Towards Inclusive Education in the Age of Artificial Intelligence: Perspectives, Challenges, and Opportunities

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Abstract In the West and other parts of the world, the ideal of an individualized, personalized education system has become ever more influential in recent times. Over the last 30 years, research has shown how effective, individually tailored approaches can be achieved using Artificial Intelligence techniques and intelligent learning environments (ILE). As new audiences of learners are exposed daily to ILEs through mobile devices and ubiquitous Internet access, significantly different challenges to the original goal of personalised instruction are presented. In particular, learners have cultural backgrounds and preferences that may not align with most mainstream educational systems. When faced with practical, cultural issues, the transfer of successful research and ILEs to underserved contexts has been naturally quite low. This chapter first takes a step back and analyses perspectives on how intelligent learning environments have transitioned over years from focusing on instructional rigour to focusing more deeply on the learner. Next, it examines some major challenges faced when ILEs aim to integrate culturally sensitive design features. The chapter then discusses several opportunities for dealing with these challenges from novel perspectives such as teacher modelling, the use of educational robots and empathic systems and highlight important concerns such as machine ethics.

1. Introduction

Advanced personalised learning was defined 10 years ago as one of the 14 Engineering Grand Challenges (Grand Challenges - Advanced Personalised Learning 2018). Personalised learning is essentially learner-centered instruction

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that has been tailored and paced according to the specific interests, educational goals, and personal preferences of an individual learner (Bray and McClaskey 2016). The grand challenges were meant to "raise public awareness of the biggest global issues of our time" (The US National Academy of Engineering 2018). If solved, the outcomes would result in radical improvements in the way that we live, and in the case of advanced personalised learning, how students learn and how they are taught.

The interest in this challenge is motivated by the issues faced in traditional classroom settings. In many educational institutions, teachers are typically required to deliver instruction, feedback, and attention to a large number of students in a limited time with the goal of students passing assessments with good grades. This is often difficult to achieve because students have varied learning styles, different prior knowledge levels and cognitive skills, diverse emotional dispositions and most importantly distinct learning needs. The fields of Artificial Intelligence in Education (AIED) and Intelligent Tutoring Systems (ITS) have been directly positioned to take on the challenge of advanced personalised learning since their formal inception in the late 1980s. Both research areas aim to provide an intelligent software tutor for every learner. By using interactive software, adaptive learning delivers paced, customised instruction with real-time feedback that allows faster student progression, encourages effective skill development, and promotes greater learner engagement with educational content (Six Key Benefits of Adaptive Learning 2013).

For over the past 20 years, there has been a growing body of positive outcomes reported in the literature where intelligent cognitive tutors perform as well as human tutors (Van Lehn 2011) when producing learning gains in students. A variety of applied Artificial Intelligence (AI) techniques have been commonly employed in achieving these results. The role of AI in shaping education is therefore critical since it has the potential to solve many problems of the previously mentioned problems (Woodie 2018). Advances in hardware, such as faster GPUs (Graphical Processing Units) and widespread access to machine learning software libraries have further spurred the use of AI, particularly in deep learning research and the use of data analytics (Janakiram 2018). A larger transformation over the coming years is expected as robots and other new technologies enter the field at a rapid pace where AI is expected to grow by as much as 47.5% by 2021 (Borgadus Cortez 2017). One of the main problems being faced however is that of transfer. Many of the intelligent systems and software tutors do not perform as well or as expected in learning environments that differ culturally from the original context of use (Ogan et al. 2015b).

In 2009, multicultural understanding was listed as a critical capability for dealing with the grand challenges in order to ensure successful uptake of solutions in intended environments (The US National Academy of Engineering 2018). Smaller, more powerful, portable devices combined with ubiquitous Internet access have toppled the ratio of users from the developing world to almost double those from the developed world in just under 10 years (ICT Facts and Figures 2017). In 2008, the ratio of developed world users to developing world users was approximately 4.2. In 2017, that ratio was 2.0. Moreover, 70% of the world's youth (aged 15-24) are online and they make up the largest group of Internet users (ICT Facts and Figures 2017).

