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COMMENTARY

Beyond Mastery: Toward a Broader Understanding of AI in Education

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Introduction

In 1964 teaching machines and programmed instruction finally scaled up. Their rise had been meteoritic, hundreds of instructional programmes had been published, societies for programmed instruction had been founded in a dozen countries and many different kinds of teaching machines had been offered for sale. Yet—Skinner (1965) lamented in his lecture on the Technology of Teaching—much of this technology had lost contact with its basic science of learning. Technology was now mainly used for testing, not for teaching.

Strictly speaking, Skinner was wrong: meteorites do not rise, they fall. For the new generation of Anglo-American psychologists and the emerging breed of computer scientists, behaviorism had been killed by the cognitive revolution. Yet, for the radical behaviorist, everything still looked like operant conditioning.

Now operant conditioning is back, with vengeance. Data-driven AI stands on the shoulders of Skinner and learns using positive and negative reinforcement just as he suggested. We now live in an informational environment that adapts its behavior to its environment—us—on a global scale. An interesting and illuminating question is: How does this learning relate to what we try and do in schools and in education?

In this article, I will look at AIED from the point of view of research on education and learning theories. For education theory, a simple but central question is why societies have educational systems and what they try to do. For learning theories, the question is what learning is and how it should be measured. Both these questions are

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relevant for research on AIED. For reasons to be discussed below, these questions have perhaps inadequately been addressed in AIED research.

What is Education for?

From the point of view of learning theory, the global network learns like an insect. In Bergson's (1983) terms, Google, Meta, Baidu, Tencent, and your local 5G base station have instincts but no intellect. With a trillion pigeons, you can make a large language model. Is this the kind of learning education is for?

According to Biesta (2010), there has been a major move towards "learnification" of education. It is, however, important to distinguish learning from education:

> "Education … is not designed so that children and young people might learn – people can learn anywhere and do not really need education for it – but so that they might learn particular things, for particular reasons, and supported by particular (educational) relationships." (Biesta, 2015).

This means that education is characterized by describing the purposes of education (curriculum) and relationships that organize the process (pedagogy). According to Biesta, education is not only practice characterized by the presence of purposes: it is practice constituted for its purposes.

In mainstream AIED research, efficiency of technological interventions and evidence of their impact have been dominant concerns over the last decades. This is what the cultures of engineering, technology development, and design science bring to the AIED table (e.g., Baker et al., 2022). The engineering approach to learning, however, gives rise to two important challenges. One is about the measurement of learning and about data that can be used as evidence for it (Biesta, 2010). The second is about the implicit objectives that drive efficiency improvement. Both require that we move beyond what and how, and ask "why?" and "for whom?" As long as we operate within a pre-defined curriculum and its learning objectives, AIED becomes an instrument for achieving these objectives. AIED, however, can be more than this.

Efficiency and improvement imply that the expected outcome is known and fixed *a priori*. Efficiency is about reduction of waste when inputs are converted into given outputs. This applies at the levels of educational systems, educational institutions and schools, as well as at the level of individual effort. Waste, by definition, is the output and "side-effect" that has no value. In innovation research, efficiency improvement is often called incremental innovation, and it is understood to occur within a given dominant design (Anderson & Tushman, 1990). Adopting an improvement-oriented engineering mindset, therefore, naturally leads to models of education where the mastery of given learning content plays a central role. Learning becomes measured based on content-related task performance and operationalized as the acquisition of declarative knowledge and skills that fit the "dominant design" of current cultural understanding.

Bloom's "learning for mastery"—or mastery learning as he later called it—aimed at closing educational achievement gaps in traditional classroom settings (Guskey, 2012). It used formative feedback to find appropriate personalized corrective action when a student made an error, and it made classrooms sites of mass-customization. It also created the problem of scaling this model in a traditionally one-to-many instructional settings. Much of AIED research during the last decades can be viewed as an attempt to solve this Bloomian scaling problem.

