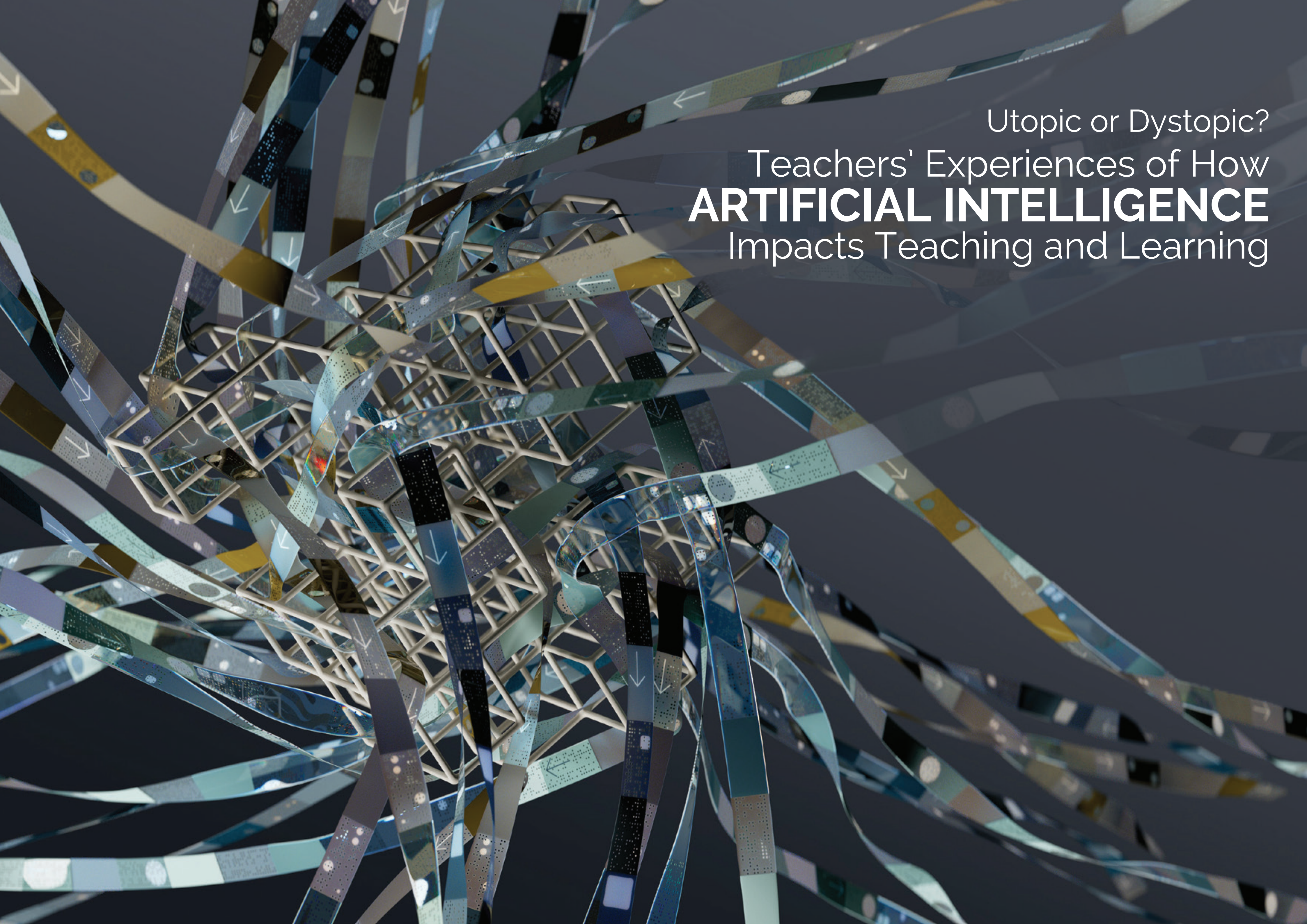

Utopic or Dystopic?

Teachers' Experiences of How **ARTIFICIAL INTELLIGENCE** Impacts Teaching and Learning

Embracing teaching and learning with the use of ai (AIED) is a complex and ill-defined decision that school-teachers would need to consider when reflecting on the overarching question:

> “*what would it mean to teach and learn in the age of AI?*”

Dear Educator,

It is envisaged that this report will shed some light on the emerging phenomenon of using Artificial Intelligence in Schools in the UK. As Anthony Sheldon eloquently describes education as the Cinderella subject of AI there is a genuine need to give the necessary thought and reflection on how AI is theorised and practiced for enhancing learning and teaching in schools. The report develops its argument for experiencing AI for teaching and learning through the eyes of the teachers. It supports that research in teaching and learning provides the threshold for understanding how AI applications and tools are employed for addressing intended learning outcomes. It is indeed a precursor that defines theories of learning, strategies and processes and inform the use of technology in qualitatively different ways as evidenced from practice.

This is not a report about school reform but rather an exploration of how educators create an awareness of teaching using AI as means to make informed decisions based on their perceptions, beliefs, intuitions, and sensations of using intelligent systems in education. It is a call to action to rethink how learning and teaching is designed and manifested. The reported teaching strategies are not only relevant to the use of AI, but they take account the entire spectrum of learning and teaching and thereby may also inform traditional educational perspectives.

This is a profoundly optimistic report that shares the knowledge, developments, and the different ways of experiencing the phenomenon of using AI in the UK's school system as evidenced from the educator's standpoint. To situate the study into a context, the report starts with reviewing current developments, trends, and the evidence-base of AI in education which synthesise Part 1 of the report. Part 2 delves into revealing empirical findings of teachers' conceptions of teaching and learning using AI along with ethical and skills development implications.

The Author,

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AIED systems would ideally be positioned to make computational inferences that would help teachers to gain deep understandings about how students optimally learn and how such learning is influenced by prior knowledge, ways of teaching and learning and physical context.

PART 1: A REVIEW ON ARTIFICIAL INTELLIGENCE IN EDUCATION

INTRODUCTION

Embracing teaching and learning with the use of AI (AIED) is a complex and ill-defined decision that school-teachers would need to consider when reflecting on the overarching question: "What would it mean to teach and learn in the age of AI?" The aim of this study is to help teachers to perpetuate on this question by reviewing, analysing, and synthesising the qualitatively different meanings, discourses, tools, and applications of AI in education. The application of AI in education has been relatively ignored compared to other fields and industries. In fact, commentators such as Seldon and Abidoye (2018) 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., (2019) 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 a pedagogical, ethical and teacher competency development perspective. Despite the slow uptake, schools are gradually starting to use AI-based systems as part of a wider digital education policy and strategy typically realised through intelligent tutoring systems, pedagogical agents, virtual learning environments, games and simulations, augmented and virtual reality and massive open online courses as means to amplify the student learning experience. 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 to this, AIED systems would ideally be positioned to make computational inferences that would help teachers to gain deep understandings about how students optimally learn and how such learning is influenced by prior knowledge, ways of teaching and learning and physical context.

1.

ARTIFICIAL INTELLIGENCE IN TEACHING AND LEARNING

The first part of this study presents an analysis on, and synthesis of, processes, practices, applications, and tools of AI in teaching and learning (AIED). In particular, the study attempts to contemplate on the question: "What do we mean by Artificial Intelligence in Education?" The study also considers the 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 role as teachers that 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 schools.

The review starts with cascading the analysis and synthesis process, including search strategy, screening, coding, and data analysis. To situate the study into the context of AI related interventions, a historical background and meanings of AI are contemplated along with a taxonomy of AI technology and its impact on innovative technology interventions. Then, AI is described and contextualised as a technology that is perceived and employed from an educational standpoint and how it has been developed in conjunction to non-AI educational technology that started to embrace multimodal learning representations, student-centred learning models, and semiotic resources. This is an important association as to delimit what AIED inherently envision to introduce, enhance, and improve in terms of the student learning experience in relation to non-AI educational technology.

Fundamentally, AIED's foci as an innovative technological intervention would be towards offering a comprehensive compound of adaptivity, personalisation and automation in subject-content, pedagogy and student's prior knowledge and ways of learning that AI would use as data for making inferences and algorithmic predictions of how students optimally learn. Designing for adaptive learning would be a sine qua non deliberation and realisation of AI's potential in teaching and learning. As such, the study provides informed accounts on designing adaptive teaching and learning along with social, emotional, and situated learning practices that are inherent to adaptability and personalisation. To compartmentalise the different AI systems, as means to help teachers to overcome precarious situations of twinning AIED with strategies, models and approaches to teaching, a representation and mapping of AIED applications is offered with teaching and learning aspects and the likely effect of emulating existing practice or propagating innovation. The study then elaborates on challenges and implications of AIED with a focus on ethics and digital skills competencies. Finally, a set of recommendations are provided for: developing a conceptualisation of AIED, designing adaptive AIED teaching and learning, AIED applications and tools, AIED ethics and AIED teacher skills.

1.1 METHOD

THE PURPOSE OF THIS EVIDENCE-BASED REVIEW IS TO ANSWER THE OVERARCHING QUESTION:

> *What do we mean by Artificial Intelligence in Education?*

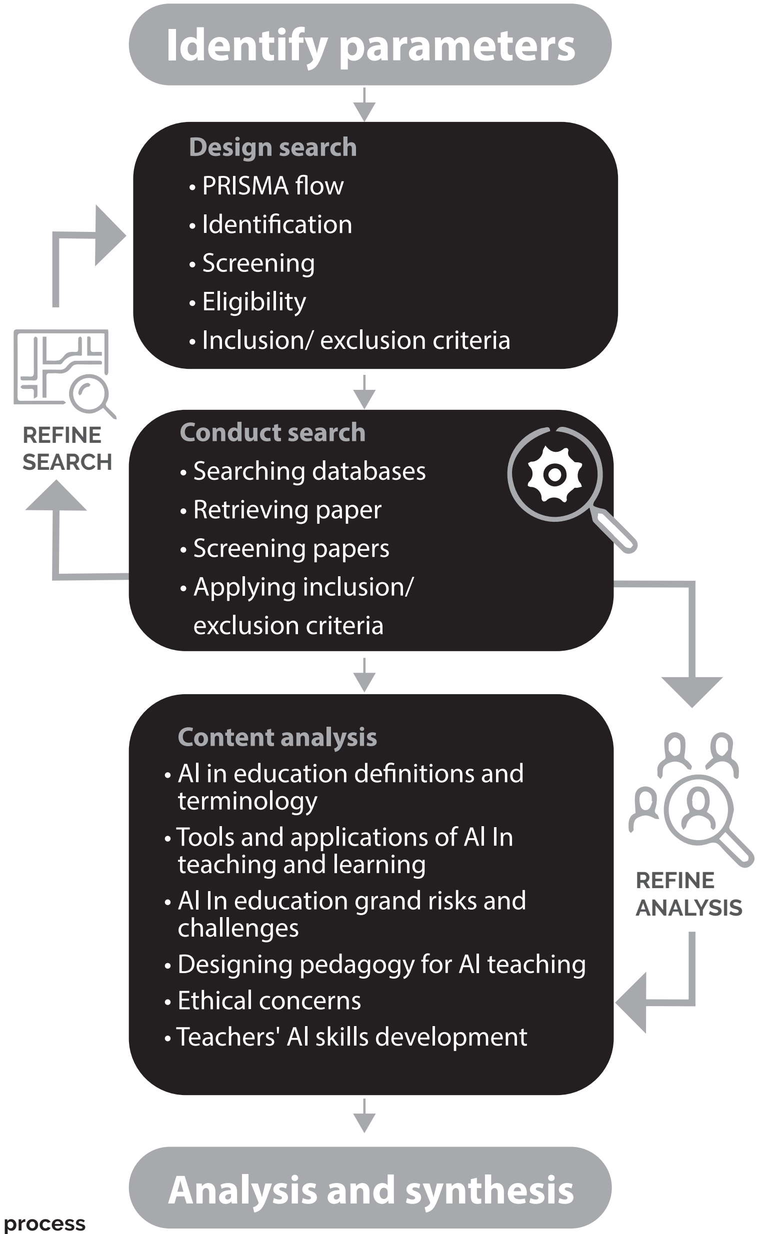
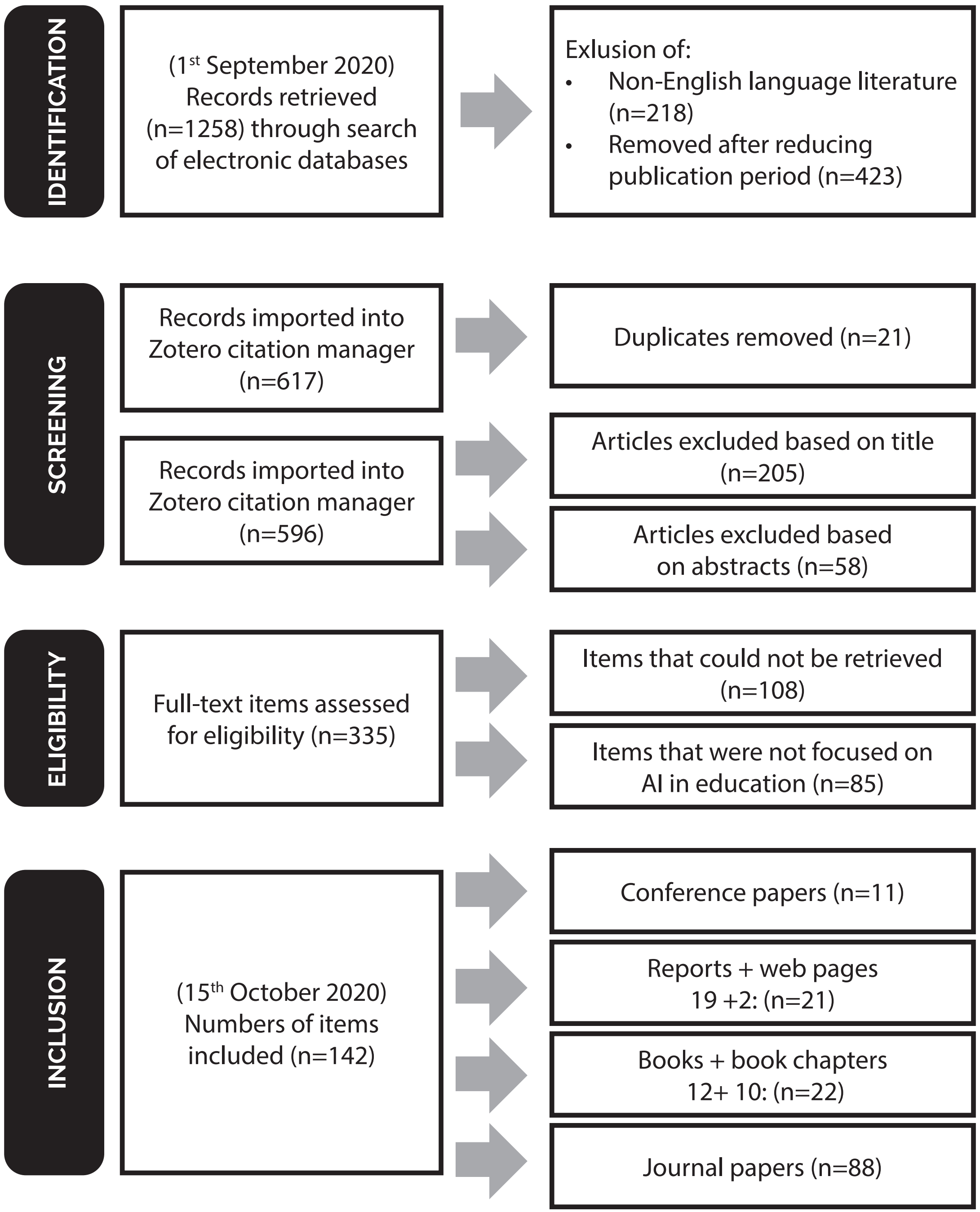


Fig. 1 Schematic on thematic analysis and synthesis process

Based on a process of search, retrieval, appraisal, extraction, synthesis and interpretation, the review attempts 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.**

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 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.

