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Empowering educators to be AI-ready

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ABSTRACT

In this paper, we present the concept of AI Readiness, along with a framework for developing AI Readiness training. 'AI Readiness' can be framed as *a contextualised way of helping people to understand AI*, in particular, data-driven AI. The nature of AI Readiness training is not the same as merely learning about AI. Rather, AI Readiness recognises the diversity of the professions, workplaces and sectors for whom AI has a potential impact. For example, AI Readiness for lawyers may be based on the same principles as AI Readiness for Educators. However, the details will be contextualised differently. AI Readiness recognises that such contextualisation is not an option: it is essential due to the multiple intricacies, sensitivities and variations between different sectors and their settings, which all impact the application of AI. To embrace such contextualisation, AI Readiness needs to be an active, participatory training process and aims to empower people to be more able to leverage AI to meet their needs.

The text that follows focuses on AI Readiness within the Education and Training sector and starts with a discussion of the current state of AI within education and training, and the need for AI Readiness. We then problematize the concept of AI Readiness, why AI Readiness is needed, and what it means. We expand upon the nature of AI Readiness through a discussion of the difference between human and Artificial Intelligence, before presenting a 7-step framework for helping people to become AI Ready. Finally, we use an example of AI Readiness in action within Higher Education to exemplify AI Readiness.

1. Introduction and background: the current state of AI within education and training

The general idea of "artificial" intelligence or a humanly constructed living being goes back at least to the Greeks and is loaded with both wonder and dread (for more recent versions of this theme, see e.g., Meyrink, 1915; Shelley, 1818). As an area of scientific research, Artificial Intelligence (AI) is now about 65 years old. Over the last half-century or so the reputation of AI has changed dramatically from being an arcane academic activity, via being ridiculed as a pipedream, to now being both over-estimated and under-estimated in its power. There are numerous definitions of AI and none that are unanimously accepted within the AI research community. However, for the purposes of this paper, following the Oxford English Dictionary, we define AI simply as: "The capacity of computers or other machines to exhibit or simulate intelligent behaviour; the field of study concerned with this" (https://www.oed.com/viewdictionaryentry/Entry/271625).

AI's power is both overestimated and made scarier given the way that it is routinely portrayed in popular culture, such as in the film Ex Machina, and underestimated such as when one tries to interact with an uncomprehending chatbot on (say) a bank's website. The truth is somewhere between the two. However, whatever view we take about the power of AI, it is crystal clear that AI is changing the way we live and work (Posner & Fei Fei, 2020). It is ever more prolific in society and is gaining momentum in the education and training space as more products and services that use AI become available (Luckin, et al. 2019). There are an increasing number of AI applications available to education and training organisations and many companies that are extremely keen to sell to this sector. Some of these systems are based on sound research, but not all. This increasing adoption and availability of AI demonstrate the need for educators and trainers to understand a little more about how to distinguish worthwhile, well-designed, ethical AI, from those systems that are not all of these and sometimes not any of them. If we look at the long history (in AI terms) of AI systems for education and training, it is easy to see the complexity of the landscape facing both developers and educators.

The concept of *AI Readiness* is a way to describe the transition that those working in education and their students need to make from not understanding what AI is and what AI can do, to being able to understand, in non-technical terms, what AI is capable of achieving. There may also be Educational Technology companies who could benefit from developing their AI Readiness, but our primary focus here is upon the educational community. AI education to date aims to enable people to learn how AI systems work in technical terms and it usually involves

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programming and building an AI application (see for example). This is not what the educational community needs.

The need for a less technical approach to educating people about AI has been highlighted, for example by researchers concerned with crowdsourcing and citizen science (see for example, Wang et al., 2019; Smith et al., 2020;Yang et al., 2018) and explainable AI (Liao et al., 2020). Their concerns are with transparency and with equity of participation and this is certainly related to the AI Readiness concept within education, because those educators who are AI Ready will be better able to leverage AI to the benefit of their students.

AI Readiness is about addressing the need of the educational community to be able to answer the following question: *"how do I know that the AI I am thinking of buying is the right AI for me and for my organization?"* AI Readiness is about helping people to understand enough about AI to make good decisions about procuring and using AI to meet their particular needs.

Despite its relatively small community of researchers, AI in Education has been around for about half a century since Carbonell's seminal work on an adaptive geography instruction system called SCHOLAR (Carbonell, 1970). Soon after, other systems that adapt their teaching strategies and/or content according to the detected needs of learners followed which led to the emergence of the Intelligent Tutoring Systems (ITSs) (Sleeman & Brown, 1982; Shute & Psotka, 1994, pp. 2–52). This short article does not have the space to reflect on fifty years of research, and neither does this work have the scope to provide such a reflection. Readers are referred to (Luckin, 2016, Mavrikis, Cukurova, Di Mitri, Schneider, & Draschler, 2021; Roll & Wylie, 2016; Woolf, 2010) for more detailed reviews of a historical view of the field. The point here is that, at least from an academic research perspective, AI in Education has a rich history. Significant contributions have been made to the design and evaluation of AI systems that can be used in educational settings. In contrast to the applied sciences, finance, and medicine; however, the adoption of Artificial Intelligence (AI) in real-world educational settings seems to lag behind (Baker & Siemens, 2014).

Perhaps, this is, at least to a certain extent, due to the limited scope of AIED solutions focusing mainly on the technical and pedagogical aspects of delivery in a closed system, rather than taking a "mixed-initiative" approach (Horvitz, 1999) aiming to combine human and machine agency in complex educational systems (Cuban, Kirkpatrick, & Peck, 2001; Meabon Bartow, 2014; Buckinghum-Buckingham Shum, Ferguson, & Martinez-Maldonado, 2019). There are also significant critical voices within educational research with regards to the educational value of technology in general (Selwyn, 2015; Slay, Siebørger, & Hodgkinson-Williams, 2008). In a sense, the criticisms that AIED systems do not have an impact are unfounded as there have been several meta-reviews of their educational effectiveness (for a summary, see e.g. du Boulay, 2016).

