A is for Adaptivity, but What is Adaptivity? Re-Defining the Field of AIED

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Abstract This paper proposes to define the field currently known as AIED not in terms of the technology used, but in terms of system behavior. Specifically, it is proposed that AIED is the science and engineering of systems that adapt to learners, so as to help bring about effective, efficient, and enjoyable learning experiences. But what, in general, is adaptivity? Intuitively, being adaptive means that the system adjusts the course of instruction in nuanced and effective ways based on learner differences, for example the goals and needs of individual learners and group of learners. It is difficult to state necessary and sufficient conditions for the concept of adaptivity. Instead, I stipulate that a system is more adaptive to the degree that: (a) its design is grounded in a thorough (empirical) understanding of learners in the given task domain, (b) it is appropriately interactive, and (c) it takes into account, in its pedagogical decision making, how individual learners measure up along different psychological dimensions. These factors help in comparing systems in terms of their degree of adaptivity. They imply that the presence of Artificial Intelligence technology is not a defining factor, even if it can be (and often is) instrumental in bringing about adaptivity.

Introduction

How we define our field (currently called AIED) influences how we position it vis-à-vis other efforts to create learning technologies. This positioning is not merely academic. It may influence public perception and acceptance of our technologies. For example, it may influence how MOOC developers see the need for AIED technology in their courses, and may influence how the technology is accepted and spreads. Experts do not agree about how to define AIED or (relatedly) intelligent tutoring systems [25, p. 21], so the issue is not straightforward. How can we define our field in a way that is inclusive and honors its interdisciplinary nature, while also honoring the range of technologies that are typically being applied, whether AI technologies or not?

adfa, p. 1, 2011.

As with all educational technology, the goal of our field is to develop a science and practice for the design and implementation of technologies that can support effective, efficient, and pleasurable learning experiences for learners, groups of learners, instructors, and other stakeholders in the educational process. What sets our field apart is that we strive to make our systems "intelligent" or "adaptive," so as to be highly effective with a very wide range of learners. But what do these terms mean? Although the notion of intelligent and adaptive educational technologies is ill-defined, a shared intuition among researchers and practitioners may be that in order to be considered adaptive, a system must be sensitive to important learner differences; a system must have a nuanced way of deciding what, for a given learner or team of learners in a given situation, might be the best way of supporting them, given their learning history and learning goals. Such systems "understand learners" or, more broadly, "care," as John Self famously argued [18].

Artificial Intelligence (AI) can often contribute to creating such systems. It has brought to our field a focus on representation and reasoning, and has highlighted modeling and investigations into the nature of knowledge as a key emphasis in the early days of AIED and intelligent tutoring systems (e.g., [19, 24]). Nonetheless, in my opinion, our field cannot and should not be defined in terms of whether the system has AI or not. One problem is that AI is an ill-defined concept – so it would merely be replacing one ill-defined concept ("adaptive learning technologies") with another. More importantly, AI is neither necessary nor sufficient in order for learning technologies to be adaptive. The use of AI does not in and of itself make a system adaptive in a manner that supports learners effectively. Conversely, not all systems that are adaptive use AI. Also, defining our technologies in terms of the underlying technology seems fundamentally to be barking up the wrong tree. What matters is how learning is supported and whether learning is supported effectively. This viewpoint implies a focus on the behavior of systems [22] much more so than the underlying technology. The question whether AI to stay married to Ed is an interesting one. Perhaps this marriage, which started out so interestingly, needs to now become an open marriage. Better yet, perhaps it needs to be reconceptualized, replaced with a broader, more productive vision, with a renewal of the vows! Definitely, AI should and will remain a central aspect of what we do but it should not be the defining characteristic.

Intuitively, What is Adaptivity?

