

An Introduction to Artificial Intelligence in Education

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Abstract: This chapter reviews the field of Artificial Intelligence in Education. It does not present a catalogue of systems but discusses general educational issues from the technical perspective offered by AI research. It considers the nature of knowledge and learning and the potential impact of AI and other new technologies in realistic educational settings. It concludes with a summary of the achievements of the field and a discussion of the on-going controversies.

Introduction

Any review of Artificial Intelligence in Education (AI-ED) should logically begin with a discussion of the (educational) problems being addressed before embarking on a survey of how AI might contribute to solutions. The main relevant issues appear to be:

- What is the nature of knowledge?
- How may knowledge be learned?
- How are the social and cultural aspects of education taken account of?
- Should systems instruct, tutor, guide or train students?
- How should new technologies be used in education?
- What are the measures of effectiveness?

Educationalists will debate such issues at great length but it is not the aim of this chapter to contribute to that debate except to the extent that it discusses the AI-ED field's views (implicit and explicit) on them. This review focusses on the technical contribution that AI is making and might make to Education.

The following six sections consider each of the above issues in turn. Each section illustrates a general discussion about AI-ED's views with exemplar AI-ED systems. The six sections do not attempt to give a comprehensive account of implemented systems (there are now too many for a short review) and those systems referred to are not discussed in detail but only to the extent necessary for the point under discussion. The review ends with a discussion of the main controversies within the AI-ED field today.

The nature of knowledge

Most AI-ED systems are intended to help their student-users become more knowledgeable in some respect. AI-ED system designers are well aware that education has broader aims - to develop ethical and moral values, to improve attitudes, to nurture better citizens, and so on - but this awareness only indirectly influences their system designs. It is rather assumed (or hoped) that the context in which AI-ED systems will be used will convey these broader goals.

So, given the focus on the knowledge-to-be-learned, it is natural that AI-ED system designers often begin by trying to specify this knowledge as precisely as possible. To achieve this, the full panoply of AI knowledge representation techniques (production systems, frames, semantic networks, predicate logic, etc.) has been applied in one or other AI-ED system. In so doing, AI-ED designers might be considered to be buying into a philosophy of knowledge called *objectivism*, which holds that the world is completely and correctly structured in terms of entities, properties and relations (Lakoff, 1987, p. 159). Thus an AI representation might be considered to be an attempt to describe this structure and hence the aim of an AI-ED system might be to help learners acquire the entities, properties and relations of this 'correct' propositional structure.

The 'classical' approach to AI-ED system design is illustrated by SPENGELS (Bos and van de Plassche, 1994), a straightforward intelligent tutoring system to help Dutch students learn the conjugation and spelling of English verbs, that is, to be able to use the correct form of verbs (such as "prefer", "begin") in sentences such as "He --- to work with pen and paper." The first step, since no spelling algorithm already existed, was to represent as a decision tree the morphosyntactic and spelling alternation rules taught in different Dutch textbooks. The decision tree effectively asks a series of questions: Is the verb form finite? Which tense is needed? Is the number singular? and so on, leading to a node of the tree showing the correct conjugation. This algorithm then becomes the basis for teaching the student, for deriving correct answers, for checking student answers, for determining misconceptions the student may have, and so on.

Some of the knowledge we wish students to acquire is objective because it is knowledge defined (by us) to be correct - for example, the syntax of programming languages or the allowable operations on an algebraic expression. It is no coincidence that the majority of AI-ED systems concern such topics. For example, GREATERP (Anderson and Reiser, 1985), a beginners' LISP tutor, will comment that "You are within a PROG so you need to use a RETURN" because there is no scope for argument about the correctness of this statement (although there is scope for arguing whether the student needs to be told so in a particular way and at a particular time).

There are many other domains where it seems necessary to adopt an objectivist view, to some extent. For example, a student on a first-aid course must be given the correct way to deal with a child suspected of being accidentally poisoned. Although, again, this does not necessarily mean that a student must just be told the correct way - one can easily imagine that students will understand and remember better if they discover the correct way, in this case, preferably by experimenting with simulated patients, not real ones.