Consider the implications of these statistics when faced with the challenge of building an adaptive, culturally-inclusive educational system. Firstly, a lot of data

is being generated daily and this will continue to increase. Secondly, not only has the sheer volume of users increased, the cultural backgrounds of these users are being quickly diversified. Thirdly, as the human sources of this data change, so does the quality of the data, and more importantly the cultural bias. The risk with using such data in these ways is that the models are trained to detect patterns that are dictated by the data. For instance, in (Donnelly et al. 2016), classroom audio data was used to detect features of teaching events, such as question and answers, that may be beneficial to student learning. A particular style of teaching may or may not be employed in certain cultural environments, and differences may occur even within such environments with temporal factors (Uchidiuno et al. 2018). When data comes from a particular source, naturally those patterns will be skewed towards the environmental conditions of the source environment, and actors and models may or may work well in alternate cultural conditions (Rudovic et al., 2018). While there is scope for error in these systems, caution is still required when using AI for important tasks especially when dealing with more complex or nuanced interpretations which are positioned in a cultural context that differs from the original developmental setting.

The rest of the chapter is structured as follows: The next section gives an overview of the different types of technology-enhanced learning systems in use nowadays that support and have the potential to support inclusive education. Sections follow on perspectives, key developments, breakthroughs and challenges faced in cultural modelling as well as opportunities for leveraging the success of AIED and ITS research.

2. Intelligent Learning Environments

Technology-enhanced learning (TEL) helps teachers to do their job more effectively by liberating them from increasing levels of administration and bureaucracy, in the form of marking, planning their lessons and less important paperwork exercises. By leveraging AI techniques, machines may be able to take over many of these functions, thereby allowing the teacher to focus on their main purpose: to teach and mentor (Ferster 2014). However, the quality and the extent of the adaptive customisations of a TEL environment varies across different implementations.

For example, Intelligent Learning Environments (ILEs) are specialised TEL systems that aim to produce interactive and adaptive learning experiences that are customised for a learner using various AI techniques (Brusilovsky 1994). These systems can vary from serious games such as the Tactical Language Training System (Johnson et al. 2004) to Intelligent Tutoring Systems such as the ASSISTments platform (Heffernan and Heffernan 2014). Learning management systems (LMSs) on the other hand simply organise and deliver content, and help with course administration (Van Lehn 2011). These systems are the most widely used in formal educational institutions. They offer customisable features such as grade books, assignments, quizzes, blogs, wikis, email, and forums for an instructor to manage courses and interact with students (Rhoades 2015). Popular open-source examples include Moodle, Sakai, .LRN—which has an enterprise-level focus, Schoology—which focuses on kindergarten to K12 learners, and Docebo—which offers eCommerce features for selling content and focuses on corporate training.

Out of any TEL environment, MOOCs (Massive Open Online Courses) reach the largest volume of learners through freely available courses from top-tier universities with large amounts of online content (Rhodes 2015). As much as 81 million learners have signed up for MOOCs (Shah 2018). Successful examples include Udacity, Coursera and edX which all interestingly have a strong AI influence either by way of the content featured or the founders' research backgrounds.

3. Perspectives

Several themes of Artificial Intelligence (AI) are at the forefront of discussions about the future of education as highlighted by the TEL environments in the previous section. This section takes a step back and examines how the definition of the term AI, has evolved in relation to the successes and breakthroughs in the fields of AIED and ITS. This is meant to give an understanding and awareness of how intelligent learning environments have transitioned over years from focusing on instructional rigour to focusing more deeply on the learner.

3.1. Defining Artificial Intelligence

A core definition of Artificial Intelligence is to skilfully imitate human behaviour. Over many years, various definitions have evolved to include more details, specifically related to technology and its applications as shown in Table 1. It can be argued that AI software now exceeds many of the capabilities of a human being due to the sheer volume and variety of computations that can be performed, the incredible speed at which complex decisions can be made, and the derivation of new knowledge and detection of trends from vast amounts of data. Despite this, the essential nature of AI's definition has not changed, and the realisation of the goal of skilfully imitating human behaviour has not been perfectly met.

Table 1 Evolution of the term "Artificial Intelligence"

Source and Year	Definition of Artificial Intelligence
Dictionary of English Language, 1979	None
Webster Dictionary, 1986	Subheading under *artificial*: The capability of a machine to imitate intelligent human behaviour.
Oxford Dictionary, 1991	Subheading under *artificial*: The application of computers to areas normally regarded as requiring human intelligence.
Cambridge Advanced Learner's Dictionary, 2003	*Full entry*: The study of how to produce machines that have some of the qualities that the human mind has, such as the ability to understand language, recognise pictures, solve problems, and learn.
Online Search - Oxford Dictionary, Aug 2018	*Full entry*: The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages.

