Designing Educational Technologies in the Age of AI: A Learning Sciences Driven Approach

Rosemary Luckin and Mutlu Cukurova

University College London

Corresponding Author: Prof Rose Luckin, University College London, 23-29 Emerald Street, London, WC1N 3QS, Tel: +44 (0)20 7907 4630

Author Short Bios:

Rosemary Luckin is a professor of Learner Centred Design at UCL and is the director of EDUCATE. Dr. Luckin has been developing and writing about the Learning Sciences, Educational technology, and Artificial Intelligence in Education for over 20 years.

Mutlu Cukurova is a lecturer in Digital Technologies in Education at UCL. Dr. Cukurova's research broadly addresses the pressing social-educational challenge of preparing people for a future that requires a great deal more than the routine cognitive skills currently prized by many education systems.

Abstract
Interdisciplinary Learning Sciences research has helped us understand a great deal about the way that humans learn, and as a result we now have an improved understanding about how best to teach and train people. This same body of research must now be used to better inform the development of Artificial Intelligence (AI) technologies for use in education and training. In this paper, we use 3 case studies to illustrate how Learning Sciences research can inform the judicious analysis, of rich, varied and multimodal data so that it can be used to help us scaffold students and support teachers. Based on this increased understanding of how best to inform the analysis of data through the application of Learning Sciences research, we are better placed to design AI algorithms that can analyse rich educational data at speed. Such AI algorithms and technology can then help us to leverage faster, more nuanced and individualised scaffolding for learners. However, most commercial AI developers know little about Learning Sciences research, indeed they often know little about learning or teaching, and we therefore argue that in order to ensure that AI technologies for use in education and training embody such judicious analysis and learn in a Learning Sciences informed manner, we must develop inter-stakeholder partnerships between AI developers, educators and researchers. Here, we exemplify our approach to such partnerships through the EDUCATE Educational Technology (EdTech) programme.

STRUCTURED PRACTITIONER NOTES

- **What is already known about this topic?**

1. The progress of AI Technology and learning analytics lags behind the adoption of these approaches and technologies in other fields such as medicine or finance.
2. Data is central to the empirical work conducted in the Learning Sciences and to the development of machine learning Artificial Intelligence (AI).
3. Education is full of doubts about the value that any technology can bring to the teaching and learning process.

- **What this paper adds?**

1. We argue that the Learning Sciences have an important role to play in the design of educational AI, through their provision of theories that can be operationalised and advanced.
2. Through case studies, we illustrate that the analysis of data appropriately informed by interdisciplinary Learning Sciences research can be used to power AI educational technology.
3. We provide a framework for inter-stakeholder, inter-disciplinary partnerships that can help educators better understand AI, and AI developers better understand education.

- **Implications for practice and/or policy?**

1. AI is here to stay and that it will have an increasing impact on the design of technology for use in education and training.
2. Data, which is the power behind machine learning AI, can enable analysis that can vastly increase our understanding of when and how the teaching and learning process is progressing positively.
3. Inter-stakeholder, inter-disciplinary partnerships must be used to make sure that AI provides some of the educational benefits its application in other areas promise us.

1. Introduction

Progress in the adoption Artificial Intelligence (AI) within education lags behind that seen in other fields such as the applied sciences, finance and medicine (Baker, & Siemens, 2014). This is not surprising given how education is full of doubts about the educational value of technology (Cuban, 2001; Meabon Bartow, 2014; Slay, Sieborger, & Hodgkinson-Williams, 2008; Selwyn 2015). It is important to note that the quantity and quality of robust evidence to show that well-designed AI *does work* in Education is increasing. There are already quite a few AI systems that have been shown to have statistically significant positive impacts on student learning including, for example, OLI learning course (Lovett et al., 2008), SQL-Tutor (Mitrovic, & Ohlsson 1999), ALEKS (Craig et al. 2013), Cognitive Tutor (Pane et al. 2014), and ASSISTments (Koedinger et al. 2010). These results are particularly important, because it is notoriously hard to achieve statistical significance in studies that investigate the positive impact of educational interventions. For instance, only 11 out of 90 randomized controlled trials undertaken between 2002 and 2013 funded by the US's coalition4evidence found positive effects of educational interventions (Coalition4evidence, 2013). Similar results can be seen from the UK's EEF funded studies where less than a quarter of the studies show positive impacts on attainment outcomes (EEF, 2019).

The relative success of AI-based systems is at least in part due to the tight connection between the design of these systems and learning sciences research evidence. However, doubts about AI technologies' educational value are not unfounded either. First of all, there is limited evidence about the adoption of these technologies at scale (Baker, 2016). Second, although they are very effective at the provision of simple instructional strategies such as optimal scheduling and feedback provision to provide foundational knowledge components, such as facts and rules, they are less effective at the provision of more complex instructions such as collaboration or self-explanations (Koedinger, Corbett, & Perfetti, 2012).

In this paper, we discuss the importance of Learning Sciences research for the design of EdTech that use AI. More specifically, we present three case studies to illustrate how learning sciences can be applied with AI to deliver complex instructions that are frequently considered as outside of AI technologies' merit. The first case study exemplifies how learning science is driving the design and implementation of AI technology to support collaborative, project-based learning, the second case study exemplifies the implementation of spaced practice (Cepeda, Pashler, Vul, Wixted, & Rohrer, 2006), and the last case study uses emotion prediction algorithms on audio data to support students in debate tutoring. Although current AI systems are limited in terms of their support for complex instructional approaches, as exemplified in all three case studies, there is great potential for AI to be also designed and used to support a broad range of pedagogical approaches.

However, the provision of effective instruction is only part of the picture when it comes to the scaled adoption of these technologies. Scaled educational implementations require system level changes. Therefore, we also present a framework driven by learning sciences research and our experience running EDUCATE at University College London (Cukurova, Luckin, & Clark-Wilson, 2018), to inform the system level change required for the scaled development and adoption of AI.