There is an increasing amount of research that shows the positive impact of using AI applications to support students' academic performance (Li, Gobert, & Dickler, 2019; VanLehn, Banerjee, Milner, & Wetzel, 2020), their affective engagement (Baker, 2016; D'Mello et al., 2010), and metacognitive development (Azevedo, Cromley, & Seibert, 2004; Laru & Järvelä, 2015) in controlled settings. There are also quite a few AIED systems that have been shown to have statistically significant positive impacts on student learning in real-world settings including, e. g., OLI learning course (Lovett, Meyer, & Thille, 2008), SQL-Tutor (Mitrovic & Ohlsson, 1999), ALEKS (Craig et al., 2013), Cognitive Tutor (Pane, Griffin, McCaffrey, & Karam, 2014) and ASSISTments (Koedinger, McLaughlin, & Heffernan, 2010). Note that the evaluation of the Cognitive Tutor was conducted as a multi-state study using matched pairs of schools across the USA. These results for AIED are particularly significant, as more general studies examining the positive impact of educational interventions are notoriously hard to reach statistical significance (see also, Du Boulay, 2016). In fact, only 11 of 90 randomized controlled trials funded by Coalition4Evidence between 2002 and 2013 found positive effects of educational interventions (Coalition for Evidence-Based Policy, 2013). Despite such strong impact results, the slow adoption of AIED systems in real-world settings might, in part, be attributable to the frequent neglect of a range of other human factors associated with complex educational systems. These include but are not limited to understanding and deliberately considering the learners' and the teachers' preferences in the AIED tool (e.g. Qi et al., 2021), why and how exactly in the system the tool will be used (e.g. Buckingham Shum et al., 2019), the social contexts in which the tools will be used, as well as the ethical (e.g. Holmes et al., 2021) and societal implications related to fairness, accountability and transparency (e.g. Sjödén, 2020).

After acknowledging that AI has been adopted relatively slowly in educational settings, let us consider a few examples of AIED from current educational systems. We categorize the examples into three groups: learner-facing AIED systems, educator-facing AIED systems, and AIED systems for institutional support (Baker, Smith, 2019). As a consequence of the complex features of many AIED systems, in reality, the examples may be grouped in multiple clusters and some dimensions may overlap.

In the following three subsections we describe the different kinds of tools employing AI that have been introduced into education and training at all levels. These tools are categorised in terms of who is expected to interact with them most directly: learners, teachers or educational administrators. This techno-centric way of looking at the educational ecosystem is useful but partial in that it ignores where the power lies in introducing such tools into educational institutions in the first place, be it government or local authority policy, the governors of the educational institution, senior teaching staff in the institution, individual teachers or even the learners themselves. Likewise, it misses the issue of who builds the tools and thus the role of the technical, social and market forces within which educational technology developers must operate.

This paper addresses the issue of providing an understanding of AI in education both to educationalists and to educational technology developers using the notion of training for "AI readiness". Such training includes an understanding of the kinds of tools that might be built and used effectively within educational institutions, as well as an understanding of how such tools might be developed ethically from an initial idea, through an evaluated prototype, to a saleable and useful product.

1.1. *Learner-facing AIED systems*

In learner-facing AIED systems, artificial intelligence is applied in systems that students use to learn specific topics or improve specific skills. These systems respond to the students' individual and evolving needs (Baker & Smith, 2019) e.g., by adapting learning content based on each student's interaction and background knowledge and skills. Some systems focus on the development of skills (Koedinger & Aleven, 2016); conceptual understanding (Biswas, Segedy, & Bunchongchit, 2016) or metacognitive support (Azevedo & Aleven, 2013), among others.

Perhaps, the most common examples of learner-facing AIED systems are referred to as intelligent online tutors or intelligent tutoring systems (ITS) (Miwa, Terai, Kanzaki, & Nakaike, 2014). However, they are also called intelligent software agents (Schiaffino, Garcia, & Amandi, 2008), or intelligent assistants (Casamayor, Amandi, & Campo, 2009). Using complex modelling techniques (from traditional rule-based models to more recent machine learning approaches), these systems can, at least in theory, directly interact with students at a very fine level of detail without human intervention. Unlike traditional computer-aided instruction systems, these learner-facing AIED systems can interpret complex human responses as they interact with the system. Therefore, incorporating AI techniques into education technology makes it possible to identify students' learning needs and provide differentiated content, feedback, and instruction.

Most existing ITSs focus on teaching the structured domains of STEM subjects (science, technology, engineering and mathematics). The use of ITSs has been demonstrated in many different subject areas, including mathematics, business statistics and accounting, medicine, and reading and writing comprehension skills for undergraduate psychology students (Weston-Sementelli, Allen, & McNamara, 2018). In terms of impact, ITSs seem to have moderate positive effects on students' learning (du Boulay, 2016). The use of ITS may be viewed as less effective than human one-to-one tutoring (dependent upon the expertise of the human tutor), but ITSs can be more effective than traditional classroom instruction, reading printed or digital texts or doing homework alone (Van Lehn, 2011; Steenbergen-Hu & Cooper, 2014; du Boulay 2016).

In addition to ITSs teaching STEM subjects, there are examples of learner-facing AIED systems that aim to support students' skill development. For instance, MetaTutor (Duffy & Azevedo, 2015) is an ITS designed to train and foster learners' self-regulated learning (SRL) processes while learning about several complex human body systems. It is an adaptive hypermedia learning environment that detects, models, tracks, and fosters students' self-regulated learning behaviour as they interact with the system. The design of MetaTutor is based on extensive research conducted by Azevedo and colleagues, which demonstrates that providing adaptive scaffolding using AIED facilitates students' ability to regulate specific metacognitive processes as well as helping them learn about specific science topics (Duffy & Azevedo, 2015). Moreover, there are learner-facing AIED systems with a particular focus on supporting the affective and motivational aspects of learning in addition to cognitive aspects, i.e in the context of mathematics tutoring (Arroyo et al., 2014).

Increasingly, there are also examples of learner-facing AIED systems that are used to personalise students' course interactions, particularly in high school education contexts. eTeacher, for instance, is a system designed to provide personalised assistance to students by observing students' behaviour when they interact with course materials and establishing a student's profile (Schiaffino et al., 2008). With this information, the system can provide specific recommendations concerning the reading material and exercises, as well as tailored courses of action.

1.2. *Educator-facing AIED systems*

Many other AIED systems have recently been developed to support teachers with data-driven decisions to improve their practice, decrease their workload, and organize their classrooms more effectively. Systems like these monitor students' progress and, based on their predictions, recommend instructional suggestions to teachers for them to adopt or ignore.

From teacher dashboards summarizing students' progress in particular tasks to grader-bots that can maintain the community in online course discussion boards, educator-facing AIED systems vary widely. A truly engaged, competent and human teacher (with all their emotional and social sensing capabilities) who excels in his or her field is irreplaceable. Modern educational settings have a range of AIED tools available to handle maintenance tasks and other routine work associated with teaching, which, in theory, allow the human teacher more time to create meaningful connections with their students (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). Here describe examples including tools for the automated grading of solutions, feedback recommendation, evaluation of student understanding and intervention suggestions, as well as engagement monitoring tools and support tools to monitor students' academic integrity.

