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EDITORIAL

Preface-Emerging Technologies and Landmark Systems for Learning Mathematics and Science: Dedicated to the Memory of Erica Melis-Part 2

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This issue of the *International Journal of Artificial Intelligence in Education* is the second of two special issues dedicated to Erica Melis, a close colleague of ours and an important contributor to the research field of Artificial Intelligence in Education (AIED) who passed away in the beginning of 2011. Given Erica's dedication to mathematics and science—and the work she did in developing intelligent tutors in the area of mathematics—it is only fitting that these volumes be dedicated to her memory. In the preface to the prior issue, we provided an overview of Erica's life and research and introduced papers on emerging educational technologies (McLaren et al. 2014). In the current special issue, we present papers on more established AIED systems, those that have become landmarks in the field.

Since the very beginning of AIED research, mathematics and sciences have been among the most popular application domains for developing AI-based technologies intended to improve learning. Many successful intelligent and adaptive systems for learning and teaching mathematical and scientific subjects have been created over the years, (e.g. (Andersonet al. 1995; Melis et al. 2001; Vanlehn et al. 2005)). These domains have been unique and important for AIED researchers and educators in general. There has always been a great demand for teaching and instructional support in these domains. Therefore, they have always provided many opportunities to apply and evaluate a wide range of AIED approaches.

From a pedagogical perspective, mathematics and science are challenging domains to learn and teach. They rely on formal concepts whose meaning is not always intuitive and require mastering a complex skill set for applying, manipulating, communicating and modeling mathematical and scientific notions and notations. Students often come to math and science classes equipped with different background knowledge,

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motivational profiles and general aptitude for formal subjects. More than in other domains, in these classes, teachers have to strive for promoting acquisition of general problem solving skills, effective self-regulation strategies, and coping with negative affective traits, such as boredom, frustration, and anxiety. Therefore, to be maximally effective in these domains, Intelligent Tutoring Systems (ITS) and other AIED technologies need to address a wide range of student characteristics and adapt to various categories of students by being cognitively, metacognitively, and motivationally aware. The three landmark systems presented in this special issue are good examples of such versatile AI-based adaptive learning platforms.

From a societal perspective, math and science are foundational subjects for any educational system and are key competencies in modern society. Many of the acquired skills and concepts trained in these domains become core prerequisites for engineering and technological disciplines in tertiary education. Therefore, they are taught to large numbers of students who have to truly master them as part of their basic cognitive toolset. The importance of these domains has been uniformly recognized around the world. A special term, STEM, has emerged to cover the range of subjects in Science, Technology, Engineering and Math that are viewed as a critical foundation for any nation's workforce. At the same time, many countries face serious problems in STEM education ranging from the decline in the mathematical skills of college freshmen (ACME 2011) to high student dropout rates in formal and technical disciplines (Becker 2010; Heublein et al. 2006; NSF 2007). A recent special issue of the journal *Science* was dedicated to Grand Challenges in Science Education (Hines et al. 2013). It discussed organizational, economical and pedagogical problems associated with providing high-quality STEM education. As one of the key challenges that "could play an important role" in improving current practice, it identified the development of "programs that seek to tailor teaching to children's learning level … and educational technology that tailors instruction to students' knowledge levels" (Kremer et al. 2013).

Finally, from a technology perspective, many problems within mathematics and science subjects belong to the category of well-defined, well-structured, formal tasks. Such tasks have unambiguously correct answers and well-defined (even if possibly large) sets of solution paths to reach those answers. In these domains, it is typically easier than in ill-defined domains, such as language acquisition, psychology, and art, to identify complementary knowledge components constituting a complex skill, or the target skill trained by a problem step.[1] Therefore, the developers of ITSs and the authors of models and content for such systems often have greater flexibility in terms of knowledge representation, pedagogical strategies and adaptation technologies.

All of these factors contributed to the development of several prominent AI-based systems for teaching and learning math and science subjects. This special issue presents overviews of three such systems each of which resulted from a long-term project that has been underway for a decade or more. Together, these three projects implement a range of well-established technologies and have been evaluated in a series of studies, both in the lab and in real classrooms.

[1] Even in these academically well-trodden domains, however, there are still many surprises to be had regarding the nature of the knowledge and the generality of the knowledge that students acquire, and investigations in that area have important implications for student learning and instructional design (e.g., Aleven and Koedinger 2013).

The first paper by Arroyo et al. describes *Wayang Outpost* (now *MathSpring*), an intelligent tutoring system for middle-school mathematics. It combines principles of cognitive apprenticeship and multimedia learning to implement a range of coaching and scaffolding approaches helping students develop problem-solving skills. *Wayang Outpost* applies a breadth of adaptation technologies both in the outer loop (by selecting the problems of appropriate difficulty and informing students of their current state of learning) and the inner loop (by providing access to instructional videos, presenting elaborate feedback and step-by-step worked-out examples of similar problems). An important feature of the system is the comprehensive personalization approach it employs, which addresses cognitive, metacognitive and affective states of the learner; it keeps track of all three dimensions of individual learners and uses them to make adaptive pedagogical decisions. *Wayang Outpost* has been used in mathematics classrooms since 2003, and the paper presents a large amount of empirical evidence for the effectiveness of the implemented technologies.

The second paper by Nye et al. summarizes almost two decades of research on the *AutoTutor* family of ITSs. Overall, the paper describes more than two dozen systems that help students learn a wide range of subjects, including physics, biology, computer literacy and math. The core approach that the creators of *AutoTutor* gradually developed over the years is to organize effective learning based on a natural conversation between a student and an automated tutoring agent. The design of the system follows pedagogical strategies exhibited by human tutors. *AutoTutor* takes up a more challenging task than most ITSs by trying to support such activities as deep reasoning, critical thinking and self-regulated learning.

The third system, by Heffernan and Lindquist, is *ASSISTments*. Unlike the two other papers in this issue, the intention of this work is not to provide a summary of the conducted studies and developed technologies. Instead, it focuses more on the mission of *ASSISTments*, sharing the lessons learned by its creators over the years. It also outlines the entire "*ASSISTments* ecosystem" that enables collecting usage data and conducting research studies, while ensuring that the normal learning process is not compromised in any way. Another important aspect of *ASSISTments* is a very teacher-centric design and a high level of teacher involvement in all aspects of the system's usage, from content authoring to planning experiments. This unobtrusive way to conduct research has been one of the primary reasons for the remarkable adoption of *ASSISTments* in actual classrooms. Every year, the system is used by tens of thousands of school children to learn math. Unlike other systems presented in this volume, *ASSITments* follows a rather minimalist approach when it comes to intelligence and adaptivity. It does not support a strong student model and does not implement a sophisticated adaptation procedure. Yet, the practical success of *ASSISTments* demonstrates that "a little intelligence can go a long way."

Together, these papers provide a comprehensive account of several landmark AIED technologies for teaching Math and Science. The systems presented here demonstrate how far the field has come and where it is heading in the years to come. They have implemented a wide range of approaches, provided a broad coverage of topics and gone through many years of research, implementation, deployment in real classrooms and rigorous evaluation. They make a strong case for the success of the overall idea to build intelligent programs to support individually optimized teaching and learning. Erica Melis, to whose memory this issue is dedicated, was a strong believer in this idea. No doubt, she would have been pleased to see the progress of AIED presented in this special issue.

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