The potential of smart technologies for learning and instruction

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Abstract: The field of artificial intelligence has been influencing learning and instruction since the 1980s with the introduction of intelligent tutoring systems. Since then, advances in artificial intelligence, cognitive psychology, instructional design, and learning science have occurred along with the introduction of powerful new technologies, including dynamic assessment and feedback mechanisms, highly interactive mobile devices, and internet-based repositories of resources to support learning and instruction. This paper provides an overview of smart technologies in education and their potential for the future.

Keywords: adaptive instruction; human-computer interaction; intelligent systems; learning analytics; personalised learning; smart technology.

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1 Introduction

The focus of this new journal is on the design, application and assessment of smart learning technologies. The goal is to foster effective, efficient and engaging applications of smart technologies to support and enhance learning in a wide variety of situations. The purpose of this article is to provide a context for smart learning technologies that includes a broad definition of smart learning technologies, a discussion of historical developments, and a framework to guide future practice and scholarship.

2 Elaborated definitions

Terminology is critical in nearly every discipline, and there are often variations in how key terms are used. For that reason, the following key terms are used in this article as defined below:

a adaptivity

b instruction

c intelligence

d learning

e personalisation

f technology.

Based on these definitions and their elaboration, the use of phrases that combine these terms is discussed at the conclusion of this section.

2.1 Adaptivity

Adaptivity refers to the ability to detect pertinent details of a situation and then select, modify and activate or deploy an appropriate response. Humans clearly possess this ability although in differing degrees in different circumstances. Things that affect adaptivity in humans include perception, prior experiences, habits, and more. Other organisms also possess various degrees of adaptivity, which can be attributed to evolution and survival value in many cases. For example, the ability to *detect* a slow moving animal and then *select* that specific animal to pursue, and *modify* the pursuit as the prey changes direction is a form of adapting to specific circumstances.

Humans who are considered creative often exhibit a high degree of adaptivity. While being adaptive is often regarded as a desirable human characteristic, it is also true that being predictable is often regarded as desirable. This apparent tension is sometimes easily resolved by distinguishing between circumstances that recur in similar ways many times and circumstances that introduce new or unexpected elements; the latter are those in which adaptivity is especially useful and creativity especially valued.

It is possible to apply the term ‘adaptive’ to computer systems, instructional technologies, learning environments and non-human agents. An early use of ‘adaptive’ in reference to an instructional system occurred in the 1950s with a system called SAKI that taught keyboard skills and automatically adjusted the difficulty level based on the learner’s performance (Pask, 1961). In the 1980s, a number of intelligent tutoring systems (ITSs) that automatically adjusted to the performance and needs of a particular learner were developed and deployed (Psotka and Mutter, 1988; Shute and Psotka, 1996; Sleeman and Brown, 1982). These ITSs typically had a representation of the knowledge domain to be learned, a pedagogical database of lessons aimed at mastering or understanding a portion of the knowledge domain, a dynamic profile of each learner that kept and updated performance and progress, and often a library of common errors in solving problems. The system then used a learner’s response to a question or problem to recommend an appropriate lesson or remediation. Clearly, an ITS has the required characteristics of adaptivity – namely the ability to detect relevant details of the situation and then select, modify and deploy an appropriate response. ITSs have had success in knowledge domains that were well structured with problems that had single correct solutions with known errors and misconceptions.

Since then, powerful technologies have emerged that extend the possibilities for adaptivity. For example, augmented reality and mediated reality systems integrate details of the real world with computer-generated representations that are relevant to a specific situation. For example, a student on a field trip of an historical site might be standing in front of an ancient edifice, take a picture and receive detailed historical information pertinent to that site.

2.2 Instruction

Simply stated, instruction is that which is intended to support, facilitate or enhance learning (Richey et al., 2011; Spector, 2012). The notion of intention is inherent in the concept of instruction, just as it is in the concept of adaptivity. While much learning is incidental in the sense that it is unplanned without a specific intention to learn, other learning, both formal and informal, is intentional (i.e., purposeful and goal-driven). Instruction is based on there being a purpose, goal or aim associated with the learning that can then be used to guide the design, development and deployment of support, facilitation and enhancement. In some cases, instructional goals can be specified in terms of things that can be easily assessed (e.g., solve a linear set of three equations with three variables), but in other cases the instructional goal might be somewhat vague and more difficult to assess (e.g., design a bridge that spans 100 metres of water with sandy soil to a depth of 10 metres in a heavily trafficked area that is prone to earthquakes).