First, many ITSs that were initially designed as learner-facing AIED systems can be adapted and improved so that the insights they provide into the students' learning can also be relayed to teachers. Such information can be presented via traditional teacher dashboards such as iPads or tablets (e.g., Alyuz, et al., 2019), or in more creative ways such via an augmented reality view of the classroom (e.g., Holstein et al., 2018). Essentially, they can monitor students' progress on particular tasks and content and provide teachers with predictions and/or recommendations, e.g. of which students need immediate help. There can also be the adaption of learner-facing AIED systems to share tutoring with the teacher by providing immediate feedback to students in some cases but leaving others for the teacher to deal with. For example, they can support the teacher with suggestions about how they might provide appropriate scaffolding for the student (Chi, VanLehn, Litman, & Jordan, 2011). Indeed, these affordances can result in a greater degree of efficacy in teaching and learning (Zeide, 2019).

Second, there are plenty of educator-facing AIED systems that focus on assessment. For instance, M-Write (Meltzer, 2017), an automated grading tool, combines automation with human oversight to lead students through writing assignments. It is designed to help students develop conceptual learning and writing skills by providing them with personalised feedback while the system generates a predicted value for the student grade (Klutka, Ackerly, & Magda, 2018). The M-Write system identifies areas where students have struggled with a writing assignment, and teachers can use this information to provide more specific feedback (Meltzer, 2017). Automated grading systems can be found in a range of disciplines, such as biology, medicine, business studies and English as a Second Language (ESL), mostly in use in higher education contexts (Perin & Lauterbach, 2018). Such systems are not limited to structured subject areas, but also can be utilised for the assessment of ePortfolios (Kalz et al., 2008). However, due to the need to calibrate and train such systems, they are more suitable for courses or programs with a large student population. With the increased access to authoring tools that would allow educators and researchers to build such assessment systems, their use will likely increase in the future. For example, LightSIDE (Light Summarisation Integrated Development Environment) (Kumar & Sree, 2014) is a free and open-source authoring tool provided by Carnegie Mellon University (TELEDIA lab). It incorporates numerous options for developing and evaluating machine learning models for assessment purposes as well as automated essay scoring. Since LightSIDE focuses on syntactic elements rather than semantics, it cannot evaluate arbitrary or particularly creative content, but it can be trained with answers to specific questions to support automated assessments for educators (Kumar & Sree, 2014).

Finally, in the context of collaborative learning, some systems can provide educators with a summary of the individual progress of each group member and the type of participation each of them has had in their workgroups (Chou, Huang, & Lin, 2011).

1.3. *AIED systems for institutional support*

Education institutions increasingly rely on AI and algorithms to target marketing to prospective students, estimate future class sizes, plan curricula and allocate resources, such as financial aid and facilities. All of these examples that extend beyond the learner- and educator-facing pedagogical AIED systems are considered to be institutional support tools. Some applications automatically schedule course loads for students, while others suggest courses and career paths - as guidance counsellors and career service offices would do. Predictive algorithms are also used at the institutional level as early warning systems to identify students at risk of failing or dropping out or having mental health problems by analysing a range of data.

In colleges and universities, for example, AI may be used to select the best candidates for admission. In part, this is due to the growth of marketing automation and predictive analytics, which help target and segment prospective students. Prospective students receive marketing materials customized for them that explain why the institution is the best fit for them. Predictive analytics in education allow the process to start earlier, with students identifying a future college major and career path as early as elementary school (Krishna, Mani Kumar, & Aruna Sri, 2018). In addition to marketing purposes, institutions also require accurate predictions of students' academic performance for making admission decisions and providing better educational services (Chen & Do, 2014). Recent AIED systems give HE institutions the ability to anticipate enrolment trends, optimise recruitment efforts and elevate academic performance. For instance, Penn State University is leveraging machine learning (ML) algorithms to predict a student's grade performance before courses begin. Based on more than 8.5 million records collected from 2005 to 2016, the university developed a model to leverage data from the Server Intelligent Storage (SIS), including transcript data and information from admission applications. A predictive algorithm was shown to aid university management in identifying students who might present with higher-than-average academic risks so that proactive strategies can be implemented before problems arise (Kardan, Sadeghi, Ghidary, & Sani, 2013).

However, many college admission decisions still rely on a more holistic evaluation rather than a fully automated process. A holistic approach, in which both humans and artificial systems work together over determining each applicant's suitability for admission, might mitigate potential bias (Alvero et al., 2020). The need to mitigate potential bias highlights an issue that needs to be constantly in the mind of those developing and using AI: is this AI bringing benefit and doing no harm? For non-technical experts, such as educators, their ability to address such important questions must be supported by helping to better understand AI.

AIED systems can also be used to plan courses so that students receive the optimum combination of courses to meet their needs, the needs of their instructors, and the requirements of their departments (Kardan et al., 2013). In addition to assisting with admissions and course planning, AI systems for institutional support can help decrease dropouts. There are plenty of examples of early warning systems to detect at-risk students in their first year or to predict the attrition of undergraduates in general (Aluko, Adenuga, Kukoyi, Soyingbe, & Oyedeji, 2016; Hoffait & Schyns, 2017; Howard, 2018). Many higher education institutions use these systems, including St Mary's University in Maryland (Zeide, 2019), the University of Osijek in Croatia (Babić, 2017), and the Open University in the United Kingdom (Hussain, Zhu, Zhang, & Abidi, 2018). Institutional support systems are often coupled with teacher- and learner-facing AIED features. Among other facilities, chatbots for student support are growing in popularity in higher education institutions as a means of increasing enrolment and reducing dropout rates (Zawacki-Richter et al., 2019).

2. The concept of AI readiness

The increasing availability of AI applications within society, and more particularly within the education and training sector as reviewed above, brings some significant implications for this sector (West and Allen, 2018). For example, there is the potential to use AI to address some of the challenges faced by educators and students. There are implications for what an education and training system must provide brought about by changes to the workplace due to AI and the consequential changes to the sorts of career that are and will be available in the future (Pandya, Patterson, & Ruhi, 2022). Plus, there is a need to educate people about AI for them to benefit safely from its potential. These implications are not mutually exclusive, but closely coupled and interconnected. For example, for a lecturer to integrate some AI technology effectively within their teaching, it would be helpful for them to understand something about what AI is and what it can and cannot achieve (Nazaretsky, Cukurova, Ariely, & Alexandron, 2021).