3.2. AIED and ITS Research

Just as the definition of AI has evolved, so too have the fields of AIED and ITS. The field of AIED was started in the 1970s (Woolf 2009). The goal was to build intelligent tutors that cared about the learner and met critical emotional, cognitive and psychological aspects of the learning process (Kay and McCalla 2003). Naturally, it was grounded at the intersection of research in computer science, psychology and education (Woolf 2009). ITS research on the other hand focused more on building ILEs that functioned as effectively and efficiently as a human tutor (Van Lehn 2011). Significant transitions in the research were observed especially when disruptive technologies were introduced. For instance, in the early years, expert systems and inference rules were commonly used in rigid step-based tutors (Van Lehn 2011). Models of domain (expert) knowledge, student mastery of a learning domain and tutoring strategies were (and still are) core components of the ILEs being developed (Dillenbourg 2016). The focus then was on modelling correct instruction, giving immediate feedback, and following a particular curriculum.

Over time, automatic courseware generation and adaptive hypermedia became the norm especially when the Internet started to be used as delivery medium through web-based systems. In addition, computer-supported collaborative learning (CSCL) and dialogue systems were actively pursued particularly in feedback systems using intelligent pedagogical agents. Knowledge representation and semantic reasoning were commonplace. A gradual subtle shift away from declarative AI models towards probabilistic models and techniques was observed as uncertainty and flexibility in the learning process were tackled (Dillenbourg 2016). As more learners interacted with ILEs through mobile devices and made use of ubiquitous, cheaper Internet access, data analytics and the global impact of big data started to draw attention. By then, many in-house ILEs were already producing effective learning gains and interest shifted towards testing and deployment in other settings and educational contexts.

The advent of MOOCs caused further excitement in being able to reach students from diverse socioeconomic backgrounds and offering large amounts of learning data (Rosé and Ferschke 2016). New technologies such as touch screens, haptic devices, and sensors changed the simple data input and output modes of keyboards, mouse clicks and screens towards facilitating richer interactions and engagement. This opened up new avenues for interactivity in classrooms. Nowadays, machine learning and various types of supervised and unsupervised learning techniques are commonly employed in the research reported in the literature. Now, there is a growing body of research that aims to deploy existing ILEs in multiple cultural settings and observe the effects such as in (Mavrikis et al. 2018; Ogan et al. 2015a) or build customised ones capable of dynamically adapting to cultural environments using AI techniques and methods such as in (Mohammed 2017).

3.3. CulTEL Research: Strengths and Successes

Cultural awareness, when applied to an ILE, refers to the use of culturally relevant data and information to shape the overall appearance, behaviour, and presentation of the learning environment (Blanchard and Ogan 2010). The field of culturally aware technology enhanced learning (culTEL) is relatively young (Rehm 2018),

but there have been several important development trends that have contributed towards culturally inclusive educational systems.

Culture has been studied extensively from sociological, psychological, anthropological and ethnographic perspectives. Based on these areas of study, formalised, abstract representations of knowledge and concepts that are central to a culture are critical for any system that aims to be culturally aware. Ontologies have been a natural fit for these representations owing to their machine readable nature and their potential for deriving meaningful conclusions through reasoning (Hitzler et al. 2010). These representations are especially well suited for the knowledge representation and inferencing needs of ILEs (Mizoguchi and Bourdeaux 2016). The More Advanced Upper Ontology of Culture (MAUOC) (Blanchard and Mizoguchi 2014) is one of the first heavy-weight ontologies that provides a neutral, computational backbone for structuring detailed computational descriptions of culture for use by ILEs. Savard and Mizoguchi (2016) outline another upper-level ontology that defines cultural variables specific to instructional design and pedagogy.

Closer to the domain level, Mohammed (2018) describes a trio of ontologies that are based off of MAUOC concepts. These ontologies can be merged to relate conceptual cultural knowledge to sociolinguistic terms that map to the cultural influences that contribute to the background of a student. Lastly, Thakker et al. (2017) present an ontology for representing the cultural variations that occur in interpersonal communication in user generated content. These efforts touch on diverse areas that allow machine-readable cultural representations to be explicitly accessed and shared across ILEs.