Because instruction is a goal-driven enterprise, instructional processes include

a needs assessments and requirements analysis

b cost and constraints analysis

c analysis of alternative approaches

d design specifications

e initial development and prototyping

f testing and refinement

g implementation

h deployment

i evaluation

j management and support.

These various processes are interrelated and often involve feedback cycles. The reason to mention these instructional processes is to emphasise the complexity of designing, developing and deploying instruction. That complexity increases when the goal is to create an effective smart learning environment. Moreover, it is possible to use adaptive technologies to support these various instructional processes. In addition, it is possible to use adaptive technologies to support learning in non-intentional situations (e.g., browsing at a museum with no particular goal or purpose in mind).

2.3 Intelligence

Human intelligence is typically associated with the ability to respond to new or unusual situations and solve problems. Intelligence is a somewhat fuzzy construct involving multiple facets (e.g., cognitive, emotional, perceptual, social). Historically, emphasis has been placed on the cognitive aspects associated with intelligence (Anderson, 1983). While there is much research and debate about the nature of intelligence, types and degrees of intelligence, and how intelligence can be effectively measured, there is general agreement that intelligence subsumes the ability to adapt (modify responses appropriately for a particular situation) and the ability to learn (establish new knowledge and skills).

As previously discussed, it happens that machines can exhibit the characteristics of intelligent behaviour in the form of adapting as well as in the form of learning (e.g., improving recommendations as the data sets upon which recommendations are made grow in terms of size and specificity). As is the case with human intelligence, machine intelligence can be considered to have degrees and take various forms. In all cases, however, one would expect the basic characteristic of generally responding to specific situations appropriately to be required of a machine said to be intelligent.

2.4 Learning

Learning can be considered an outgrowth or consequence of intelligence and adaptive behaviour. Human learning is characterised by stable and persisting changes in what a person or group of people know and are able to do (Spector, 2012; Spector et al., 2013). The notion of change is an essential characteristic of learning, which is why assessment to determine if and to what degree a change occurred is generally appropriate. Changes in knowledge and skills could not occur if a person were not capable of change; that is to say that intelligence and adaptivity are required for learning to be possible. Moreover, learning can be made more effective and efficient with appropriately designed and implemented instructional resources and environments conducive to learning.

Interactive computing systems can also exhibit similar characteristics of learning. That is to say that a computer program can acquire information about a learner and use that information to adjust which instructional resources are presented, how they are presented, and how their effectiveness might be evaluated. ITSs were capable of doing that, and machine learning is now a recognised discipline (Carbonell et al., 1983; Psotka and Mutter, 1988). Intelligent agents can also recommend to a specific learner a learner-controlled change in the environment in which learning is occurring (Kim and Bennekin, 2013). Indeed, learner empowerment might well be considered a key characteristic of a smart learning environment.

As with intelligence, there are degrees of learning. Relevant factors include the speed at which new knowledge and skills are acquired, the speed and appropriateness of adjusting to a new situation, and the stability and persistence of what has been learned. There is a generally accepted association between the quality of instruction and the degrees of learning (Merrill, 2013; Richey et al., 2011); that is to say that well designed instruction is likely to result in desired learning outcomes. Smart learning environments should certainly be effective and efficient g in terms of learners achieving desired learning outcomes. A learning environment that is engaging and that empowers learners is likely to be both effective and efficient.

2.5 Personalisation

The notion of personalisation in the context of learning and instruction has evolved over the years. Related concepts include individualisation and differentiation. Individualised learning and instruction can be traced back thousands of years. Apprenticeship represents an early form of individualisation (Klein et al., 2004). In apprenticeship, the master teaches the apprentice based on what the apprentice has already learned, what remains to be learned, and which skills need additional practice. Apprenticeship was typically accomplished on a one-to-one or one-to-few basis. One-on-one tutoring by a human content expert might be considered the modern academic counterpart to apprenticeship in a particular craft.