The expansion of AI for education and training can be daunting for those involved in designing and delivering education provision in schools, colleges and universities (Walia & Kumar, 2022). AI is opaque, largely 'black box' and impenetrable for anyone who does not have specialist expertise or a keen interest in the subject (Andrada, Clowes, & Smart, 2022, pp. 1–11). As was recognised by the 1% project in Finland (https://www.reuters.com/article/us-finland-education-ai-idUSKBN1YE1B6), the general public, including educators and trainers, have very little, if any, knowledge about AI. This situation is exacerbated by the focus of many funding initiatives on the provision of funding for specialist courses to build a workforce of people ready to build AI systems (see for example, https://www.gov.uk/government/news/2500-new-places-on-artificial-intelligence-and-data-science-conversion-courses-now-open-to-applicants). It is therefore not surprising that most people within education and training are largely oblivious to what AI is all about, and yet it is likely to bring about significant changes to their lives within the next decade (Hossain, Nurunnabi, Nadi, & Ahsan, 2021). And yet, we do not need the overwhelming majority of people involved within education to know how to build an AI system, rather, we need them to know how AI could be used to enhance and augment their human teaching expertise. Without such knowledge, how can educators make sensible decisions about what kind of AI software to purchase, or whether they are able to give their own informed consent to the use of AI and effectively explain to other people what an AI is going to be doing, so that they too can provide their informed consent?

2.1. The important differences between AI and human intelligence

The key to deciding how AI can be applied effectively in any setting is to understand *why* AI is going to be used, and *what* the AI is going to achieve that cannot be achieved without AI. To identify and specify the tasks the AI is going to do, because these are the tasks that AI is better at than humans, and to identify and specify the tasks that are better done by humans (Luckin, 2018).

However, as we have already discussed, when it comes to education, the very people who understand an educational problem that we want AI to help us solve are likely to have so little understanding of AI that they will not be able to make these decisions. By contrast, the people who understand the AI and who will design and build the AI system are unlikely to understand the educational context sufficiently to understand the problem or to know what the AI needs to do to help humans to achieve success. There is also a risk that those who understand the AI, but not the context will make over-optimistic and possibly inappropriate decisions about what the AI will be able to achieve, and that they will underestimate the complexity of the problem and its context, as well as the value of the contribution required by human intelligence (Russell, 2021).

As has been recognised, we have been all too quick to recognise the power of massive data crunching deep learning, without always recognising its limitations with the same speed and vigour (see, for example, the UK House of Lords Select Committee on AI report, April 2018). By contrast, the opposite is true for our human intelligence – we can be quick to recognise its limitations and slow to recognise all its unique and powerful capabilities (Luckin, 2018).

We need to redress this imbalance. A key element of the concept of AI Readiness is for people to understand the complexity of the intricate, sophisticated and subjective nature of human intelligence. We need them to appreciate the ways in which human intelligence is far superior to AI, as well as the ways in which AI is superior to human intelligence.

For example, social intelligence is a good example of the impressive nature of human intelligence. It is the basis of thought (Vygotsky, 1978; 1986), and important to the way we perceive intelligence. It is also the foundation of communal intelligence, and it is hard for AI to achieve in anything like a sophisticated manner. However, perhaps the most important features of human intelligence are those that involve our relationships with ourselves: our meta-intelligence. Humans are capable of learning to plan, monitor and regulate their own thinking and action: metacognition, our knowledge and control of our own cognitive processes. They are also able to develop a finely sensitive awareness of how they feel, as well as how others feel, and how these impact upon knowing and learning: meta-emotion. We are also able to develop an awareness of our interactions with the world, including our social interactions, our physical and our mental abilities as we move through different settings, interactions and experiences: meta contextual awareness. This ability to be self-aware and *meta intelligent* makes humans capable of accurately perceived self-efficacy, something that is not available to any AI.

A further, uniquely human, aspect of our intelligence, can be seen in our ability to understand each particular setting in which we interact, the people, the artefacts and tools, the environments, the entire context with which and in which we interact and between which we move seamlessly, for the most part. The interconnectedness of these settings is so deeply ingrained in our understanding of the world that we hardly notice it unless it causes some sort of problem or challenge. For example, we can travel across the world and still find our way from the airport to our destination, work out the local transport system, find food and lodgings and meet the people we intended to meet. Similarly, we mostly recognise with ease the relationships between different people and different communities, so much so that we often underestimate their importance and the huge challenge they present for those attempting to build AI systems that can attain a fraction of what we can attain with ease (see, for example, Sharkey, 2011).

2.2. The interconnected nature of human society and our intelligence

Similarly, we often underestimate the importance of recognising the connections between different elements of a problem or challenge when designing interventions and potential solutions, including those that involve AI. This is no less true in education and training than elsewhere. Education and training systems are ecosystems of interconnected communities, environments and expectations. They need to be treated as such. And yet, we often fail to recognise that changes and interventions that are made to one part of the ecosystem impact way beyond the particular community who are the focus of the intervention (Hutchins, 2000, p. 138).

For example, the Covid-19 crisis, aside from being a pivotal period for most people around the world, also opened a substantial opportunity for educational research. Specifically, the disruption of school work has illuminated many existing structural vulnerabilities in existing educational ecosystems around the world. A 2021 report (EDUCATE Ventures research et al., 2021) based on findings from a dataset collected from the key stakeholders in the education ecosystem: teachers, parents, educational leaders and EdTech companies during the months of disruption in 2020 illustrates several points of disconnection between the various educational communities in the UK. For example, there was little connection between existing research evidence and the educational practice that took place when schools transferred to online learning. This resulted in the inappropriate adaptation of the curriculum and instruction methods to the online environment, to the capabilities of different families and the various needs of learners. Furthermore, the ineffective dialogue between the government and school leaders prevented many learners and teachers from accessing the support they needed to ensure continuity of learning and the maintenance of young people's well-being.

The importance of building, sustaining, and supporting educational ecosystems is also key to the connectedness of the types of implications that AI brings for education, outlined earlier. The more educators and students use AI within their practice, the more they will understand about AI and what it can achieve (Luckin & Cukurova, 2019). This increased understanding of AI will also help them understand the ethical implications that AI brings and will increase their appreciation of the dramatic changes that AI is bringing to the workplace and the implications that result from these changes for education and training.

The interconnected nature of human society and the way our human intelligence has evolved to appropriate and perpetuate this are also important to AI Readiness for education and training. Learning is inherently social (Vygotsky, 1978; 1986). The concept of AI Readiness must both recognise the superiority of human intelligence when it comes to contextual and meta-contextual intelligence and prepares the sector to see AI as a tool to build better interconnections between and within education and training ecosystems.