In Bloom's model, the objectives for learning have to be clearly defined and can include "higher-level skills" such as creativity, application of principles, and analytical skills. Bloom proposed an instructional model leaving open—for the teachers to decide—the question "mastery of what?" Mastery learning itself, therefore, remains a generic instructional model that aims at efficient implementation of Skinnerian reinforcement learning when a group of students with different abilities, personalities, and backgrounds are taught by a single teacher.

This model has also often been misinterpreted. Guskey points out that:

> "Some early attempts to implement mastery learning were based on narrow and inaccurate interpretations of Bloom's ideas. These programs focused on only low-level skills; attempted to break learning down into small, patchy segments; and insisted that students master each segment before being permitted to move on… Nowhere in Bloom's writing, however, can this kind of narrowness and rigidity be found. In fact, Bloom emphasized quite the opposite." (Guskey, 2007, p. 21).

Although curricula and learning objectives are now extended towards social and emotional skills and the new requirements of the 21st century knowledge society, the ghost of Bloom's (1984) personalized tutors still looms large over the AIED community, commercial spin-offs, and policy debates (Holmes & Tuomi, 2022). The epistemic model that underpins many AIED systems, including the influential idea of tracing student knowledge as binary truth statements, easily leads to exactly those small, patchy segments of mastery that Guskey labeled as misrepresentations of mastery learning.

Two important questions, therefore, must be asked about mastery learning: To what extent the problem Bloom was trying to solve remains relevant? Where can Bloom's understanding of learning be located among the various theories of learning?

Personal Reinforcement in Mastery Learning

Educational achievement—measured in micro-level educational practice as content mastery—of course, plays an important role in education. For example, according to Biesta (2010), education has three domains of purpose. One is *subjectification*. This has to do with how education contributes to how we can exist as human subjects. One is *socialization*. Through education, people become part of existing traditions, cultures, ways of doing and ways of being. The third domain of purpose in education is *qualification*. This has to do with the transmission and acquisition of knowledge, skills, dispositions, and understandings that qualify people to do certain things. Bloom himself, however, also emphasized the role of the development of higher-level mental processes that "are retained and utilized long after the individual has forgotten the detailed specifics of the subject matter taught in the schools." (Bloom, 1978, p. 578).

Different ways and domains of knowing provide the foundations for subjectification, socialization, and qualification, and in different theoretical approaches to learning and education these three objectives of education appear in different mixtures. Subjectification and socialization are natural starting points for developmental, progressive, transformative, and sociocultural models of learning, whereas qualification and task performance are the predominant focus for Skinner, Bloom and in traditional cognitivist, neuro-cognitive, and information-processing approaches (cf. Illeris, 2018). The key assumption in the mastery learning model is, however, that although the students are different, the indicators of achievement are shared. In effect, when mastery learning works, the students are successfully socialized into a common dominant knowledge model. Learning occurs through reinforcement, and mastery learning, itself, can properly be viewed as a behavioristic learning model that is organized at the meta-level of group-based classroom instruction.

AIED has been partly successful in mathematics teaching because mathematics is the prime example of a culturally accumulated formal conceptual system. Mathematics has a dominant conceptual design that under normal conditions changes only incrementally. Its truths are independent of the concrete reality, and they are not corrected by experimenting with nature. Since the early 20th century, this disembodied and materially detached domain of knowledge was often viewed as the purest form of subject-independent knowledge. Among other things, learning mathematics requires the mastery of concepts that are used to build new concepts. Rooted in formal statements and rules that describe their transitions, it can easily be translated to programming languages and represented as hierarchical ontologies and context-free states that are "true" or "false." The progression through the increasingly sophisticated abstractions and procedures of elementary mathematics, therefore, provides a natural model for the gradual acquisition of mastery and suggests means for testing it.