Fig. 2: PRISMA diagram representing a sequential process for compiling final corpus



SEARCH STRATEGY

The search strategy was carried out by adopting the PRISMA approach (e.g., Moher et al., 2009) for constituting the final corpus. A sequential process of identification, screening, eligibility, and inclusion was used to comprise a final corpus of 142 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 being ignored to be indexed in international databases. Normally using Boolean and Proximity search for scanning titles, abstracts and keywords embroiling search strings as seen in **Table 1.**

Table 1: Search terms & 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 "training" OR "capacities" OR "capabilities" OR "literacies" OR "support" OR "teacher preparation"
AND	
Education level	"secondary education" OR "middle school"OR "high school" OR "K-12" OR "higher education"

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 as 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).**

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

Table 2: Final inclusion and exclusion criteria

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 except for key papers and selected prior items. Peer-reviewed items in English encompassing primary and secondary research were included as to ascertain rigour and trustworthiness across the items in the corpus.

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. 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 142 items endured 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 48 items representing 33.8% of the corpus. The most prevailing quantitative method was quasi experimental with 39 items that entailed 81.2% of the quantitative methods employed. Such studies attempted to estimate causal relationships without random assignment. Randomized Control Trials (RCTs) were utilised in 9 studies making just 18.8% of the total quantitative studies encompassing a random assignment to control or experiment group.

Table 3: Research methods used in corpus items

Research design	Numbers of papers
Quasi-experimental	**48**
RCTs	39
Qualitative	**9**
Thematic analysis	18
Ethnography	17
Published between 2008-2020	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 12.6% of the corpus. Studies that used thematic analysis were 17, resembling 94.4% of the qualitative studies and only 1 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. 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 conceive the use of AI in teaching and learning. In light of this methodological incongruity, more qualitative studies may be needed as 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 5 comprising 3.6% of the corpus. All 5 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% of the corpus. Systematic literature reviews were evidenced in 7 studies making 9.8% of the literature review items whilst 64 studies employed evidenced-based reviews encompassing 90.2% of the literature review items.

CODING AND DATA ANALYSIS

A coding scheme has been 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 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.

A coding scheme has been developed to code and extract data from the items in the corpus.

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

LIMITATIONS

Whilst 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 3 main databases that were used to access and retrieve items may not have returned the entire gamut of items, including grey literature, that negotiate the use of AI in education in other languages other than English or in other formats. Therefore, a caveat is needed to be highlighted as some articles, conference papers, books and reports may had been missed due to language and other search restrictions. Depending on scope and scale of research, future studies may consider employing wider set of databases and inclusion criteria with proffered multiple language search strings and varied databases to accommodate a wider corpus regime.

1.2

BACKGROUND AND MEANING 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 (2017) 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 consisted of multiple types including acquiring and understanding concepts and ideas, problem-solving, creativity, negotiating and planning, social and emotional learning. To accommodate the notion of multiple intelligences Baker et al., (2019) 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".

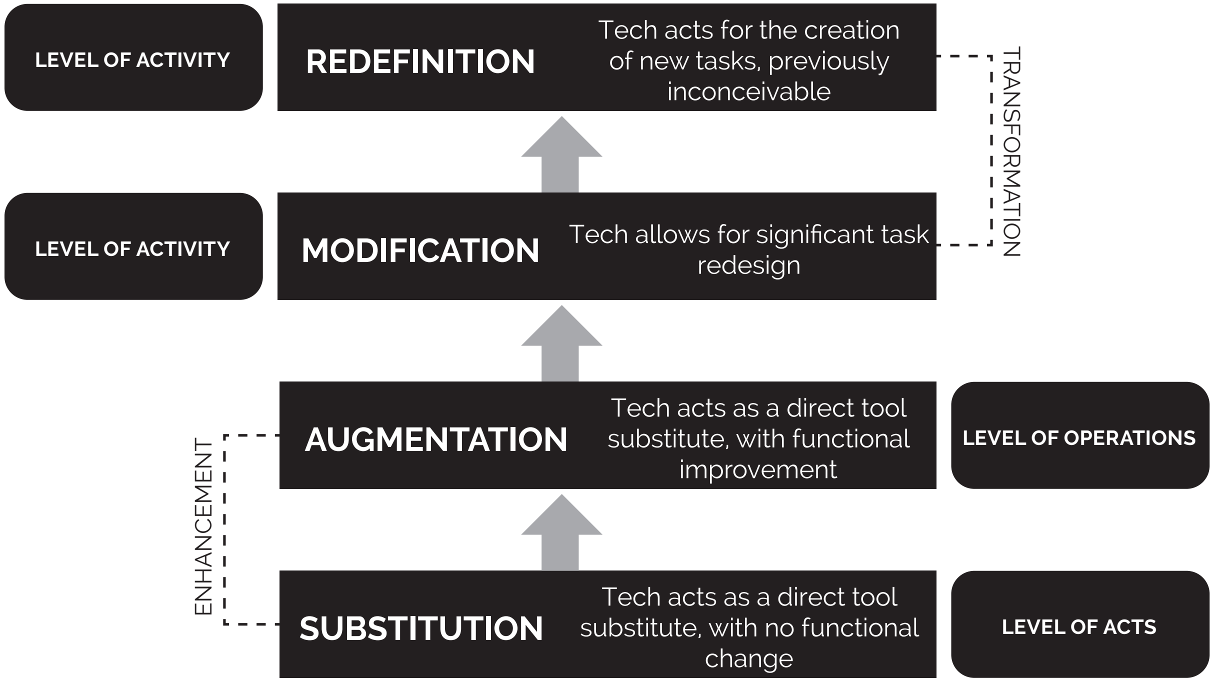
To differentiate intelligence that is enacted by humans or by machines Seldon & Abidoye (2018) referred to AI as Machine Intelligence (MI) denoting a digitally controlled mechanical process by a human-centred machine which perceives its environment and adapts to it for achieving its objectives. This meaning of AI pertains 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 & Lamb, 2018) or hybrid augmented intelligence (e.g., Zheng et al., 2017) were favoured by researchers as means to develop a hybrid form of AI which 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., 2019), optimisation of procedures and parameters (e.g., Noothigattu et al., 2019), autonomy (e.g., Duan et al., 2019) and understanding of human natural language (Kaplan & Haenlein, 2019).

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., (2018) developed a conceptual model that frames three levels of human and machine intelligence pertaining 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 (2013), as a developmental ontological framework that demonstrates how AI will increasingly influence the dynamics of technology development as means of entering a state of transformational activity underpinned by advanced forms of human intelligence **(see Figure 3).**

Fig.3 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 from Zanetti et al., (2019) and Dodigovic (2007) 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. Dogidovic 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., Tegmark, 2017). 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, 2019).

In the 1950s, the term AI was coined by John McCarthy during a workshop organised at Dartmouth College in 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 had created an impact across sectors. For example, AI can accumulate and assimilate data for creating patterns and make predictions. The UK based company DeepMind acquired by Google, adopts 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) (Popenici & Kerr, 2017), 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, (2017) 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 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. Berendt et al., (2020) argued that there is a need to find a balance between benefits and risks when AI is designed, marketed, and implemented considering AI's global impact.

1.3

A STIMULUS FOR AI IN EDUCATION

Having proliferated an understanding of AI, enables to rationalise, and delimit how AI may be conceptualised and realised in teaching and learning contexts. Often referred 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 which have been the focus of attention for about 30 years. Luckin et al., (2016) 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 student's prior knowledge, ways of learning, assessment, and feedback (e.g., Zhou et al., 2020; Kukulska-Hulme et al., 2020; Luckin et al., 2016).

The fast-approaching revolution of AI has already been acknowledged and there is consensus that AIED has potential to address teaching and learning related challenges that schools and universities currently experience. For example, Seldon & Abidoye (2018) 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 as means to situate AIED developments within a broader educational technology research base.

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., 2012), 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, 2016). 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 as means 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 learning and flipped learning to demonstrate the impact of technologies on 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 (1954) 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 to 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 (Seldon & Abidoye, 2018).

The key principle of Instructional Systems Design is that learning is formed step by step from previous knowledge or cognitive schemata that constitute a new and more holistic learning structure.

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, 1985). 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 a 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 & Liber, 2004; Conole et al., 2004). The first generation 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., Britain & Liber, 2004).

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 student's contextual behaviour (e.g., Öman & Sofkova-Hashemi, 2015; Jewitt, 2008). 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 developing 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 constructivist theory of knowledge (1970). 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 being 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., (2007). These systems managed to provide an interoperable and integrated experience that encouraged students to construct learning but did not considered a more holistic role to constructing learning based on 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 (1978) emphasis on the significance of social interactions for the development of complex cognitive functions influenced Duffy & Cunningham (1996) 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 & Duffy (2000) 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 & Wenger (1991) 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 was 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 seeing, hearing, feeling, and tasting integrated into multimedia software like games (e.g., Gee, 2003), and 'multimodality' drawing on the process of creating meaning through connecting and combining teaching modes, multimedia and technology (Lameras & Papageorgiou, 2020). Such multimodal resources were coined as 'learning objects' (e.g., Conole, 2007) 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.

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., Roll & Wylie, 2016; Holmes et al., 2019; Baker et al., 2019). 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., Tuomi et al., 2018; Timms, 2018). 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 is interesting to be highlighted as 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., Baker, 2013). Such questions revolve around 'What students should be learning?' and 'How such learning may be designed, represented and assessed through AI?' Answers to these questions underpin much of the debate of what constitutes good learning (e.g., Ellis & Goodyear, 2010) and how AI could become adaptive to the needs of individual students (e.g., Conati & Kardan, 2013). Following Ellis & Goodyear, (2010) 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.

1.4 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 assumption that AIED could possibly provide a tailored learning experience, a relational assumption is made that teachers need to design adaptive learning activities that describe 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 resources that are relevant to 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 initiated discussion around a topic that a student is mostly interested to learn, comparing, and evaluating arguments based on student's understandings or solving problems that are tailored to 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 that the advent of adaptive learning technologies (e.g., Pinkwart, 2016) aim to provide individualised and tailored learning content matched to student's performance on set tasks. To design learning that is individualised and tailored to student's needs, the learner and pedagogical models that underpin adaptive learning technologies may be necessary to computationally represent students': (a) subject-specific experience, knowledge and competence; (b) motives for learning and expectations of the learning situation; (c) prior experience of learning, including the specific mode (e.g., blended or online); (d) preferred approaches to learning; (e) social and interpersonal skills; (d) confidence and competence in the use of adaptive learning systems (Beetham, 2007).

Bartolomé et al., (2018) have 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's et al., (2005) '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. asserted that the role of AIED for enabling adaptive learning is to help on 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 foster '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: (a) adaptive collaborative learning support and (b) learning through conversation and social and emotional learning.

ADAPTIVE COLLABORATIVE LEARNING SUPPORT

There is increasing research on Computer Supported Collaborative Learning (CSCL) especially as a sub-research strand of AIED (e.g., Rienties et al., 2020; Kowch & Liu, 2018; Adamson et al., 2014). CSCL emphasises on how students learn and solve problems (e.g., Cukurova et al., 2018) by participating in collaborative learning activities and how such collaborative activities may be supported by technology. Tchounikine et al., (2010) argued that an approach to support collaboration through technology is via macro-scripts for introducing structure that guide 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 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., Jones, 2007). 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 means of scaffolding intelligent interactive assistance between students with different performance traits. Casamayor et al., (2009) developed and tested a collaborative intelligent interface that provided a summary of student progress which 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 a holistic development of 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., (2011a) 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 praise 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. (3) ACLS design for relevance as 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., (2011b) assessed an adaptive peer tutoring assistant with 122 students and discovered that ACLS is more effective when it is relevant to student's behaviour and support was perceived as adaptive when students felt accountable for their actions. Kent & Kukurova (2020) suggested a novel method for measuring the process of collaboration from a collective and adaptive prism, Collaborative Learning as a Process, that utilises social network analysis for balancing interactivity gains and coordination costs within communities of learners resulting to gain better understanding on the collaborative process rather than its linear outcomes.

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 (Lave & Wenger, 1991) 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, 1978). 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., (2016) 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 measuring interactivity in online discussions by establishing a relationship between interactivity and learning outcomes. Adamson et al., (2014) 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., (2013) 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.

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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 means to recognise and manage emotions, develop empathy for others and establish positive relationships (Chatterjee-Singh & Duraiappah, 2020). 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., (2020) perceived SEL as a set of individual and functional skills that can be nurtured from the student. Such skills are divided in 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 & Duraiappah, (2020) emphasised Social and Emotional Competence (SEC) as intrapersonal and interpersonal. Intrapersonal are knowledge skills and attitudes directed towards oneself such as cultivating a growth mindset or self-efficacy and interpersonal 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 (2012) 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 student's affective states. For example, Mavrikis et al., (2007) investigated how a student's emotional state can be detected using machine learning to developing patterns for diagnosing students' affective states. Similarly, D'Mello & Graesser (2013) 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 (2007) 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., (2016) used computer vision, learning analytics and machine learning to detect 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., (2017) 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 moving 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 being the subject of previous intelligent affective support research. McStay, (2019) enunciated some of the implications of adopting emotional AIED especially around effectiveness, student's well-being and how it is exaggerated from mining aspects of subtle emotional situations, and the problematic application of using inferences of students' emotions to train neural networks as means of making predictions on student's affective states.