Another important success story has been the development of enculturated conversational agents (ECAs). For example, Cassell (2009) studied children's acceptance, usage and recognition of African American Vernacular English (AAVE) using ECAs. Endrass et al. (2011) describe virtual characters with physical appearances adapted to suit particular cultural backgrounds. In (Aylett et al. 2009), the ORIENT system features characters, modelled using agent technology, that exhibit culturally enriched behaviour directed by emotive events. Lugrin et al. (2018) explain that two approaches have been used to build ECAs thus far: data driven approaches and theory driven approaches. Theory driven approaches have classically been used to predict expected human behaviour in particular contexts based on established cultural theories (Rehm 2018). Theoretical models of culture commonly referenced in culTEL research include the works of Hofstede (2001), Hall (1966), Trompenaars and Hampden-Turner (1997), Bennett (1986), and Brown and Levinson (1987). Data driven approaches are becoming more popular with the availability of machine learning (ML) tools. These approaches tend to rely on large amounts of sample data such as video recordings, audio samples or images for training models that can uncover patterns in new data sets for generalising predictions in a domain of interest such as agent behaviour.

A final key development has been the use of weighted approaches for approximating cultural values. Weights have been used to prioritise values assigned to particular cultures based on theoretical models (De Jong and Warmelink 2017; Mascarenas et al. 2016). Mohammed (2017) also used a weighted, theory-driven approach to model the sociocultural and demographic influences that contribute to a student's cultural affinity or ignorance of linguistic terms native to a local language. Nouri et al. (2017) show that these approaches are useful when there is no data on which to base the weights and demonstrate that the

weights can be learnt from data using ML techniques resulting in more accurate models of cultural decision-making. Rather than assigning blanket cultural values to a student, weights allows a more nuanced approach towards the modelling of subcultures. This is essential in ILEs especially when students have multiple cultural identities.

4. Challenges

Blanchard (2015) observes that research in the ITS and AIED fields has been strongly biased towards western, educated, industrialized, rich and democratic (WEIRD) nations (Henrich et al. 2010). He reports that 82-95% of the research published over 10 years (2002-2013) has been dominated by researchers from WEIRD nations with clear cultural imbalances with respect to the data sets used in models and systems, and socio-cultural group representations. Furthermore, the kinds of research being conducted do not tend to focus on cultural contexts and practical ILE issues of application and deployment (Mohammed and Mohan 2013; Nye 2015). It makes sense therefore, that much of the successes of ILEs reported for a WEIRD context are not often transferable to other cultural contexts (Ogan et al. 2015b). Despite these observations, there is growing awareness of the need for culturally inclusive research within the AIED and ITS communities (Nye 2015; Pinkwart 2016; Roll and Wylie 2016). There are many challenges that need to be overcome before culturally inclusivity becomes a mainstream consideration in TEL software systems and this section examines some of these key issues.

4.1. Cultural Granularity

Many TEL projects use Hofstede's (2001) national indices as a measurement of the cultural influences on students in order to adapt system appearance and behaviour, and select and modify educational content. This is a common starting point and it has yielded positive results in some areas of research particularly those with enculturated agents (Endrass et al. 2013; Mascarenas et al. 2016; Rehm 2017). New challenges are being observed with country-level categorizations however such as the broadness of the scope and generic categories for typifying students who happen to have some interaction with a particular country. For example, mismatches have been documented with the expectations of student preferences based on Hofstede's values for a country and the actual preferences of the students from that country (Chandramouli et al. 2008). This means that the level of cultural granularity provided by broad cultural models are not typically designed with computational applications in mind (see Blanchard et al. 2013 for an overview) and may be too high-level to meet the requirements for culTEL environments.

Finer-grained measurements sensitive to the subtle but critical differences across student cultural backgrounds caused by their differing degrees of membership to cultural groups are required for educational applications (Mohammed 2017). Furthermore, the reliance on the values assigned at a country-wide or national-level can introduce potential flaws if the values were collected from small or biased samples. Related to this issue is the granularity of cultural data that can be collected from users. Studies have shown that various important pieces of information are required from users (Mohammed and Mohan 2013) but cannot be collected uniformly across countries (Blanchard 2012).