There are also domains where an objectivist view is adopted (temporarily, perhaps) as part of an academic game, by students and teachers. For example, the equations for uniform acceleration ($s = (u+v)t/2$; $s = ut + at^2/2$, etc.), although perhaps understood to be not always applicable, are adopted as axioms to solve problems. In the case of English verb endings (discussed above), a pedant might point out that these endings are not fixed - they may be different in medieval

English and American English - but if the learner's context is 'preferred' (i.e. U.K.) English, "preferred" is accepted to be correct.

There is of course a great debate within AI, and specifically within expert system research, about the extent to which 'correct' knowledge can be specified in areas where it does not obviously exist. In the case of English verb endings this seems a reasonable expectation but in more substantial areas of English use such an approach would probably not be contemplated. To the extent that 'correct' knowledge can be specified such expert system representations may be used to convey it to students. The prototypical attempt to carry out this programme was the adaptation of the MYCIN expert system for medical diagnosis into the GUIDON tutoring system (Clancey, 1979, 1987).

However, even within domains for which objectivism seems reasonable, it soon becomes apparent that the real learning problems lie not in the objective knowledge but in its relation to less objective knowledge. For example, in programming the focus moves from the syntax of the language to aspects such as programming design or debugging, where there is no definitively 'correct' knowledge. So, for example, in the BRIDGE Pascal tutor (Bonar and Cunningham, 1988) the focus is on guiding the student through the stages of planning a program, from the initial English-like description through to the Pascal code.

Similarly, in algebra the issue is not so much what the operations are (syntactically) but when they should be applied. Thus, AI-ED algebra systems do not just check the correctness of operations (in fact, they often perform the operations themselves since that is assumed not to be the student's difficulty) but provide students with an environment in which they can experiment with the operators. For example, ALGEBRALAND (Foss, 1987) displays a problem-solving tree of the student's solution attempt. This is intended to make it easier for students to monitor their on-going solution and to reflect on their solution attempts afterwards. ALGEBRALAND itself gives no explicit tutorial support to these aspects - it only checks that an operator is applicable. The hope is that, relieved of the need to worry about the low-level detail of operator application, students will be more likely to engage in the desired metacognitive activities.

Even when a successful expert system can be built it does not follow that the expertise embedded in it is a suitable basis for an educational interaction. The expert's performance-oriented knowledge may not be based on a conceptual structuring of the domain which a learner will understand (Clancey, 1984). Or, to put it another way, many studies have shown expert-novice differences which suggest novices may not learn well from experts. This conclusion is explicit in GREATERP, where the student's solution is not compared to an expert solution but to that of an 'ideal student'. Thus the production rules of GREATERP do not summarise expert knowledge but are aimed to correspond to conceptual units that novices can understand.

A view of knowledge which is often presented as opposed to objectivism is that of *constructivism*, which holds that meaning is imposed on the world by us, rather than existing in the world independently of us. Constructivists therefore emphasise the processes of actively structuring the world and that there are many meanings or perspectives for any event or concept, rather than there being a single correct meaning which a student must be guided toward.

It does not follow that an AI-ED system which possesses an objective representation of knowledge has to adopt an interaction style which violates all constructivist principles. For example, the Socratic dialogues of WHY (Stevens and Collins, 1977) do not simply tell students the 'correct' conception but aim to help them construct one through subtle sequences of counter-examples and so on: "Do you think that any place with mountains has heavy rainfall?" "Yes." "Does southern California have a lot of rain?"