Yet, despite the hopes of 20th century formalists and some pioneers of AI, this mode of knowing is a very extraordinary one. For a 20th century positivist, such as Skinner or Turing, two very different numbers of two look the same because they are observed by an immaterial, external, history-less, unmotivated, omniscient but culturally ignorant and fictional observer. In practice, although a child and a mathematics professor both know the number two, the meaning of the number may be very different. For the former, it may be a digit that denotes fingers, for the latter it may be an integer, a set, or an initial object in a category of rings. Similarly, a concrete material product of technology, such as a mobile phone or a working computer program, has different meanings in different social and cultural contexts (Tuomi, 2002). This situational understanding of knowing, of course, has been a main thread in the many variants of constructivism in sociology, science studies, and in learning theories. Some forms of constructivism have emphasized the social nature of knowing, others have highlighted the technological and material embeddedness of thought, but all the variants have viewed learning as an active and creative process that goes beyond operant conditioning.

An important driver for this contextual understanding of the nature of knowing emerged in the 1980s as ethnography-oriented studies on learning highlighted the role of social and cultural practices that underpin knowing. These ranged from the

Vygotsky-inspired work that emphasized learning as progression in the zone of proximal development (e.g., Cole, 1974) to more theory-driven models of learning as change in technology-mediated social activity systems (Engeström, 1987), Schön's (1983) work on reflective practice-oriented learning, and the influential ethnographic work in and around the Institute for Research on Learning in Palo Alto and Menlo Park (e.g., Brown and Duguid, 1991; Lave and Wenger, 1991; Suchman, 1987). This turn toward out-of-school environments was amplified by the emergence of life-long learning, adult education, and andragogy as key policy concerns in what became to be known as the "knowledge society" and "innovation economy" (Drucker, 1993; Jarvis, 2007; UNESCO, 1996).

Given the richness of present conceptual understanding of learning and the social, cultural, and personal functions of education, AIED researchers could ask what, exactly, we mean by "learning outcomes." What outcomes, for whom, and why? Unless the objectives of education are discussed and negotiated in an essentially political process, optimal achievement and tools that aim for efficiency cannot but become instruments for totalitarianism, hegemony, and technological colonialism. This suggests that instead of personalized feedback that guides learners towards the same learning outcomes, the outcomes themselves should be personalized. This may look radical as qualification based on educational achievement, indeed, has been an important function of educational systems in the last century. The new infrastructures of knowing, including data driven AI and new credentialing systems, potentially, however, make the Bloomian model of mastery learning an artifact of the past.

The Emergence of Non-Epistemic Competences

In many educational cultures, test-based qualification has an important role in sorting people and structuring and stratifying the society. This is now challenged by the ongoing turn towards competence-based models of education. Although there is no consensus on what "competence" is (cf. Tuomi, 2022), it is useful to view competence as a capability to get things done that emerges at the intersection of epistemic and non-epistemic competence components. This is depicted in Fig. 1. In the last two centuries, education has focused on the epistemic part, including knowledge, domain-specific skills, and experience. These epistemic competence components often link knowledge, domain-specific skills, and experience with given tools, technologies, and material context. Because of this, they are often labeled with explicit reference to the linked technology, for example, as in "vehicle repair experience," "java programming skills," and "e-learning knowledge." Many elaborated taxonomies and knowledge ontologies now widely used for curriculum planning and educational guidance, therefore, can be understood as reflections of existing technology-mediated social practices. This intersection of a given material context and expertise has been the implicit focus in mastery learning, and it has also provided the foundation for many influential implementations of open learner models, where the learner is provided with formative feedback on the mastery of technology-specific skills (cf. Bull, 2020). The intersection of the cultural context and expertise, in turn, has been the focus on culturally developed theoretical and normative systems, for example, mathematics, theoretical sciences, law, and philosophy of ethics. In both these areas, learning