2. The Importance of Interdisciplinary Research in the Learning Sciences and AI

The Learning Sciences are replete with foundational theories and methods, along with a significant bank of empirical evidence that is relevant for the development and application of technologies in education (Kay, & Luckin, 2018). The *Learning Sciences* field is interdisciplinary and encompasses psychology, sociology, computer science, education, and cognitive science. Researchers contribute a variety of approaches to theory and method (Hoadley and Van Haneghan, 2012) to explore how best we can understand and support the teaching and learning process. A recent study conducted by Sommerhoff et al (2018), based on an analysis of the public representation of 75 graduate Learning Sciences programmes in the USA. They describe the Learning Sciences as focusing on: "the analysis and facilitation of real-world learning in formal and informal contexts." Cognition, metacognition, and dialog are the primary foci for analysis with respect to learning activities and processes, and the learning environment is considered to be fundamental to the facilitation of learning. Importantly for our objective here, Sommerhoff reports that: "Technology is key for supporting and scaffolding individuals and groups to engage in productive learning activities" and that Design Based research (DBR) is the "signature method".

The empirical foundations of the Learning Sciences are concerned with data and its analysis. Data is also important to the design of EdTech, AI and the related fields of Learning Analytics (LA) and Educational Data Mining (EDM). Since the recognition of 'big data' as a new concept, there have been many claims that it will revolutionize education (see for example, Tulasi, 2013), accompanied by a rapid growth in the quantity of data being collected from students in schools and higher education. It is interesting to note that within educational contexts the possibilities for collecting the rich data that educational analysis requires are increasing rapidly. This can be seen for example, in the way that multi-modal data, including eye tracking, physical movement and face recognition for emotion detection are being used at scale in some parts of the world (Blikstein, 2013).

In addition, more education systems and universities are tracking student achievement data online and this data often connects to other student records to provide a more complete picture of learners and their contexts. Increasing numbers of educational institutions use some type of online learning platform for homework, assessments and communication with parents or other stakeholders (Ferguson, 2012, Templaar, Rienties, & Giesbers, 2015). Some platforms track student progression, or record their progress on various learning tasks. In addition, the data itself is becoming easier to use, thanks to some standardized data formats, and better analytical tools to manage and explore large datasets (Baker & Siemens, 2014, Karkalas & Mavrikis, 2016). Researchers agree that there are great opportunities for learning analytics (LA). For example, for presenting visual representations of data, developing profiles of learners based on similar characteristics and performance, and giving teachers the opportunity to continually develop and improve their practice based on evidence (Bienkowski et al, 2012). However, the use of data and analytics is still patchy. Not least, because many teachers still lacking the skills and expertise, especially with respect to data literacy, to make best use of the data available to them (Luckin, 2018).

We need partnerships to develop learning science driven AI. Partnerships that bring together educational AI developers, educators and learners and researchers. There is far too little understanding of AI amongst educational practitioners, and this leaves them prey to the unscrupulous practices of any technology company who wishes to increase their profits, and who see education as a lucrative marketplace. There is also far too little understanding about teaching and learning within those who develop AI. Brokering effective partnerships between educators and AI developers would help both communities to understand critical issues of relevance to their work. These partnerships should be facilitated and engendered by skilled researchers. In order to support our arguments, in the next section we present three empirical case studies.

3. Empirical Case Studies

The first case study demonstrates the interdisciplinary nature of the related fields of educational AI, LA and EDM, and their relationship to the collection and analysis of increasingly rich and varied data sets. The second and third case studies illustrate the powerful connection that can be made when the Learning Sciences are used to inform the development of educational AI.

Case Study 1 PELARS (see http://www.pelars.eu for more information)

The first case study, PELARS, demonstrates that nonverbal interactions of learners can be effectively used to interpret complex learning process of collaborative Problem-solving (CPS) (Cukurova et al., 2018). Although, CPS has been widely studied in the Learning Sciences domain, there are very limited number of studies that focus on the nonverbal aspects of it. In PELARS project, we used Learning Sciences literature to derive the constructs of synchrony, equality, mutuality, and individual accountability as potential observable features of effective CPS, and then designed a multimodal learning analytics system that can detect such features automatically (Spikol, et al., 2018). Such learning sciences-driven approaches to design and implementation of multimodal learning analytics are rare compared to more inductive data-driven approaches in the field (Cukurova, 2018).