But the designer of a system which possesses knowledge which is deemed to be correct is sorely tempted to use that knowledge (usually acquired after great effort) in a direct knowledge communication mode: "No, southern California doesn't have a lot of rain." To avoid such temptations an extreme constructivist might argue that an AI-ED system (assuming that it is still to be deemed an AI-ED system) should possess no such knowledge and simply present an environment for the student to explore. The deceptive word here is 'simply', for it is by no means easy to design environments in which knowledge (of any kind, intended or not) can be discovered. The most well-known such system is LOGO (Papert, 1980) which has now been subjected to numerous studies and its constructivist foundation has become rather shaky as the extent to which LOGO needs to be buttressed by other supports has been documented. Similarly, the recent enthusiasm for developing hypermedia and multimedia systems (Kommers, Jonassen and Mayes, 1992) for students to explore has to be tempered by the fact that unaided students have some difficulty in negotiating the vast search spaces. The technologists' manifestation of constructivism as microworlds and other exploratory environments - often contrasted with the tutoring systems of objectivists - is a rather pale image of the comprehensive philosophy of constructivism, which is "a discursive practice that provides the means through which one can describe the social, political and economic circumstances that surround and give meaning to a given piece of educational technology" (Sack, Soloway and Weingrad, 1992).

An intermediate, but technically difficult, position is to argue that *both* agents, the AI-ED system and the student, should adopt a constructivist approach. In this case, the system would not contain a priori correct knowledge but would attempt to discover it in a joint endeavour with the student. The PEOPLE-POWER system (Dillenbourg and Self, 1992a) illustrates this approach. The student and the system are supposed to design experiments to carry out on a simulated political system in order to determine what makes a system democratic in the sense that seats gained in a parliament are proportional to the votes cast for the corresponding parties. Both the student and the system can make (fallible) suggestions and interpretations. There is no target 'correct' knowledge available to the system.

Situationism shares some tenets of constructivism but emphasises that the constructed knowledge does not exist in memory but rather emerges from interaction with the environment. It is argued that traditional AI, with its emphasis on symbolic knowledge representations, has assumed (sometimes explicitly, as in the classic Newell and Simon (1972) studies) that those representations have some psychological reality, that is, they correspond, not literally but functionally, with structures in the learner's memory. Situationists argue that representations are created in the course of activity but are not themselves knowledge, knowledge being a capacity to interact. Thus both constructivists and situationists deny that knowledge of the world can be defined (correctly) independently of a mind, while the former but not the latter might accept that an individual mind creates its own idiosyncratic knowledge structures in memory.

The status of situationism is still a subject of debate (Clancey, 1992; Sandberg and Weilinga, 1992; Hoppe, 1993) and there are as yet no AI-ED systems which clearly illustrate its principles. Most discussions of situationism in AI-ED refer to the idea of cognitive apprenticeship (Collins, Brown and Newman, 1988) but cannot point to any exemplar systems in the way that objectivists might point to GREATERP, etc. Clancey (1993) has, however, listed some principles for designers of such systems, contrasting them with the perceived emphases in objectivism-based AI-ED approaches:

- participate with users in multidisciplinary design teams;
- adopt a global view of the context in which a computer system will be used;

- be committed to providing cost-effective solutions to real problems;
- aim to facilitate conversations between people;
- realise that transparency and ease of use is a relation between an artifact and a community of practice;
- relate schema models and AI-ED systems to the everyday practice by which they are given meaning and modified;
- view the group as a psychological unit.

Some commentators (e.g. Bredeweg, 1992) have related the situationist view to that of *connectionism*, another view of knowledge which is presented as a contrast to the symbol-processing version of objectivism. Connectionism holds that knowledge is implicitly represented in the weights and links between large numbers of nodes modelled on neural networks. However, while connectionist representations lack the kind of symbolism characteristic of objectivist representations they are still very much concerned with representations in memory, rather than in the situation. Connectionist methods have been used to develop components of AI-ED systems, as mentioned below, but no AI-ED system follows a wholly connectionist philosophy, presumably because the representations themselves, with only implicit understanding, do not easily support learning interactions.