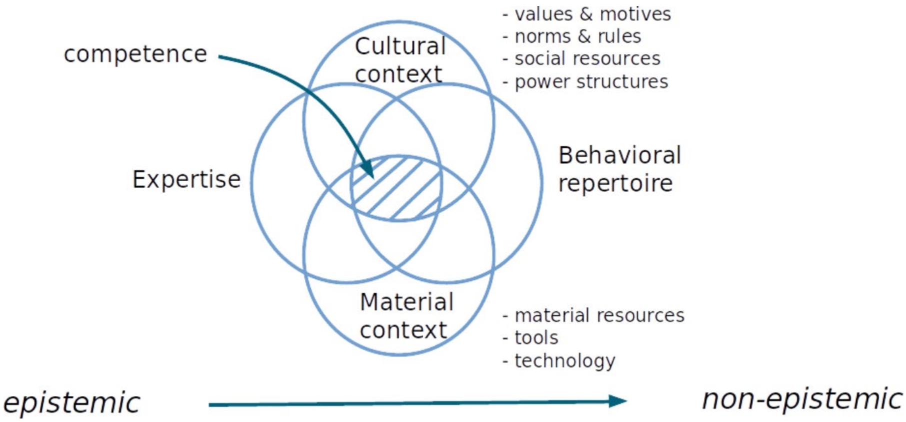

Fig. 1 Components of competence(source: Tuomi, 2022)

has commonly been understood as a progress towards knowledge-related outcomes and their mastery.

At present, the focus in education policy is moving towards non-epistemic competence components. These are variously labeled as “soft skills,” “transversal skills,” “meta-cognitive competences,” “socio-emotional skills and competences,” “behavioral dispositions,” “attitudes,” “character skills,” or—simply—21st century skills. These non-epistemic competence components are qualitatively different from the epistemic ones as many of the non-epistemic competence components are rooted in personality characteristics, typically measured using scales discovered through factor-analytic methods.

Research on personality psychology and individual differences suggests that people can be sorted at a very early age based on these non-epistemic competence components (Tuomi, 2022). Although it is now conventional to define, for example, a hypothetical subset of “malleable social and emotional skills” (e.g., Chernyshenko et al., 2018), it is not clear to what extent they can be taught after children enter school. The move towards competence-based curricula, therefore, poses important challenges also for AIED research and learning analytics. Collaboration, communication, critical thinking, creativity, and other “21st century skills” are known to be associated with abilities and traits that are exactly those sources of diversity that Bloom’s mastery learning was expected to make irrelevant.

Social and emotional skills, motivation, creativity, grit, conscientiousness, problem-solving and self-regulation skills, therefore, do not easily fit the mastery model of instruction. It is not obvious how emotional skills, conscientiousness, or creativity could be maximized or optimized, what such optimization would mean, or to what extent they can be learned by correcting errors. Although Skinner argued that any behavior can be taught using operant conditioning, non-epistemic competence components are fundamentally open-ended and context dependent. Conceptually, operant conditioning cannot make the shift from a closed world to an open one. Because of this, Skinner was forced to note that “teaching truly creative behavior is, nevertheless, a contradiction in terms.” (Skinner, 1965, p. 441).

The Epistemology of Learning in an Open World

The Skinnerian model of learning is in clear contrast with Vygotsky's model of learning. For Vygotsky (1986), cognitive development occurs through qualitative change that is driven by practical action and social support. In Vygotskian cultural-historical activity theory, learning is about the development of conceptual structures that make new "higher" forms of thinking possible. Learning, in this sense, is not about incremental acquisition or assimilation of knowledge; it is about disruptive capability to think and act differently. Knowledge building is a necessary precondition in this process, but not its final objective. The "outcome" of learning is also about the expansion in the variety of ways the world can be understood and operated on. In contrast to Piaget, who emphasized biological maturation, Vygotsky and his followers saw cultural accumulation and its material articulations as an important form of learning (Luria & Vygotsky, 1992). Epistemologically, the acquisition of "higher forms of thought" opens up new worlds that have not been available before.