Proposing that adaptivity should be the defining characteristic of AIED system begs the question, what is adaptivity? Intuitively, we assume that learners differ along (possibly) many dimensions (e.g., prior knowledge, affect, self-regulated learning skills) and that, all else being equal, instruction that takes these differences into account tends to be more effective than instruction that treats all learners as the same. Adaptivity is not binary, something a learning environment either has or does not have. Adaptivity is a matter of degree. Below I offer a more formal definition of adaptivity, first presented in Aleven, Beal, and Graesser [4]. The discussion in the current paper discussion in a paper currently under review [6], although it also broadens and elaborates that discussion. Before I do so, perhaps it helps to get some obvious examples and non-examples on the table. We can then look at more borderline cases and offer a general definition for what it means for a system to be adaptive.

Obvious (i.e., non-controversial) non-examples of adaptive learning technologies are for example textbook problems with final answers to each problem in the back of the book, especially when every student in the same class is assigned the same problems. Other examples that are probably not controversial are online text, lectures with Powerpoint slides, video lectures of famous professors, and documentaries. I am not claiming that these types of instructional material have no place in the educational process [14, 17]. They very well may but they seem to lack adaptivity.

An obvious example of an adaptive learning technology may be an intelligent tutoring system, but what is it that makes it adaptive? A typical answer from our field may be, a rich student model with many student-related variables (knowledge, affect, metacognition, motivation, social factors), updated in real-time, in a sophisticated manner, inferring the unobservable from the observable, and used in sophisticated pedagogical decision making at multiple levels. Each learner or team of learners gets the instruction that is most effective, efficient, or pleasurable for them. Instructional decisions are always based on nuanced, fully up-to-date information.

It may be relevant also to point out that in many discussions about MOOCs and e-learning, a very low bar is used when talking about personalization or adaptivity. For example, Daphne Koller, one of the Coursera co-founders, in her Ted Talk (https://www.youtube.com/watch?v=U6FvJ6jMGHU), hails the ability to provide an error-specific feedback message (on an error discovered through data mining) as an important aspect of personalization of instruction in MOOCs. Further, in a widely-used learning management system such as Moodle (https://moodle.org/) [16], even simple branching structures are considered to be adaptive forms of instruction, in contrast to the intuitions of many ITS researchers.

A Somewhat Unsatisfactory Way to Define Adaptivity?

Let me now examine a prior proposed definition of our concept of interest. The argument has been put forward that a key criterion for adaptivity in learning technologies is that the system has an inner loop [22], meaning that it provides step-level guidance during complex, multi-step problem solving or dialogues. This form of guidance is to be contrasted with answer-level guidance, in which feedback is provided only at the end of each problem. In his 2006 paper, VanLehn views the presence of an inner loop as a defining criterion for intelligent tutoring systems: "Systems that lack an inner loop are generally called Computer-Aided Instruction (CAI), Computer-Based Training (CBT) or Web-Based Homework (WBH). Systems that do have an inner loop are called Intelligent Tutoring Systems (ITS)" [22, p. 233]. In a later article [21], however, he seemed to back off: "Most intelligent tutoring systems have step-based or substep-based granularities of interaction, whereas *most other tutoring systems* [emphasis added] (often called CAI, CBT, or CAL systems) have answer-based user interfaces." Importantly, he points out that systems that provide step-based tutoring tend to have a stronger positive effect on student learning outcomes, compared to no tutoring conditions (i.e., a greater effect size) than systems that provide answer-based tutoring (i.e., do not have an inner loop). VanLehn's definition is attractive in many ways: It emphasizes adaptive behavior as a hallmark of intelligence, which seems right to us. It avoids debates about system architectures or about the thorny question, what is AI? It aligns with key empirical evidence. On the other hand, it is not without its shortcomings, reason perhaps that VanLehn seems to have backed off. Step-based guidance may not be very adaptive if the tutor can only recognize one particular set of steps through each problem. Also, certain desirable forms of adaptivity may not easily be viewed as step-level support (e.g., reacting to student affect or adaptive selection of problems in the system's outer loop). Also, some systems that are commonly considered intelligent or adaptive have rather minimal inner loops such as ASSISTments [12], Wayang Outpost/Mathsprings [9], and Hint Factory tutors [20]. These systems all have a legitimate claim to being adaptive and intelligent. ASSISTments and Wayang Outpost/Mathsprings may not have an elaborate inner loop, but they have other features, such as being designed with a fundamental and sound understanding of student learning. Also, Wayang Outpost in its outer loop adapts to student metacognition and affect in certain ways. Similarly, Hint Factory tutors do not have on-board intelligence, yet behave like an intelligent tutor because of the next-step hint capability.