3. AI readiness training

3.1. What should people know about AI?

One of the key questions to address when considering the design of AI Readiness training for any community, is what do people need to understand about AI? There is certainly value in most people understanding some of the general capabilities of AI and how it works at a high level. For example, it is useful for people to understand that AI is involved when their satnav figures out a good route to get them from A to B, potentially avoiding heavy traffic or motorways if you select those options. That their smartphone, when used as a camera, will draw a box around a human face and in some cases will recognise that you are snapping one of your friends. When someone makes a credit card purchase, AI at the credit card company sifts through the millions of daily transactions and then raises an alert if that purchase looks suspicious.

The general level of understanding of how the AI works that we have in mind is as follows: the satnav example involves the use of an algorithm (i.e a computer program) to explore an internal representation of the road network to find a good route from A to B. Using live data about road traffic, some bits of road in this network will be labelled as having dense traffic or roadworks and will be avoided and a workaround found. Rather than searching through every possible route from A to B, the satnav works out how to do the main part of the journey that gets from the nearest main town to A to the nearest main town to B, and then does extra searching at each end of the journey. It does not always have to conduct each new search from scratch as it can re-use the data on past searches to save time.

Similarly, to find a face in a landscape, the phone camera uses a prototype facial outline – two eyes, nose and mouth – as a way of searching through the picture. Sometimes it can't find a face if it is too small in the picture, or if the person is facing away from the camera. This means that a photosystem on a laptop may make a tolerably good job of collecting pictures of someone's daughter into one folder and their son into another folder, even though the photos are not labelled with their children's names, but it does need at least one photo of each child to get the separate collections started. This is achieved by internally rescaling and re-orientating the photos to ensure that they can be compared and then measuring how similar a new photo is to those already in the folder.

These examples provide a route into exploring the way that many AI systems rely on finding patterns in very large amounts of data, as in the credit card fraud example or the pixels of a face in the pixels of a scene. Other examples can also enable the introduction of the challenges that can arise with AI. For, example AI's ability to find patterns in huge amounts of data is also helpful in medicine. The computer can be shown many examples of MRI brain scans (say) and told by a human expert for each scan whether it showed evidence of a particular kind of tumour or not. AI collates all this information together so that when presented with a new (unlabelled) scan it can identify whether it is more similar to the scans with that tumour or more similar to the scans without that tumour. Some kinds of AI can support and explain their diagnosis, many others cannot and are just black-box systems. The issue of who decides what to do next is not usually taken by the AI system, but by a human radiologist who has the training and experience to judge the quality of the computer's diagnosis in the light of all the other contextual evidence. Part of the worry about AI is when the human expert is left out of the loop, and the AI system not only generates a suggestion for a diagnosis or a decision but also takes the decision or acts on the diagnosis. Within medicine this is unlikely but in other fields, it is less clear. For example, suppose you have a system checking applications for bank loans. It may have been trained, based on past evidence, to detect which applications are risky and might lead to a default on the loan and which applications look relatively less risky. The problem can be that without any further human intervention the applicant for the loan can be told "the computer says no", and the manager in the bank may not be able to interrogate the system to see why it says no, so the computer's decision stands, even if it was wrong because of a bias built into the pattern-finding mechanism or because it was trained on inadequate or biased data.

The examples discussed in this section provide useful introductions, but the contextualised nature of AI Readiness requires that we soon move on to examples that have greater relevance for the audience, in this instance those in education and trainers.

Once individuals and organisations are **AI-ready,** they **will be able to identify**:

- **What activity or challenge within their organization** could best be addressed by leveraging the power of data and AI. The AI Readiness programme includes tasks to identify the type of Human Intelligence that the organisation wants to develop within their students, pupils or customers as well. For example, perhaps the data they have collected has demonstrated that a particular profile of student will need more support with a course that has an essay as part of its assessment. The organisation might therefore identify that the provision of a writing mentor for such students would be a good challenge for AI and Human expert mentors to work together to provide.
- **Where AI would best be applied.** For example, the AI readiness training may show that an organization is recruiting some staff who are not likely to be effective without a significant amount of professional development. This knowledge allows the organisation to decide whether to invest in an AI-enhanced support service for staff that is particularly suitable for the type of staff identified through the data analysis OR the organisation might decide that it is at the recruitment stage that they need to change the type of staff they appoint – again AI can help here too
- **Why AI**? The imperative of any AI the organisation intends to apply. The most important aspect of any Machine Learning (ML) AI algorithm is the imperative for its design – the unique contribution that the ML is going to provide for the organization. The same data can be used to achieve very different outcomes, depending on the imperative of the ML algorithm. For example, facial expressions and spoken audio data from learners could be used to identify their emotional state to provide some targeted support when they look disappointed with their performance. The same data and algorithm could also be used by regimes and countries with a less supportive perspective to provide punitive feedback when they look disappointed. The data and algorithm are essentially the same, the imperative is not.
- **Who** will be involved? This will be staff and it could also be learners, customers, parents, broader stakeholders and partners. This is about identifying the people in the organization who will be working with the AI or working to provide the resources the AI needs, such as data, to ensure that the organisation has involved them in the next steps of the design process of the way that AI is going to be used. It is also the point at which looking for other partners to work with the organisation is important.

3.2. How can people be empowered with respect to AI?

A second key question is how can we help people feel empowered? For the non-specialist in education, the use of AI can seem innately worrying for several reasons. In addition to ethical concerns, there are the questions of whether AI is there to take away jobs from humans or will it further increase the existing inequalities?

One way to help people to feel more empowered with respect to AI is to help them to understand enough about AI to question and assess the integrity of the role of AI. We might, for example, help people working in the education and training sector to consider such questions by dividing the issues into three broad kinds. Both the general kinds and the questions associated with them are intended to be illustrative rather than exhaustive and were drawn from the authors' experience in this area.