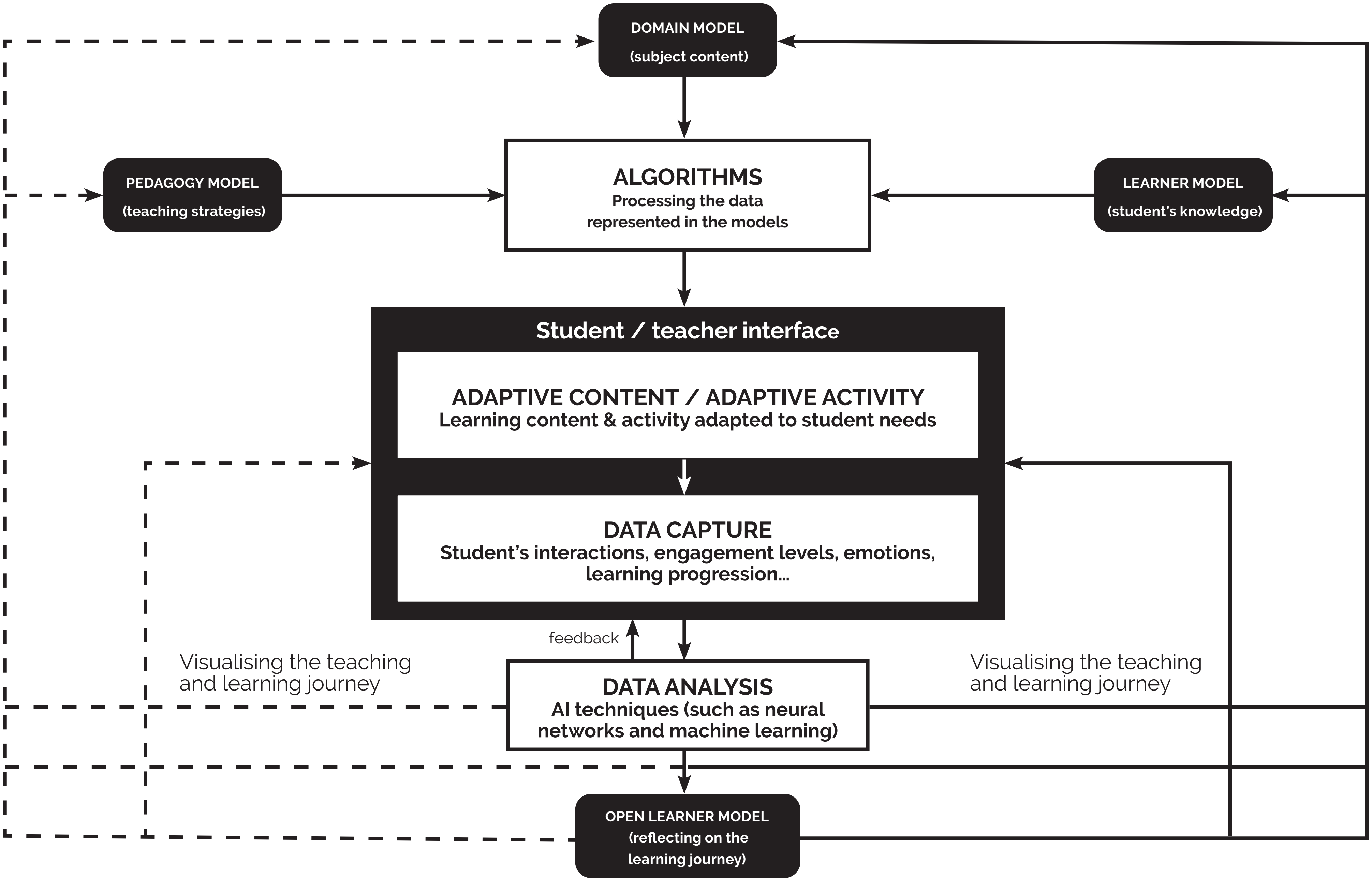
The preferred approach to understanding teaching and learning through using AI-based systems is relational, which considers how teachers and students think about teaching and learning in general, think about teaching and learning using AI in particular and what models, approaches and strategies are employed in relation to particular AI applications.

1.5 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 thirty years (Kukulska-Hulme et al., 2020). 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., 2019). Baker et al., (2019) 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., 2018). Such software can help teachers to understand how students learn by gaining insights on 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.

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., (2019) 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., 2018) that visualises and makes explicit the outcomes of the teaching and learning process 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 as 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 4** shows how the pedagogy, domain and learner models may be augmented to provide an adaptive and personalised learning activity.

Fig.4. The interaction between the domain, pedagogy, learner, and open-learner models for providing adaptive support through an ITS (adapted from Luckin et al., 2016)



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 to formulate 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 seen 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 means to establish more meaningful and integrated relationships.

1. **AIED for preparing and transmitting learning content**
2. **AIED for helping students to apply knowledge**
3. **AIED for engaging students in learning tasks**
4. **AIED for helping students to improve through assessment and feedback**
5. **AIED for helping students to become self-regulated learners**

Fig.5. The five aspects of teaching and learning (adapted from Seldon & Abidoye, 2018)

This relational perspective may help the design of AIED systems to support the personalisation of learning through making explicit or visible: (a) 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); (b) the importance of what is in the AI system in terms of content, processes and features; (c) 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 Seldon & Abidoye (2018), which considers five broad aspects of teaching and learning and how AIED may support them in tandem. The predominant focus of this study is on teachers' experiences of AIED and therefore Seldon & Abidoye's five aspects of teaching and learning are 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 5)**. AIED applications and tools are mapped to each different aspect of teaching and learning as 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.

1 AIED FOR PREPARING AND TRANSMITTING LEARNING CONTENT

Learning content can be variously perceived, but in this context, it may be understood in conjunction to print-based artefacts such as books or digital content-based artefacts that use representational media like 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, 2019). 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 student's learning queries and misconceptions (e.g., Erümit & Çetin, 2020). As the student addresses misconceptions from recommended content, the system constantly tests student's knowledge, identifies mistakes, tracks misconceptions, and guides them towards finding and retrieving learning content. Baylari & Montazer, (2009) developed an ITS that discovers student's learning difficulties by using a neural network approach for recommending adaptive learning content to the student. A key feature in matching student's learning with the difficulty level of the recommended content is content sequencing. Chen et al., (2006) developed an intelligent system to match student' 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 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 student's capabilities for preventing student's disorientation through filtering out unsuitable material, reducing cognitive load, and ensuring concept continuity.

To facilitate ITS with implementing content sequencing, teachers may provision the preparation of content creation by conglomerating content with student's perceived skills and abilities. Thalmann, (2014) proposed a classification of adaptation needs to which adaptive arrangements to content may be undertaken by teachers with less technical expertise. A set of ten 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., (2012) 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 student's information interests which may be used for recommending future personalised but also contextualised learning content.

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 student's cognitive processes for understanding how the problem may be solved. For example, Conati and Kardan, (2013) presented a user-modelling framework, that can be embedded into a learner model, to analyse student's interaction with a problem-solving task. The model contains a log with 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 (2016) 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 (2011) analysed studies for different types of tutoring systems that are designed particularly for scaffolding 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 give feedback on each step); and (4) substep-based tutoring (i.e., scaffolding on a more detailed level). Van Lehn 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 but to replace the whole learning experience. Ma et al., (2014) 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 student's understanding in terms of whether it was used as an aid to homework, as predominant means of instruction, as a supplement or an integral component of teacher-led instruction.

Attempts to utilise ITSs capabilities to enhance 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, augmented and virtual reality, that use rules and agent technologies to guide a virtual character's reasoning to support learning and instruction (Richards & Dignum, 2019; Veletsianos & Miller, 2008). 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., (2013) 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 facilitate student's understanding. Kim et al., (2020) 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 emerge in terms of the role of 'machine teachers' in designing, orchestrating and assessing teaching and learning.

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., (2016) 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 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, (2014) 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 means to challenge 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., (2020) 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 orientate students towards undertaking a learning task. Kukulska-Hulme et al., (2021) perceived that the optimal use of a chatbot is through identifying its role spanning from task facilitator, problem analyser or guidance provider. Katchapakirin & Anutariya (2018) 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., (2019) 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 & Schreiberova (2020) 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 & Fernandes (2019) 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.

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 student's needs. An adaptive feedback system or a computerised adaptive test system (e.g., Grivokostopoulou et al., 2017; Barker, 2010) may offer improved functionality to ascertain student's level of knowledge and thereby adjusting assessment and feedback to delineate controllable levels of complexity. For example, Whitelock et al., (2013) 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., 2017).

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., 2012; Mavrikis et al., 2019). There is consensus that ELEs enable formative adaptive feedback as means to scaffold students' efforts to learn and consolidate knowledge from ill-defined tasks and open-ended activities (e.g., Grawemeyer et al., 2015; Holstein et al., 2018). Narciss et al., (2014) 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., (2015) 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 & Koedinger, (2017) 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 inferred 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 student's prior knowledge and from the domain model as means of associating feedback with learning outcomes.

To further demonstrate the value of intelligent adaptive formative feedback for open-ended tasks, Basu et al., (2017) 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 student's actions and therefore the design and provision of meaningful AI-generated feedback that improves 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 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 that did not receive scaffolding and did not demonstrate effective modelling strategies.

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 & Zimmerman, 2003). 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 & Winne, 1995). Self-assessment is also perceived as a self-regulatory feature that encourages students to assess progress, level of effort and own ways of learning in relation to personal learning goals and expectations (e.g., Hattie & Timperley, 2007). 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., (2016) 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 student's shared representations. In essence, students are supported to teach Betty and then to query Betty as 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., (2016) showed that students were making progress in becoming self-regulated learners, especially students characterised as engaged and efficient. Kay & Kammerfield (2019) 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 & Durlach (2014) 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 incorporate different game mechanics, dynamics, and aesthetics as 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 is adopted by Matsuda et al., (2013) as 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., (2013) 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 student's self-regulated behaviour, Winne, (2020) proposed an open-learner model that tacitly support 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., (2021) 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 that 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 s whilst 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 & Schwartz (2020) 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 weights and the position of each team member selected by the students affected the win and the loose dynamics of the game. The results of the evaluation showed that students' inquiry strategies influenced learning outcomes and were predictive for overall learning achievement.

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 4)**. 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 instantiations 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 4: 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 '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 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 '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 there 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 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.


AI

1.6

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 & Aleven, 2017; Kulik & Fletcher, 2016). 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 emanate 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 is 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., 2016; Dillenbourg, 2016; Luckin & Cukurova, 2019) 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 and thereby increasing teachers' confidence to effective use of AIED in schools.

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.

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 may impact the design and enactment of teaching and learning through using AIED systems. (e.g., Holmes et al., 2021; Holmes et al., 2019). 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 ethical use of AI to raise awareness on of designing and orchestrating AIED systems. For example, one of the earliest ethical principles of using AIED systems were introduced from Aiken & Epstein (2000) focused predominantly on rudiments of design that would encourage more ethical use of AIED. Certainly, these overarching AIED principles could be characterised as ethical dimensions underpinned by human principles corresponding to system design that encourage 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 has been researched extensively for developing a plethora of ethical AI principles focusing predominantly on 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 April 2019) for accessing and retrieving different AI frameworks and principles that may pertain to the ethical use of AI. Floridi, (2019) contested 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 convolutive ethical requirements, Jobin et al., (2019) 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 that 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, 2018) providing a framework for identifying ethical principles and values which 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 & Jirotka (2018) explored the phenomenon of ethical governance in AI and robotics as a more holistic and agile governance of AI from an institutional perspective as 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., Holmes et al., 2019). It seems however that the AIED ethics landscape is starting to materialise with UNESCO's (2020) recommendations on the ethics of artificial intelligence. The recommendations pertain 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 do no harm, safety and security, fairness and non-discrimination, sustainability, privacy, transparency, responsibility and accountability, awareness, and literacy. To this line, UNESCO, (2019) 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, bias and trust in science have been particularly relevant to the use of AI in educational contexts.

UNICEF (2020) 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 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, 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., 2020; Kitto & Knight, 2019) 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 & Ibars, 2017; Berendt et al., 2017). AIED ethics frameworks and principles would need to embroider the ethics of the learning science (e.g., Holmes et al., 2021) incorporating ways of designing, orchestrating and assessing AIED in pedagogically-rich ways and in conjunction to teachers' and students' perceptions of and approaches to 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., (2021) 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 concerted when planning and enacting teaching and learning with AIED.

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., (2016) contemplates on the particular skills that teachers would need to develop in terms of: (a) developing awareness and understanding of the properties and features of AIED systems as to enable them to make informed decisions about how to select, use and evaluate AIED tools; (b) to develop research skills as to enable teachers to collect, analyse and interpret the data provided by the system as to guide students on how to develop their learning following a data-driven approach; (c) teamworking and management skills as to enable teachers to create ethical relationships with AI teaching assistants as means to complement human teaching assistants (e.g. Eicher et al., 2018). 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 as means 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 whilst AIED is facilitating more data-driven tasks (e.g., Pedro et al., 2019).

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 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 **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 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 connect digital material with physical objects
F. Fostering student digital inclusion, social influence, and relatedness	**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

Table 5: The AIEDComp: Teachers' digital competencies of teaching and learning using AIED

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-dated 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, 2019). The purposes of acquiring digital competencies are eminent in two types of competencies: (a) for helping students to use digital technologies in the classroom and (b) for designing rich-mediated digitally enabled learning environments (e.g., Tondeur et al., 2016). A third type of competences complementing the two, are competencies that promote inclusive, creative, meaningful, and personalised teaching and learning that may enable to track student's progress through meaningful and formative feedback. This alludes to the premise that digital competency development and subsequently AIED competency growth should not only focus on data, algorithmic and system-based skillsets but most importantly on learning science skills particularly related to human-centred design for learning, rich-mediated pedagogy, stealth assessment, empathy, and student empowerment.

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, 2017; UNESCO, 2011; Law et al., 2018; Valencia-Molina et al., 2016). One of the most important digital competency frameworks is the European Union's DigiCompEdu (Redecker & Punie, 2018) 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 twenty-two competencies in total. Lameras et al., (2021) discerned a set of six overarching digital competencies for helping teachers to develop capabilities in technology-enhanced teaching and learning, and thereby sensibly perceived as competencies closely related to and relevant with competencies for teaching and learning with AIED.

Digital competencies for teaching and learning using AIED may be perceived as the twinning of knowledge, skills, and attitudes to successfully develop, implement, and achieve a set of learning goals and outcomes to be orchestrated with the use of AI agents or systems. To enable teachers to aggregate and reflect on existing and new AIED competencies, a self-assessed progression model is proposed. The model is consisted of different progression levels that describe variation in AIED-based teaching competency development. The six AIED digital competences stages are twinned to six proficiency levels used by the Common European Framework of References for Language (CEFR), ranging from A1 to C2 as to inculcate familiarity and simplicity for teachers to interpret the progression levels and delineate a subjective understanding of their competencies in teaching and learning using AIED. Deconstructing the competencies to different levels would allow teachers to focus on the proffered nuances whilst attenuating complexities in the application of the competencies in actual practice. The progression model is no meant to be viewed as an assessment tool for performance appraisal but rather is it evoked as a supportive metric for identifying, understanding, and delineating progress and self-reflection **(see Figure 6)**.