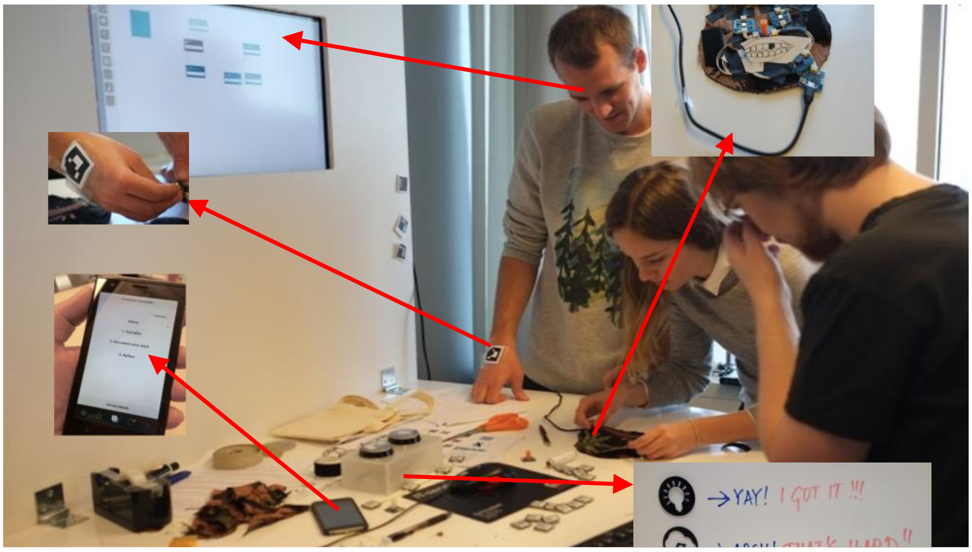

Figure 1. PELARS Data Capture Learning Environment

We captured a range of data about student interactions through a specifically designed data capture learning environment that employed multiple sensors to collect data during practice-based activities. Web and mobile tools were also available for learners to document their activities. The learning environment (see Figure 1) accommodated up to 4 students and enabled researchers to collect a range of data: log files from the Arduino physical computing kits (Katterfield *et al.*, 2018), facial and object tracking (fiducial marks), self-report data through two large buttons that students could push to signify sentiment (positive or negative). Students could also document their problem-solving process by entering brief text descriptions through a mobile device through which they could also capture photographs and video (for more date about this data capture environment see Cukurova, et al., 2017).

We explored four constructs from the Learning Sciences: synchrony, individual accountability, equality and intra-individual variability (Cukurova et al., 2018). These concepts were interpreted via nonverbal indexes of students' physical interactivity, both at the individual and at the group levels, to identify students' CPS competence. In the analysis, we used data from both high school and university students to compare the behaviours of high competence CPS groups with the behaviours of low competence CPS groups drawn from secondary and tertiary education. Our results showed that students in high competence CPS groups (as evaluated by expert teachers) demonstrated high and equal individual scores for physical interactivity and low and equal scores for intra-individual variability. High competence CPS groups also appear to have high levels of student synchrony and individual accountability. The results aligned with existing research findings in the Learning Sciences field (Damon & Phelps, 1989; Lakens & Stel, 2011; Lakens, 2010; Schneider & Pea, 2013 and Dillenbourg et al., 2011).

This empirical example illustrates that we can collect data, both passively and actively, that can be analysed in a manner that is informed by Learning Sciences research. The increasing sophistication of technology that can collect and process extremely detailed data about the interactions of learners, suggests the potential of such approaches to support collaborative, project-based learning. However, the sophisticated capture and analysis of data is unlikely to be effective unless this data collection and analysis is informed by what we have learnt from the interdisciplinary study of learning (Ferguson, 2012).

Case Study 2 CENTURY Tech (see https://www.century.tech for more information)

CENTURY Tech aims to improve learner outcomes and reduce the achievement gap between advantaged and disadvantaged learners by providing personalised learning, real-time data for teachers, and reduced workload. The algorithms within CENTURY Tech are informed by findings from cognitive science and neuroscience: both part of the Learning Sciences family. CENTURY design implementations of various theories and then use the data they collect to evaluate whether they are successful for learning. For example, spaced learning is the principle that information is more easily learnt when it is taught through short time slots and repeated multiple times, with time passing between repetitions (Cepeda et al., 2006). Century have used this research in the design of their learning 'nuggets', which are small topics of learning each of which includes a formative assessment. These nuggets are built into a Recommended Learner Path (RLP) for each learner with frequent reviews and nuggets from different topics interleaved to produce 'micro-gaps' even when students are studying in one longer single stretch of time.

In Luckin and Issroff, (in press), we propose the Teaching And Learning Acts (TALA) framework in which we identify the essential teaching and learning activities that the combined forces of the AI, the human educator and the learner need to undertake. We propose that TALA provides a way to index which of the teaching and learning activities that a particular AI system can provide in order to help educators leverage AI to address the educational challenges their students face. The framework is informed by previous research from Manches et al. (2010) and from Seldon & Abidoye (2018) that identifies the core components of technology enhanced teaching and learning. Manches' Learning Acts proposes a language that can be used to think about the different types of learning interactions that could occur when technology is used to support teaching and learning. Seldon & Abidoye (2018) characterise the teaching and learning process through specifying the roles that teachers need to complete and the responsibilities of learners. Table 1 illustrates the TALA framework.

Table 1 The TALA Framework

Teachers	**Learners**
Plan knowledge domain	Attend school
Collect resources	Organise themselves and their equipment
Define/modify learning activities	Exhibit appropriate behaviour for learning
Define/modify assessment and tracking activities	Memorise knowledge
Assess before and after learning activities	Recognise knowledge
Assess during the lesson to decide what to do next	Recall knowledge
Marking	Evaluate information
Written feedback	Answer written questions
Tracking	Answer verbal questions
Differentiation	Ask questions
Reporting	Assess their own work
Verbal feedback	Assess others work
Behaviour management	Assess their own emotions
Pastoral care	Record their own learning
Monitor attendance	Work collaboratively
Communicate with parents	Research
CPD	Reflection
Performance Management	Learn, exhibit and practice domain specific skills e.g. writing, drawing, dancing

CENTURY Tech can be characterised using the TALA framework as illustrated in Table 2 (please note, the learners' responsibilities are presented after the teachers' roles rather than side by side for ease of presentation). This type of description is more closely aligned with the language with which educators are familiar, and could be used to engage educators' interest in AI technologies.