A variant of apprenticeship involving computer-enhanced systems that emerged in the 1980s is called cognitive apprenticeship (Collins et al., 1987). Cognitive apprenticeship had six teaching methods (modelling, coaching, scaffolding, articulation, reflection, and exploration) and a number of associated principles (e.g., as students gain competence and confidence provide less scaffolding so as to promote metacognition and self-regulation). Essentially, cognitive apprenticeship is a form of differentiated instruction in which learners are categorised as belonging to a group, and then learning activities and instructional resources appropriate for that group are provided. Identifying the appropriate group and selecting the appropriate activities and resources can be considered a form of personalisation. The kind of personalisation associated with cognitive apprenticeship tends to promote engagement and can result in a sense of empowerment on the part of the learner.

A much weaker form of personalisation is simply using the learner's name or a gender-specific avatar in system-delivered responses and prompts to the learner. Many educators would not consider such simple forms of personalising learning and instruction to reflect intelligent or adaptive behaviour on the part of the system, although these simple forms of personalisation may have some impact on learning effectiveness.

A stronger form of personalisation involves adapting to and using the learner's specific situation, as mentioned previously with regard to augmented reality. Technologies that are context aware and can make use of that context awareness when providing resources and feedback to learners have the qualities of being adaptive and exhibiting a form of intelligent behaviour. These technologies, and their number and type are likely to grow rapidly, can be and typically are called smart technologies.

A still stronger form of personalisation, and that which is the core concern of this journal, involves dynamically adjusting to a particular learner's interests, goals, focus, progress, and problems (Spector, 2014). That is to say that a 21st century personalised learning environment is one that keeps a dynamic profile of individual learners (including interests, hobbies, learning goals, previous courses, previous problems, and more) as well as a repository of learning activities and instructional resources pertinent to a domain of inquiry or interest. As the learner engages in activities and uses resources, a personalised learning environment keeps track of progress and problems and makes appropriate adjustments based on the system's accumulated knowledge of what worked well for other similarly situated learners. Such a learning environment would be much like an experienced tutor engaging in a one-on-one tutoring session with a particular learner.

Finally, it should be noted that there is a difference between a personal learning environment and a personalised learning environment. The former (personal learning environment) generally refers to a learning environment constructed and controlled by the learner; it may or may not support formal learning goals and objectives. The latter (personalised learning environment) refers to a learning environment or system that adapts more or less automatically to the interests and needs of individual learners; it can support both formal and non-formal learning goals and objectives.

2.6 Technology

Technology is *the practical application of knowledge for a purpose* that is of value to a group of people (Spector, 2012). This definition includes things that can be touched (i.e., physical things) as well as things that are conceptual or abstract (i.e., sorting algorithms, methods to determine the load on an object, etc.). It is noteworthy that the concept of purpose appears here as well as with regard to learning, instruction, and more generally adaptivity and intelligence.

In the context of education, relevant technologies include such physical things as personal computers and handheld devices as well as non-physical things such as algorithms used to mine data from large data-sets and use findings to make adjustments in terms of information representation and delivery as well as in terms of assessment and evaluation.

2.7 Smart learning technologies

As a conclusion to this definition section and a precursor for future articles in this journal, the concept of smart learning technologies is discussed next. The concept of *smart technology* is already in popular usage. Unfortunately, popular usage is broad, vague and somewhat weak. For example, the term *smartboard* is used to refer to a digital technology that allows a screen to be projected in a manner that supports touch-based interaction with the projected screen rather than with the computer whose screen is projected. That use of *smart* does not satisfy the criteria indicated above or elaborated below. Likewise, early *smartphones* lacked adaptivity and intelligence, although smartphones can be said to be getting smarter as they now provide such capabilities as auto-completion of text based on built in dictionaries and frequently used words by a user and context aware feedback, such as information about a picture taken at a museum.