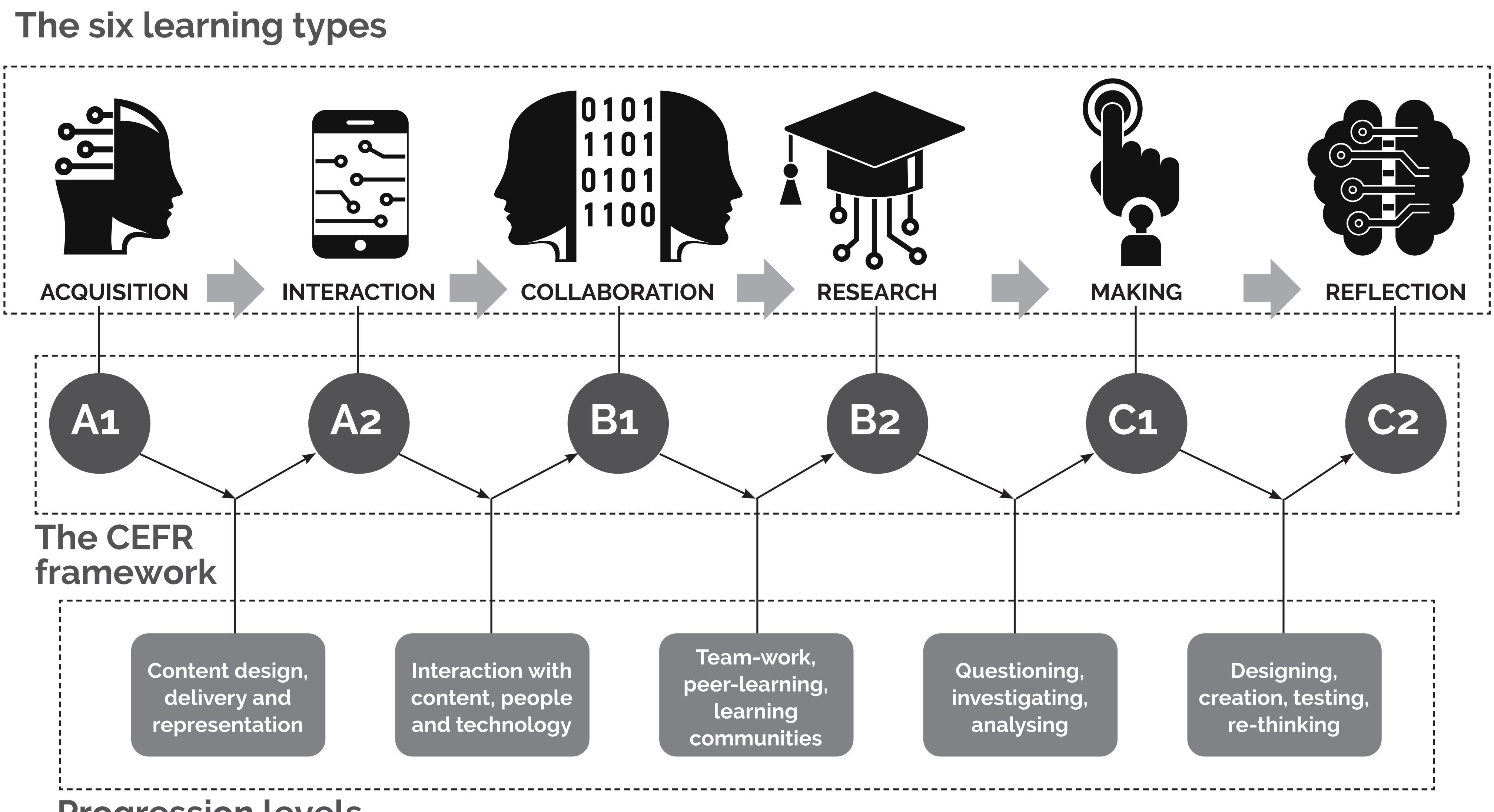


Fig.6. The AIEDComp progression model

Specifically, the learning goals descriptors that run through the six categories are qualitatively different to inform associated competencies. The descriptors were inspired from Laurillard's (2001) six types of learning spanning from acquisition, discussion and practice to production, collaboration, and investigation. In the first two stages, Acquisition (A1) and Interaction (A2) the focus is on content design, delivery, and representation (A1) and on interaction with teachers, peers, content and technology (A2). In Collaboration (B1) and Research (B2) the focus is on working in teams and creating online learning communities based on interests and needs (B1) and transitioning to conducting research through, posing questions, initiating investigations, analysing, and constituting evidence (B2). Then, the focus shifts from Research (B2) to Making (C1) with emphasis on creating, tinkering, and making tangible products and artefacts to Reflection (C2) for critically reflecting on what it has been learnt across the six themes **(see Table 6)**.

THE 6 THEMES OF AIED-BASED TEACHING AND LEARNING	PROGRESSION LEVELS					
	Acquisition (A1)	Interaction (A2)	Collaboration (B1)	Research (B2)	Making (C1)	Reflection (C2)
1. Content design and delivery	Designing, developing and delivering subject content for helping students to acquire information	Designing, developing, and delivering subject content for helping students to interact with teachers, peers, content, and technology	Designing, developing, and delivering subject content for helping students to engage in collaborative learning	Designing, developing, and delivering subject content for helping students to engage in research	Designing, developing, and delivering subject content for helping students to cultivate creative and making mindsets	Designing, developing, and delivering subject content for helping students to critically reflect on subject-content
2. Acquiring student data, information, and data ethics	Collecting, analysing, and visualising data on student's subject content and information acquisition	Collecting, analysing, and visualising data on student's interactive processes with teacher, peers, content and technology	Collecting, analysing, and visualising data on student's collaborative learning processes	Collecting, analysing, and visualising data on student's research-based learning processes	Collecting, analysing, and visualising data on student's creativity and making processes	Collecting, analysing, and visualising data on student's reflective processes
3. Activity-led AIED strategies	Employing activity led-strategies that support students to acquire adaptive information and personalised subject content	Employing activity-led strategies that support students to interact with teachers, peers, content and technology	Employing activity-led strategies for designing collaborative activities	Employing activity-led strategies for designing research-based activities	Employing activity-led strategies for designing activities that encourage students to create and make	Employing activity-led strategies for designing activities that encourage students to critically reflect on learning
4. AIED tools usage proficiency	Selecting and utilising AIED software and hardware that enable students to find, access and retrieve information and subject content	Selecting and utilising AIED software that enable students to interact with teachers, peers, content, and technology	Selecting and utilising AIED software that enable students to participate in and contribute to collaborative learning	Selecting and utilising AIED software that enable students to participate in and contribute to research-based learning	Selecting and utilising AIED software that enable students to participate in and contribute to creative and making processes	Selecting and utilising AIED software that enable students to critically reflect on their learning
5. Digital creativity skills	Designing and using AIED environments that support and guide students to acquire information and subject content creatively	Designing and using AIED that support and guide students to interact with teachers, peers content and technology creatively	Designing and using AIED that support and guide students to engage in creative collaborative learning	Designing and using AIED that's support and guide students to participate in and contribute to research-based learning creatively	Designing and using AIED that supports and guides students to cultivate creativity and a do-it-yourself culture	Designing and using AIED that support and guide students to critically reflect on their creative learning
6. Digital inclusion, social responsibility, and data compliance	Designing and delivering inclusive, accessible, and ethical information and subject content	Designing and using AIED environments that support and guide students to interact with teachers, peers, and content in inclusive, accessible, and ethical ways	Designing and using AIED environments that support and guide students to engage in collaborative learning in inclusive, accessible, and ethical ways	Designing and using AIED environments that support and guide students to engage in research-based learning in inclusive, accessible, and ethical ways	Designing and using AIED environments that support and guide students to engage in making and creativity in inclusive, accessible, and ethical ways	Designing and using AIED environments that support and guide students to engage in reflective thinking in inclusive, accessible, and ethical ways

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

The labels of each phase capture the experience of the competence that needs to be developed. For example, in Acquisition (A1), the competence-focus in on the acquisition of learning through the design and delivery of subject content and information. In Interaction (A2), the focus of attention is to utilise interactive processes with teachers, peers, content, and technology running through each digital competence. In Collaboration (B1) the focus is on encouraging collaborative processes and participation in online communities and in Research (B2) the focus is on participating in, and contributing to, research processes. In Making (C1) the focus is on creativity and crafting digital objects and in Reflection (C2) the focus is on re-thinking on learning and teaching already experienced as well as planning out future learning.

The progression model may also scaffold the process of identifying and mapping roles and competencies of different teachers participating in a project. For example, if a particular teacher is more confident with Interaction (A2), they can work towards developing interaction with content, people, and technology across the six digital competency themes. If a teacher is more familiar with Research (B2), then they can engage in ways of designing and delivering research-based learning and teaching across the themes. Teachers may also be familiar with more than one dimension simultaneously such as with Acquisition (A1) and Reflection (C2). Amalgamating multiple competency levels developed by a teacher may provide a more consistent, systematic, and strategic approach to planning, assessing and consciously reflecting on competencies for AIED teaching and learning. In this sense, different espoused and actual competencies perceived by one teacher could be combined and complemented with competencies that other teachers may have in their repertoire of skills and capabilities. Essentially, the progression and the development of competencies achieved from one level constructs and delimits the competencies and skills to be developed in the next level making the competency skill development process compartmental, relational, connected and total.

1.7 RECOMMENDATIONS FOR ENACTING TEACHING AND LEARNING USING AIED

From the findings of this review, several recommendations are proposed for helping teachers in schools to understand, plan and reflect on processes, strategies, tools, and frameworks that would facilitate the use of AI in the classroom. The recommendations delimit aspects related to: (a) 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; (b) propositions of human-centred aspects that may help to design for adaptive AIED-based teaching; and (c) 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.

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.

DESIGNING ADAPTIVE TEACHING AND LEARNING FOR AIED

- It is proposed that AIED is employed as means to support teachers to design and orchestrate adaptive learning content and individualised learning activities aligned to student's knowledge levels and skills
- It is proposed that AIED is employed as means 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 as means to support teachers to design emotional awareness support and to diagnose social and emotional learning for developing partners of student's affective states
- It is proposed that AIED is employed as means to support teachers to design intelligent formative feedback focusing on the process of learning aligned to students' needs

AIED APPLICATION 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 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

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 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 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.

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

1.8 CONCLUSIONS AND FUTURE RESEARCH

In the first part of this study, an evidence-based review is conducted to address the question "What do we mean by Artificial Intelligence in Education?". The process of thematic analysis and synthesis was perpetuated, 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 is 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 whilst make 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 amongst 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 rapid use of AIED in schools and for allowing a better understanding between 'doing ethical things' and 'doing things ethically' (e.g., Holmes et al., 2021). 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, tools in ethical and informed ways is central to enhancing the student learning experience and attainment of learning outcomes. Comprehensive AIED competency frameworks are needed to help teachers to plan, self-assess and reflect on existing and new skills that would be required 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 designing learning that 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, 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.

PART 2:

EMPIRICAL STUDY ON TEACHERS' EXPERIENCES OF AI-BASED TEACHING AND LEARNING

INTRODUCTION

The second part of this research aims to investigate UK school teachers' experiences of teaching and learning with the use of AI. It is anticipated that the results of this empirical study will shed light on different ways of designing and enacting AI-based teaching and learning interventions in blended, hybrid and distance learning modes. In line to this, the research questions addressed are:

1. *What are school teachers' conceptions of and approaches to AI-based teaching and learning?*

2. *How do these experiences and understandings impact ethical and skills-related aspects for enabling AI-uptake in UK schools?*

AI-enabled implementations and investments in educational settings are rising exponentially for enabling teachers to design and deliver learning that is tailored to the needs, experiences, and interests of prospective and existing students.

Despite increasing interest from educators and education leaders to exploit AI for enhancing and personalising the student learning experience, there is no empirical evidence that pinpoints the varied ways AI is conceived and utilised especially for transcending to the fourth education revolution (e.g., Seldon & Abidoye, 2018). Indeed, the most imminent momentum is on technological advancements around datasets, algorithms, prediction models and AI techniques and not on the meanings, practices and processes that would potentially proliferate a holistic and disentangled subjective experience of AI for teaching and learning beyond the latest technical hype. Nevertheless, AI-enabled implementations and investments in educational settings are rising exponentially for enabling teachers to design and deliver learning that is tailored to the needs, experiences, and interests of prospective and existing students. However, AI is not always visible to the teachers and to the students who are the main actors that utilise the technology because it may be hidden under visual interfaces, applications and tools which infer associated data for executing requests. This may cause confusion, unawareness, and an elusive assumption that AI for learning and teaching is not linked to and related with theories and methodologies from the learning sciences whilst reinvigorating epistemological and ontological underpinnings in terms of: What data should be processed by an AI system? What information should be discerned? What is the nature of knowledge and skills and how they are communicated? How learning is constructed, assimilated, and represented? How is assessment and feedback designed and facilitated? It is perceived that AI may help to open the black box of learning (e.g., Luckin et al., 2016) by employing computational models and techniques to understand aspects of learning accommodation and assimilation that were not possible to be identified before and applied to learning situations supported either with AI or not.

This part starts by presenting the methodology employed for carrying out this research encompassing the theoretical underpinning cognisant to the phenomenographic research method, recruitment of educators, data collection and analysis. Then the document continues with the findings, discussion, and conclusions.

2. METHODOLOGY

The study employed phenomenography as an interpretive research approach to investigate the different ways in which educators perceive, experience, and make sense the phenomenon of teaching and learning using AI within a classroom setting. The phenomengraphic method is illuminating because the deep analysis processes applied to identify variation into experiences can be exploited to bring to the fore teachers' understandings of AI-based teaching and delineate the development of the strategies, methods and processes adopted as means to achieve a more holistic understanding of the application of AI in education. As such, the predominant focus of the phenomenographic approach was not only on the phenomenon per se, nor just the educators who were experiencing the phenomenon but also on the intrinsic connections and relationships between the phenomenon and the subjective experience as experienced by the teacher (Marton, 1986) and which constitutes the anatomy of the experience. The study denotes 'conceptions of teaching and learning using AI' to illustrate different aspects of the experience and its collective meaning as experienced by people. This alludes to the fundamental theoretical underpinning of phenomenography, the second order perspective, which underlines the importance of variation as being an integral part of the experience. This contrasts the first-order perspective which examines the general and objective truth of a phenomenon (Marton and Pang, 2008).

The outcomes of phenomenographic research are consisted of a logical set of 'categories of description' 'dimensions of variation' and the 'outcome space' (Marton & Booth, 1997). Categories of description delimit the meaning of the experiences from less to more completed ways of experiencing the phenomenon. Categories are then assembled to delimit the dimensions of variation which portray the structural elements in each category and their disparity between the meanings of the different categories. The outcome space is the configuration that combines the referential aspects of the experience demarcated in the categories of description with its structural aspects resembling a foundation of 'how' the experience was constructed at a collective level.