1) Where the AI is *making decisions*, e.g., in choosing the next task for the learner in an online educational tool (for a review see, e.g. Garcia-Martinez & Hamou-Lhadj, 2013):
   a) Do the decisions seem sensible?
   b) On what basis were these decisions initially programmed into the system? In other words, were these just educated guesses by the programmer or derived from an analysis of the decisions of highly effective human teachers, or by some other method?
   c) Are there any biases embedded in the decisions whether they are based initially on human experts?
   d) Can the system explain why it made these decisions if challenged either by the learner or the human teacher.
   e) Was the data on which the system trained properly representative of the population affected by the decisions?
2) Where the AI is *offering advice* or information for a human to make a decision, e.g., in a dashboard for admissions tutors assessing student applicants (see e.g., Zawacki-Richter et al., 2019):
   a) Does the advice seem well-balanced?
   b) On what basis was the advice initially programmed into the system? In other words, were these just educated guesses by the programmer or derived from an analysis of the advice from highly effective admissions tutors, or by some other method?
   c) Are there any biases embedded in the advice whether they are based initially on human experts?
   d) Can the system explain its thinking behind the advice if challenged by the admission tutor receiving the advice?
   e) Was the data on which the system trained properly representative of the population affected by the advice?
3) Where AI is looking for and *finding patterns* in data, e.g., a pattern of behaviour suggesting that an incoming student may be at risk (see e.g., Howard, Meehan, & Parnell, 2018):
   a) Is the data from which the patterns were derived properly representative of the kinds of applicants who might be affected by the insights derived from these patterns?
   b) Does the pattern-finding method introduce its own sources of bias into those patterns?
   c) Can the patterns be explained in humanly understandable ways that make sense for the context of concern, or do the patterns seem to lack any semantics?

In many ways empowering people to ask and get answers to the kinds of questions posed above is one of the aims of the AI readiness Framework, described in the next section. Many of the questions relate to the data on which the AI was trained and its relation to the data on which it acts in the educational context. This is because bias can creep in at many stages of developing an AI tool unless great care is taken. For an example of how these questions apply to the design of a dashboard for teachers interested in the social aspects of their students learning, see Kent and du Boulay (2022).

4. The AI Readiness Framework

Here we present the 7 Step EThICAL AI Readiness Framework that we have developed over a number of years working with a range of educational organisations to assist them to embrace and benefit from AI. We have subsequently used this framework to structure interactions with educators and trainers and have found it to be beneficial. The design of the framework is also informed by the Organizational Readiness CRISP-DM iterative cycle process - Business understanding, Data understanding, Data preparation, Modelling, Evaluation and Deployment (Wirth & Hipp, 2000)):

a. STEP 1: EXCITE what is AI and how can each organisation and their workforce develop their AI Readiness? This step is very much about helping an *organisation* to engage their staff with the idea of becoming AI Ready.

b. STEP 2: TAILOR and HONE - what is the specific challenge the organisation wants to focus on? This part of the process involves exploring the types of challenges faced by the organisation and selecting 1–3 challenges that are to be the focus of the rest of the AI Readiness activity. When selecting these challenges, it is also essential to make explicit the assumptions that an organisation is making when identifying each challenge. A further component of STEP 2, and one that is extremely important is to identify and explicate the 'essence' of the organisation that is embedded within the challenges that are selected.
c. STEP 3: IDENTIFY - what data do the organisation have access to and how can the organisation collate it? At this stage, attention turns to the data that is currently available to the organisation. Data appropriate to the challenges selected must be collated, cleaned and prepared for analysis.
d. STEP 4: COLLECT - what new data do the organisation need to collect to address the challenge the organisation identified in STEP 2? The training explains different data collection methods and the practicalities of each of these.
e. STEP 5 APPLY - what AI techniques are relevant for the data the organisation has and intends to collect? A range of analytical and AI techniques are explained along with the criteria for the selection of those techniques most appropriate for their particular context.
f. STEP 6 LEARN – what can the organisation learn from the AI applied in STEP 5? The training programme helps illustrate how the results of the analysis and AI modelling that STEP 6 has applied to the data can be completed and it will help the organisation interpret this analysis and modelling to identify where AI could best be applied within their organisation, the type of AI and its main purpose.
g. STEP 7 ITERATE and Iteration – do the organisation need to go back to STEP 1? How is the organisation conducting the approach to AI – is it ethical? This is the point at which discussion about the extent to which the iteration of the EThICAL AI Readiness programme just completed has produced AI Readiness within them and their workforce. If AI Readiness has not yet been achieved, then another iteration through the programme is recommended. If AI Readiness has been achieved, the customer is ready to select and apply the AI that is best for them or to develop their own AI if appropriate.

5. AI readiness in action

Since 2019, we have applied the AI Readiness Framework across a range of organisations from different parts of the education and training sector. For example, from within the Financial Services Sector, we have used the AI Readiness Framework with a company that trains and then employs derivatives traders (Kent et al., 2021). This work aimed to help the organisation better understand their workforce and their needs. Their key initial challenge was to understand why so many of the employees whom they trained left the business within the first few months of moving from training to working. We have also been applying the framework with a Face-to-Face education provider who works across primary and secondary schools and wants to empower teachers to orchestrate different sorts of 'intelligent' lessons that will drive data collection and make possible data-driven feedback to students and teachers. Plus, a Higher Education organisation, who wish to demonstrate whether their students are 'learning how to learn' as well as learning the subject discipline/s they are studying.

Here, we provide a more detailed description of one of these examples to explain the AI Readiness framework in action. The organisation is a large Higher Education provider in the US: Arizona State University, whose educational innovation team have been set a challenge by their Provost:

How do we know students in each modality are meeting the articulated outcomes for a particular degree program? How do we know they are also meeting the "unalterables" that universities should provide (learning how to learn; a sense of civic and social responsibility; and the capacity to master the skills of their particular career calling in the future (which is a different nuance than learning to learn))?

5.1. EThICAL AI Readiness Framework STEP 1 EXCITE

Work was conducted with the educational innovations lab: 'ASU Action Lab' at the university, a senior manager and an independent advisory group who worked with the educational innovations lab to engage all of them in the possibilities that AI might bring to teaching and learning within their university. Further meetings with the senior manager and lab director were held to identify two faculties with whom work would be conducted. Workshops were then held with senior managers from each of these faculties to explain the role that AI might play and to enthuse them about the process of trying to address the challenge set by their Provost through the application of AI. These workshops also enabled the research team to find out more about the teaching practices in these faculties.

5.2. EThICAL AI Readiness Framework STEP 2 TAILOR and hone

The initial challenge was created by the Provost at the HEI prior to the start of the AI Readiness process. It was however quickly narrowed to: How do we know students are learning how to learn?

A rapid evidence review was completed by the research team to identify sub-constructs of Learning how to Learn and to develop potential observable behaviours associated with these sub-constructs. Learning to learn (LTL) was conceptualised as a *process* that starts before the students arrive at the HEI, develops during their time studying and this process continues after graduation.