It is also worth noting that global positioning navigation systems used in many cars and also in mobile applications are becoming smarter. Early systems merely showed current position and a route to a destination. More adaptive systems, now suggest alternative routes based on traffic and previous patterns of getting to a particular destination. These systems also push information to users based on previous behaviours (e.g., showing fuel stops of a kind based on a user's past fuel stop preferences), which represents a form of adaptivity and a kind of personalisation.

Spector (2014) offered an informal definition of a smart learning environment as one that effectively and efficiently supports planning and innovative alternatives. Hwang (2014) provided a more elaborate definition that included these characteristics:

a context awareness

b adaptive support

c adaptive interface

d adaptive content

e personalised support

f tracking and updating learner progress

g an inference or recommendation engine.

These characteristics fulfil the strongest form of personalisation discussed previously.

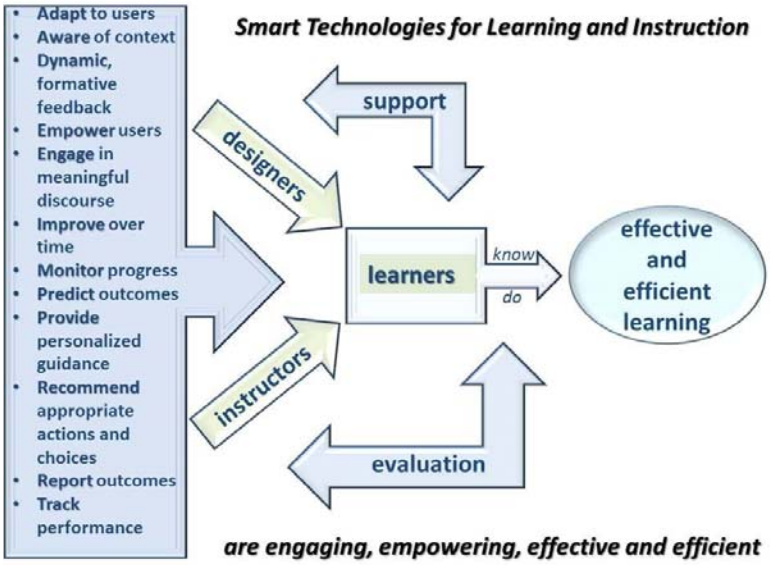
Smart learning technologies do need to exhibit support for learning, either directly or through support for instructional design processes intended to promote learning. Not every smart technology is a smart learning technology. The support for learning and instruction should be a primary consideration. How that support is provided through a particular technology is secondary, in this author's opinion. The goal is to support, facilitate and enhance learning. Innovative and adaptive technologies have that potential, but unless and until there is evidence of systematic support for learning it is premature to consider a technology a learning technology. As Spector and Merrill (2008) have argued, the idea of learning that is engaging, effective, and efficient should be the focus. Moreover, technologies that *empower* learners, instructors, or instructional designers by adapting to their needs and situations can be considered smart learning technologies.

Another characteristic of a smart learning technology pertains to the interface. Human tutors engage learners in dialogue. A technology with a conversational interface has a characteristic often associated with human behaviour, and when the computer-generated voice responds in a manner pertinent to the situation and generally within the realm of the expected, then that interface might be considered adaptive and thereby *smart*.

It is worth emphasising that the notion of a smart learning technology often includes the notion of empowerment in addition to engagement, effectiveness and efficiency. Empowering learners is a particular strength of many emerging technologies. As Kim and Bennekin (2013) argued, urging learners to take control of things within their control is what human counsellors tutors often do, and when computer programs and digital applications do so, then that kind of pedagogical agency can be regarded as a smart learning technology. The same logic applies to support for teachers and instructional designers.

In addition, because instruction is defined as that which supports learning, smart technologies that support instructors and instructional designers should be included in the domain of smart learning technologies. This broadening of the concept of smart learning technologies to include any technology that has the relevant characteristics (e.g., adaptivity, context awareness, intelligence, etc.) and that supports instructional planning, implementation, and evaluation as well as supporting learners and instructors, is an important consideration. Consider learning to fly an airplane and pilot training as an analogous case. There are many people in addition to those being trained to be pilots involved; likewise, there are many technologies involved in flight training. Planes, cockpits, and flight controls are continually being updated with new technologies. The same is true with regard to learning environments, digital technologies and learning tasks. As a consequence, to maintain currency with all of the relevant technologies as they change and evolve, a broad conception of smart learning technology is required. Figure 1 depicts how one might conceptualise smart learning technologies.