This creates a curious philosophical complex where epistemology and ontology become two sides of the same coin. In such a world, it is not obvious, for example, what a learner model would mean. In much of existing work on open learner models (cf. Kay et al., 2022), ontology characterizes the domain under study; in a Vygotskian perspective, learning is about change in the ontology used by the learner to know the world. In this perspective, learner model is, literally, a model of a changing learner.

A key characteristic that differentiates cultural-historical activity theory from many other forms of constructivism is that it views the material environment as an element of knowing. For Vygotsky, knowledge is partially embedded in culturally accumulated material products. Learning is not about abstract representations but rooted in "object-oriented" practice and concrete activity (Leont'ev, 1978). This activity-theoretic view has inspired much research on extended, distributed, and situated cognition, and it also resonates with Dewey's (1958; Miettinen, 2000) model of learning as reflective action. Successful learning, therefore, does not only change the mind of the learner; it also changes the learner's world.

In the context of innovation and anticipatory systems research, I have called this phenomenon "ontological expansion" (Tuomi, 2012, 2017). Qualitative, disruptive, and socially important innovation creates things, concepts, and realities that did not exist before. Innovation and knowledge creation therefore generate new domains of experience and meaning that cannot be reduced to earlier realities or existing knowledge.[1] In epistemological terms, we cannot have empirical knowledge or data of such emerging realities as they don't exist yet. Learning these new realities requires exploration, and it cannot be based on knowledge transfer or incremental addition to existing knowledge structures.

For Vygotsky, a similar expansion of reality occurs when a child moves toward advanced forms of culturally situated thinking, for example, by learning systems of theoretical concepts with the help of more competent adults. Although these concep-

[1] Formal modeling of such qualitative changes requires the use of category theory, see (Ehresmann & Vanbremeersch, 2007).

tual systems are accumulated in a cultural process, they remain fundamentally open and evolve across time.

Here is also a key difference between human learning and state-of-the-art machine learning systems. Human systems of knowledge are rooted in evolving social and technology-mediated practices, whereas data-driven AI simply represents the contemporary outputs of this process (Tuomi, 2018b). Using the activity-theoretic distinction between activity, act, and operation (Leont'ev, 1978), or the related three-layer model of why, what, and how (Harré et al., 1985), data-driven AI rests solidly on the bottom operational level (Tuomi, 2018a). It has no way to represent the "why," or Aristotelian final causes. Therefore, it also remains futile to search for "ethical AI" from within the system itself or its algorithms, outside the context of social practice.

The concept of "knowledge creation," as it was introduced in organizational learning and innovation studies in the 1990s, highlights the idea that learning is not just about assimilating and accommodating existing stocks of knowledge. Operant conditioning is not enough. Nonaka (1991), for example, argued that new knowledge is created by an interplay between internalization and externalization where socially shared tacit knowledge is articulated into explicit representations and then again internalized in the organizational practice. This tradition also strongly emphasized the dynamical and process-oriented nature of knowing (e.g., Nonaka et al., 2008), contrasting it with the "object-oriented" view where knowledge can be represented, stored and stacked into increasingly impressive constructions. The appearance of tacit knowledge as part of this knowledge creation cycle also highlighted the challenge of modeling knowledge with computers (Tuomi, 2000). Explicit knowledge, in this view, is just the top of the iceberg. For Polanyi (1967), it is the focal gestalt that emerges from the tacit background which necessarily remains peripheral. The tacit component of knowing remains the unarticulated background that enables the articulation of explicit knowledge that can then be represented using computers.