An interesting question, after reviewing how philosophies of the nature of knowledge relate to students' knowledge, concerns how those philosophies relate to teachers' knowledge (or AI-ED systems' knowledge of how to teach). Some researchers (e.g. Clancey, 1987) have attempted to apply the expert system paradigm to teaching knowledge and to specify 'tutoring rules' to be interpreted by an AI-ED system. This, then, reflects an objectivist view that such knowledge exists and can be specified. Most AI-ED systems, however, do not have explicit knowledge of how to teach: it is implicit in the way they react to certain situations. This might appear to be a situationist approach but in fact is not since the knowledge is clearly possessed by the system but not in a form which it is easy for observers to analyse. A few people (e.g. O'Shea, 1982) have adopted a constructivist view and considered whether an AI-ED system might be able to build an instructional strategy from 'experiments' with students interacting with it.

The nature of learning

Philosophies of knowledge imply philosophies of learning, to some extent. For example, connectionism, with its assumption that knowledge exists in the weighted links between the nodes of large neural networks, implies that learning is a statistical process whereby the weights are adjusted as many examples and non-examples are encountered. Unfortunately, there is no unequivocal mapping from philosophies of knowledge to philosophies of learning and it is one of the difficulties of AI-ED research that heated arguments about the nature of knowledge often lead to similar conclusions about the nature of learning and hence of teaching and AI-ED system design. For example, an objectivist might not demur from some of the principles derived from situationism listed above, for example, that it is time to move on from 'laboratory studies' to putting more emphasis on 'real-world applications'.

One of the few attempts to link a theory of learning to that of AI-ED system design is that to relate ACT* (Anderson, 1983) to GREATERP and similar systems. The following principles are supposed to follow from ACT*:

- Represent the student as a production system.
- Communicate the goal structure underlying the problem-solving.
- Provide instruction in the problem-solving context.

- Promote an abstract understanding of the problem-solving knowledge.
- Minimize working memory load.
- Provide immediate feedback on errors.
- Adjust the grain size of instruction with learning.
- Facilitate successive approximations to the target skill.

These principles do not follow in the mathematician's sense of being derivable from axioms of the theory but are more like implicit implications. Moreover, the principles do not lead directly to design prescriptions. These weak links make it hard to argue that the success (or otherwise) of the systems implemented can be attributed to the psychological theory.

ACT* is an objectivist theory emphasising stored schemas in the student's memory. Recently, ACT* has been modified to encompass some aspects of situationism but these modifications have yet to lead to significantly modified principles for AI-ED system design. As they stand, GRETERP and its brothers are remediationist systems based on the assumption that learning is failure-driven.

Many other approaches have the basic idea of failure-driven learning. For example, SOAR (Laird, Rosenbloom and Newell, 1986) is intended to be a comprehensive cognitive architecture based entirely on a process of 'impasse-driven learning'. An impasse is a situation where the architecture has insufficient knowledge to determine how to proceed. The impasse triggers a heuristic search to create a new operator to overcome it. Similarly, VanLehn's theory (VanLehn, 1991) is an impasse-driven one, derived from the influential 'repair theory' (Brown and VanLehn, 1980) originally developed to explain how students learned 'bugs' in subtraction.

The 'failure' does not have to be a blatant exhibition of lack of success: it could just be some evidence which causes the student to consider whether their current conception is sound. For example, the idea of case-based learning (Schank, 1990), derived from the field of case-based reasoning in AI, is that students learn from stories (cases) presented at the precise point of becoming interested in knowing the information conveyed by the story. For example, DUSTIN is a language-training system with which students enter a multimedia simulated environment in which they interact with (images of) people they will deal with in their work environment. The student attempts authentic tasks, such as checking into a hotel, and on failure is shown a relevant example before re-attempting the task. This approach is thus an interesting merger of objectivist methods (there are ostensibly correct representations of how to perform the task) with a constructivist philosophy (with rationales such as "in order to assimilate a case, we must attach it someplace in memory") and a situationist style (with the emphasis on authentic tasks).