The multi-layered identity of an individual presents a significant challenge when attempting to model the cultural contextual backgrounds of students. Globalisation, the redefinition of national identities (Sharifian 2013) and the multiplicity of cultural influences (Rehm 2010) add even more complexity to the problem. Country-level categorisations are commonly used to profile students as evidenced by the heavy use of Hofstede's (2001) national indices but these are not at a deep enough level of granularity to differentiate between the layers of a student's cultural identity. In the absence of ontological models of culture, it is therefore difficult to modify cultural features in an ILE without requiring extensive recoding and modification of the underlying system as is the case for many existing ILEs.

4.2. Cultural Bias

The most common challenge is guarding against cultural bias (Blanchard 2015; Mohammed and Mohan 2013; Rehm 2010). Cultural bias stems from subjective, personal descriptions and perceptions, also called folk approaches. When these narrow interpretations are used to determine cultural features it introduces problems from conceptual and developmental perspectives. From a conceptual standpoint, folk approaches lack neutral abstractions that can be generalized and reused in different features of culTEL. This is a critical flaw because it works against the goal of 'coherent global views of the cultural domain' identified by Blanchard and Mizoguchi (2014), and prevents the interoperability and standardization of cultural representations.

From a developmental standpoint, folk approaches make developer bias more difficult to deal with. This kind of bias occurs when developers knowingly or unknowingly skew the design and software architecture of TEL environments towards their own preferences and instincts which would most certainly influenced by their cultural backgrounds. For situations where the developer is native to the target culture, the consequences may not be so severe. However, when there is a serious mismatch a culTEL environment can be seriously affected as discussed in (Rehm 2010), to the point of being irrelevant and even offensive.

Cultural bias can also occur in the data sets that are used to train models. For example Rudovic et al. (2018) reported that the training sets used to train models that detected affect in autistic children was biased toward physiological features linked to cultural expressions of engagement. Using country-level generalisations for detection of affect and engagement therefore presented challenges in detecting a particular emotion cross-culturally which required retraining of the models.

4.3. Cultural Realism

In the past, shallow cosmetic applications of cultural symbols have been criticised as tokenistic and stereotypical in TEL. Early attempts focused on digital images or languages used in web-based systems. Simple approaches were common because of the lack of computational models that could facilitate deep cultural modelling. Simple, culturally grounded features can however have a significant impact on user acceptance and attitudes. McLoughlin and Oliver (2000) describe an online environment for Australian indigenous learners with the intention of a culturally responsive design. The system used cultural dimensions in the design of authentic learning activities which were supported by different online tools and offline

groups. In (Robbins 2006), a more detailed online system is presented which targets students from the South Pacific. Dialogic contextualisation was used which framed educational multimedia content as personified interactions or static conversational items. The system featured semiotic contextual elements heavily and stressed the importance of conversations in establishing rapport with students.

Since then, the cultural realism of TEL systems has advanced greatly particularly when ITSs or serious games are used. On the lower end of the cultural realism scale, examples such as the ActiveMath system (Melis et al. 2011), the Assistment plugin described in (Vartak et al. 2008), the CAWAS platform (Chandramouli et al. 2008), and the AdaptWeb system (Gasparini et al. 2011), incorporate simple cultural elements into system content and behaviour. On the higher end of the cultural realism scale, examples such as the Tactical Language Training System (TLTS) (Johnson et al. 2004) and the CRITS system (Mohammed and Mohan 2015) adapt and change system responses to suit user language preferences. Both the TLTS and the AAVE tutor (Finklestein et al. 2013) present virtual agents that resemble users in cultural appearance similar to TLTS.

Cultural realism is also particularly observable when virtual agents are used as in the CUBE-G Project (Rehm et al. 2007). ILE appearance changes are more prevalent in systems with virtual characters and enculturated conversational agents (ECAs). Cassell (2009) studied children's acceptance, usage and recognition of African American Vernacular English (AAVE) using ECAs. Endrass et al. (2011) describe virtual characters with physical appearances adapted to suit particular cultural backgrounds. In the ORIENT system (Aylett et al. 2009), cultural characters are modelled using agent technology and demonstrate culturally enriched behaviour directed by emotional events. An interesting observation in the literature is that learners opt to design pedagogical avatars that look like themselves (Allessio et al. 2018). Exploration of how learners respond to pedagogical agents that resemble their physical appearance was conducted in another study (Wang et al. 2018). Early results indicate that whilst this has no effect on learning, it is the first study of its kind to test this type of hypothesis since the technology did not exist prior. Either way, more research is needed regarding how best to design pedagogical agents that have character appearances within an acceptable range of cultural realism and how to define appropriate behaviours that will promote learning.