2.1 RECRUITMENT

The recruitment strategy of the 25 science and technology educators started in April 2020 by sending invitation letters to UK schools and educators via email to participate in the study. However this strategy was not deemed successful due to the pandemic restrictions. An alternative strategy was then established through searching, finding, and recruiting educators from science and technology online teaching communities via social media and sending invitation letters specifying the purpose of the study along with the profile of the participant that was required for this research. From 46 invitations in total (via email and via social media) 25 educators teaching science and technology in primary (Year 5 to Year 6) and secondary education (Year 9 to Year 13) participated in the study for eliciting rich descriptions and conceptualisations of orchestrating teaching with the use of AI. Purposive sampling assured that the selection of participants will be varied and diverse based on associated interests, characteristics, and backgrounds in: (1) teaching using educational technology; (2) teaching using AI; (3) awareness of AI-based teaching (whether participants have a basic understanding of AI in teaching including definitions, applications, tools and implications) (4) taught STEM subjects with identifiers of subject area (BIO = Biology; CHE = Chemistry; PHY = Physics), COM = Computing and (5) gender. The purposive sampling participant profile is presented in **Table 1.**

Teaching	Teaching via Ed Tech	Teaching via AI	Subjects taught	Learning mode	Gender
32 years	30 years	10 years	BIO	Blended	Female
35 years	30 years	5 years	PHY	Hybrid/distance	Female
38 years	27 years	5 years	PHY	Hybrid/distance	Male
33 years	22 years	5 years	CHE	Blended	Male
22 years	18 years	4 years	CHE	Blended	Male
30 years	15 years	4 years	BIO	Blended	Female
25 years	14 years	4 years	BIO	Blended	Female
20 years	12 years	2 years	PHY	Blended	Female
21 years	11 years	2 years	PHY	Distance	Male
27 years	10 years	2 years	BIO	Blended	Female
16 years	10 years	2 years	BIO	Blended	Male
17 years	10 years	2 years	COM	Hybrid	Female
19 years	10 years	2 years	COM	Hybrid	Male
24 years	10 years	2 years	BIO	Distance	Male
14 years	9 years	1 year	PHY	Blended	Male
15 years	9 years	1 year	PHY	Blended	Male
17 years	8 years	1 year	CHE	Hybrid	Female
11 years	8 years	1 year	COM	Hybrid	Female
12 years	8 years	6 months	CHE	Blended	Female
14 years	7 years	6 months	CHE	Hybrid	Female
10 years	7 years	6 months	BIO	Distance	Female
13 years	6 years	6 months	PHY	Distance	Female
9 years	4 years	4 months	COM	Hybrid/distance	Female
6 years	2 years	4 months	PHY	Hybrid/distance	Male
4 years	2 years	2 months	BIO	Hybrid/distance	Male

Table 1: Participant Profile

To obtain as much variation as possible on the experiences that educators had in terms of understanding and employing AI in teaching and learning, it was important for the participants to have diverse experiences in conventional teaching, teaching using educational technology and teaching using AI. The learning mode was a contextual factor that drove the discussion and since the interviews were realised during the pandemic, participants described practice in different learning modes based on their current context of practice: (1) blended – students learn in the classroom using technology (2) hybrid – students attend face-to-face classes and have some learning online and (3) distance – students learning is only online and detached from the classroom. To maintain a gender balance, 14 of the participants were female and 11 were males. Participant identifiers are purported with a pseudonym for indicating gender.

2.2 DATA COLLECTION

Phenomenographic interviews were employed to elicit participants' experiences of using AI for teaching and learning. In line to this, the aim was to capture the way teaching with AI was conceived and described by the educators, and therefore interviews were flexible to allow participants to explain deep understandings of what teaching with AI meant to them. When the interview started, it was articulated what AI means and how it may be used in educational settings. Interviews lasted for about 60 minutes with key questions to encourage participants to start thinking and reflecting on their own practice. The first question was formulated around "Could you please describe what do you mean by employing AI for teaching and learning?" The second question was purposefully looking to extract strategies, methods and practical ways of using AI "What do you mean by creating impact with the way teaching is enacted with AI?" The third question attempted to highlight ethical implications such as "What do you mean by using AI ethically for teaching and learning?" The fourth question was about investigating professional development aspects for enabling teaching with AI: "What do you perceive as skills development in using AI-based systems?" Follow-up questions, were employed to stimulate clarification in pertinent aspects, such as "What is the role of the teacher in using the AI? "How a students could be helped to learn with AI"? "What is the role of AI" for adding breadth and depth to elements that were emerging through the discussion. To comply with ethical research procedures, all participants signed an information sheet and a consent form making explicit what is expected from them, the right to withdraw and our obligations towards them and towards the data we collected about them in terms of treating data confidentially, their voluntary participating nature and their right to withdraw at any time. Participants were well-informed of the study's overall research design strategy having been validated externally to ensure that the questions asked would address the research's objectives.

2.3 DATA ANALYSIS

The interviews with each individual participant were tape-recorded and transcribed verbatim for proceeding to data analysis. The qualitative analysis software Dedoose was used for coding, analysis, and data management and for identifying the relationships and the structures through which the experiences emerged. The analysis process started with familiarising with the meanings and inferences from the first 13 transcripts to constitute a tentative set of categories and configure the initial dimensions of variation. An attempt to search for new data and integrate them to the existing categories by analysing the remaining 12 transcripts. The entire process of constituting the categories of description, the dimensions of variation and outcome space was a process of code, analyse and infer meanings from an amalgamation of participants' views and experiences and the researcher's interpretation of the meanings as extrapolated from the analysis. Finally, the outcome space was constructed through mapping each experience with its structural aspects.

3. RESULTS

The results of the study are presented in this section comprising of a set of categories of description and the dimensions of variation that materialised from the data analysis process. Four categories of description and nine dimensions of variation had emerged to delimit meaning and structure of experiences of teaching using AI. The ten themes of awareness portrayed in the dimensions of variation pass through the four categories of description with qualitatively differences that are highlighted in the description of the dimension. Drawing on these findings, the study reveals aspects of teaching with AI along with implications of AI usages such as ethical dimensions and professional development that will most likely influence the uptake of AI in the classroom.

3.1 CATEGORIES OF DESCRIPTION

AI was conceived as a medium for:

(A) **Reducing time for procedural learning**

(B) **Optimising knowledge acquisition**

(C) **Developing skills that enable deeper learning**

(D) **Transcending learning to transdisciplinary and experiential contexts**

CATEGORY A: AI FOR REDUCING TIME FOR PROCEDURAL LEARNING

The overarching focus of this category is on helping teachers with administrative work such as having an AI system to track attendance, organising learning content and essentially automating administrative activities that required extensive time for the teacher to implement. Automated marking processes was also perceived as a fundamental aspect of introducing an AI system for automating the marking process as it was perceived that this will alleviate the processes of reviewing and grading the tests and exercises of the students. The main AI-enabled system prevalent in this category was an institutional Learning Management System (LMS) that had embedded an AI component responsible for supporting the teacher with administrative work. Sharing and communicating students grades with the school's registry and with the head teachers was also perceived as a task that the AI can execute.

Utilising the AI to help teacher with searching, organising, filtering, and retrieving learning content was seen as an important supportive task especially in terms of having the AI to provide a list of resources that would certainly allow time for teachers to focus on the actual teaching process in the classroom. A key support provided by the AI was in terms of undertaking specific operations that support the realisation of learning. Such operations were in line with having an AI to help students to make calculations, look up for word definitions or keeping a digital glossary for students that don't retain information easily. Interestingly, a teacher felt that by using a text-based chatbot may help students with step-by-step guidance on how to install and configure scientific software on computers. A teacher perceived that the provision of real time translation and language processing from AI is key for alleviating communication barriers and for facilitating large multi-cultural classes where many students do not speak the same language. The focal aspect of this category is using AI mostly integrated into an LMS (e.g., learning analytics for managing and automating assessment, finding, and organising content, and helping students with supplementary procedural learning processes (calculations, glossary, installations).

Table 2: Representative quotations for Category A

Representative quotations *"A system that supports marking in an automatic way. A task for example that I would perform as a teacher but in a more, in a quicker way" (Mary). "the children can do their work on the system and the system automatically grades it and it makes it quicker and easier for me" (John). "I may save time from searching resources" (Adam). "By setting specific criteria and allowing the AI system to provide me a list with resources that may meet these needs" (Louise). "Because in the UK context there are a lot of admin processes that take a lot of the teacher's time. So AI may help in speeding up such processes, such admin activities so the teacher may have some more time for supporting students" (Maria). "A text-based chat box to help the students to install software on their computer to configure their settings" (Nick). "[..] an AI system to help with translation, either to students or to teachers, this would have achieved a better communication between us" (Anne)*

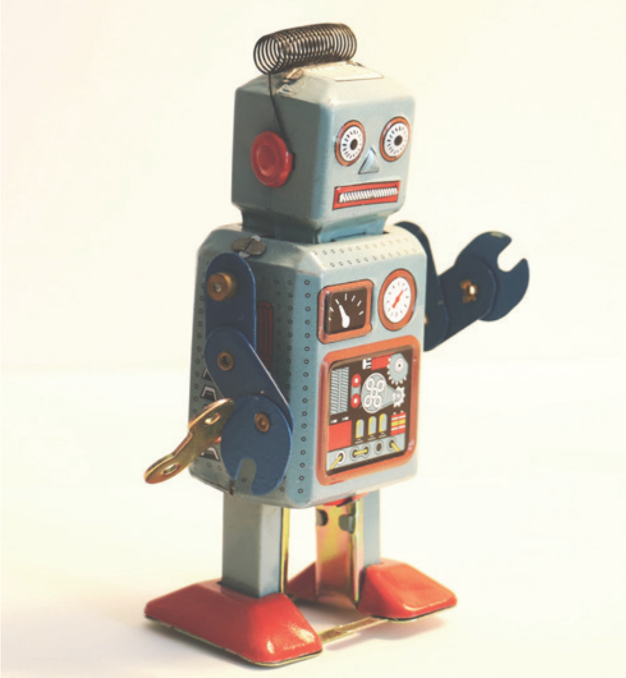
CATEGORY B: AI FOR OPTIMISING KNOWLEDGE ACQUISITION

In this category, the focal point of attention is the use of AI for increasing student engagement with learning material which may lead to knowledge acquisition. Similarly, to Category A the importance of finding, accessing, and retrieving information is key but the essence now in knowledge acquisition and retention. AI is therefore perceived as a supporting tool for helping students to reinforce and improve pre-existing and new knowledge schemata. The AI elements, as in category A, is mostly part of an LMS representing an Intelligent Tutoring System (ITS) with an imminent role to suggest and provide learning content based on student's needs and interests. The ITS then learn student's learning content preferences and suggests a tailored learning path that contains content, tests, and exercises for assisting the student to optimise knowledge acquisition and retention. The ITS provides an initial assessment protocol and tool such as an adaptive diagnostic tool for diagnosing prior and current knowledge, learning performance and misconceptions and then it proposes lessons, topics, digital learning content, quizzes with multiple-choice questions, tests, and exercises for the student to revise based on whether the student is less advanced or more advanced with learning, which determines the level of learning content adaptation. In this category AI follows a structured and linear learning sequence through providing to students test results, grades, monitoring engagement and suggesting learning material. This approach to using AI resembles a conventional model of teaching and learning that is based on information transmission, rote learning, facts memorisation and static knowledge.

Knowledge acquisition and mastering content is highly correlated with achieving the intended learning outcomes and through the ITS, the teacher attempts to identify students who experience difficulties with their learning and help them to overcome such learning difficulties by working on the detected misconceptions for bringing all students at the same learning level. The ITS therefore, engages students with personalised learning content, adaptive exercises, and tests and through the learning analytics component, the teacher reviews and identifies reasons behind student disengagement. The teacher also validates and reviews the grades provided by adaptive test systems before releasing them to the student. Educators highlighted the importance of rich-mediated content that the AI provides as a predominant factor that amplifies student engagement. For example, through offering personalised content in the form of diagrams, mind maps and displaying learning content from the Web that is curated to meet the learning needs of the students or through providing suggestions of learning materials for the teacher to encompass into the design of the lesson plan. As in Category A, learning analytics is widely utilised for data-driven inferences on student engagement and course interaction metrics and progression levels. The variation however is that in Category B, the teachers are interpreting the data from analytics to provide support and rapid intervention for helping the student to address learning problems.

Table3: Representative quotations for Category B

Representative quotations *“Using an ITS to find rapidly small chunk of information, a definition of this, a diagram of that” (Julie). “If we are very clear about what knowledge to be acquired by the students, the AI can help via proposing additional learning materials and alternative paths to knowledge” (Andrew). Run another ITS called BTSB. It does an initial assessment then actually gives them a current level. And what it does is these are the areas [...] this is what you need to improve on” (Mark). “If you give correct answer or if you get like eight, or full, if you get all questions right it (the AI) gives a grade” (Natalie). “The AI would help them achieve those learning outcomes they thought they couldn’t do” (Nick). “To understand through analytics why they don’t engage, they don’t engage because they are completely lost, they are not engaged because they found material easy, to using AI to identify what is the issue that the students don’t engage (Linda). “Educake a diagnostic assessment tool where we set quizzes for kids” (Laura) “I’m going to do the percentage questions because I’m good at percentages whereas actually if AI kicking out decimals which I’m not so good at, that’s what I’m going to be doing today because I’m not so good at it”. (Mark). “The algorithm analyses what the student has done well at and therefore reduces the frequency of that style of question, be it content, still or type of question it puts in front of you and increases the areas that you haven’t done very well at, the idea of adapting content” (George). “[AI to provide suggestions] for teachers, for example exercises, assignments or examples that are proved to be effective from previous users could be suggested to a teacher when they develop their own learning materials or when he wants to employ some examples in a presentation or within a learning material that they prepare (Bianca).*



CATEGORY C: AI FOR DEVELOPING SKILLS THAT ENABLE DEEPER LEARNING

As in Category 2, this category continues to emphasise adaptive learning content placed in the periphery of the experience however the focal awareness changes to using AI applications and tools for helping students to develop skills and competencies that enable transformation of knowledge to deeper learning processes. By deep learning processes, participants meant the ability and capacity to develop skills to solve complex problems and for developing meaningful learning experiences through engagement in learning activities. Social and emotional learning combined with collaborative learning skills were perceived as key for participating into learning activities that encourage students to engage in deeper learning experiences. AI applications and tools that were employed for skills development and deeper learning were task-oriented chatbots, conversational agents (e.g., virtual assistants), intelligent simulations, AI-enabled games (for gameful and playful stealth learning) and other storytelling applications, virtual reality and task-based ITS. This expansion of applications and tools as opposed to Categories A and B, seems to enable a more active, empathic, and activity-based orientation to using AI. Assessment is not only focused on tracking misconceptions, visualising and reviewing data on progress, levelling learning across students, and automatic grading, but most importantly on rapid and intrinsic feedback that helps students to clarify misinterpretations and make informed decisions on their next learning steps and envisaged future educational endeavours.

Soft-skills development through virtual assistants and chatbots perceived as an adaptive process to help students develop broad skills such as communication, collaboration and personal expression beyond the scientific skills embroidered into the scientific curriculum. Participants felt that a task based ITS could create an automated student group based on similar characteristics such as learning level, skills, culture, language and needs. Intelligent match-making applications were used for classifying students with similar needs and interests, culture and personality traits. An envisaged application of intelligent matchmaking was to couple students with teachers that can accommodate the needs, learning level, subject content, demographics of a student. Encouraging students to pose questions to task-based chatbots for receiving constructive feedback was also a key element for deep learning. Participants also combined the activity of asking questions to chat-bots and virtual assistants with multimodal tasks for entangling different ways of learning supported by an array of media (e.g., auditory, visual, reading / writing). For example, participants highlighted the importance of having a conversation with a chatbot for applying skills in practice. There are varied ways that the chatbot learns about the student's current skills. Firstly, it executes a series of questions designed by the teacher, and then the chatbot renders the questions for building a profile with current and new skills for the student to develop. Secondly, by using machine learning, the chatbots student data from the interaction with the student and build a skills and competency student profile. This algorithmic profile could also be used to extricate between advanced and less-advanced students for tailoring activities and learning resources with current level of skills. Discovery-based learning, learning-by-doing and visualising outcomes from discussions with AI for reflection is at the centre of the experience of teaching using AI where the actual learning gained is the most essential aspect rather than just covering the subject matter.

