

Whither or wither the AI of AIED?

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Abstract. This position paper explores the relationship between the historic roots of AIED and the challenges of restricting our vision to EdTech that has AI. It argues that the founders of AIED had a broad vision of the field, primarily driven by the *goals* of creating advanced technology for personalised learning. They were not wedded to a techno-centric view, demanding use of particular techniques that are now thought of as “AI”. The paper argues that we have accepted work with no AI, notably in Open Learner Modelling. We discourage, either directly or just because of our name, work that is true to the AIED founders’ vision. In doing so, we miss many exciting and promising ways to create better technology for education.

1 What was the AI in the initial vision of AIED?

So how did we come to be called AIED in the first place? In the early days of computing research, AI had a very broad brief. It was driven by the vision that computers would one day be able to emulate the actions we describe as intelligent when people do them. What a bold vision this was --- at a time when computers were very slow, expensive and available only in research labs, military and business contexts. AI research stood in stark contrast to other the major areas of computing, such as hardware, operating systems, programming languages and numerical analysis. It was AI that looked to real world applications and creating the visions of science fiction.

AIED was born in the 1970s, with its first conferences in the 1980s (Self, 2015). It aspired to create applications that could help people learn. This was long before it was possible for most learners to even see, let alone use, a computer. A widely cited driver for our AIED research was the vision that computers could help achieve Bloom’s famous 2-sigma learning benefits from *personalized teaching* by an expert teacher (Bloom, 1984). Our community is still committed to this goal. But it is useful to consider what it meant.

The classic early work in AIED identified four key elements:

- domain expertise;
- teaching expertise;
- student model; and
- user interface.

And so, the goal of researchers was to explore any or all of these architectural elements, towards building what was called an Intelligent Tutoring Systems (ITS) or AIED system. Overall, for both AIED and ITS, one key goal was to create computer systems that could provide *personalised teaching*, just as a knowledgeable teacher with expert teaching skills could do. We still aim to do this. And another goal was to support excellent *user interfaces* --- with what we may now call natural user interfaces (such as natural language and speech) and rich forms of interaction (such as graphical user interfaces that are now the norm). The spirit of their vision included creating systems and interfaces that both mimic human expert teaching and to use other techniques that are better suited to machines.

Since our early days, when the AIED community chose its name, a great deal has changed for AI, computing broadly, even for the behemoth of formal education and the commercial interests associated with those institutions and broader education. In parallel, AIED research has evolved in important ways. The next part of this paper explores these differences as a foundation for arguing that AI still has a place in AIED, but that it is not necessary for the still worthy and, as yet, unreached core vision of our founders.

2 How has AI changed since the birth and naming of AIED?

AI has become mainstream in the sense that it is part of the technology that each of us uses each day. This is well illustrated in the following descriptions from the EdX Introduction to AI¹.

Artificial intelligence is already all around you, from web search to video games. AI methods *plan* your driving directions, *filter* your spam, and *focus your cameras on*

¹ <https://www.edx.org/course/artificial-intelligence-uc-berkeleyx-cs188-1x-0#.VQzBWUa10k4>

faces. AI lets you guide your phone with your *voice* and *read foreign newspapers in English*. Beyond today's applications, AI is at the core of many new technologies that will shape our future. From self-driving cars to household robots, advancements in AI help transform science fiction into real systems.

I have added the bold font to highlight the sampler of technical areas alluded to: planning, filtering, vision, natural language translation. AI has been so successful that it has resulted in many off-the-shelf tools for these tasks, and for many other core AI tasks. AI has also changed from its focus on deep reasoning to large-scale statistical methods. This partly reflects the huge drop in the cost of memory and processing, along with the availability of networking. So, for example, an area like natural language translation has shifted from an early focus on user modeling and deep reasoning to statistical techniques for machine learning that makes use of large corpus data, particularly text which occurs naturally in online materials such as books, newspapers, social media sites, Wikipedia.... Where early work often involved complex reasoning, now it is possible, and sensible, to explore far simpler methods that harness huge amounts of data to achieve more robust and practical systems.

AI has earned a place as part of a standard computing undergraduate degree. Similarly, some other core areas of the computing syllabus include databases, HCI, software engineering, graphics. Such areas have now established a substantial collection of techniques that belong in the computing professional's toolkit. All of these, not just AI methods, should be used to achieve the core goals of AIED.