The 'case' presented to a student may be

- a very short piece of text (as in a counterexample in a WHY dialogue, as above);
- a complex photograph (as in the Sickle Cell Counselor (Bell and Bareiss, 1993), a system designed to teach museum visitors about sickle cell disease);
- a paragraph giving a case history (as in DECIDER (Bloch and Farrell, 1988), which gives summaries of events such as the U.S. invasion of Nicaragua while the student is expressing political beliefs);
- a longish video (as in JASPER (Crews and Biswas, 1993), where students are presented a story in which the characters are faced with challenges that the students must solve).

In the last example, the video becomes a motivating way to present complex problems for students to solve. Implicit in this approach (apart from the use of video and the avowed constructivist philosophy, since the emphasis is on students constructing knowledge in realistic situations, rather than receiving divorced classroom instruction), is a belief in learning by problem-solving, an approach also characteristic of an objectivist philosophy, which would also

emphasise that an AI-ED system itself should be able to solve the problems it sets. (In fact, of the systems mentioned in this and the previous paragraph only DECIDER does not have (or cannot work out) a correct solution.)

Thus a learning by problem-solving approach can be rationalised by many different philosophies and supported by many different styles of AI-ED system. For example,

- GREATERP students solve problems and receive immediate feedback on mistakes (the system being able to monitor each step of a solution);
- LOGO students receive feedback from the system when solutions are executed but receive no didactic help;
- WEST students (who learn arithmetic skills in the context of a simple board game (Burton and Brown, 1979)) are given hints from the system if certain constraints are violated;
- JASPER students may receive hints to help them improve their solutions (earlier versions of JASPER had students solving the problems off-line).

So to say that most AI-ED systems reflect a learning by problem-solving philosophy is not very illuminating unless the nature of the problem and the degree of system support are clarified.

A standard scenario is a problem-solving environment in which students perform experiments and are guided by the system in their interpretation. For example, QUEST (White and Frederiksen, 1990) provides a graphic simulation of circuits to enable students to understand principles governing the behaviour of those circuits by performing troubleshooting operations. For such an interaction to be useful to students the system's interventions must be couched in terms analogous to those of the student: thus, for novices the system needs representations of naive qualitative physics. The topic of qualitative reasoning is another broad field of AI whose application to AI-ED has still to be explored in detail although it was arguably initiated by early AI-ED studies of the SOPHIE system (Brown, Burton and de Kleer, 1982).

The tension between extreme objectivist and constructivist/situationist views is well illustrated by discussions about how students might learn the kinds of causal models needed in science. An objectivist might present the standard formulae ($F = ma$, etc.) and require students to apply them to various (textbook) problems; a situationist might expose the student to many real-world instances and hope that generalisations will (implicitly, perhaps) evolve. White (1993) argues that causal models of an intermediate degree of abstraction can foster learning provided that they are:

- Understandable, i.e. they build on intuitive notions of causality and mechanism;
- Learnable, i.e. they generate explanations of key domain phenomena;
- Transferrable, i.e. the objects and actions within them are represented in a decontextualised form;
- Linkable, i.e. they help link different levels of abstraction and different model perspectives;
- Usable, i.e. they can be used to predict, control and explain physical phenomena.

When students interact with a simulation it has been found (Roschelle, 1990; Byard et al, 1992) that they tend to focus on tweaking the simulation to achieve the desired short-term effect without addressing the mistaken beliefs and conceptions which will continue to cause difficulties in the longer-term. Thus there appears to be a need to engage the student in a dialogue to get at the fundamental misconceptions. This dialogue may be with a human teacher, other students or a computer-based learning environment - but in any case reflects a constructivist view that knowledge is structured by interpreting events, albeit that this interpretation requires the mediation of other agents rather than isolated cogitation. Along these lines, Pilkington, Hartley,

Hintze and Moore (1992) describe an environment with which students express (and withdraw) commitments during some debate, the system acting as a 'referee' using the guidelines of dialogue game theory to determine the validity of moves. Such an interface, it is argued, might help students not only clarify their conceptions of the domain under debate but also develop general reasoning skills. Eventually, perhaps, the nature of such a debate may be sufficiently understood that the system itself may adopt the role of a player as well. As Baker (1994) describes, this work is derived from many fields of AI (belief revision, agent theory, distributed AI) and elsewhere (in cognitive and social psychology and the language sciences).