Table 2: Century Tech using the TALA framework

Teachers	CenturyTech
Plan knowledge domain	√ Teachers decide what learning material learners can access and they can choose to set a learner specific tasks.
Collect resources	√ Teachers can collect and upload their own resources.
Define/modify learning activities	√ In addition to 1 and 2 above: Teachers can modify existing learning material for automarking by CENTURY. Teachers can upload individual or group-level feedback.
Define/modify assessment and tracking activities	√ Teachers can set learners specific assessment activities and they can create or adapt the assessments which are automatically marked by the platform.
Assess before and after learning activities	√ Teachers can assess learners’ knowledge before completing learning activities and after activities. These assessments typically take students 5-10 minutes to complete and the questions are auto-marked, with data automatically populating teacher data dashboards.
Assess during the lesson to decide what to do next	√ Teachers are provided with question-by-question level analysis.
Marking	√ CENTURY automarks to reduce teacher workload, BUT teachers do mark learners’ longer answers and they can provide in depth written, audio and/or video feedback.
Written feedback	√ see above
Tracking	√ Teacher data dashboards, illustrate how much work learners have done, their performance, and effort using data gathered automatically by the platform.
Differentiation	√ The CENTURY platform personalises for each learner by recommending the topics that will most appropriately support and stretch them. Teachers can also assign differentiated tasks to particular groups of learners.
Reporting	√ Reports detail the learner’s overall performance, their strengths and areas for development, the extent to which they have completed a given course of study, and how they have performed in relation to subject specific skills. These reports also provide suggested next steps to help learners improve further, and can be made available to a learner’s guardian via the guardian portal app.
Verbal feedback	√ Teachers can provide feedback on students work using CENTURY’s in-built video and/or audio recording tools. This feedback is attached to specific work submissions from the student and can be accessed by the student any time.
Behaviour management	X
Pastoral care	X
Monitor attendance	X
Communicate with parents	X

CPD	X
Performance Management	X

Learners	CenturyTech
Attend school	X
Organise themselves and their equipment	X
Exhibit appropriate behaviour for learning	√ monitors learners' levels of effort and reports to teachers and leaders.
Memorise knowledge	√ Memory Boost algorithm prompts students to actively recall previously studied material at appropriate intervals to ensure successful memorisation of material.
Recognise knowledge	√ provides learners with instant feedback after giving answers, allowing instant recognition of knowledge. Learners can access a comprehensive learning dashboard, with summaries of performance, of skills gained and of areas for development.
Recall knowledge	√ After completing learning material, learners then recall and apply their knowledge by answering a range of questions.
Evaluate information	√ Learners answer questions that require them to demonstrate a wide range of skills, including evaluating information, methods and solutions.
Answer written questions	√ Learners can complete written assignments on the platform and submit these to teachers for feedback.
Answer verbal questions	X
Ask questions	X
Assess their own work	X
Assess others work	X
Assess their own emotions	X
Record their own learning	X
Work collaboratively	X
Research	X
Reflection	X
Learn, exhibit and practice domain specific skills e.g. writing, drawing, dancing	√ The assessments allow learners to exhibit skills and further activities are available for learners to practice. Educators are encouraged to add longer-form activities on which they will feedback and students can upload images or record audio and/or video directly to the platform to demonstrate their skills.

Case Study 3 DebateMate (see https://debatemate.com for more information)

The second example of the powerful connection that can be made when the Learning Sciences are used to inform the development of AI for education is Debate Mate. Debate Mate offers a range of programmes and competitions to participating schools and aims to tackle educational disadvantage in some of most deprived communities. It does this by recruiting, training and placing university students to run extra-curricular debate workshops in schools with above average numbers of Free School Meals pupils. In order to move from DebateMate's initial face-to-face educational programme to a scalable AI-based EdTech, we followed these steps:

1) An evaluation of the business process, and eliciting the domain knowledge relevant to the process, using interviews of DebateMate's experts and observations;
2) A review of the Learning Sciences literature, relevant to the processes within DebateMate's specific orientation (argumentation and debating);
3) Collecting, cleaning, organizing and integrating the data that is currently being collected within the context of the process;
4) Modeling the identified decision-making bottlenecks using computational methods, such as statistical analysis, machine learning and data exploration;
5) Suggesting guidelines for an elaborated data collection process, to accommodate the challenges associated with DebateMate's current data collection strategy;
6) Suggesting potential options that could be used to automate/semi-automate the process based on data collected from the new strategy suggested in this document.

In this case study, we reviewed the Learning Sciences literature about personality features and skills for argumentation and debating, which revealed that it is essential to provide students with sufficient knowledge and argumentation techniques when teaching debating. In addition, broader tutor characteristics should not be ignored (Evagorou & Dillon, 2011; Zohar, 2008), in particular, tutors' personal (Klassen, & Tze, 2014), emotional (Battistich et al., 2000) and social traits (Lee et al., 2014). We collected data using psychometric measures to interpret personality traits, plus 90 second audio data via OpenSMILE software to predict emotional traits (Cukurova, Kent, & Luckin, 2019). Decisions about the type of data to collect, analyse, and model were driven by Learning Sciences research. These data sources and classification models were used to automatically predict the debate tutors' success. New sources of data were merged with the existing sources of data to build a DebateMate tutor success prediction model. The model can classify candidates into categories of high competence (those that are considered as currently able to tutor debating), medium competence (those that need some training), and low competence (those considered not able to tutor debating).

Table 3 illustrates that during the progress from DebateMate's initial face-to-face educational programme to a scalable AI-based EdTech, there are various steps that require an interdisciplinary approach to research and design.

Table 3. Interdisciplinary nature of the DebateMate case study

<table>
<tr><th>Step</th><th>Leading Area of Expertise</th><td rowspan="8">Constant and iterative collaboration between the disciplines and approaches to optimize the processes</td></tr>
<tr><td>Knowledge Elicitation</td><td>Interviewing and Qualitative Data Analysis</td></tr>
<tr><td>Literature Review</td><td>Educational Psychology</td></tr>
<tr><td>Data Cleaning</td><td>Educational Data Mining</td></tr>
<tr><td>Modelling</td><td>AI in Education</td></tr>
<tr><td>Data Collection Strategy</td><td>Research Methods</td></tr>
<tr><td>Automation</td><td>AI in Education</td></tr>
<tr><td>Commercial Product Dev.</td><td>Design Thinking and Design Methods</td></tr>
</table>

4. EDUCATE: working across disciplines and across stakeholders

The three case studies presented here, demonstrate how interdisciplinary findings from the Learning Sciences can be used to inform the design of learning analytics and AI technology. We now progress to the second element of our argument: that in addition to applying the findings from the Learning Sciences, we also need to work across educational, technical and research stakeholders. This is what we aim to achieve through EDUCATE at University College London (UCL) (Cukurova, Luckin, Clark-Wilson, 2019), which we now describe. EDUCATE is available to any EdTech startup or company with fewer than 250 employees not just those who develop AI EdTech.

