learning including activities, tasks, feedback, assessment, and any preferences of analogue and digital learning environments. Secondly, the framework is not based on empirical results that would entail a data-driven approach of how educators would conceive the use of AIED teaching and learning situations from a second-order perspective. It would be central to understand how teachers, students and education leaders would experience the use of AIED as to pinpoint specific conceptions and understandings whilst underlining challenges, risks and possibly propositions or leap thoughts on how AIED could support aspects of existing teaching practice.

VIII. Conclusion

This paper presented a preliminary framework for understanding the plethora of AIED applications and tools and how they may be used teaching and learning instances. The framework may be considered as an initial version of identifying some overarching teaching and learning aspects that could be used for classifying or associating models of teaching with AIED applications and tools. The framework will be granularised to encompass sub-aspects of teaching, especially in terms how AIED could provide specific support in collaborative learning by grouping students to tasks and activities based on similar performance levels, personality traits, prior knowledge, or task difficulty. The role of AIED teaching assistants could be analysed not only in terms of automating trivial activities most often related to administrative tasks but especially in terms of facilitating adaptive learning. This it does not mean that AIED will be a catalyst in orchestrating learning but as a transformative process that will help teachers to focus on what really matters: utilising experience, expertise, and knowledge to leverage and optimise learning as a social, cultural, and emotional process.

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References

[1] A. Seldon and O. Abidoye, The fourth education revolution: will artificial intelligence liberate or infantilise humanity. Buckingham: The University of Buckingham Press, 2018.

[2] W. Holmes, M. Bialik, and C. Fadel, Artificial intelligence in education: promises and implications for teaching and learning. 2019.

[3] W. Holmes et al., 'Ethics of AI in Education: Towards a Community-Wide Framework', Int J Artif Intell Educ, Apr. 2021, doi: 10.1007/s40593-021-00239-1.

[4] A. Kukulska-Hulme et al., 'Innovating Pedagogy 2020: Open University Innovation Report 8', The Open University, Milton Keynes, UK, 2020. Accessed: Jan. 19, 2021. [Online]. Available: https://iet.open.ac.uk/file/innovating-pedagogy-2020.pdf

[5] M. Tegmark, Life 3.0: being human in the age of artificial intelligence. London: Allen Lane, 2017.

[6] T. Baker, L. Smith, and N. Anissa, 'Educ-AI-tion Rebooted?', Nesta, Nov. 2019. Accessed: Jul. 09, 2020. [Online]. Available: https://media.nesta.org.uk/documents/Future_of_AI_and_education_v5_WEB.pdf

[7] A. Lui and G. W. Lamb, 'Artificial intelligence and augmented intelligence collaboration: regaining trust and confidence in the financial sector', Information & Communications Technology Law, vol. 27, no. 3, pp. 267–283, Sep. 2018, doi: 10.1080/13600834.2018.1488659.

[8] R. Luckin, W. Holmes, M. Griffiths, L. B. Corcier, Pearson (Firm), and L. University College, 'Intelligence unleashed: an argument for AI in education', 2016. Accessed: Jul. 08, 2020. [Online]. Available: https://www.pearson.com/content/dam/corporate/global/pearson-dot-com/files/innovation/Intelligence-Unleashed-Publication.pdf

[9] R. M. Cameron, A.I. - 101: a primer on using artifical intelligence in education. 2019.

[10] I. Roll and R. Wylie, 'Evolution and Revolution in Artificial Intelligence in Education', Int J Artif Intell Educ, vol. 26, no. 2, pp. 582–599, Jun. 2016, doi: 10.1007/s40593-016-0110-3.

[11] I. Tuomi, M. Cabrera, R. Vuorikari, Y. Punie, European Commission, and Joint Research Centre, 'The impact of artificial intelligence on learning, teaching, and education: policies for the future.', 2018. Accessed: Jul. 09, 2020. [Online]. Available: https://data.europa.eu/doi/10.2760/12297

[12] M. J. Timms, 'Letting Artificial Intelligence in Education Out of the Box: Educational Cobots and Smart Classrooms', Int J Artif Intell Educ, vol. 26, no. 2, pp. 701–712, Jun. 2016, doi: 10.1007/s40593-016-0095-y.

[13] R. A. Ellis and P. Goodyear, Students' experiences of e-learning in higher education: the ecology of sustainable innovation. New York: Routledge, 2010.

[14] N. Pinkwart, 'Another 25 Years of AIED? Challenges and Opportunities for Intelligent Educational Technologies of the Future', Int J Artif Intell Educ, vol. 26, no. 2, pp. 771–783, Jun. 2016, doi: 10.1007/s40593-016-0099-7.

[15] H. Beetham, 'An approach to learning activity design', in Rethinking pedagogy for a digital age: Designing and delivering e-learning, H. Beetham and R. Sharpe, Eds. Oxon: Routledge, 2007, pp. 26–40.