5. Opportunities

Many of the challenges described in the previous section are difficult to address because they relate directly to cultural modelling. This section describes several promising avenues that have the potential to break down the complexity of these challenges by tackling contributing factors. Areas such as teacher modelling and multimodal interaction, empathic systems and the use of educational robots offer opportunities for untapped research when dealing with cultural diversity. A discussion of ethical concerns rounds off this section since social interactions and research that involve young learners and technology need to be prioritised along the lines of good conduct and moral decisions that benefit the learner.

5.1. Teacher Modelling

We must recognise that it is unlikely and probably undesirable that intelligent systems, robots and machines might entirely replace teachers in the future. Teachers and students together form part of a broader learning culture. AI machines can improve the learning process (and may do so significantly for many students), yet they are no substitute for a shared culture of learning where an inspirational teacher and a class of engaged pupils work together to explore and learn.

AI however can be used to help teachers reflect on and improve the effectiveness of their instructional activities in classrooms. For example, Donnelly et al. (2016) used Naïve Bayes classifiers to automatically detect five instructional activities used by teachers simply using audio data of the teachers' speech collected in live classrooms. This type of research essentially confirms the advent of teacher modelling where successful strategies can be identified, encoded and used to develop cognitive tutors patterned by best practices from teachers in actual classrooms. Another example described in (Holstein et al. 2018), used real-time analytics and live feeds of student activities involving the use of an ILE for learning math. Feedback on student performance was synchronously delivered to a teacher through a mixed-reality glasses connected to the ILE. The experiment reported significant increases in learner gains when the teacher used the glasses to assist the students compared to when the students simply used the ILE without the analytics-led interventions. In these classroom contexts, assessment of a student's learning process was done instantly, giving the teacher access to rapid results on the student's progress. This means that the teacher does not have to wait for the test results before making decisions on a learning plan. Adjustments can be immediate and rapidly iterative. In both cases, the focus is clearly on assisting the teacher.

In order to have an authentic representation of what works, why it works and why things are the way they are in classrooms, we need to model not only students but teachers as well. Most times when a student uses an e-learning system we get only one side of the equation: the digital traces of how the student uses the system. A deeper question could be: why does the student use a system this way? Personal choices and learning preferences account for part of the answer. The other part is that students have been trained to learn a particular way by the teachers they encounter in their classrooms and schools. The way that these teachers instruct largely shapes how students learn, and the ways of instruction are heavily culturally dependent (Savard and Mizoguchi 2018). Therefore, we need to have some insight into the cultural factors engrained in teachers as well as students and whether they match, differ or complement each other. This then needs to be factored into the learning systems that are being built and used.

5.2. Multimodal Interactions

The embodiment of an ILE is extremely important. Tims (2016) explains that ILEs have been using hardware and platform technologies that were designed for business settings rather than for education. Sensing technology, ambient classroom tools, and educational robots introduce interesting dynamics into the learning environment by increasing the levels of interactivity, engagement, and feedback

about the learning process for both students and teachers. These modes offer untapped potential for reaching students in ways that classic ILEs have not been able to. For instance, Alavi et al. (2012) describe the Lantern project where an ambient light placed in a classroom setting was used to signal help-seeking behaviour details to teaching assistants such as whether a group required assistance, when they last requested help, and which problems they were working on. Experiments showed that the light encouraged more frequent problem solving discussions amongst students in collaborative groups especially while waiting for help.

ILEs complemented with sensing technology currently produce as good learning gains as the expertise of traditional intelligent systems, and in some cases exceeds the benchmarks. Gaze tracking technology was shown to provide as good feedback to a learner as a pedagogical conversational agent (Hayashi 2018). Real-time analytics using mixed-reality tools such as the Lumilo glasses project (Holstein et al. 2018) augment and extend the reach of what a teacher can glean from sitting behind a desktop computer and interacting with an ILE console. Being able to assist struggling students in real-time essentially personifies what happens with expert teachers, and the technology is now catching up to promoting that ideal. A common problem with MOOCs identified in the literature is the issue of low engagement (Rhoads 2015). Pham and Wang (2018) describe an interesting approach in the AttentiveLearner2 system that uses the back camera of a mobile phone to detect physiological changes in the blood levels of a learner's fingertip (holding the phone) and the front camera to detect affective engagement based on facial expressions. They show that these simple sources of data were useful for detecting six emotional states with a high level of accuracy and offers more informative data than the click-stream analytics currently available in MOOCs.