Evidence has shown that the design and use of an EdTech plays a big role in its impact on educational outcomes and on the nature of the evidence generated regarding its efficacy (see for instance Reeves 2008; Pilkington 2008). EDUCATE addresses the lack of access to, understanding of, and engagement with research evidence among most EdTech practitioners. It also brings together the key stakeholder groups who need to collaborate for EdTech to be designed and applied effectively: the educators, the developers and the researchers. Groups of EdTech companies EDUCATE programme for 6 months. The goal of the programme is to incubate within the startups and SMEs, *a research mindset* as they work with researchers and educators to understand evidence-informed design. Unlike other programmes that are located within an academic frame, such as the Swiss edtech collider (https://edtech-collider.ch/#about), our participants are explicitly taught research methods, including how to access existing research evidence and about the basic tools and methodologies that might be implemented in research. They are also provided with guidance in the implementation of these research tools and methods through their personal research mentor. The aim is that they will then conduct their own evidence gathering research study.

The research training aims to help participants to use existing research findings and conduct their own research to generate evidence about the extent to which their product or service delivers the goals of its designers and the extent to which it brings benefit to learners and educators. EDUCATE participants are taught how to use a logic model (or theory of change) as a core construct, represented as a diagram that explains how a piece of technology might have an impact on its users. The logic model outlines the design features of the technology, the ultimate impact that it aims to have on its users and the potential outcomes that could lead or contribute to the technology meeting its designers' aims. Each participant's logic model articulates the definition of their product or service and its potential use case scenarios. We emphasise that different types of evidence have different advantages and disadvantages (Marshall, & Cox, 2008). We stress that the suitability of each type of evidence for each participant's product or service should be judged with appropriate evidence quality criteria, and that its appropriateness should be considered with respect to the context of use and the stage of innovation of the product or service.

Alongside the research training, EDUCATE offers business and product development support through workshop sessions and mentorship to support SMEs to enhance and commercialise their products as well as to ensure their contextual validity. We also provide participants with a co-working space where they work alongside researchers and educators, and an online tool called 'Lean' that integrates business and research planning, and we provide activities and events to help leverage research findings for investment. In the first 18 months of EDUCATE, we have supported some 200 startups and SMEs and have refined our methodology to ensure that the partnerships we build between researchers, educators and technology developers are effective and productive. The success of the programme can be seen in the progression of a substantial number of companies through the programme to completion (over 90% to date), the appointment of research staff within companies (58 new staff hires to date), the uptake of the research tools we provide by over 90% of companies. It is important to bear in mind that the evidence takes time to manifest itself as the companies grow and mature at different rates, but the evidence of impact on developer behaviour is strong and growing.

5. A framework for AI educational technology development

The TALA framework makes explicit the acts that a learner and a teacher needs to *engage* with as part of their education. We use the word *engage* here to stress the active nature of the behaviours involved. It is one thing to expect this range of engagement from teachers and learners when acting within the familiar surroundings of their class and institution. Once we start introducing AI systems into this environment and they start to take on some of the actions for teachers, then we need to ensure that teachers and learners understand enough about what the AI can and cannot be expected to do in order for teachers and learners to act in the collaborative and complementary manner needed for these AI technologies to bring the benefits they promise. One way in which we can help teachers (and learners) to gain the understanding of and confidence with AI is to engage them in co-design processes with AI developers in multi stakeholder partnerships, such as that exemplified by EDUCATE.

EDUCATE is built on the belief that bringing together educators and developers in interdisciplinary, inter-professional co-design teams is an effective way to help our participants to develop a research mindset. We also believe that collaboration between technology developers and educators helps developers to understand much more about teaching and learning, and it helps educators to understand much more about the process of developing technology for use in education and training. The special case of AI technology for use in education increases the need for this collaboration, because AI is a less familiar technology to educators than much other EdTech. The case studies for Century Tech and Debate Mate illustrate two of the companies who have undertaken EDUCATE. In addition, it is interesting to note that the growing number of companies who are using AI in their technology are particularly successful within EDUCATE and all have completed the programme. The success of EDUCATE has informed the development of our proposed framework for the development of effective AI within education, which we illustrate in Figure 2.

There is much to be positive about when it comes to the impressive developments in AI technologies and the benefits they could bring for education and training. AI can help us to scaffold learning and increase our own intelligence. It can also help us to solve some of the greatest challenges within education across the globe (Luckin et al, 2016; Luckin, 2018) However, in order to ensure that we can all benefit from our AI, we all need to know enough about AI to use it effectively. Teachers, in particular, will be in the forefront of our expectations for the education and training of the future and the current workforce about AI and how best to work and learn alongside it. But, who will educate the educators and how will they gain the requisite understanding about AI? This question about how best we build AI capacity within our educators and trainers is at the heart of the framework for AI in Education and Training that we present here. It is a framework that also seeks to improve the quality of the AI that is applied within education and training, so that it can effectively help us tackle the all-important educational challenges that face us today. The framework is designed to make sure that:

1. The AI that is to be used for education and training is designed in a pedagogically as well as a technically sound way;
2. Educators develop an understanding about AI, what it is and what it can do, that they can then use as they educate their students and trainees, and AI developers better understand the teachers' perspective and the process of teaching and learning.