[16] B. Rienties, H. Køhler Simonsen, and C. Herodotou, 'Defining the Boundaries Between Artificial Intelligence in Education, Computer-Supported Collaborative Learning, Educational Data Mining, and Learning Analytics: A Need for Coherence', Front. Educ., vol. 5, 2020, doi: 10.3389/feduc.2020.00128.

[17] D. Adamson, G. Dyke, H. Jang, and C. P. Rosé, 'Towards an Agile Approach to Adapting Dynamic Collaboration Support to Student Needs', Int J Artif Intell Educ, vol. 24, no. 1, pp. 92–124, Jan. 2014, doi: 10.1007/s40593-013-0012-6.

[18] M. Cukurova, R. Luckin, E. Millán, and M. Mavrikis, 'The NISPI framework: Analysing collaborative problem-solving from students' physical interactions', Computers & Education, vol. 116, pp. 93–109, Jan. 2018, doi: 10.1016/j.compedu.2017.08.007.

[19] P. Tchounikine, N. Rummel, and B. Mclaren, 'Computer Supported Collaborative Learning and Intelligent Tutoring Systems', in Studies in Computational Intelligence, vol. 308, 2010, pp. 447–463. doi: 10.1007/978-3-642-14363-2_22.

[20] C. Jones, 'Designing for practice: practicing design in the social sciences', in Rethinking Pedagogy for a Digital Age, H. Beetham and R. Sharpe, Eds. Oxon: Routledge, 2007, pp. 166–179.

[21] L. S. Vygotsky, Mind in society: the development of higher psychological processes, Nachdr. Cambridge, Mass.: Harvard Univ. Press, 1978.

[22] C. Kent, E. Laslo, and S. Rafaeli, 'Interactivity in online discussions and learning outcomes', Computers & Education, vol. 97, pp. 116–128, Jun. 2016, doi: 10.1016/j.compedu.2016.03.002.

[23] G. Dyke, D. Adamson, I. Howley, and C. P. Rose, 'Enhancing Scientific Reasoning and Discussion with Conversational Agents', Learning Technologies, IEEE Transactions on, vol. 6, pp. 240–247, Jul. 2013, doi: 10.1109/TLT.2013.25.

[24] N. Chatterjee Singh and A. Duraiappah K., 'Rethinking learning: a review of social and emotional learning frameworks for education systems', UNESCO MGIEP, New Delhi, 2020. Accessed: Mar. 17, 2021.

[25] M. Donnelly, C. Brown, I. Batlle C., and A. Sandoval-Hernández, 'Social and Emotional Skills: Education policy and practice in the UK home nations', Nesta & University of Bath, London, UK, 2020. Accessed: Mar. 17, 2021. [Online]. Available: https://media.nesta.org.uk/documents/Developing_Social_and_Emotional_Skills.pdf

[26] S. M. Jones and S. M. Bouffard, 'Social and Emotional Learning in Schools: From Programs to Strategies and commentaries', Social Policy Report, vol. 26, no. 4, pp. 1–33, 2012, doi: https://doi.org/10.1002/j.2379-3988.2012.tb00073.x.

[27] M. Mavrikis, A. Maciocia, and J. Lee, '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, NLD, Jun. 2007, pp. 169–176.

[28] S. D'mello and A. Graesser, 'AutoTutor and affective autotutor: Learning by talking with cognitively and emotionally intelligent computers that talk back', ACM Trans. Interact. Intell. Syst., vol. 2, no. 4, p. 23:1-23:39, Jan. 2013, doi: 10.1145/2395123.2395128.

[29] W. Burleson and R. W. Picard, 'Gender-Specific Approaches to Developing Emotionally Intelligent Learning Companions', IEEE Intelligent Systems, vol. 22, no. 4, pp. 62–69, Jul. 2007, doi: 10.1109/MIS.2007.69.

[30] N. Bosch et al., 'Detecting student emotions in computer-enabled classrooms', in Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence, New York, New York, USA, Jul. 2016, pp. 4125–4129. Accessed: Jul. 13, 2020. [Online]. Available: https://www.ijcai.org/Proceedings/16/Papers/615.pdf

[31] B. Grawemeyer, M. Mavrikis, W. Holmes, S. Gutiérrez-Santos, M. Wiedmann, and N. Rummel, 'Affective learning: improving engagement and enhancing learning with affect-aware feedback', User Model User-Adap Inter, vol. 27, no. 1, pp. 119–158, Mar. 2017, doi: 10.1007/s11257-017-9188-z.

[32] A. McStay, 'Emotional AI and EdTech: serving the public good?', Learning, Media and Technology, vol. 45, no. 3, pp. 270–283, Jul. 2020, doi: 10.1080/17439884.2020.1686016.

[33] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, 'Systematic review of research on artificial intelligence applications in higher education – where are the educators?', Int J Educ Technol High Educ, vol. 16, no. 1, p. 39, Oct. 2019, doi: 10.1186/s41239-019-0171-0.

[34] D. Laurillard, Rethinking University Teaching: A Conversational Framework for the Effective Use of Learning Technologies, 2nd edition. London ; New York: Routledge, 2001.