In this discussion, it is interesting to consider the degree to which specific forms of adaptivity are supported by empirical investigations (e.g., task analysis) and/or rigorous research. For example, step-level feedback and cognitive mastery are strongly supported in the empirical ITS literature, as enhancing student learning [7, 8, 11, 15]. Although the ability to support multiple student strategies within a given problem is widely viewed as desirable, the only study I know that tested this assumption did not find evidence to support it [23].

Adaptivity: A Proposed Definition

Given these considerations, let me now highlight an alternative definition of adaptivity, first presented in a recent article by Aleven, Beal, and Graesser [4], who listed three key elements of advanced learning technologies. For purposes of the current discussion, we can take this term to be synonymous with AIED; the key elements can therefore be viewed of key elements of the kind of adaptivity or intelligence we would like to see in our smart systems for education.

> "Although defining ALTs (advanced learning technologies) is difficult, ALTs have 3 key elements to varying degrees:
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> - First, these technologies are created by designers who have a substantial theoretical and empirical understanding of learners, learning, and the targeted subject matter.
> - Second, these systems provide a high degree of interactivity, reflecting a view of learning as a complex, constructive

activity on the part of learners that can be enhanced with detailed, adaptive guidance.

- Third, the system is capable of assessing learners, while they use the system, along different psychological dimensions, such as mastery of the targeted domain knowledge, application of learning strategies, and experiences of affective states. On the basis of these assessments, the systems make pedagogical decisions that attempt to adapt to the needs of individual learners."

This definition lists factors, rather than necessary and sufficient conditions, thus acknowledging that adaptivity is an open-textured concept, that is, a concept whose meaning needs to be interpreted as we go, perhaps on a case-by-case basis, and perhaps with a shift in meaning over time, as our field evolves and develops new and innovative forms of instructional support. Listing factors helps with defining the concept flexibly in a way that enables us to talk about degrees of adaptivity, rather than view it as binary. It is interesting to point out, further, that these elements are technology-agnostic; no specific technologies are mentioned or assumed. It is reasonable to think that the second and third key elements (interactivity with detailed guidance based on learner variables assessed by the system) will often involve AI technology. AI might be a particularly good match, given its emphasis on knowledge representation, reasoning, and problem solving, its concerns with diagnostic processes needed to infer and update learner models, and its concern with the nature of knowledge to be learned (e.g., [24]). Nonetheless, AI cannot be the one defining ingredient of what makes our systems adaptive.

On a personal note, this definition marks an expected return to a central theme of my dissertation, which dealt with a tutoring system, CATO, for case-based legal argumentation, a quintessential ill-defined task domain [1, 2, 3]. CATO was designed to help beginning law students learn skills of argument by analogy, a common form of argument in the legal domain. That is, this work addresses debates about whether a given new case (a problem situation about which a legal claim has arisen) properly belongs to an open-textured category, which, as in our current discussion, was defined by factors, rather than necessary and sufficient conditions. A key mode of analyzing, exploring, and arguing is to compare the new case to carefully selected past cases with favorable and unfavorable decisions [10], with the factors functioning as key dimensions of comparison. In the legal domain, comparisons with past cases that have been authoritatively classified often bring substantial clarity, although not often provably correct answers. And so it is with our question of what it means for a learning environment to be adaptive, although with an interesting twist: Our own domain lacks authoritative classifications; we do not have a supreme arbiter of whether systems are officially AIED systems or not (nor, of course, should we strive to have such an arbiter). We do have paradigm cases, however, landmark intelligent tutoring systems and even the hypothetical intelligent tutoring system sketched above. These systems can play an important role as anchors in enlightened discussions about the foundations of our field.