AI has achieved much in its long history, often resulting in new communities that are more problem-, rather than technique-focused. For example, robotics researchers have their own publication venues; while they may also publish in AI venues when they create a new contribution to the body of knowledge in AI, their core goals are to create effective robots. High impact research may be based on new ways to make effective use of *existing* software tools for AI, database, graphical, language, vision systems.... Similarly, separate communities have emerged in areas that are central to the AIED vision of effective interfaces, notably natural language generation and understanding and systems based on vision and depth sensing to provide NUI, natural user interaction. This offers support for learning away from the desktop. It

opens possibilities for just-in-time learning, teachable moments and kinesthetic interaction that can be valuable for learning.

In summary, AI is pervasive and it is just one, of many, software tools that AIED researchers should draw upon to create the future of technology to enhance learning and education.

3 How has education changed since the birth and naming of AIED?

Over the history of AIED, computing has changed radically. Every potential learner in the developed world now has easy access to many forms of computers in their daily lives. And they will have many more, including personal devices, wearables, mobiles, portables and desktops and well as embedded systems such as interactive tables and walls and smart environments. The interface will have input modalities that include natural language, speech, gaze and gestures as well as keyboard and mouse. Diverse sensors will provide indirect input, such as eye-tracking, mood detectors and activity trackers. Even in the developing world, there is increasing availability of personal technology, particularly mobile phones.

This explosion of computing devices has finally begun to have a deep impact on education, both formal and informal. Our educational institutions make extensive use of computers. Those uses range from core productivity tools, through to tools for particular disciplines as well as personalized and collaborative learning tools. They link the formal and informal, for life-wide learning support.

This has seen the emergence of communities that follow the AIED founder vision for using technology to enhance education. One recent example has seen the emergence of the *Learning Analytics* community. They represent the mainstream of education exploring ways to harness data from even administrative tools (such as those used to capture details of student demographics) and certainly for widespread learning tools, such as Learner Management Systems.

Another emerging example, this time for lifelong, life-wide learning is due to *sensor technology*. For example, wearable activity trackers can be viewed as a valuable data source to an AIED system. They are a form of the interface element, just as surely as a keyboard, drawing tablet or spoken input is. Such sensors can play a key role for personalized teaching, such as interfaces to help people set effective goals and plans, self-monitor progress on these, discover which personal strategies are effective for achieving goals and to learn about new strategies.

Yet another recent EdTech innovation is the *MOOC*. This is exciting on several levels. MOOCs offer the possibility for a very broad population of learners to have access to high quality personalised learning opportunities. MOOC platforms emerged from the elite computer science research world. This is striking as computer scientists, with outstanding expertise in diverse areas of computing, have so clearly committed to creating innovative teaching systems. MOOCs provide exciting green fields for EDM and for translating our years of AIED research into widely used software systems.

These illustrate just three of many trends that matter for AIED. They are pervasive and have high impact. All are currently outside the core of what some members of our community see as AIED. There is a real risk that a paper reporting any of these would be rejected for lacking AI. And authors may assume this, and submit such work elsewhere. Yet all three do offer personalized learning, as the term is described in the broader community. All have data about learners and it is widely recognized that this data is important for informing the learning. Should we call that data a learner model? Why not? Do those communities consider it a learner model? Probably not. Should we object to calling such data a learner model representation just because it is simple by AI standards, rather than complex. Surely these classes of EdTech are within the scope of the vision of the AIED founders.

4 How has AIED changed? And not? Personal case studies.

The last section suggested that AIED has not changed enough to keep up with the dramatic shifts in the real world of education. This section explores some of the ways that the AIED community has already made steps towards accepting research that has little or no AI. There have

been AIED papers dealing with essentially the software engineering aspects of sophisticated AI systems. For example, these include the creation of interfaces to make it easier for non-technical users to design and modify the teaching in a complex AIED system; such work tackles the problem that an AIED system needs a better user-friendly interface.

But there has also been work that has no element of AI at all. Lest I risk offending others, I illustrate this in terms of my own work that has been published in AIED and ITS venues but does not have AI. As a young researcher, I was excited at the AIED vision of creating personalized teaching system. I concluded that a key is the learner model because it drives the personalisation, based on its data about the learner. But I was also committed to treating the learner model as the personal data of the learner and to respect the asymmetry in the relationship that should exist between a person and a machine, where the person should be able to maintain a sense of control.