[35] C. Conati, K. Porayska-Pomsta, and M. Mavrikis, 'AI in Education needs interpretable machine learning: Lessons from Open Learner Modelling', arXiv:1807.00154 [cs], Jun. 2018, Accessed: Jul. 13, 2020. [Online]. Available: http://arxiv.org/abs/1807.00154

[36] B. du Boulay, 'Escape from the Skinner Box: The case for contemporary intelligent learning environments', British Journal of Educational Technology, vol. 50, no. 6, pp. 2902–2919, 2019, doi: 10.1111/bjet.12860.

[37] A. K. Erümit and İ. Çetin, 'Design framework of adaptive intelligent tutoring systems', Educ Inf Technol, vol. 25, no. 5, pp. 4477–4500, Sep. 2020, doi: 10.1007/s10639-020-10182-8.

[38] A. Baylari and Gh. A. Montazer, 'Design a personalized e-learning system based on item response theory and artificial neural network approach', Expert Systems with Applications, vol. 36, no. 4, pp. 8013–8021, May 2009, doi: 10.1016/j.eswa.2008.10.080.

[39] C.-M. Chen, C.-Y. Liu, and M.-H. Chang, 'Personalized curriculum sequencing utilizing modified item response theory for web-based instruction', Expert Systems with Applications, vol. 30, no. 2, pp. 378–396, Feb. 2006, doi: 10.1016/j.eswa.2005.07.029.

[40] C. Conati and S. Kardan, 'Student Modeling: Supporting Personalized Instruction, from Problem Solving to Exploratory Open Ended Activities', AI Magazine, vol. 34, no. 3, Art. no. 3, Sep. 2013, doi: 10.1609/aimag.v34i3.2483.

[41] B. du Boulay, 'Artificial Intelligence as an Effective Classroom Assistant', IEEE Intelligent Systems, vol. 31, no. 6, pp. 76–81, Nov. 2016, doi: 10.1109/MIS.2016.93.

[42] G. Veletsianos and C. Miller, 'Conversing with pedagogical agents: A phenomenological exploration of interacting with digital entities', British Journal of Educational Technology, vol. 39, no. 6, pp. 969–986, 2008, doi: https://doi.org/10.1111/j.1467-8535.2007.00797.x.

[43] N. L. Schroeder, O. O. Adesope, and R. B. Gilbert, 'How Effective are Pedagogical Agents for Learning? A Meta-Analytic Review':, Journal of Educational Computing Research, Oct. 2013, doi: 10.2190/EC.49.1.a.

[44] V. Aleven, E. A. McLaughlin, R. A. Glenn, and K. R. Koedinger, 'Instruction Based on Adaptive Learning Technologies', in Handbook of research on learning and instruction, R. E. Mayer and P. Alexander, Eds. New York: Routledge Handbooks Online, 2016, pp. 522–560. doi: 10.4324/9781315736419.ch24.

[45] A. Kukulska-Hulme et al., 'Innovating Pedagogy 2021: Open University Innovation Report 9', The Open University, Milton Keynes, UK, 2021. Accessed: Jan. 19, 2021. [Online]. Available: https://iet.open.ac.uk/file/innovating-pedagogy-2021.pdf

[46] K. Katchapakirin and C. Anutariya, '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, New York, NY, USA, Dec. 2018, pp. 1–7. doi: 10.1145/3291280.3291787.

[47] S. Ruan et al., 'BookBuddy: Turning Digital Materials Into Interactive Foreign Language Lessons Through a Voice Chatbot', in Proceedings of the Sixth (2019) ACM Conference on Learning @ Scale, New York, NY, USA, Jun. 2019, pp. 1–4. doi: 10.1145/3330430.3333643.

[48] F. Grivokostopoulou, I. Perikos, and I. Hatzilygeroudis, 'An Educational System for Learning Search Algorithms and Automatically Assessing Student Performance', Int J Artif Intell Educ, vol. 27, no. 1, pp. 207–240, Mar. 2017, doi: 10.1007/s40593-016-0116-x.

[49] S. Narciss et al., 'Exploring feedback and student characteristics relevant for personalizing feedback strategies', Computers & Education, vol. 71, pp. 56–76, Feb. 2014, doi: 10.1016/j.compedu.2013.09.011.

[50] D. H. Schunk and B. J. Zimmerman, 'Self-Regulation and Learning', in Handbook of Psychology, American Cancer Society, 2003, pp. 59–78. doi: 10.1002/0471264385.wei0704.

[51] G. Biswas, J. R. Segedy, and K. Bunchongchit, 'From Design to Implementation to Practice a Learning by Teaching System: Betty's Brain', Int J Artif Intell Educ, vol. 26, no. 1, pp. 350–364, Mar. 2016, doi: 10.1007/s40593-015-0057-9.

[52] J. Kay and B. Kummerfeld, 'From data to personal user models for life-long, life-wide learners', British Journal of Educational Technology, vol. 50, no. 6, pp. 2871–2884, 2019, doi: 10.1111/bjet.12878.