Element 1: Design Based on an Empirically-Grounded Understanding of Learners

Perhaps it helps to elaborate on each of the three key elements (or factors). Interestingly, the first element (i.e., the requirement that the designers have "a substantial theoretical and empirical understanding of learners, learning, and the targeted subject matter") relates to the *design* of the system, not to system features or techniques/methods/algorithms under the hood. (The discussion of this factor is informed by debates I have had with my colleague Ken Koedinger.) This requirement could be met in many different ways. Specific to the concerns of the field of AIED, the first part of this definition emphasizes (implicitly) the use of cognitive task analysis and educational data mining to guide system design or redesign, development, and cyclical improvement. A particularly attractive scenario is that the designers carry out cognitive task analysis activities up front to study learners' ways of thinking in the given domain including their strategies and informal shortcuts, but also including the specific conceptual and procedural difficulties they experience. This scenario continues with the data-driven refinement of the system, preferably in ways in which the overall effectiveness of the system, in terms of out-of-system transfer of learning outcomes, preparation for future learning, learner (and instructor) satisfaction, and so forth, is continuously assessed, so that improvement from cycle to cycle is clearly visible. It may be clear that this vision fits particularly well with the current emphasis of big data in education. The fields of EDM and AIED can be at the forefront of this movement (see, e.g., [5]).

A somewhat different way of thinking about this requirement may be that the project team has specialists in a variety of fields, not just technology experts but also researchers in relevant branches of psychology, in education in the given subject area (e.g., math education, science education, legal reasoning, and so forth), as well practitioners.

This first factor implies a substantial broadening of how we think about adaptivity, compared for example to the intuitive notion discussed above and more generally, compared to how we, as a field, have construed the notion of adaptivity up until now. It raises the possibility of considering the design of systems, including even the choice of problems sets and detailed learning objectives, as part of what makes a system adaptive. It may even make it possible to see a modicum of adaptivity in some of our prime examples of instructional materials previously considered as non-controversial non-examples, such video lectures. When designed to target known challenges in learning, they meet the first factor, the more so when based on extensive empirical investigations of what is hard for learners to learn. They would however not be strong examples, as they would not meet the second and third factors.

Element 2: Interactivity

The second requirement for adaptivity is that a system supports a high degree of interactivity, to provide guidance in complex and constructive learning activities. I do not mean to say that more interactivity is always better; rather, in emphasizing the adaptive nature of the guidance that the system gives, the system is capable of providing an appropriate amount of guidance for the given learner(s) at the specific junction in their learning process. How much guidance is appropriate at what stages of learning is an interesting question [13].

The second factor was included to help capture the emphasis that our field places on constructive learning activities and on learning by doing, rather than learning by (merely) reading, watching or listening. An interesting data mining study of data from a psychology online course suggests that learning by doing yields six times greater learning than reading online text in the course or watching the video lectures [14]. A clear cut case of the second factor would be an intelligent tutoring systems with detailed guidance in their inner loop, even if we do not consider the presence of an inner loop as a defining characteristic. I do not mean to rule out systems or projects that focus on enhancing reading, watching, or listening by means of interactive support for comprehension or metacognitive strategies, for example. The second factor was included partly to help rule out (or at least, help view as low on the adaptivity scale) the non-controversial non-examples listed above, such as fixed problem sets with only answer-level feedback in the back of the book, or long video lectures without interactive activities

Frankly, this second factor is the factor that I am the least sanguine about; it may be somewhat redundant with the third factor, and it is difficult to view interactivity per se as a good thing, contributing to learning. Then again, discussions around the notion of interactivity are interesting, as long as the discussants are mindful that it is not interactivity per se that matters, but how it supports learning or other desirable educational outcomes. Further, this factor highlights an important connection, namely, that of our field with the broader field of human-computer interaction.

Element 3 –Change Instruction Depending on Learner Differences

The third requirement, as mentioned, is that the system in its pedagogical decisions takes into account that learners differ and that the same learner is not the same for very long; learners change as they learn. For example, different learners have different prior knowledge, may experience different affect during a given learning task, tend to have different goals for learning the material, and may differ in how they regulate their own learning. In collaborative learning situations, learners may have different collaboration skills and social skills; they may be a good or a poor match regarding prior knowledge or personality, and so forth. A system should be considered as more adaptive to the extent that it adjusts its instruction, both in the inner and outer loop, based on these learner variables and perhaps others.