This focus led me to work on creating learner models that respected the learner's right to *control* their own data, to help the learner to be *responsible* for their own learning. As a foundation for learner control, I concluded that it was important to create learner modeling middleware that was designed, from its foundations, to enable the learner to *scrutinize* the *learner model* and the associated *personalization processes*. Issues of personal data privacy are not mainstream AI concerns. But they are important for real world deployments. This is reflected in the 2012 workshop by leaders of the MOOC community, resulting in the Asilomar Convention for Learning Research in Higher Education². While the philosophical standpoint of learner control was a key driver for my research, there are also more pragmatic aspects. One relates to the deeply fallible process of learner modeling. Since the data about learners is generally noisy, unreliable and incomplete, I wanted to create interfaces to the learner model, Open Learner Models (OLMs), that enabled the learner to see their model and how teaching applications interpret and use it. This could enable them to correct it. They could also alter it in other ways if they wished to introduce incorrect data. (The underlying representation avoids this from corrupting the model, and supports multiple views and interpretations of the model). That work was accepted by the AIED and ITS communities, as evidenced by

² <http://asilomar-highered.info/>

publications, such as Kay (2000; 2000a), Kay & Lum (2005) and Czarkowski et al (2005). The learner model representations in that work did not require, or make use of, sophisticated AI.

Concerns for *systems* aspects led to my work on user and learner model servers. This is important for practical systems, but it is not AI (Kay et al 2002; Brusilovsky, 2003; Brusilovsky et al, 2005; Assad et al, 2007; Kay and Kummerfeld, 2012). Designing OLM interfaces is essentially HCI, with a strong focus on user-centred design, rather than AI. The challenge of building systems that work effectively also makes it desirable to create the simplest technical solution that is effective, in that it achieves the intended task. This is good software engineering, good sense and also an excellent foundation for creating OLM interfaces that are simple enough make the model understandable and scrutable. In line with the view of learning data as belonging to the user and under their control, even my earliest implementations of the learner model placed it outside any single application (Kay 1994). The move to learner model servers (Kay et al, 2002) continued the move towards a cloud-based independent learner model as a first class citizen (Kay 2008; Bull and Kay 2010). None of these concerns are AI.

Learner models are clearly core to AIED; they are one of the four elements of personalized teaching. Papers on OLMs have been published in our journal and conferences, as reviewed by Desmarais and Baker (2012). Some have used sophisticated AIED representations, such as cognitive and constraint-based models and Bayesian nets. However, my own work, and key work by other prominent OLM researchers has typically had rather simple learner models. There was no need for complex AI techniques. The defining characteristic of an OLM is that it provides an interface onto a data structure where both were explicitly designed to provide a view of the learner model that would be useful to the learner.

A foundation for designing a learner model is the definition of the domain ontology and the processes to transform learning data into inferences about that learning ontology. In my work, it could more accurately be described as defining the curriculum in terms of the learning objectives. Then the inference is essentially a mapping from learning data onto that curriculum, using the simplest effective interpretation. While

some reviewers have criticized some of this work for the lack of AI, they have never explained why a more complex AI approach would be useful or how such modest and simple approaches are inadequate to the task. Nor have they argued the work is not useful. I believe that OLM research is true to the aspirations of the founders of the AIED community, even if it has no element of what is currently AI.

While OLM research is accepted in AIED, my other current research involves creating interfaces for surface computing, with large screen interactive tabletops and walls. This is exciting stuff. Some of it has made it into AIED venues (Martinez-Maldonado et al, 2011, 2012, 2013, 2014). This work used the data from small group interaction at a tabletop to model the effectiveness of collaboration. This used EDM methods to interpret the raw data, to distinguish more, and less, effective collaboration in groups of students. We trialled that work in a lab setting. However, when we moved into the wild, with real classrooms and real teachers, the actual demands of the classroom called for far simpler learner models. For this real world context, we took the same digital footprints of the learners, but this time presented them in very simple OLMs (Martinez-Maldonado et al, 2012, 2014). That was what met the teacher's needs; it did not have or need AI for the core of the research. Some of it seemed to have enough AI or OLM content to make to our conferences, much did not.

In summary, the publications of the AIED community already include some research that provides innovative teaching systems but does not need AI and reports none. But we still exclude other interesting and innovative work, or authors self-exclude it.

5 Summary

This position paper has argued that the foundation vision for AIED was to create personalised learning systems, with highly effective interfaces, and that this vision is still relevant to the AIED community. There is much that remains to be done if we are to create the four core components of AIED architectures. But over the last 25 years, AI has changed, as has education and EdTech. We run the real risk of being left behind some of the most exciting and novel directions if we insist on restrict-

ing our research to systems that create or use AI, as it is understood today.

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