5.3. Educational Robots and Empathic Systems

Empathy, in its straightforward dictionary definition, is usually described as: "the ability to understand and share the feelings of another" (Empathy 2018). However, empathy is more complex than this straightforward understanding. Minter Dial (2018) points out, that we are mainly social animals and, therefore, empathy is considered to be a fundamental or desirable trait in human beings. It facilitates positive human interaction and can be considered as a cornerstone of our intelligence alongside logic, cognition, and emotion (Dial 2018).

Robots can sometimes be described as 'empathic', despite obviously not being able to accurately model human emotions, nor possessing any internal affective qualia or felt senses. Making a machine appear to be empathic through encoding is a complex task. Yet when we consider the potential value of such robots to the development of young children, as well as adults, it is vital that machines of learning are empathic as they can also encourage children to adopt positive behavioural characteristics. It is a good match therefore that one of the main goals of AIED is to build systems that care about a learner (Kay and McCalla 2003, DuBoulay et al. 2010).

Empathic ILEs are currently able to interact with learners, infer and recognize (through speech, facial and gesture recognition) the emotions and feelings of the learner, draw on data models of appropriate interventions, and then react accordingly. The AttentiveLearner2 system (Pham and Wang 2018) described in the previous section is a key example of this. Affective technology has been

developed extensively in software systems in AIED and ITS research but are at a relatively early stage of development in robotic and embodied systems. Many of the intended users of educational robots tend to be young children and K-12 students. For example, a trial in operation in Finland uses robots to teach language and math by encouraging students to code the robots (Finland schools 2018). In particular, children are the target users because they respond positively to these types of systems due to anthropomorphized characteristics of "feelings" and "eyes", as well as the ability to express emotions (Druga et al. 2017; Johnson and Lester 2016; Tims 2016).

Another key finding is that children tend to respond to devices that appear and behave human-like (Druga 2018). In (Druga et al. 2017), the voice and tone of various devices such as Alexa (a voice-controlled, virtual assistant), Google Home (a speaker and voice assistant), Cozmo (a robot toy), and Julie (a chatbot) affected the extent to which children wanted to interact with the machines. For instance, Julie the chatbot was seen as friendly and having "feelings" compared with Google Home's emphasis on knowledge. Two boys described Cozmo in a positive light due to its humanised characteristics (physical features, such as eyes in particular), as well as its ability to express apparent affect such as happiness or anger. When describing the other devices the children remarked: "they didn't have eyes, they didn't have arms, they didn't have a head, it was just like a flat cylinder"(Druga et al. 2017). Work by Yadollahi et al. (2018) also confirms that children treated a reading robot with empathy. The children were required to correct the robot when they detected reading mistakes, and they did so with explicit care and concern for the robot's feelings even though they understood that the robot was inanimate.

Robots, in particular, due to their embodied form, offer the potential to interact with children who have special needs. For instance, young people with autism will often find it difficult to interact with other human beings. In Luxemburg, LuxAI[1] has developed a social robot named QTrobot for research purposes, but also for children with autism. The robots tend to make the children feel less anxious than they might around other humans and it was noted that children flapped their hands (a common manifestation of autism) less frequently in the company of the robot. The robot operated alongside a human therapist to interact with the child in a relaxed environment. It essentially allowed the therapist to form a more rewarding relationship with the autistic child. The research also made a further discovery: the embodied robot was more effective than an app or a tablet in helping the child to learn (Biggs 2018).

Empathic robots may therefore be more effective when it comes to bonding with the child through "features such as shared gaze, synchronization of gestures and sensitivity to certain movements on the side of the human" (Castellano et al. 2013). These experiments have now proved that embodied empathic robots are not only contributing to the individualisation of the learning process, but also have the potential to take the fear that some children may feel during that process, turning it into engagement and enjoyment (Finland Schools 2018). The implications of these interactions however require careful design since certain gestures can be interpreted with different emotional outcomes in certain cultures (Rehm 2018). It is also important to explore how student behaviours can be influenced with particular interventions using empathic, educational robots and systems.