Figure 1 Conceptualising smart technologies for learning and instruction (see online version for colours)



It is recommended that these definitions and considerations guide (but not confine or restrict) future contributions to the journal. Having consistent terminology is a hallmark of many academic disciplines, although one finds variations in nearly every discipline. It would be useful to use these definitions or extensions, variations or deviations that are documented in future articles so that the body of knowledge about smart learning technologies can grow and flourish.

3 Historical developments

Some historical developments pertinent to smart technologies for learning have already been mentioned. Table 1 shows how smart technologies have been getting more adaptive, more intelligent, more context aware, more portable and more powerful.

The examples and characteristics in Table 1 are meant to be suggestive of the progressive development of smart technologies in the broad areas of learning and instruction. Several things are worth noting. There are examples of applying smart technologies to support learners, teachers and instructional designers throughout the short history of smart technologies. The support offered has become more adaptive and flexible over time. Moreover, the applications have become more focused and context aware in recent years. With improvements in natural language processing, interfaces have become more conversational, and there is now dynamic, near-real-time support for open-ended natural language input. What has yet to occur on a large scale is the ability to develop recommendation engines based on large data sets to create personalised learning environments that respond to individual learners based on how similarly situated learners with similar backgrounds and characteristics have benefits from particular activities, resources and feedback. However, the potential for such strong personalised learning environments exists, and such smart personalised learning environments are likely to emerge in the next five to ten years.

Table 1 Historical overview of smart learning technologies

Years	*Characteristics and systems*	*Examples*
1950–1969	Computer-controlled systems; adapted to learner performance (e.g., SAKI}; interactive; empowerment of learners with choices and feedback mechanisms (PLATO)	Self-Adaptive Keyboard Instructor (SAKI); Programmed Logic for Automatic Teaching Operations (PLATO)
1970–1989	Component display theory; learner control; dynamic feedback to learners; instructional development systems; early intelligent tutors; bug libraries; computer-supported task analysis; emergence of cognitive apprenticeship	Time-shared, Interactive, Computer-Controlled Information Television (TICCIT); DEBUGGY; LISPITS; SOPHIE; SHERLOCK; TUTOR
1990–1999	Instructional advising systems; intelligent tutoring systems; learning management systems; conversational interfaces; knowledge tracing; cognitive architectures; computers as mind tools	Andes; Cardiac Tutor; Courselnfo; Didactic EngineeringWorkbench (AGO); FirstClass; ID Expert; GAIDA; Management Flight Simulators;Why2-Atlas; XAIDA
2000–2009	Natural language capabilities; tools to create intelligent tutors; pedagogical agents for engagement and motivation; cognitive task analysis; focused pedagogical agents; gamification elements; measurement of flow; semantic web applications	AutoTutor; CODES; Cognitive Tutors; Crystal Island; ELEKTRA; eTeacher; GeoGebra; Knowledge Modeling Tool (MOT); Prime Climb; Second Life applications; TELOS; ZOSMAT
2010–2015	Non-cognitive modelling; support for motivation and affective factors; enhanced natural language capabilities with choice of voices and languages; integration of visualisation support; augmented realities; integration of brain imaging and neuro-feedback	Eco-MOBILE; visual knowledge and competency modelling (G-MOT); Go-Lab; LearningVersion of Memory Match Game; PlayPhysics; Talking Island; TradeRuler

3.1 Framework for practice and scholarship

In order to facilitate practice and scholarship with regard to the application of smart technologies in learning and instruction, a framework focused on key characteristics and capabilities is proposed (see Table 1). In addition, a list of potential metadata or identifiers is then suggested. There are five clustered parts of the framework depicted below.