Table 4: Representative quotations for Category C

Representative quotations *"... but for me it's AI for developing those skills" (Luca). "Using an agent for transformation of knowledge, so this is a different level of knowledge, it's not just understanding definitions and understanding sort of basic level of covering a certain topic but it demonstrates they've made the knowledge their own and they are able to apply it.." (Mina). "Learning about the skills of students, we give students 3 choices; how would you evaluate your skills in bubble sort for example, simple, medium, advanced? And based on the selection you can have a conversation with a chat-bot, and you can get learning material (Joyce). "For instance, a chatbot could provide additional resources, you can go there online and find out, find more exercises to do in loops or if you could read that xyz URL to find out more about loops" (Maly). "Having a chatbot for instance as my assistant it could help students with low skills in programming to cover the simple exercises quite quickly and also jump to the medium exercises and also to the advanced exercises" (Ian). AI being capable of learning, having machine learning algorithms running in the background, I would imagine that that system would be capable of learning about the skills of students based on interactions with the system" (Damian). "the chatbot would have some initial discussion with the student, where the chatbot would try to evaluate the skills of the student – how good the student is at programming and then it would automatically adapt the conversation, the content, as well as any exercises to the skills of the student" (Michael). "Help them develop a general and broader set of skills including connectivity, soft skills, communication, aspects that are not only related to science" (Luca). "microphone and a camera, so the camera can use computer vision algorithm to recognise face and gestures which shows my emotions on feedback and this can be trained in order to understand whether I am angry, whether I am distressed, distressed, and the tone of the voice, taking that as accumulation, together with the question, you have really what you want for getting feedback from the agent" (Dino). "I also believe that supporting the creation of groups and social networks between students also can can profit a lot from AI, for example, with whom should I co-operate in a project? Or what kind of collaboration should I seek in order...? "So suppose I am going to teach them cell structure, about human cell, So what are the components of cell, so it, we can make it some certain AI game and interacting with all the organisms of a particular cell" (Moly)*

CATEGORY D: AI FOR TRANSCENDING LEARNING TO TRANSDISCIPLINARY AND EXPERIENTIAL LEARNING CONTEXTS

Category's D focus is on using AI for self-direction and independent learning as means of applying learning to different learning situations, environments, subjects and real-world contexts. Aspects delimited in Categories C, B and A such as skills development through activities for deeper learning, knowledge acquisition and procedural learning are in the background of the experience whereas the transdisciplinary application of learning through activities enacted through AI is now a key tenet. Creativity as a process of becoming independent and self-regulated is perceived as the vehicle for using and applying learning in other educational and knowledge -building practices and for identifying early career development directions. Skills are perceived as cross-curricular capabilities and literacies, involving competencies on AI techniques, that can be transferred to solve problems in other subject areas or to experiment with applications that contain properties and attributes from an array of scientific knowledge domains and real-life problems. AI applications and tools are ranged from Exploratory Learning Environments (ELEs) for open-ended tasks, dialogue-based virtual assistants, text-based chatbots for open-ended tasks, to virtual reality, augmented reality, games, simulations, and automated creative story generators for making creative work. Commissioning an AI to help with the creation, implementation, and expansion of transferable learning where diversity of skills, knowledge and expertise formulates a compound of learning dexterities that are holistic, relevant, and evolving in terms of building understandings of how the world operates. AI is seen as an application for encouraging self-assessment and for fluidly probing students to make meaning individually and collaboratively.

AI is perceived as a scaffold for helping students to be self-regulated through enabling inquiry and scientific research, critical thinking and learning transfer. For example, ELEs are being deployed for open explorations, research self-assessment and independent learning activity. Assessment and feedback are focused more on having conversations with virtual assistant or texting with a chat box on how learning may be transferred to other contexts and prioritising on next learning development opportunities.

Table 5: Representative quotations for Category D

Representative quotations *"I can see the use of AI in any subject, and I'd like to think that because we are preparing students for the wider world and we know that it is going to be AI based that actually there would be an opportunity regardless of what subject and domain that we're using it in, that there are opportunities for children to use it" (Edward). "I'm preparing children for the unknown, so I need to give them as much experience with the possibilities of their future environment and it is going to be very technologically led so I need to expose them to as many different forms of computing systems, AI systems as possible. They're going to be using things that we don't even know of yet" (Mary). "Using an ELE for research purposes and I could get different groups of students to different areas of research independently" (Nick). The kids must use their imagination about building a house in VR. So, when they're done constructing it they've actually built an actual structure in their mind cause that's what they see. So, it helps with their imagination and it taps into reality in ways that provides for their interest and helps them connect in real life (Maria). I may utilise a game simulation that is something that they can click on and find the data themselves and drive the investigation how they see fit (George).*

“They could actually do a computer simulation and they could tweak the prey amount, or the predator amount and they can get live time feedback very similar to what scientists do in the field” (Linda). “Let them to do something, independent learning with a virtual assistant like Alexa. Exploring say a cell or a blood system or exploring even the solar system (Damian). I am using an open learning task via an ELE there is incorporating a lot more sort of cross curricula. Cause you’re incorporating history and science and then incorporating maybe a bit of physics and science and maths. That’s where the improvement, via the AI, would come in a classroom (Ian). “Like using maths in an augmented reality came like maybe a Monopoly game where you’re running round the college trying to solve financial problems with maths” (Andrew). Getting artificial intelligence write an essay and have children to reflect on the nuances, vocabulary, grammar, story and differences with human creativity (Moly). “I can see that it would be interesting for a computer to, for example to extend the creativity in a child resetting a fairy tale into a science fiction context” (John) “I think the students need AI skills; it’s a skill which I would say is at cross curricular. It’s like even though I don’t teach English, I’m still teaching my students English. So even though I don’t teach computer science, I think it can still be developed and taught in all lessons and I think it’s a skill, especially if we look at the job market and the way that their future careers, we need to be preparing our students to be able to use AI and technology efficiently and effectively, so I think it should be used across lessons (Adam). “We’d ask to use the ELE and self-assess about where they feel they are on those topics and have a dialogue with points to improve” (Joyce).

3.2

DIMENSIONS OF VARIATION

The four dimensions of variation that emerged from what educators' implicitly or explicitly denoted as conceptions of and approaches to AI-based teaching may be resulted from an interplay of structure and agency. That is, the experiences of using AI for teaching are physically situated into a context are influenced by the qualities of a place (e.g., school, learning environment, technology, in-class artefacts) and the way that physical things, such as AI tools and applications, become intertwined and affect the experience (Goodyear et al. 2016). Table 6 outlines the variation of nine individual dimensions across the categories and thereby it constructs its developmental nature.

Table 6: Dimensions of variation on AI-based teaching

	A	B	C	D
Focus on knowledge dimension	Procedural	Transmissive	Applied	Transferrable
Learning mode	Blended	Blended	Hybrid	Hybrid / Distance
AI applications & tools	LMS, analytics, recommenders	ITS, adaptive diagnostic tools, content recommenders	Chatbots, virtual assistants, games, task based ITS	ELEs, dialogue based ITS, chatbots, story generators
AI-based assessment and feedback	Automated grade management	Factual assessment	Rapid and intrinsic feedback	Adaptive self-assessment
Role of the teacher	Managing data	Providing data	Facilitating meta-learning	Facilitate transfer
Role of the student	Familiarising	Acquiring	Clarifying	Embracing
Role of the AI	Tracking	Engaging	Interacting	De-contextualising
Focus on ethics	System-design variability	Non-maleficence	Autonomy	Explicability
Focus on teacher development	Gaining confidence	Data and information literacy	Ergonomics (human factors)	Situated and Epistemic co-design with AI

FOCUS ON KNOWLEDGE DIMENSION

The knowledge dimension characterised the nature of knowledge in terms of how it is perceived by the educators and how it develops through the categories. In to this, the focal points are running through procedural and transmissive to applied and transferable. In category A, the emphasis is on perpetuating and managing procedural learning in an automated and linear way, ensuring that procedural knowledge (calculations, annotations, dictionary, glossary) are being provided and catered from the AI system. In Category B, there is a shift in how knowledge is viewed propagating a model of knowledge transmission, taking a positivist perspective that knowledge is the absolute truth, and it is proven through the provision of facts and thereby AI is used for knowledge acquisition through the provision of adaptive content. It resembles some of the most modern techniques adopted to train an algorithm using reinforcement learning principles denoting a paradigm of repeating learning interventions and rewarding the correct execution of fundamental concepts. “It's very good just to know the multiplication table by heart and it's very good to know the periodical system by heart and it's very good to know the rules of writing” (Jules). In Category C, the nature of knowledge is becoming more situated, applied and activity-based, alluding to constructivist principles that learning is subjective, personal, and meaningful to demarcate a more interactive and socio-cultural perspective of AI usage “using that AI technology, there is a lot of problem solving, a lot of discussion, sharing ideas, trying and again, I guess, it comes back to that trial and error element of it, that you try something, it doesn't quite work, you de-bug, you try again” (Adam). Similar with category C, category D is about activities, investigations, self-regulation and transferability or even better transformation of existing knowledge to a different form, perspective or even model that drives knowledge to stay applicable and relevant and not inert “They could put together a simple construct of their garden on a plug and play version of an intelligent VR and then tweak things and get accurate data to facilitate their curiosity and keep them engaged in the situation”(George).

FOCUS ON LEARNING MODE

A critical dimension that may wove into and affect how AI is being interpreted and used is the learning mode. In Category A, blended learning was used as an umbrella mode to host in-class learning and teaching through a blend of AI-enabled learning interventions. Using AI mostly for administrative activities can be related with the nature of the epistemic design of the learning giving more gravity to the learning outcomes that are realised at learn-time in class and hence the AI is collecting, monitoring and classifying student data mainly for class-based teaching “if learning happens in a blended format, because as a teacher I'm very interested to see what my students do, how much time they may spend on specific activities, what's their performance have some insight of their activity. Where they struggle, where they spend more time” (Bianca). In line to this, in Category B participants felt that blended learning facilitates the use of AI mostly for factual knowledge and content recommendations whereas most of the knowledge optimisation, refinement and validation is propagated in class “So we go through it the old-fashioned way on a board and then they would use AI to try different material or different examples” (Mary). In category C, the learning mode is hybrid meaning that the dynamics between online and in-class teaching are balanced. As students have a weighted portion of learning in-class and another portion of learning online, the AI-enabled activities are more prevalent and core to students learning advancing the design of learning to involve ubiquitous and omnipresent activities that are facilitated and orchestrated by the AI “I would say that chatbots could create a hybrid environment where students can get support all through the classroom as well as outside the classroom” (Maly). In category D, participants perceived that the learning mode is either hybrid or fully distant and therefore shifting the usage of AI towards encouraging self-direction, reflection, and transfer of learning to other topics, subjects, lessons, and applications. “The ELE will tackle social and communicative aspects between them, which will help them potentially increase their understanding around the course, which the course itself is distanced learning” (Natalie). The assumption of using AI to facilitate students' interactions may well be that in a distance learning mode, the physical presence of the teacher and the students are non-existent, and the responsibility of learning should be placed primarily on the student, designed by the teacher-designer at design-time and orchestrated by the intelligent agent at learn-time.

AI APPLICATIONS AND TOOLS

The use of a diverse set of AI applications and tools is varied and may be influenced by teachers' conceptions of teaching, theoretical underpinnings of educational science and enactment of AI in practice. In category A, AI applications and tools are mainly through the institutional LMS and associated applications such as learning analytics, learning content recommender systems, and automated test systems mainly for organising, managing, and tracking student activity and for mitigating procedural learning routes. "For using metrics, so for automating organisation of lessons, counting absence, managing student's work, monitoring parent's contacts, whatever, administrative tasks" (Anne). In category B there is an identical espousal of AI, but the focus is now on proliferating tools such as ITS, automated diagnostic tools, adaptive test systems as means for diagnosing and levelling what the student already knows, ways of learning with predominant weight on the acquisition of factual knowledge through digital information transfer. Ensuring that the students are engaged is paramount, tracked via student data visualisations and representations in learning analytics embedded in LMS and automated tests interfaces. "Having an ITS by presenting content in different ways and then looking at how that impacts student progress" (Bianca). In Category 3, there is a shift in the application of AI tools, mostly likely to support open, flexible learning and applied learning. Such tools span from chatbots and virtual assistants to games, simulations, virtual and augmented reality, and task based ITS. Activity-based AI-enabled learning, research, investigations, and group-based activities are designed by the teacher and enacted by the AI. "I design interactive exercises for the chatbot and then students in groups are interacting with the chatbot to solve them" (Michael). In Category 4, analogous applications and tools are employed as in Category 3, along with ELEs, dialogue based ITS and intelligent story generators to propagate automated creative endeavours, self-regulated learning enmeshed together for accomplishing learning that is socially, epistemically, and physically situated. "ELE applications with AI and combined with VR and augmented reality, and I think this, this immersive way of learning is very interesting for the students because they can see spaces like in physics and biology, they cannot see in the physical world and then they can change functional groups of chemical molecules like being real scientists" (Linda).

AI-BASED ASSESSMENT AND FEEDBACK

Intelligent assessment and feedback are varied based on the dynamics and the pragmatics of using AI in specific learning instances. In Category A, administrative and organisational aspects of assessment is the focus, particularly relevant for saving time and effort towards automating the management of the grading process. Teachers perceived that this helps with classes that involve a relatively large number of students and thereby helping the teacher to achieve an efficient and resourceful tool for managing grades. "Children can do their work on the system and the system automatically grades it. And it makes it quicker and easier for me." (Mark). In Category B, the focus shifts from automating the management of grades to factual assessment through multiple-choice questions. Using automatic test generators may help students to gain a better understanding on performance through assigning grades and then clarifying with the teacher the learning processes needed that will improve the grades. "The system knows the correct answer and so you could have a bank of multiple-choice questions that are put together and are randomly selected in each topic group. Say for example cell biology I have a question bank of about 50 different questions related to cell biology and if I want to put an exam paper together for the students, I just select cell biology, choose from options that come up and the system gets a grade for each" (Joyce). In Category 3, focus is on rapid and meaningful feedback in a sense that grades are accompanied with automated feedback that helps students to identify and target on the misconception that needs to be rethought. "The AI analyses each question and provides a response straight away. So if they've done something wrong they know straight away. What it's improving there I suppose you correct the mistakes quickly and you're giving deep explanations on the mistake" (Moly). In Category 4, the focus is on adaptive self-assessment, where the AI probes with questions and dialogical activities for student to reflect not only on actual learning but also on future learning instanced situated in other physical, social and epistemic contexts "The students type their answers to the questions and the Educake looks for key words in the student's answers and if it finds the key answers, it marks it as correct and if it doesn't it marks it as incorrect, or if it's unsure, it flags it for me as a teacher to review. So, if it can't find it, if it's unsure or if the student's unsure it will then flag it to me. I will then get sent the answer by the Educake system, I can then click if it's correct or incorrect and over-rule it" (Joyce)