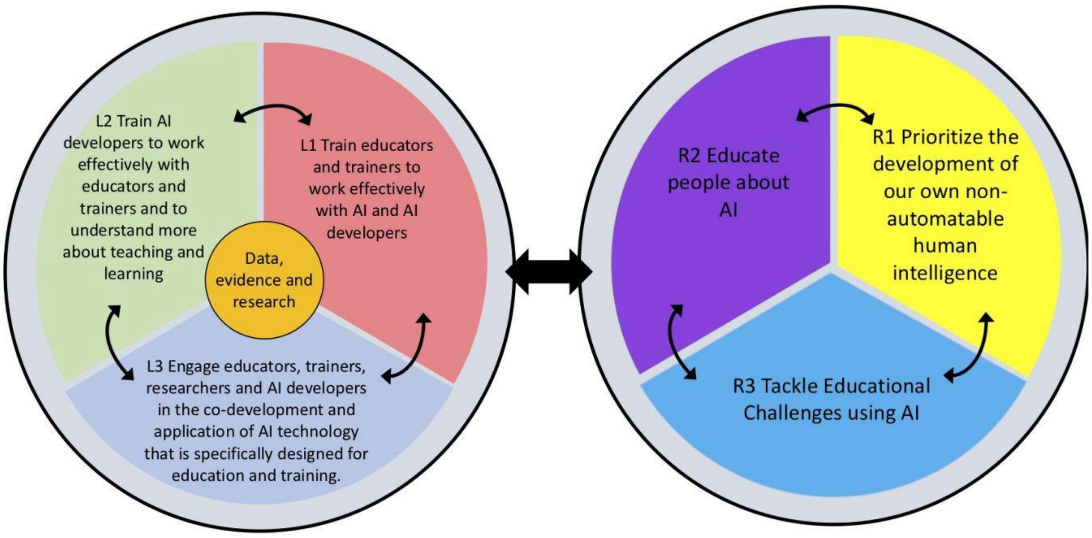

Figure 2: A co-design framework for AI to be used in education and training

The proposed framework requires an ecosystem that supports the development and application of AI for education and training that is achieved by instilling at its heart a process of co-design. The two concentric circular elements in Figure 2 are interconnected and interdependent. The left element has at its core the data, because data powers AI, data underpins evidence about learner progress and data can be analysed to demonstrate the value and educational effectiveness of the AI application. This central core is surrounded by three interconnected activities that represent the partnership between stakeholders that needs to be in place to support the development of educational AI.

Activity L1, specifies that Educators need to be trained to understand AI so that they can use it effectively and so that they can educate and train learners to work alongside AI.

Activity L2, specifies that AI developers need to be trained to understand a great deal more about teaching and learning if they are to build AI applications for use in education and training. AI developers also need to better understand the educator and trainer perspective, the learner perspective and the educational and training context.

Activity L3, specifies that educators and trainers, AI developers and researchers need to work together to develop AI applications for education and training. In the process of working together, educators will better understand AI, and AI developers will better understand education. Both communities will also benefit from working with researchers, because they will develop research mindset that will enable them to generate better evidence about the extent to which an AI application supports education effectively.

The three activities that surround the data core at the centre of the left-hand circular element in Figure 2 are inter-connected, because, progress in one area of activity will support progress in the other two areas of activity and vice versa. It is through engaging in the co-design process that educators and trainers will increase their understanding about AI, and AI developers will increase their understanding of education. The end result will be more knowledgeable developers and educators, and more education appropriate AI.

The right-hand circular element in Figure 2 also consists of three activities, each of which benefits from each other. These are the activities that need to take place within education and training in order for society to get the greatest benefits from AI.

Activity R1 is the activity that must happen within our education and training systems to give a higher priority to the elements of our human intelligence that we cannot automate with our AI. This includes for example, social intelligence, and emotional and subjective intelligence, metacognition, meta contextual intelligence, and accurate perceived self-efficacy.

Activity R2, is the prioritisation of educating everybody to understand enough about AI to use it safely and effectively. Activity R3, is the development and use of AI to solve some of our biggest educational challenges, such as tackling global teacher shortages, achievement gaps between the brightest students and those who struggle, and taking away some of the routine administration and marking that takes too much of human teacher's precious time.

In section 2, we stressed the importance of designing *data* analytics that are appropriately informed by the interdisciplinary Learning Sciences to create *learning* analytics. The framework for AI for education and training is likewise inherently interdisciplinary. It is also inter-professional, because it is the combination of the different professions within AI, education, training and research, that must be harnessed for us to truly benefit from our advanced AI technologies.

6. Discussion and Conclusions

There is no question that the interdisciplinary research conducted within the Learning Sciences has contributed a great deal to our increased understanding of the processes involved in learning and the nature of the teaching practices that can support these learning processes. It is this understanding of teaching and learning that we must bring into the design of the AI technology that is used within education and training. This understanding of the Learning Sciences can come from the researchers active within the Learning Sciences and it can come from educators active in the practice of teaching.

We argue, that partnerships that support inter-stakeholder co-design provide a method for bringing together the worlds of Learning Sciences research and practice with those developing the AI to be used in education and training. We use EDUCATE to illustrate how these co-design partnerships can be achieved. The proliferation of AI development for education and training adds a yet more urgent need for such inter-stakeholder approaches, because we must ensure that educators and trainers are able to support AI developers to better understand teaching and learning. We must also ensure that AI developers are able to support educators and trainers to better understand AI and its application to education. The framework for the development of AI for education and training presented in this paper outlines how such inter-stakeholder working might be structured to deliver 3 core aims for AI within education and training: prioritising human intelligence, tackling educational challenges, and educating everyone about AI.

Inter-stakeholder, inter-disciplinary partnerships can be used to make sure that AI provides some of the educational benefits its application in other areas promises. However, we also urge a note of caution concerning the way that such partnerships are set up. Large technology companies already dominate a great deal of the EdTech landscape, and we therefore need to ensure that they do not also monopolise relationships with educators. If teachers only co-design with one AI developer, their understanding of AI will be severely limited. If the partnerships between AI developers and educators also lead to those educators only applying one particular brand of AI in their practice, then we will have a very biased and narrow educational AI future. It is therefore essential that the partnerships between AI developers and educators and trainers are as diverse and varied as the educational challenges we face and the possible AI technologies that can be designed to address them.