This requirement is consistent with Woolf's emphasis on a system having a student model and using it to adapt instruction [25], traditionally viewed as a hallmark of "intelligent" tutoring. The system builds up and maintains a student model by continuously assessing learners along various psychological dimensions (cognitive, metacognitive, motivational, and so forth). This student model is then used as the basis for individualization. Perhaps the requirement that it is the system doing the assessing is too stringent. Perhaps the viewpoint that what is being assessed is the learner is too stringent as well. Alternative viewpoints would be that a group of learners is being assessed or perhaps that the system interprets the situation more than the learner(s) or group of learners, if that distinction makes sense (it may not). I do not mean to argue, however, that we define our field in terms of whether or not systems have a student model. That is, I do not mean to equate AIED with the field of UMAP. For example, it is conceivable that a system could be strong with respect to the first two factors but not the third and be generally accepted as belonging to the field of AIED.

There are many interesting open questions regarding how systems (as well learning environments not strongly supported by technologies) *should* adapt to learners and which learner variables (or learner group variables) are most important in this regard. In my opinion, our field is uniquely positioned to extend the science of how instruction should adapt to individual differences. Of the three factors, the third reflects most clearly how we have traditionally viewed our field.

Final Remarks

In closing, it may be worth re-iterating that the proposed definition of adaptivity does not place emphasis on particular technologies; rather, it emphasizes the behavior of systems, much in line with VanLehn's seminal 2006 article [22] and also in line with the Turing test as a behavioral test of intelligence. Another attractive property of this definition is that also honors the interdisciplinary foundations of our field. In my view, AIED was never only about technology (CS/AI, computational linguistics, and so forth); its strength has always been that it included people and methodologies from different fields, such as human-computer interaction, psychology (cognitive, educational, developmental, social), education, design, statistics, and so forth. The field and its methodologies are interdisciplinary. Empirical evaluation of systems building has always been highly valued in our field, sometimes even to a fault (e.g., when interesting new technology developments were not given air time at conferences before there are proven results). The emphasis on high-quality empirical work is enormously important toward the goal of creating a science for the design and implementation of technologies that can support effective, efficient, and pleasurable learning experiences for a wide range of learners.

An implication of the proposed definition is that reviewer comments that "there is no AI in the system" or "the work does not push the envelop in terms of AI algorithms applied to education" should be a thing of the past. Instead, reviewer feedback should refer to the factors listed above: systems not being designed with deep insight into learning and learners' difficulties, not being interactive, and not being able to react in nuanced ways that make learning better.

The way for AI to stay married to Ed is perhaps not to declare it an open marriage, but rather, to re-define the marriage so it is appropriately broad and open-ended, a way of renewing the vows. We hope that the thoughts offered in this paper can be helpful.

Finally, what's in a name? A lot, I would argue. Our name reflects how we view ourselves, and in turn, how the rest of the world views us. Our current name honors AI as a central component as we do. I would much prefer that the disciplinary diversity and focus on behavior of systems be central. How about:

AIED = Adaptive Instruction: Evaluation and Design?

Or, if we are willing to tolerate AIEDD, how about:

AIEDD = Adaptive Instruction: Evaluation, Development, and Design

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References

1. Aleven V.: Using background knowledge in case-based legal reasoning: A computational model and an intelligent learning environment. Artificial Intelligence 150, 183-237 (2003)
2. Aleven V.: An intelligent learning environment for case-based argumentation. Technology, Instruction, Cognition, and Learning 4, 191-241 (2006)
3. Aleven V., Ashley K.D.: Teaching case-based argumentation through a model and examples empirical evaluation of an intelligent learning environment. In: du Boulay B., Mizoguchi R. (eds.) Artificial Intelligence in Education, Proceedings of AI-ED 97, pp. 87-94. IOS Press, Amsterdam (1997)
4. Aleven V., Beal C.R., Graesser A.C.: Introduction to the special issue on advanced learning technologies. Journal of Educational Psychology 105, 929-931 (2013, Nov)
5. Aleven V., Koedinger K.R.: Knowledge component approaches to learner modeling. In: Sottilare R., Graesser A., Hu X., Holden H. (eds.) Design recommendations for adaptive intelligent tutoring systems, pp. 165-182. US Army Research Laboratory, Orlando, FL (2013)
6. Aleven V., McLaren B.M., Sewall J., Popescu O., et al: Towards tutoring at scale: Reflections on "A new paradigm for intelligent tutoring systems: Example-Tracing tutors". International Journal of Artificial Intelligence in Education (under review)
7. Anderson J.R., Conrad F.G., Corbett A.T.: Skill acquisition and the LISP tutor. Cognitive Science 13, 467 - 505 (1989)
8. Arroyo I., Beck J., Woolf B.P., Beal C.R., Schultz K.: Macroadapting AnimalWatch to gender and cognitive differnces with respect to hint interactivity and symbolism. In: Gauthier G., Frasson C., VanLehn K. (eds.) Proceedings of the 5th International Conference on Intelligent Tutoring Systems (ITS 2000), pp. 574-583. Springer Verlag, Berlin (2000)
9. Arroyo I., Woolf B.P., Burleson W., Muldner K., et al: A multimedia adaptive tutoring system for mathematics that addresses cognition, metacognition and affect. International Journal of Artificial Intelligence in Education 24, 387-426 (2014, Dec)

10. Ashley KD. Modeling legal argument: Reasoning with cases and hypotheticals. Cambridge, MA: MIT press; 1991.
11. Corbett A., McLaughlin M., Scarpinatto K.C.: Modeling student knowledge: Cognitive tutors in high school and college. User Modeling and User-Adapted Interaction 10, 81-108 (2000)
12. Heffernan N.T., Heffernan C.L.: The assistments ecosystem: Building a platform that brings scientists and teachers together for minimally invasive research on human learning and teaching. International Journal of Artificial Intelligence in Education 24, 470-497 (2014, Dec)
13. Koedinger, K. R., & Aleven, V. (2007). Exploring the assistance dilemma in experiments with cognitive tutors. Educational Psychology Review, 19(3), 239-264.
14. Koedinger K.R., Kim J., Jia J.Z., McLaughlin E.A., Bier N.L.: Learning is not a spectator sport: Doing is better than watching for learning from a MOOC. In: Kiczales G., Russell D.M., Woolf B. (eds.) Proceedings of the Second (2015) ACM Conference on Learning @ Scale, pp. 111-120. ACM, New York (2015)
15. McKendree J.: Effective feedback content for tutoring complex skills. Human-Computer. Interaction 5, 381-413 (1990, Dec)
16. Rice W. Moodle 2.0 e-learning course development a complete guide to successful learning using moodle 2011:
17. Schwartz D.L., Bransford J.D.: A time for telling. Cognition and Instruction 16, 475-5223 (1998)
18. Self J.: The defining characteristics of intelligent tutoring systems research: ITSs care, precisely. International Journal of Artificial Intelligence in Education 10, 350-364 (1998)
19. Sleeman D, Brown JS. London: Academic Press; 1982.
20. Stamper J., Eagle M., Barnes T., Croy M.: Experimental evaluation of automatic hint generation for a logic tutor. International Journal of Artificial Intelligence in Education 22, 3-17 (2013)
21. VanLehn K.: The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. Educational Psychologist 46, 197-221 (2011)
22. VanLehn K.: The behavior of tutoring systems. International Journal of Artificial Intelligence in Education 16, 227-265 (2006)
23. Waalkens M., Aleven V., Taatgen N.: Does supporting multiple student strategies lead to greater learning and motivation? Investigating a source of complexity in the architecture of intelligent tutoring systems. Computers & Education 60, 159 - 171 (2013)
24. Wenger E. Artificial intelligence and tutoring systems: Computational and cognitive approaches to the communication of knowledge. Los Altos, CA: Morgan Kaufmann; 1987.
25. 24. Woolf BP. Building intelligent interactive tutors: Student-centered strategies for revolutionizing e-learning. Burlington, MA: Morgan Kaufmann; 2009.