ROLE OF THE TEACHER

There is pertinent variation on the role of the teacher as a dimension that passes through the categories which also influences the role of the AI. In Category A, the role of the teacher is mostly seen as administrator and being responsible for overseeing the different operations run by the AI. From attaining to technical problems, training the data for AI to process to validating the predictions and outcomes made by the AI, teacher's role is in terms of making sure that AI is operationalising learning outputs. "The educator acts as an administrator at this stage, say for all technical bits, validating the data or the training data that we get, to see if they're actually correct" (Damian). In Category B, the role of the teacher shifts from checking on data to providing data, information, and resources for the AI to analyse and infer predictions on student's learning. "by feeding (data) to the AI system, I would like to be able to find scientific valid resources that are applicable to my students" (Nick). In Category 3, the role of the teacher is in terms of designing the learning activities that the students will be engaged with the AI. The design of such AI-based learning activities is in terms of sequencing and structuring the learning activities and scenarios of meaningful feedback for AI to be trained on. "The design of learning with the AI is done by me the teacher. I'll use a biology example, I need to teach the biochemical basis for DNA before I can teach protein production, for example, or I know that I would need to teach the effect of temperature on particle movement before I can even attempt to teach diffusion or osmosis.
I understand how to structure that so I think it would be very difficult for an AI to independently gain that so I think a teacher would have to inform the AI's teaching" (Moly). In Category 4, the role of the teacher is perceived as facilitating meta-learning processes especially in terms of connecting constructs of learning and making implicit and explicit rationales on how students can be independent learners. "By the end of the AI learning, I want you to be able to understand about climate zones around the world, however, how you get to that goal, we'll work together on how you want to get to that goal. If you want to create, for example, a game in Scratch to teach it to other children, that would be one way. If you want to do me a painting that shows your understanding of it, that would be acceptable." So, it's the pupil thinking about their learning journey and the output there, that's what they have control of. The teacher knows what they need the child to learn but the child then takes that responsibility" (Mina)

ROLE OF THE STUDENT

The role of the student varies and interrelates with the role of the teacher, and the role of AI. In Category A, the role of the student is in terms of taking responsibility of and familiarised with how AI works, especially with how data is collected and analysed for making prediction on student learning, performance, and tracking engagement. "They need to take responsibility for using it appropriately, more of the likes of how it collects data, analyses and ultimately how AI can help on supporting their learning. "To understand what it's (AI) trying to do for them (Luca). "Learn the technology but learn how it processes data to support and monitor their learning" (George). In Category 2 student's role is towards using content recommendation systems to acquire material and information that allow them to build a sufficient knowledge base. In In Category 3, there was a feeling that students are able to interact with AI to clarify and strengthen areas that they need refinement and modifications through responding and asking questions to task-based chatbots, virtual assistants and game-based interventions with intelligent agents in them. "Using the AI technology to check understanding with asking and answering some questions" (Louise). Clarification is also achieved with the teacher, after the interaction with the AI took place as means to reiterate and reflect on learning experienced with the AI. "And then later on after they finished with the ITS they could discuss with the teacher what they found difficult, what they want to go over again" (Edward). This interaction with the teacher also served as a strategy for avoiding over-reliance to technology which may cause addictive behaviours, cognitive decline, and fading social skills. "About addiction to an AI machine, that a student cannot act independently, that the student could be very tied to, to the machine, and they get caught up in the technology and they don't do the thinking or the communication with others" (John). In Category 4, the role of the student is characterised by the notion of embracing learning with AI. Teachers were felt that through maintaining a mindset that learning can be realised through an intelligent system, students will likely have more opportunities to become self-regulated and transfer learning in other domains. This process of embracing learning with AI for self-regulation and transfer may be instantiated through providing feedback to the AI in terms of the learning support it provided "they would reflect on how effective they found the system, just like we hear students talk about lessons" (Anne); leading, guiding and enquiring their learning with the use of AI "their role is to be inquisitive because if it's just a teacher standing and talking, all that the students doing is listening or copying information down which is very one sided, very spoon fed, whereas if they're using AI then the students are being inquisitive and having to research to find things out".

ROLE OF THE AI

The role of the AI system varies, and it is influenced by the many shapes and forms of the AI tools and applications, the knowledge dimension and the teaching strategies employed by the teacher to achieve the intended learning outcomes. In Category A, the role of the AI is viewed as just another learning tool "It's just another tool, like a pen, like a book (Bianca), and as such it is another tool to track and automate student's actions, attainment, and interaction metrics with the class and with the system which usually takes extended time from the actual teaching. In Category B, tracking is complemented with using visualisations, data analytics and representations as means of increasing engagement with adaptive learning resources. The acquisition of facts and knowledge is at the centre of this category and therefore the AI is used to enmesh ways of increasing engagement with such resources through visual information provided to the teacher. "So I can see from the visualisations and data how students are responding, the engagement from the AI, the questions they're asking, their overall behaviour throughout the class, the time, all these parameters, it is, I think it is quite impossible for one academic to put them together and analyse them" (Joyce). In Category C, the role shifts from engaging to interacting, where the role of the AI is to creative interactive, playful, and creative endeavours with the students for the purpose of levelling learning, identifying misconceptions, and helping students to develop skills. "AI could be an assistant that does not replace the responsibility and the role of teacher, but it interacts with the student to know about how the students learn, what they learn and why they don't learn (Natalie). "In this way by using an application which provides the interactions with students and the scaffolds for me, based on activity students may get some extra support". In Category D, interactions are further advanced to viewing the role of the AI as de-contextualising learning to contexts beyond the current scientific topic to applications in other relevant subjects areas, lessons and applications to real-life situations "If you were doing something on gathering data and statistics and you applied it to both maths and science, as in terms of collecting valid data and valid statistics and things like ecology studies, the open dialogue system then would ask 'How valid is your data? What are the statistics? How could that give you the story in science?' and using the mathematical principles that you need to be able to deal with the statistics" (John).

FOCUS ON ETHICS

The ethical dimensions that passed through the categories denote the focus on ethical AI in each dimension and deliberate on the implications that may arise in terms of guiding the principles and values that guide the theoretical assumptions and development of AI for teaching and learning. In Category A, the focus is on the design of AI that will offer multiple ways of selecting resources, artefacts, and objects for alleviating the possibility of exerting implicit and indirect unethical use of AI. "it is important that the way you are training the system is to avoid having standardised levels on the training, so always to have a variety behind it. This will give opportunities, even between the students, to have discussions, so, for example, if you always have the same avatar definite, which is always, for example, a white person, discussions behind the speculations will be but if, for example, you have variety, it makes even the student understand when they have background conversations that, hey, my avatar was a black man or was a Chinese" (Luca). In the second category, the focus is on non-maleficence particularly relevant to data privacy, security, and misuse of technology. "it would certainly be fraught with concerns about privacy and bias because you're, in order to interact with the computer the computer has got to turn that information to data and it's got to be associated with that particular person" (Linda). In Category C, the focus is on promoting autonomy in relations striking a balance between decisions made by the teacher and decisions made y the AI. "all this software should provide safety, transparency, that means can we define the rationale the machine uses when it decides A, or B, or C, if it's clear to us how, how the algorithms functions to make decisions (Andrew). In Category D, participants felt that it is imperative for the teachers and students to understand, and hold account the decision-making process made by the agent. Both transparency and accountability are variants entangled with interpreting the inner processes of AI which are often invisible to the student define the explicability aspect of the dimension. "In other words, I really think that the goal should be clearly stated as to what the AI is being used for prior to any usage. If the goals are not explicit and clearly stated, if the users aren't fully aware then I think that is more of an ethical issue (Mina).

The AI therefore is viewed as a 'teaching assistant' helping the teacher to record, update and monitor course and student administrative information. "It records all the students that they attended, the duration that they have been in my class. So I don't have to manually go and download all this information, the AI identifies the ones that they haven't been in my class and record this for a number of weeks, and, then it may contact them and find out why they are not attending or why they haven't accessed the LMS. All this is done for me without me wasting time" (Adam).

FOCUS ON TEACHER DEVELOPMENT

Educators felt that for AI to be systematically exploited in schools, skills, capabilities, and competency development in certain areas need to be attained. In Category A, special emphasis was given on gaining confidence in using AI. An all-round continuous professional development on developing awareness of AI in teaching including ethical AI use, technical skills and the impact of AI in teaching as means to gain the foundational elements of AI implementation "they would need training to understand what are the benefits that they get from an AI tool, where exactly it would help them, to, to, to be able to adapt the method of teaching, purposeful use of the AI, so, they, they should also be provided with training to prevent a phobia in the use and in the recreation of AI" (George). In Category B, the focus shifts to developing data, information, and adaptive content preparation skills as to provide the parameters for the AI to generate personalised resources to students. "How to prepare the system to provide all the data for these recommendations and functionalities that are given to students (Mary). In Category C, teachers felt that human factors in relation to learning how to design AI-based learning and how interactions with AI should be manifested and facilitated by teachers during learning-time and design-time. "Using the AI but more looking at the pedagogical design approach of how to structure a lesson in which you're making best use, effective use of, AI but you're also changing your teaching methodology to use the AI with learning design element in it to help the children learn through AI" (Michael). In Category D, the focus is on perceiving AI as co-designer and developing skills both design-like and how AI works (data collection, analysis, predictions) that would facilitate this design process between the teacher and the AI situated in the context and epistemic fluency of the student "In the long-term, there might be advanced and design-like systems that could help us to co-design teaching and learning solely situated in intelligent and immersive environments. We need to understand in advance how such co-designs will be realised, the roles and dynamics between ours and the AI's understandings of the cognitive, pedagogical, emotional, and situated domains" (Maria).

4. DISCUSSION

The purpose of this study was to investigate the impact of using AI in teaching and learning. In particular, the study delimited schoolteachers experiences of teaching using AI and identified qualitative variation in the way teachers adopted different AI-based applications and tools that informed practice. This section outlines the findings and associated categories of description with the structural elements of the conceptions as means of formulating the outcome space (Table 7). Then, a brief discussion follows on implications of AI in education as highlighted by the educators around ethics and teacher professional development.

4.1 OUTCOME SPACE

To delineate the structure of the experiences, there was a constellation to associate the four categories of description with distinct computational models, domain, learner, and pedagogy models, that are employed from AI researchers to collect data on learning aspects for generating optimal learning paths (e.g., Luckin et al., 2016; Holmes et al., 2019). The domain model encompasses knowledge on the subject being learned and the related processes that are being used to achieve subject-content knowledge. The learner model holds knowledge about the learner and all the strategies, existing and prior experiences and ways of learning that define an individual learner. The pedagogy model embraces knowledge on learning design (design-time) and knowledge on implementing learning design models including learning activities, learning theories, assessment, and feedback at learn-time.

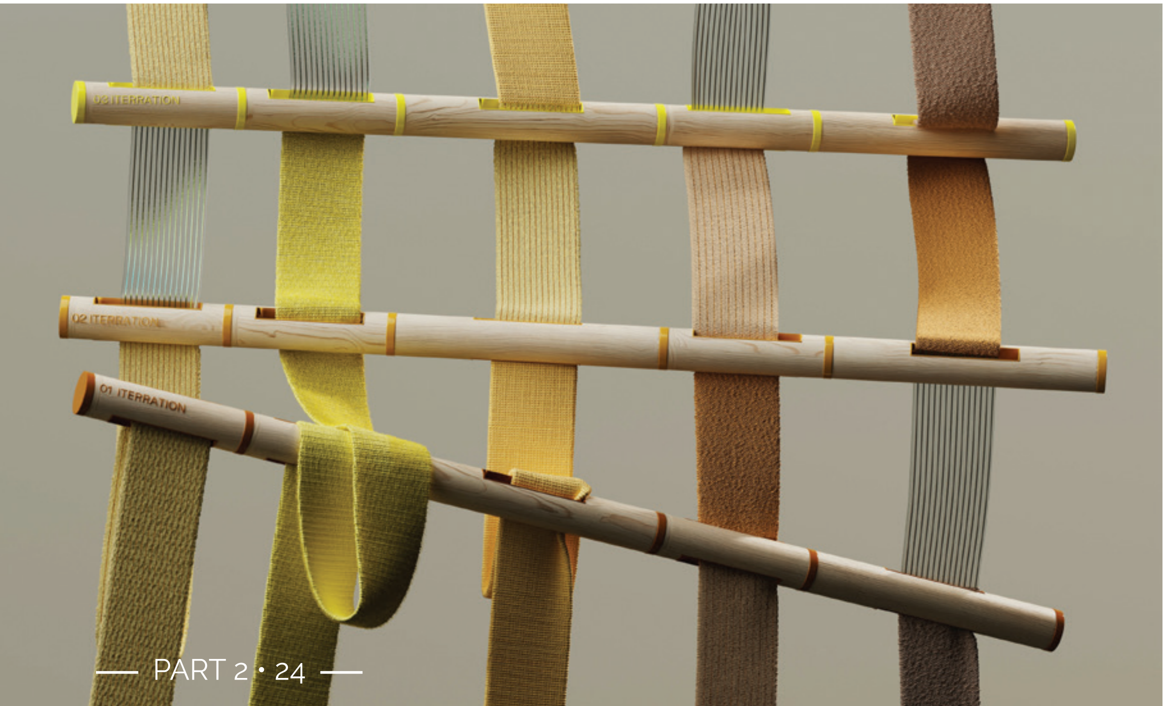
Table 7: Dimensions of Variation for AI-based teaching

Referential ('what' of the conceptions)		Structural ('how' of the conceptions)		
		Domain model	Learner model	Pedagogy model
A	AI for reducing time for procedural learning	A		
B	As in (A) and for optimising knowledge acquisition	B		
C	As in (B) and for developing skills for deeper learning		C	
D	As in (C) and for transcending learning to transdisciplinary and experiential learning contexts			D

To delineate the structure of the experiences, there was a constellation to associate the four categories of description with distinct computational models that are employed to collect data on learning aspects for the AI to process and then to generate an optimal learning path for the student based on their own interests, needs and ways of learning (e.g., Luckin et al., 2016; Holmes et al., 2019). The domain model encompasses knowledge on the subject being learned and the related processes that are being used to achieve subject-content knowledge. The learner model holds knowledge about the learner and all the strategies, existing and prior experiences and ways of learning that define an individual learner. The pedagogy model embraces knowledge on learning design (design-time) and knowledge on implementing learning design models including learning activities, learning theories, assessment, and feedback at learn-time.

In Category A, 'AI for reducing time for procedural learning' was delicately linked with the domain model as it consisted of aspects that enabled the AI system to assist with procedural learning aspects that were mostly related to the subject-domain level. It echoes therefore a distinctive propagation to exploit AI's capabilities for helping the student to accommodate peripheral subject-content related aspects (looking for a glossary of terms, spelling, and pronunciation, translations or how to fine grain objectives, tests, and exercises,) that were perceived as crucial for learning subject content. This contributes to the research on decomposing the properties and attributes of the domain model by suggesting 'procedural learning', as a sub-property. At the same time and since Category A is linked with helping teachers to automate administrative tasks (e.g., monitoring attendance) such experiences of using AI could most likely be labelled as system-facing applications (Kukulksa-Hulme et al., 2020). In Category B, knowledge acquisition is achieved largely through providing or recommending adaptive content by the intelligent system. The adaptive content illuminates and enmeshes the subject-content that needs to be covered as part of presenting a specific scientific topic embedded in the intended learning outcomes. In this sense, sub-properties of the domain model may be 'learning outcomes', 'exercises and tests', 'access to adaptive learning content'. Category B can be categorised either as system-facing because it may incorporate applications that help the teacher to track student use of AI or as teacher-facing in terms of helping the teacher to automate teaching processes such as grading and feedback and automated adaptive content provision.