Access to Data and Ethical Approval

The data from the PELARS and EDUCATE projects that is reported here is available on request from the authors in an anonymized format and within the constraints of GDPR. All empirical research reported here has been conducted within the ethical regulations in place at UCL and ethical approval has been granted by the relevant UCL ethics committee.

7. References

Baker, R. S. (2016). Stupid tutoring systems, intelligent humans. *International Journal of Artificial Intelligence in Education*, *26*(2), 600-614.

Baker, R., & Siemens, G. (2014). Educational data mining and learning analytics. In Sawyer, K. (Ed.) *Cambridge Handbook of the Learning Sciences*: 2nd Edition. Springer, New York, NY.

Bienkowski, M., Feng, M. and Means, B. (2012). Enhancing Teaching and Learning through Educational Data Mining and Learning Analytics: An Issue Brief. In *Proceedings of conference on advanced technology for education*. US Department of Education, Office of Education Technology.

Blikstein, P. (2013). Multimodal learning analytics. In *Proceedings of the third international conference on learning analytics and knowledge* (pp. 102-106). ACM.

Cepeda, N. J., Pashler, H., Vul, E., Wixted, J. T., & Rohrer, D. (2006). Distributed practice in verbal recall tasks: A review and quantitative synthesis. *Psychological bulletin*, *132*(3), 354.

Coalition for Evidence-Based Policy (2013). *Randomized Controlled Trials Commissioned by the Institute of Education Sciences Since 2002: How Many Found Positive Versus Weak or No Effects*. Retrieved May 2019 from http://coalition4evidence.org/wp-content/uploads/2013/06/IES-Commissioned-RCTs-positive-vs-weak-or-null-findings-7-2013.pdf

Craig, S. D., Hu, X., Graesser, A. C., Bargagliotti, A. E., Sterbinsky, A., Cheney, K. R., & Okwumabua, T. (2013). The impact of a technology-based mathematics after-school program using ALEKS on student's knowledge and behaviors. *Computers & Education*, 68, 495–504.

Cuban, L., Kirkpatrick, H., & Peck, C. (2001). High access and low use of technologies in high school classrooms: explaining an apparent paradox. *American Educational Research Journal*, 38 (4), (pp. 813–834).

Cukurova, M., Mavrikis, M., & Luckin, R. (2017). Evidence-Centered Design and Its Application to Collaborative Problem Solving in Practice-based Learning Environments. In *Measurement in Digital Environments White Paper Series*. Publisher: Menlo Park, CA: SRI International https://a4li.sri.com/archive/papers/Cukurova_2017_Collaborative_Problem_Solving.pdf

Cukurova, M., Luckin, R., Millán, E., & Mavrikis, M. (2018). The NISPI framework: Analysing collaborative problem-solving from students' physical interactions. *Computers & Education*, 116, 93-109.

Cukurova, M. (2018). A Syllogism for Designing Collaborative Learning Technologies in the Age of AI and Multimodal Data. In *European Conference on Technology Enhanced Learning* (pp. 291-296). Springer, Cham.

Cukurova, M., Kent, C., & Luckin, R. (2019). The value of multimodal data in classification models to interpret social and emotional aspects of tutoring. *International Conference of Artificial Intelligence in Education*. Springer, Cham.

Cukurova, M., Luckin, R. & Clark-Wilson, A., (2019). Creating the Golden Triangle of Evidence-informed Education Technology with EDUCATE, *British Journal of Educational Technology, 50*(2), 1-23.

Damon, W. & Phelps, E. (1989). Critical Distinctions Among Three Approaches to Peer Education. *International Journal of Educational Research*, 13, 9–19.

Dillenbourg, P., Zufferey, G., Alavi, H., Jermann, P., Do-Lenh, S., & Bonnard, Q. (2011). Classroom orchestration: The third circle of usability. In *International Conference on Computer Supported Collaborative Learning 2011* (pp. 510–517). ISLS.

EEF Blog – Stringer E. (2019). Teacher training – the challenge of change. Retrived May 2019 from https://educationendowmentfoundation.org.uk/news/eef-blog-teacher-training-the-challenge-of-change/

Evagorou, M., & Dillon, J. (2011). Argumentation in the teaching of science. In: Corrigan D., Dillon J., Gunstone R. (eds) *The Professional Knowledge Base of Science Teaching*, (pp. 189-203), Springer, Dordrecht.

Ferguson, R. (2012). Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, 4(5), 304-317.

Hoadley, C., & Van Haneghan, J. P. (2012). The learning sciences: Where they came from and what it means for instructional designers. In R. A. Reiser & J. V. Dempsey (Eds.), *Trends and Issues in*