Further refinement to the way that LTL was to be conceptualised by the HEI was achieved through conversations arising from the production of the rapid evidence review. The following concepts related to LTL were identified: Motivation, Engagement, Personality traits – conscientiousness, self-efficacy. Further conversations between the research team and lab director resulted in the description of LTL as a process involving changes in the students' capability for self-regulated learning (SRL). Thus, the process of refinement resulted in a honed version of the challenge as one that focused upon students' self-regulated learning (SRL) capability, itself a complex capability with many related constructs and sub-constructs.

5.3. EThICAL AI Readiness Framework STEP 3 IDENTIFY

The process of identifying data sources was a constant one and one that took a considerable amount of time. All students have touchpoints with a range of systems through which data about them is collected, however, none of that data is explicitly labelled as being about LTL or SRL. Data that exists in LMSs is usually quite general and certainly not of the granularity that we would need. However, the LMS data still has a role to play, and it is identifying the right mix of data that becomes crucial to the process of being able to identify some aspect of something as complex as LTL. The elements within the data that we need to identify are indirect and in the form of "proxies" - data that indirectly suggests some factor of interest (in this case a feature of LTL or one of its subcomponents) has occurred. Potential data sources included daily assignments, enrolment and demographic data, in addition to clickstream data from the LMS.

In parallel with the process of identifying data sources, we also designed an ontology that would connect the theoretical concepts of LTL with the available raw data. The ontology defines the possible ways in which the key concepts identified through the detailed specification of LTL can be operationalized via observable behaviours that are reflected in data. It is this method that enables the application of Machine Learning techniques to a range of integrated data sets to gain significant advantage with respect to what can be learnt about student (or teacher) behaviour. The process of mapping the Learning to Learn ontology to the available data sources is not a 'one-shot- process, it takes several iterations to close the gap between the raw data and the concepts that one wants to learn about from that data (Kent et al., 2022).

The theoretical concepts and constructs that we wish to understand sit on the left-hand side of the ontological bridge, in this example, these relate to LTL. The main span of the bridge is represented by the classes in the ontology that are operationalized. These operationalized classes describe observable behaviours that students engage in, such as sending an email, taking part in a group assignment, or undertaking some peer review.

For example, to operationalize student engagement one might want to collect data about student interactions in class discussions, as well as their engagement with the course materials. The other way around is also possible. Namely, a single observable behaviour might contribute to the operationalization of more than one theoretical construct. For example, a student attending their instructor's office hours might operationalize a behaviour of help-seeking but can also indicate their engagement and motivation in the course. At the right-hand end of the bridge are the rules and scripts that link the behaviours to the available raw data. Finally, across the bottom are core notions, which are educational constructs like a Course, a Session, and Program.

The ontology is a formally defined entity that can be used to structure analysed datasets and that can be reasoned about. The main relationship expressed in the ontology in this LTL example is that of membership: either of a "sub-class" to a "class", or of an "object" to a "class". Thus, the class "person" contains the sub-classes "student" and "teacher", and John Smith might be an "object" within the class "student". "Objects" and sub-classes "inherit" the properties from the classes that they are within. For example, every "person" has an age and an email address, which means that every student and every teacher has these properties, as does John Smith.

5.4. EThICAL AI Readiness Framework STEP 4 COLLECT

A key part of the AI readiness process is the collection of data that will complement that data that exists already and that can be accessed. For example, an LMS may record the fact that for a particular course, a student submitted (or did not submit) a certain type of assignment, but, without more contextual data, we are not able to learn anything about their motivation, their own interpretation of their ability to learn the concepts that the assignment was testing or their planning behaviour. A survey, for example, could be a useful additional data source if the questions are designed carefully to cover some of the areas where existing data is particularly sparse or does not exist. However, the collection of additional data can be problematic. For example, if it is vacation time, or is perceived as an activity of little value for the respondent. In this current example, we were unable to collect additional data of any scale.

To complement the gaps between the data which is typically collected and the data that is semantically related to LTL, we enriched the ontology with a set of new features, engineered from the existing features, to create a new LTL layer of semantics. For example, we annotated each event such as submission of an assignment of a particular type, delay in a submission or click in the LMS, with an associated numerical value, indicating how strong was the evidence that this event contributed from an LTL perspective.

5.5. EThICAL AI Readiness Framework STEP 5 APPLY

The data that was collected eventually included academic performance data, enrolment data (such as admissions information, courses taken and scholarships received), socio-demographic data, assignment data (such as when assignments were submitted and whether it was in time and their grade) and clickstream from the LMS (such as length of sessions, clicks and duration).

The cohort that was chosen to collect the data for were students from two courses: 2056 students taking biology, and 1895 taking psychology at the terms of Spring to Fall 2019 and 2020.

Data was referred to as either dynamic or static. Dynamic data included all snapshots that were timestamped such as students handing in assignments of various types. Static data did not change in time for a particular student taking a particular course, but rather provided the necessary context for the dynamic data, which was more indicative of students' behaviours. Static data included for example the student's age, demographic background, financial support, GPA or the name of the course. All the data, whether static or dynamic was transformed into a common format that could be analysed.

Once the dynamic and static data sets had been cleaned, prepared and integrated, we undertook exploratory analyses, followed by dimension reduction and clustering techniques as well as process mining which was applied specifically on the dynamic dataset. Here the focus was on the temporal analysis of the data, to see how it changed through the sessions and weeks in the context of LTL, and which 'suspect features' (e.g., features of interest) might have an effect on those changes. We also created a third dataset, which aggregated the dynamic features (such as clicks, duration and LTL evidence) to integrate with the static features. Here the focus was at an aggregated level, and not on the week-by-week changes. Dimension reduction was used with the aggregated dataset to try and identify whether LTL features formed a unified dimension and whether this was a distinct dimension from other, well-researched dimensions, such as academic performance and engagement. Using the dimensions identified, we clustered the aggregated dataset to identify various learner profiles.

Process mining was applied to the dynamic dataset, to model the LTL process and to identify process models that reveal different LTL processes for different contexts and on different learner clusters. It also helped us visualize how students navigate within a course. For more details on the analysis taken, please refer to Kent et al., (2022).

5.6. EThICAL AI Readiness Framework STEP 6 LEARN

The first step towards developing an organizational AI understanding would typically be for an organization to use their own data to better understand their learners and trainees. In the case study of LTL described, as in many other AI readiness instances, the pedagogical construct which was chosen to be modelled and explored would not be typically assessed or evaluated within the organization before. This sets the need to learn from the data what learners' behavioural patterns which are related to LTL even look like, and whether they indicate a learning dimension that is distinctive from other more commonly assessed dimensions, such as academic performance and engagement.