The work on self-explanation (that is, the hypothesis that better students spend more time on explaining examples to themselves (Chi, Bassok, Lewis, Reimann and Glaser, 1989)) can be interpreted as a theory about the benefits of arguing with oneself. The self-explanation line of research has recently (VanLehn, 1993) been developed into a general proposed methodology for AI-ED research:

- Collect experimental protocols of learners and divide them into good and poor learners (on the basis of outcome measures);
- Investigate what behaviours and processes were different in the two groups (e.g. self-explanation);
- Develop a cognitive simulation model to account for the identified differences (e.g. the CASCADE system (Jones and VanLehn, 1992));
- Design appropriate interventions to cause the more effective behaviour to occur (e.g. strategically hide information to encourage self-explanation);
- Test the resultant AI-ED system.

Overall, then, AI-ED system design reflects a rather eclectic view of the nature of learning, regardless of one's view of the nature of knowledge. Clearly, many different kinds of event and activity can lead to learning and many of them have been supported, to some extent, within AI-ED systems (usually without the dogmatic claims that accompany discussions about the nature of knowledge).

Social and cultural aspects

AI-ED research has not taken much account of the social and cultural settings within which AI-ED systems have to be designed and used. Until recently, the emphasis has been on the technical challenge of constructing interesting systems within research laboratories. However, when such systems are used in classrooms, the effects are not usually as intended (perhaps not surprisingly).

For example, Schofield, Evans-Rhodes and Huber (1990) showed that when a geometry tutor (based on the Anderson principles itemised above) was trialled in schools both teachers' and students' behaviours changed in not entirely anticipated ways. While teachers devoted more time to slower students and adopted a more collaborative style and students increased their effort on tasks (all presumably welcome changes), it was also found that the system increased competition among the students. Because students could progress at their own pace (unlike in the normal classroom) and could easily determine the progress of their co-students a race developed between them - in fact, 40% of the students attributed their greater effort to the increased competition. The self-pacing feature also led to a modification in teachers' grading practices since it was now less appropriate to mark students on the percentage correct. Instead they tended to assess on the effort invested.

These kinds of observation lead naturally to proposals for 'socio-technical design' (Clancey, 1993), where the emphasis is on designing a system within the social and physical context in which it is intended to be used. Such proposals are often couched in political terms, presenting such an approach as more 'democratic' since it involves user groups in the decision-making and control of the systems they will use (as opposed to a 'dictatorial' approach in which designs are delivered to users).

In particular, user-participatory design, a trend in human-computer interaction and usability research, has recently been applied to AI-ED system design (Murray and Woolf, 1992). The project involved developing a representational framework for domain content and tutoring strategies that was understandable by educators, implementing a set of knowledge acquisition tools, and involving educators in building the system, through conception, design, implementation and evaluation. This line of work is part of a broader discussion about the general principles of instructional design theory and knowledge acquisition in AI.

An extreme objectivist might argue that when all the knowledge-to-be-learned and the knowledge-of-how-to-teach-it has been fully specified, the delivery of AI-ED systems to the classroom will not be problematic. The design will take account of all situations and the system will adapt itself accordingly. This assumes that a complete cognitive analysis will subsume the affective dimensions. As Lepper, Woolverton, Mumme and Gurtner (1993) remark, most AI-ED systems only indirectly consider issues such as motivation, whereas studies of human tutors, especially for certain classes of learners such as remedial students, show that they devote more time and attention to motivation and affect than to the strictly cognitive content. Human tutors' techniques for maintaining or increasing motivation - based on manipulating the goals of confidence, challenge, control and curiosity - can be seen to be implicitly encoded in some AI-ED systems to the limited extent that some of these techniques seem applicable to such systems.