It is, therefore, not clear what, for example, knowledge tracing could mean in such an epistemology. In fact, Nonaka's model was based on an epistemological view that was partially rooted in Kitaro Nishida's phenomenological philosophy, developed in Kyoto in the first decades of the 20th century. This shift from empiristic to phenomenological epistemology, and the associated constructivist models of learning, turned the focus from "knowledge," as understood by some cognitivists and symbol-processing AI researchers, into "knowing" as a process of sense-making and meaning processing. This epistemological turn now makes philosophers such as Whitehead, Bergson, and continental phenomenologists such as Husserl and Merleau-Ponty relevant also for AI researchers, once again questioning the historical and conceptual foundations of cognitive sciences and AI and their models of learning rooted in computer science.[2]

[2] Historically, mainstream AI researchers have struggled with these epistemological questions since the 1960s when Hubert Dreyfus used Husserlian phenomenology to argue that strong symbolic AI was a dead end. Edward Feigenbaum's reaction to Dreyfus's critique is illustrative: "Phenomenology! That ball of fluff! That cotton candy!" (quoted in McCorduck, 1979, p. 197).

Toward the Future of AIED

Research on AIED has traditionally focused on AI as a tool to improve "learning outcomes." It is now gradually "escaping from the Skinner box" (du Boulay, 2019) toward non-epistemic skills and competences. If current research is right (cf. Tuomi, 2022), and many of these non-epistemic competence components are difficult to learn and measure in educational settings, the bright future of AIED may well be in compensating the lack of behavioral and personality-related capabilities that are necessary for learning. Conceptually, such a shift would be related to the augmentation approach in AI. Instead of automating and sequencing knowledge delivery it would emphasize support for learning and development. This approach would be aligned, for example, with work on open learner models, metacognitive support, and self-regulated learning, but it would put particular emphasis on modeling the user and the user's epistemic and non-epistemic competence components, as well as their development.

As Biesta has pointed out, this still would leave open the question why and what we learn. It is not enough to ask what education is for; instead, we have to ask what it will be for in the future. It is also useful to ask whether such an instrumental view on education is something that is necessary in the future. Education, although partly aimed at cultural transfer, is also oriented towards the future and its anticipated needs. At present, AI is transforming social and economic processes that underpin learning and knowledge creation. AI is also cutting the traditional links between education and work life, questioning the social legitimation of educational investments. AI, therefore, is not only a tool that can be used to solve existing problems in education; it is also challenging the traditional objectives of education. The "why" of education has functional, sociological, and historical answers, but it also requires that we agree on the objectives of education. This is fundamentally a question about the ethics of education, and it therefore also requires that AIED researchers make their ethical assumptions explicit (Holmes et al., 2021).

Perhaps paradoxically, in the knowledge society the value of knowledge is diminishing as knowledge and expertise will be widely available. It is not clear that society-wide systems of qualification will have social relevance in the future. Socialization and enculturation now increasingly occur on social media, and blockchain-based self-sovereign identities and credentialing may well change institutional infrastructures that underpin industrial-age systems of education.

A capability-based approach that supports subjectification, may well be a major domain for purpose in future education. Education is also an instrument of social development, and in the capability-based approach social development is linked back to expansion of individual capability to realize ways of doing and being that the person has reason to value in their cultural and practical context (Sen, 1993). For this reason, I have argued that innovation should be called progress only when it expands human capability. In this sense, technological progress can be understood as a form of learning, expressed in material artifacts and related practices.

The emerging future could, therefore, imply a rather radical change in AIED research. The objective of technology design would not be about efficient mastery of given universal learning objectives. Instead, it would be about developing systems that augment and complement personal capabilities that are useful and necessary for learning and well-being. In this approach, the content of learning would be of secondary importance. An intelligent tutoring system would not be a computer that makes the achievement of learning objectives faster and more efficient. It would be a system that helps the learner in the process of learning, in a world where global information systems are full of declarative knowledge, access to expertise, and infrastructures of machine learning.

Perhaps, as Skinner predicted: "It is possible that education will eventually concentrate on those forms of behaviour which 'survive when all one has learned has been forgotten.'" (Skinner, 1965, p. 442).

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