[1]http://luxai.com/

5.4. Ethical Issues

Unlike adults, who tend to show a higher degree of caution when interacting with robots, young children are more susceptible to their influences. They tend to regard robots as psychologically sound, moral beings that can offer friendship, trust, and comfort (Kahn Jr et al. 2012). Research has confirmed the results of earlier work that children between the ages of 4-10 see robots as trustworthy (Williams et al. 2018). Further research was conducted to find out whether the "moral judgements" and "conformity behaviours" of children from this age group might be directly influenced by AI machine toys. A talking doll was discovered to wield influence and could persuade children to alter their moral judgements, but it was not able to make the children disobey an instruction (Williams et al. 2018). Johnson and Lester (2016) further confirm that after 25 years of research experience that pedagogical agents are especially more effective at promoting learning for K-12 students rather than post-secondary ones.

The clear ethical danger here is that empathic robots could be set up in order to benefit the manufacturer or other interested parties more than the personal development of minors. The potential for emotional manipulation or "nudging" that could infringe the personal liberty of an oblivious child is substantial. In a similar manner to other forms of media, it is likely that many commercial robots will try to sell certain brands to the child or even exercise the development of political and social outlooks through subtle propaganda. There are also potential privacy and child safety issues. The AI machines may draw on a range of intimate details about the child's cognitive, physical and emotional state through a sophisticated system of audio, touch and biometric sensors.

Robots may also gather details about the child's home environment. If this data is well protected and controlled this may be palatable; however, many of these devices may have unsecured online links, specifying the locations and personal activities of children. This also raises the issue of transparency when it comes to the data that a given robot may gather in its interactions with the child. It may be that the robot is set up to share information with third parties about those interactions (The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems 2018; Wang 2018).

Governments need to either prompt or take on board examinations of the ethics around empathic robots and their potential inculcation of children. This is already being done in some cases, such as the European Parliament (Rise of the Robots 2017). It is likely that recommendations and regulations will be introduced to protect both adults and vulnerable children from manipulation. For example, the IEEE Global Initiative points to several measures including the ability to differentiate between various nudges, including those aimed at more social goals, for example, healthy lifestyle choices or manipulation to promote the sale of products (The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems 2018). They propose other measures, such as "an opt-in system policy with explicit consent" or where children are unable to give their consent other safeguards may be necessary.

The domain of Machine Ethics (i.e. the actual process of loading values into machines) is building momentum. Practical efforts at collecting information of the

social values of communities such as MIT's Moral Machine[2], and the EthicNet[3] datasets of pro-social behaviour, promise to provide practical solutions for instructing machines on the nature of social interactions which best suit the cultural and individual preferences for given communities and their members.

6. Conclusion

In conclusion, it is clear that the development of AI in education is rapidly changing conventional thinking about teaching and learning. Traditional models of schools and classrooms are likely to see dramatic changes over the coming years and decades as technological advances filter down into educational institutions. For many years, AIED and ITS systems have been shown to live up to the potential of tailoring learning to the specific needs of individual students along cognitive, emotional, and instructional dimensions (Baker 2016). Technology-enhanced learning environments such as content management systems, though not as sophisticated as the systems currently under development in research, can also liberate teachers from bureaucracy, so that they can concentrate on working with machines to facilitate the progress of each child. MOOCs should be considered not simply as courses but as vessels for interactive textbooks (Rosé and Ferschke 2016) where text-based adaptations are driven by the cultural factors important to students, and dictated by students (Mohammed 2017). The effectiveness of educational robots will be improved over time, although, it is important that regulation is introduced to ensure that they properly serve their purpose from ethical perspectives. Irrespective of the type of technology enhanced learning environment being used, the cultural factors that govern the presentation, delivery and customisation of content and system behaviour needs to formalised using neutral, well designed AI techniques.

Furthermore, the issues in education that occur in the developed world manifest differently in the developing world. Key problems should be approached with the limitations of sparse and incomplete data sets, low resource settings and lack of technical skills at the forefront of any AI technique or approach for successful uptake in developing world contexts (De-Arteaga et al. 2018). When novel, innovative technologies converge with new paradigms of instruction, pivotal points occur that drive radical changes in intelligent educational research (Dillenbourg 2016). The pivotal point at this time is the need for culturally appropriate inclusive education, and the age of AI is here to facilitate it.

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[2] http://moralmachine.mit.edu/

[3] https://www.ethicsnet.com/

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