To achieve an understanding of whether LTL is a dimension on its own, we carried a dimension reduction using principal components analysis (PCA). The PCA revealed three components that had eigenvalues greater than one and which explained 46.69%, 13.66% and 8.79% of the total variance, respectively, explaining 69.15% of the total variance. The interpretation of the data was consistent with the theoretical assumptions about LTL with strong loadings of engagement items on Component 1, grades on Component 2, and LTL evidence items on Component 3.

Using K-means cluster analysis on these three dimensions helped us to identify three clusters of students, as shown below. The clusters were chosen to maximize the differences among cases in different clusters. All variables had a significant impact on determining the clusters (details about the variables and analysis can be found in Kent et al., 2022) (See Fig. 1)

The proportions are not ideal, with Cluster 1 very small. However, in further analysis, Cluster 1 is more distant from 2 & 3 than they are between themselves, and it seems potentially interesting (taking into account other variables), so we decided to investigate this solution. Post-hoc analysis of the clusters characterised the clusters roughly as Cluster 1: quite a minority, high grades, high LTL, Cluster 2: the majority,

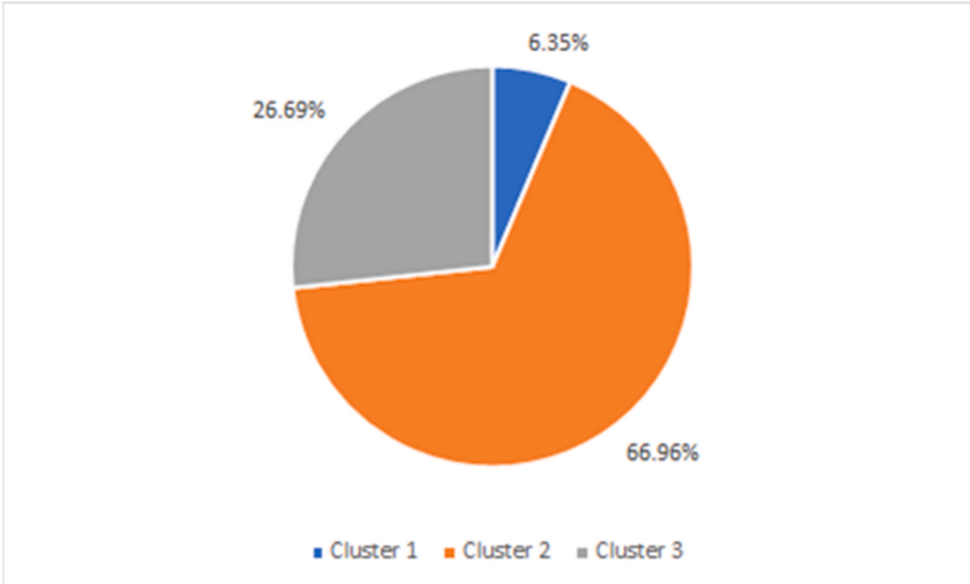

Fig. 1. Three clusters were identified.

highly engaged, Cluster 3: low engagement, low grades, and low LTL.

A post hoc analysis showed that (i) the differences between Cluster 1 and the other two in LTL evidence, and in the grades component are statistically significant, (ii) that both Clusters 1 & 2 have a statistically significantly higher level of the LTL component over Cluster 3, and (iii) that Cluster 2 has a statistically significant higher level of the engagement comp over Cluster 1, which is statistically significantly higher than Cluster 3. Based on this analysis, we were able to suggest rough student profiles, that would be the basis for the next step of designing appropriate LTL-informed interventions (Kent et al., 2022).

In a similar attempt, to understand the learners of the financial training company that we worked with, we conducted an analysis, contextualised to their pedagogical vision, with the same aim of characterizing groups of trainees manifesting different behavioural patterns, which might require a targeted approach to intervention or support (Kent et al., 2021).

5.7. EThICAL AI Readiness Framework STEP 7 ITERATE

This is the stage when a decision can be made about whether enough is understood about the way AI relates to and might help to address the challenge identified in Step 2.

6. Concluding discussion

There can be little doubt that AI is changing the way we live and work and that education and training as a sector is now a focus for the development of AI products and services. There is already a substantial AIED research community and now there are commercial providers making AI available at scale. However, the education and training sector is ill-equipped to make the best decisions about what product or service is most likely to address their needs effectively, or how to leverage the benefits of AI.

We have suggested that the needs of those working within the education and training sector require something more nuanced than a general AI course. They require an approach that presents AI in a way that is contextualised to their specific setting and its requirements, an approach that requires them to be active and participatory. We have suggested that such an approach could be based upon the concept of AI Readiness and that this would need to make clear the differences between human and artificial intelligence and the importance of applying AI to tasks where it has key strengths, whilst allowing humans to continue to apply themselves to the tasks that benefit from their strengths and superiority. In addition, we have stressed the importance of recognising the inter-connectedness of education and training systems in the way that we prepare people through AI Readiness training. In short, AI Readiness must both recognise the superiority of contextual and meta-contextual human intelligence and prepare educators to see AI as a tool for connecting.

The design of an AI Readiness training programme necessitates specifying what such a programme would enable people to achieve, what they need to know and what sort of questions they need to be able to ask. The 7-step ETHICAL AI Readiness framework offers a structure upon which to build AI training and to apply AI Readiness thinking. The example from the HE sector that we provide in this paper offers an illustration of the way each step in the AI Readiness framework has been applied. It demonstrates how even when no new data can be collected and the data to which the AI Readiness approach is applied was originally collected for purposes different to those for which it is now being used, there is valuable understanding to be gained through the application of the framework steps.

The process of working through the 7 steps of the framework requires each organisation or individual to identify and collect data, apply AI techniques and learn from the results about an important challenge that the educational organisation or individual has identified. The approach tackles the development of AI understanding through the application of Machine Learning AI to that challenge. In doing so it asks the people being trained to 'get inside' the black box of machine learning AI through its application to their own data. The expectation is not that the people being trained can themselves apply the AI to their data, but that the trainer applies the AI *with* those who are being trained. Taking them through the application process step by step.

The HE example discussed in this paper has led to follow on discussions and workshops with members of the faculties whose students' data was used for the LTL analysis. Their appetite for further work involving AI is strong and suggests that the application of the AI Readiness framework and training has helped them to understand more about how their organisation could benefit from further applications of AI.

These are early results and there are obvious limitations to the work presented here. For example, whilst the appetite within the HEI for further AI Readiness work is encouraging, further evaluations of the impact of the first piece of work are needed as well as time to conduct and evaluate any further work before any real conclusions can be drawn about the impact of the AI Readiness approach.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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