instructional Design and Technology (3rd ed.). Boston, MA: Allyn & Bacon.
Katterfeldt, E. S., Cukurova, M., Spikol, D., & Cuartielles, D. (2018). Physical computing with plug-and-play toolkits: Key recommendations for collaborative learning implementations. *International Journal of Child-Computer Interaction*, *17*, 72-82.
Karkalas, S., & Mavrikis, M. (2016). Towards analytics for educational interactive eMbooks: the case of the reflective designer analytics platform (RDAP). In Proceedings of the Sixth International Conference on Learning Analytics and Knowledge, 143-147.
Kay, J., & Luckin, R. (2018). Preface in Kay, J. and Luckin, R. (Eds.) Rethinking Learning in the Digital Age: Making the Learning Science Count, *13th International Conference of the Learning Sciences (ICLS) Volume 1*. London, UK: International Society of the Learning Sciences.
Koedinger, K. R., Corbett, A. T., & Perfetti, C. (2012). The Knowledge‐Learning‐Instruction framework: Bridging the science‐practice chasm to enhance robust student learning. *Cognitive science*, *36*(5), 757-798.
Koedinger, K. R., McLaughlin, E. A., & Heffernan, N. T. (2010). A quasi-experimental evaluation of an on-line formative assessment and tutoring system. *Journal of Educational Computing Research*, 43(4), 489–510.
Lakens, D. (2010). Movement synchrony and perceived entitativity. *Journal of Experimental Social Psychology*, 46(5), 01-708.
Lakens, D., & Stel, M. (2011). If they move in sync, they must feel in sync: Movement synchrony leads to attributions of rapport and entitativity. *Social Cognition*, 29(1), 1.
Lovett, M., Meyer, O., & Thille, C. (2008). The Open Learning Initiative: Measuring the Effectiveness of the OLI Statistics Course in Accelerating Student Learning. *Journal of Interactive Media in Education*, JIME, http://jime.open.ac.uk/2008/14.
Luckin, R. (2018). *Machine Learning and Human Intelligence*. IOE press, London.
Luckin R. and Issroff, K. (in press). AI and Personalised Learning and Assessment, New South Wales Department for Education publication.
Luckin, R., Bligh, B., Manches, A., Ainsworth, S., Crook, C. and Noss, R. (2012). Decoding Learning: The proof, promise and potential of educational technology. London: Nesta. Retrieved April 2019 from www.nesta.org.uk/sites/default/files/ decoding_learning_report.pdf
Luckin, R., Holmes, W., Forcier, L., & Griffiths, M. (2016). *Intelligence Unleashed: An argument for AI in education*. London: Pearson Education.
Manches, A., Phillips, B., Crook, C., Chowcat, I., & Sharples, M. (2010). CAPITAL-Curriculum and Pedagogy in Technology Assisted Learning. Retrieved April 2019 from https://hal.archives-ouvertes.fr/hal-003082/document.
Martinez-Maldonado, R., Pardo, A., Mirriahi, N., Yacef, K., Kay, J. and Clayphan, A. (2015). 'The LATUX workflow: Designing and deploying awareness tools in technology-enabled learning settings'. *Proceedings of the 5th International Conference on Learning Analytics and Knowledge*, (pp. 1-10), New York: ACM.
Meabon Bartow, S. (2014). Teaching with social media: Disrupting present day public education. *Educational Studies*, 50(1), 36-64.
Mitrovic, A., & Ohlsson, S. (1999). Evaluation of a constraint-based tutor for a database language. *International Journal of Artificial Intelligence in Education*, 10, 238–256.
Pane, J. F., Griffin, B. A., McCaffrey, D. F., & Karam, R. (2014). Effectiveness of cognitive tutor algebra I at scale. *Educational Evaluation and Policy Analysis*, 36(2), 127–144.
Pilkington, R. (2008). Measuring the impact of IT on students' learning. In J. Voogt & G. Knezek (Eds.), *International handbook of information technology in primary and secondary education*. Berlin/Heidelberg/New York: Springer.
Reeves, T. C. (2008). Evaluation of the design and development of IT tools in education. In J. Voogt, & G. Knezek (Eds.), *International handbook of information technology in primary and secondary education*. Berlin/Heidelberg/New York: Springer.
Ritter, S., Anderson, J. R., Koedinger, K. R., & Corbett, A. (2007). Cognitive tutor: Applied research in mathematics education, *Psychonomic Bulletin & Review*, 14, 249–2
Roth, B., Becker, N., Romeyke, S., Schäfer, S., Domnick, F. and Spinath, F.M. (2015). Intelligence and school grades: A meta-analysis, *Intelligence*, 118–37.
Schneider, B., & Blikstein, P. (2015). Unraveling students' interaction around a tangible interface

using multimodal learning analytics. *Journal of Educational Data Mining*, *7*(3), 89-116.
Schneider, B., & Pea, R. (2013). Real-time mutual gaze perception enhances collaborative learning and collaboration quality. *International Journal of Computer-Supported Collaborative Learning*, 8(4), 375-397.
Seldon, A. & Abidoye, O. (2018) *The Fourth Education Revolution: Will Artificial Intelligence liberate or infantilise humanity?*, The University of Buckingham Press.
Selwyn, N. (2015). *Technology and education—Why it's crucial to be critical. In Critical perspectives on technology and education*. Palgrave Macmillan, New York.
Siemens, G. (2012). Learning analytics: envisioning a research discipline and a domain of practice. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, (pp. 4-8).
Slay, H., Siebørger, I. & Hodgkinson-Williams, C. (2008). Interactive whiteboards: Real beauty or just lipstick?, *Computers & Education,* 51, (pp. 1321–1341).
Sommerhoff, D., A. Szameitat, F. Vogel, O. Loderer, and F. Fischer. (2018). "What Do We Teach When We Teach the Learning Sciences? A Document Analysis of 75 Graduate Programs." *Journal of the Learning Sciences*. doi:10.1080/10508406.2018.1440353.
Spikol, D., Avramides, K., Cukurova, M. (2016). Exploring the interplay between human and machine annotated multimodal learning analytics in hands-on STEM Activities. *Proceedings of the International Conference on Learning Analytics & Knowledge* (pp. 522-523). Edinburgh, United Kingdom: ACM.
Spikol D, Ruffaldi E, Dabisias G, & Cukurova, M. (2018). Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. *Journal of Computer Assisted Learning*, doi.org/10.1111/jcal.12263
Tegmark, M. (2017). *Life 3.0: Being Human in the Age of Artificial Intelligence*. Knopf Publishing Group.
Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning Analytics in a data-rich context. *Computers in Human Behavior*, *47*, 157-167.
Tulasi, B. (2013). Significance of Big Data and Analytics in Higher Education. *International Journal of Computer Applications*, 68(14), 21-23.