1 The *ability to adapt* is a critical factor in most smart technology applications. Adaptations can be to user characteristics, to the learning task, to the context, to historical developments and so on. Moreover, adaptations can be system generated or generated by users (e.g., learners, teachers, designers, support personnel, evaluators, etc.). Understanding the purpose and intended use of the smart technology

application is likely to suggest relevant kinds of adaptivity for targeted uses and users.

2 Primary users include instructional designers, instructors (teachers, tutors, trainers, etc.), and learners and learning groups. In addition adapting to the interests and needs of these users, there is a general need to provide *dynamic formative feedback* with regard to the task or activity that is currently the focus of use. The nature of that feedback should be specific to the context and aimed at improving task performance or the quality of the activity.

3 In order to provide meaningful feedback, there is a need to *monitor and track progress and performance*. Based on the individual user's progress and performance and a database of related efforts, there is the possibility of predicting outcomes (if no adjustments are made), providing guidance, and recommending specific changes and courses of action.

4 Critical factors for effective and efficient learning include *engagement and empowerment*. Providing individually engaging experiences and activities and supporting the development of metacognition and self-regulation by empowering users are critical characteristics of intelligent learning systems.

5 Just as humans improve over time, in large part as a result of interactive discourse with knowledgeable others, a smart learning or instructional technology should be able to achieve effective and efficient outcomes, engage in *meaningful discourse, and improve in capability and performance over time*.

One way to rate applications of smart technology in learning and instruction would be to weight such critical factors as those in Table 1 or in the five-part framework indicated above. Since this area is quite new, the ratings would be primarily suggestive. For example, each of the above five clusters might count up to 20 points each, with three levels of points allocated: 10 (or less) to low-level applications; 10 to 15 for mid-level applications; and 16–20 for high-level applications. However, such ratings are a secondary concern compared with impact on learning. What matters most is the extent to which a technology results in improved or enhanced learning and instruction. Impact on engagement, meaningful feedback, and levels of empowerment are likely be significant contributing factors in such an analysis.

4 Concluding remarks

It is still quite early in the 21st century, although many are inclined to know what knowledge and skills are significant for success in this century. It is also quite early in the history of applying smart technologies to learning and instruction to know what will work best in various circumstances and situations. Meanwhile, technologies continue to emerge at an ever-increasing rate. These technologies are getting more powerful, more mobile, more pervasive, more adaptive, and less expensive. While much is not certain and the future generation of smart technologies is not known, it seems fairly certain that these technologies will continue to be integrated into learning and instruction. What likely developments are likely to have a significant impact on learning and instruction?

As previously mentioned, personalised learning environments have yet to be implemented on a large scale. What is needed are accessible data repositories of previous learner characteristics and their performance on various tasks in using different learning activities and resources. When those data sets are available and with further development of learning analytics, personalised learning environments are likely to emerge as a significant smart learning technology.

The development of intelligent tools to support instructional designers is a neglected area. Tools for instructional designers experienced a growth spurt in the 1980s and 1990s, along with a parallel growth spurt in the domain of ITSs. However, there has not been much growth in the area of smart technologies to support instructional designers.

There have been a few minor efforts of smart technology aimed at supporting teachers, but these are also in a very early state of development and have yet to emerge as a focus area for the application of smart technology. One such application is simSchool (https://www.simschool.org/), which would rate perhaps in the mid-range of the scale suggested above.

The Pittsburgh Advanced Cognitive Tutor Center (PACT) focuses on the development of cognitive tutors that could in principal support both designers and instructors (see http://pact.cs.cmu.edu/). PACT is growing in scale but systemic improvements on a large scale have yet to emerge, although this is clearly a very promising area.

In summary, there is much that is happening in the broad area of applying smart technologies to learning and instruction, and the future appears quite promising. However, large-scale, systemic improvements have yet to emerge. An emphasis on fidelity of implementation and impact studies of new developments will be critical for steady and sustained progress. Cloud-based and mobile technologies provide a basis for flexibility and adaptivity not previously possible. In conclusion, one might say that the future of smart learning technologies is *cloudy with a slight chance of gain* (the theme of ICALT 2011).

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