In Category C, skills development is manifested through diagnosing student's ways of learning, misconceptions, interests and needs. It would be enlightening therefore to further break down the learner model into a more granular architecture that will incorporate elements that provide a more holistic identification of the learner's characteristics such as 'prior knowledge', 'ways of learning', 'learner interests', 'learner needs', 'emotional state (sad, happy, overwhelmed)', and 'personality traits (introverts vs. extroverts)'. Category C can be categorised as student-facing because the focus is on student activity using AI. In Category D, transdisciplinary experiential learning can be exhibited in the pedagogy model as self-regulated learning is viewed as the pedagogical driver for achieving learning transfer. As such, properties that can be included under the pedagogy model can be 'information transmission' collaborative learning, 'game-based learning 'self-regulated learning' 'research-based learning', 'activity-based learning'. As in Category C, Category D is typified as student-facing because of the extended support provided by the AI to apply learning in other situations.



Comparing the experiences of AI-based teaching and learning revealed in this study, with research that constituted similar empirical evidence, there are certain similarities but also there are some new findings that this study contributes that may shed light on how AI is conceptualised and enacted in educational settings. For example, Seldon & Abidoye (2018) identified five aspects of teaching and five aspects of learning which can be optimally reflect the process of enabling AI-based teaching and learning. The five aspects of teaching were: (1) preparing materials; (2) organising the learning spaces; (3) presenting the material to engage students; (4) assessing student learning and giving feedback and (5) preparing students for terminal assessments and write reports. The five aspects of learning were: (1) Memorising the material; (2) Applying the knowledge; (3) Turning knowledge into understanding; (4) Developing self-assessment ability and (5) becoming an interdependent learner. This study was specifically aimed to investigate the use of AI in teaching, and it did not represent conventional teaching and learning methods which were then adjusted to AI-based teaching. However, to inform practice, the findings may be used to enhance the design and orchestration of teaching with or without the use of technology. Category A "AI for procedural learning" was not found in Seldon and Abidoye aspects of learning and teaching although the Category represents an accentuating phenomenon that teachers struggle to cope with in relation to providing an efficient and automated way for students to have access to conscious recollection (e.g., Koziol & Pudding, 2012). Category 2 is focused on providing or recommending adaptive content for optimising knowledge, it complements the aspect of information preparation and visualisation as well as the teaching approach concomitant to factual and rote learning representations through content recommender systems. Another interesting element that is pertinent in Category B is the use of AI for increasing engagement through diagnosing student's prior knowledge, misconceptions, interests and needs that would enable the algorithm to render the data for recommending material that address tailored student requirements. The use of AI as a diagnostic tool is not omnipresent in Seldon and Abidoye. 'Applying the knowledge' and 'turning knowledge into understanding' is corroborated in Category C which further enhanced how knowledge is produced and transformed to skills through collaborative, dialogue-based and multimodal intelligent activities. In Category D self-assessment and independent learning are further expanded to denote ways that AI systems provide support for students to practice self-regulation and self-assessment predominantly via using open tasks in ELEs.

Such expanded outcomes revealed ways for using intelligent tools and applications for situating knowledge and skills in other scientific topics, learning domains and real-life settings. Variation in assessment and feedback across the four categories were demarcated to exemplify the qualitatively different ways teachers experienced the use of intelligent assessment systems, from adaptive testing systems for linear and factual assessment tracked via learning analytics to virtual assistants, chatbots and exploratory learning environments for deep and meaningful feedback. 'Organising the learning spaces' was not found as relevant to any of the categories of this study as using AI for amplifying the physical learning environment including adaptive acoustics, lighting and seating positions, however it could be further investigated and classified within 'system facing' AI tools that are centred around combining hardware, software and data analysis for proposing tailored learning environments based on student's physical posture, sociocultural traits and emotional states.

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4.2 ETHICAL IMPLICATIONS TO USING AI IN THE CLASSROOM

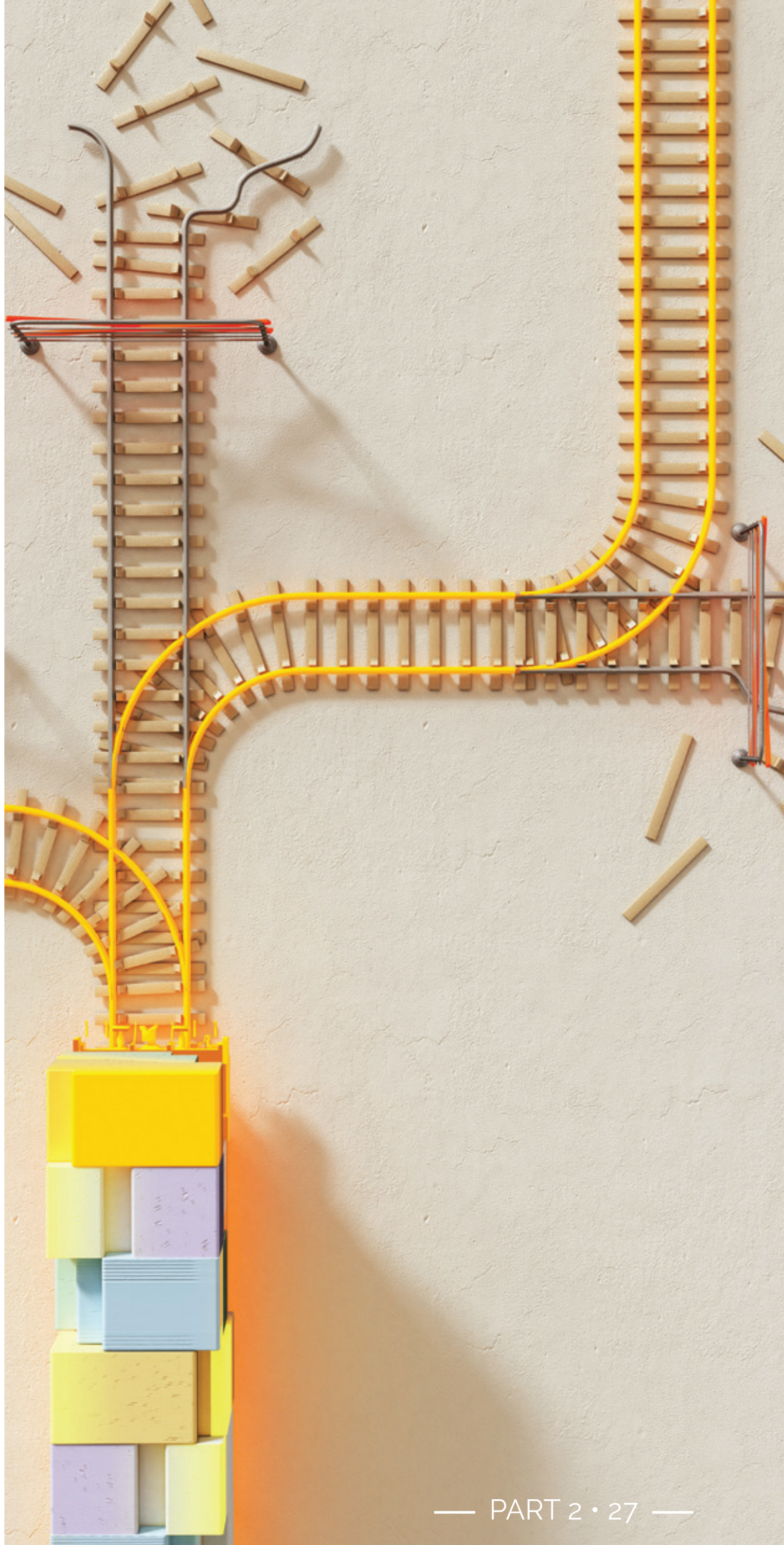
There were qualitatively different ways of experiencing ethics in relation to using AI for teaching and learning. This variation in experiencing ethics was depicted as a dimension of variation across the four categories. The ethical framework developed by Floridi et al., (2018) was utilised to convey most the ethical nuances as described by the participating teachers. In Category A, there was consensus that intrinsic properties of an intelligent system should be designed carefully to enable self-realisation of learning in intelligent ways. Smart agency enabled by the AI could be effectively coupled with human agency for designing AI systems that are not complex for educators, AI ethics specialists, learning designers, and AI researchers to understand and action and thereby structure robust intelligent learning principles that are developed to produce ethical outcomes delegated to AI systems. System design variability may be seen as a new enabling ethics principle for AI in education in a sense that purports implicit ethical design aspects that need to be featured as inherent parts of the system's architecture. In terms of identifying bias, system design variability may be associated with automation bias in a sense that automated decisions, when not designed in a moral way, may override social and cultural considerations (Chou et al., 2017). In Category B, privacy, security, and data are the overarching aspects that were in play and grouped under the non-maleficence umbrella. Infringement of privacy is a major concern, especially when the stakeholders are young students, and there is no control of how personal data are being used, but again it is unclear as to whether the developers of AI should provide necessary assurances that infringements on personal data will be abolished or the actual AI system. Access to personal data may severely influence dataset bias as large data sets from the learner model may exploit personal data to make decisions around critical learning aspects such as grades, examinations, or student profiling.

In Category C, autonomy was a central ethical dimension, especially in terms of overriding the decisions made by the AI if it is deemed as prejudicial or unmoral. Affirming the principle of autonomy in AI-based teaching and learning means that the educator has the authority and control to set the standards and norms of what will be ultimately accepted or rejected towards the accomplishment of learning objectives. This might cause certain implications in terms of reinforcing human biases in the training of datasets thus perpetuating stereotypes and cultural bias leading to an association bias. In Category D, explicability is reflected in the educators' ethical understandings. It references the need to hold account the decision processes of AI placing emphasis on transparency and accountability in terms of biased data, either fed into the system by a human or generated by the AI through inferences from similar biased data. Legal and organisational guidelines would aid the process of mitigating ethical concerns as such guidelines would explicate responsibilities, roles and what it means to design, use, and sustain AI in education. Explicability complements design variability, automation and non-maleficence and firmly supports that the educator defines, enacts, and validates the ethical principles that are underpinned by the AI tool, the institution, the subject, learner, and pedagogy computational models. Interaction bias may be associated with explicability and with using interactive intelligent systems such as chatbots, mostly used in Categories, C and D, when attempting to humanise AI with no precautions against human toxicity. The justice ethical principle from Floridi's et al., (2018) was not widespread as an explicit dimension but it could cerebrally be part of the explicability principle alleviating injustice from biased intelligent decision making between culturally different student groups.

4.3 COMPETENCIES AND SKILLS RELATED IMPLICATIONS IN USING AI FOR TEACHING AND LEARNING

Education seems to be one of the areas with the least AI permeation (Acemoglu & Restrepo, 2019). The reason for this is the luck of designing and implementing training models that would encourage teachers to develop skills and competencies that would go beyond technical nuances that add in complexity in getting a clear view of how teaching and learning with AI is designed and enacted in the classroom. Such training models should focus on an all-round approach to using AI for teaching in two distinct phases: The first phase should focus on developing skills on using AI for designing learning and teaching (design time) and the second phase should focus on the actual orchestration or delivery of teaching with AI. This separation could act as a function of consciousness in terms of firstly gaining the confidence needed to design a course or a lesson from the outset and then consider how AI applications and tools along with the dimensions in Table 6 could solicit a design that emancipates ideas, sensations, perceptions, feelings, ideas and tangible design plans on how student activity could be manifested via an intelligent system as means to achieve multiple learning outcomes mediated by what actually students do. For example, it is imperative for the educator during design time to design AI-based learning in conjunction to the dynamics of the learning mode. If it is blended learning, then the entire design may focus on interactions and roles that persist on teacher guidance and support in class whereas the AI is more assistive in its role. In hybrid environments there may be a balance of direction, designing the role of the teacher as more prevalent in in-class and the role of the AI more dynamic in the online learning mode. In a distance learning mode, the role of the teacher may be more supportive, empathic, supervisory, and assistive whereas the AI is more active, interactive, and responsive to student's online activity. These design considerations will establish priorities across modes of learning and the roles each (teacher, student, AI) takes within them. Once this consciousness has been established, then the educators enter the second phase of the training model for deliberately executing or implementing the designs. Against this backdrop, teachers are re-skilling and up-skilling their capabilities and are becoming virtuosos in understanding how AI works, the juxtaposed ethics, the particularities of data and information and media literacy, AI inclusion, social influence, and well-being.

The development of AI-related skills for teaching does not mean that such training involves a hand-over of the responsibilities, roles, and subject-related expertise to the machine. On the contrary, it means that teachers will act as catalysts and central agents on deciding how the data-driven predictions and insights that these systems provide will help students to enhance their learning experience. Training models on teachers' AI-based teaching and learning competencies should be holistic, interpretive, transdisciplinary, and predominantly focused on the learning science with its rich-mediated theoretical models that resonate the way an artefact, a resource, a learning space and technology are working together to meet changing circumstances. This alludes to Selwyn's assertion that data, algorithms and automated decisions do not solve educational dilemmas, rather it is an act of human consciousness to deal directly with events and phenomena as they are experienced, developed and transformed for recognising, rationalising and prioritising student's agency.



5. CONCLUSION

The second part of this report investigated the qualitatively different ways educators experience the use of AI in teaching and learning. Four categories of description were identified and nine dimensions of variation that run through and between the categories of description were discerned. Most importantly the, this study has provided a framework for understanding constellations and manifestations of AI in school settings. The key stakeholders that can exploit the findings of this research are educators that teach science courses in schools but also instructional designers, learning technologists, AI researchers, policy makers and parents that have an inherent interest to develop their understandings and conceptualisations of a phenomenon that will certainly be ubiquitous for the next decades, especially in terms of accelerating and amplifying the characteristics of the UK's educational system. This study creates a momentum for reflecting profoundly on the impact of AI and the different learning opportunities it brings to the fore. The study certainly does not conclude that intelligent agents or automated decision-making systems are the 'holy grail' for personalised learning experiences in UK schools, at least not yet, but there is research evidence on prototyping tools and techniques for providing adaptive content, activities, assessment, and feedback. Such developments are in line with the empirical evidence that this study has provided through an inclusive set of categories described as AI for: reducing time for procedural learning, knowledge acquisition, developing skills that enable deeper learning and transferring learning to transdisciplinary and experiential contexts. These combined aspects develop a structure that help teachers to understand how different AI applications and tools support teaching strategies, espoused and theories in use, learning modes, roles, knowledge dimensions, assessment and feedback, ethical considerations, and continuous professional development. Essentially the findings of the study lay the grounds for deconstructing the attributes, and properties of the three key computational models (domain, pedagogy, and learner models) as means to provide granular data on how learning can be designed, orchestrated, and transferred for blended, hybrid and distance learning settings. Rethinking the dynamics between the roles of the teacher and the AI in different learning modes, new dynamics, realisations, and strategies will come into play that will underline the transformative role of the teacher in guiding, leading, and extending the use of AI through the process of collective indwelling and through professional development for reskilling and upskilling data literacy, research and epistemic design capacities and capabilities. Future developments in the field of AI for teaching and learning could use the findings of this research to focus on adaptability and personalisation (e.g., experiences of designing teaching for personalised learning support), standalone AI applications and tools (e.g., experiences of teaching and learning using chatbots) in particular learning modes (e.g. conceptions of using AI in hybrid learning) and in different subjects (e.g. experiences of designing for AI teaching in arts and humanities)

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