In any case, situationists would not accept that the goal of explicitly defining all relevant knowledge in deliverable AI-ED systems is a sensible one. It simply does not take account of the fact that the teacher-learner culture is too rich and that the people involved in the use of such systems are able to (indeed, must) contribute to successful design and use of the systems.

Since situationists hold that knowledge does not reside in individual heads, they would also move away from one-to-one tutoring systems (which are caricatured as aiming to transfer knowledge to individuals) and encourage more collaborative learning systems, where understanding is developed by group negotiations (as constructivists would accept). Thus they have a different image of the context of use than some tutoring system designers. They would tend to play down the role of AI *within* computer-based systems, that is, to provide explicit symbolic reasoning, and argue that AI's role is to mediate the collaborative interactions, and they would therefore seek bridges to work on computer-supported collaborative work (CSCW) and computer-mediated communication (CMC). This opens up a debate about the nature of educational institutions and students' activities within and without them which would be too broad to pursue in this review.

Instruction, tutoring, guiding, training

The view of teacher expertise embedded in present AI-ED systems is, it has to be admitted, rather naive. This is because AI-ED system designers generally do not have substantial teaching expertise themselves, nor have access to it. In addition, perhaps surprisingly, the teaching component has often been considered to be of less importance than, for example, the representations of domain knowledge and hence has often been bolted on as an afterthought.

However, the earlier sections have given many examples of the various teaching styles adopted by AI-ED systems. The old distinction between theories of learning as being descriptive and theories of instruction as being prescriptive, with no necessary connection between the two, is rejected by AI-ED research. For example, VanLehn's proposed methodology, given above, assumes that identifying learning differences will lead directly to prescriptions for instructional interventions.

The criticisms of the styles of present AI-ED systems which are often made are rather misplaced. None of these systems aims to provide a comprehensive coverage of either a significant part of a curriculum or the range of teaching styles. Rather, each system is an investigation of one style applied to one rather circumscribed topic. Thus we should consider whether the teaching style of a system is appropriate for the limited aims that its designers have.

For example, it is inappropriate to criticise GREATERP for its domineering style of putting students right immediately they stray off the correct path if this is an effective strategy for bringing large numbers of beginning LISP programmers up to a standard of competence after which more subtle strategies may be needed. Similarly, those systems which have a clear training objective, e.g. the Space Shuttle Fuel Cell Tutor (Duncan, 1992) and SHERLOCK (Lesgold, Eggan, Katz and Rao, 1992), an avionics troubleshooting tutor, where it is essential that students master the operation of complex equipment, may quite justifiably adopt an essentially objectivist approach of defining the knowledge-to-be-learned and ensuring that students acquire it as effectively as possible.

For many AI-ED systems, however, the aims are not so clear-cut. Often there is a 'surface' objective for the student (to write a program to draw a specific shape; to manipulate parameters to maintain an economic simulation in a stable state; to solve a specific algebraic equation) which masks the real objective (to develop various higher-order skills, such as planning and monitoring solution attempts). System interventions directed at the former objective (e.g. to point out that a program is incorrect) are irrelevant or harmful if they interfere with the latter objective. Many years ago the designers of the WEST system (Burton and Brown, 1979) proposed instructional guidelines such as "do not tutor on two successive moves" which only make sense if it is accepted that the system's aims are more than to ensure that the student obtains the 'right answer'. With such systems the balance between 'guiding', 'telling' or 'leaving' the student, and hence the whole vexed issue of the balance of control between the learner and the system, is a continuing debate. The specification of precise and general guidelines has proved elusive and the design of the instructional component of AI-ED systems remains more an art than a science, as it does for other educational systems.

New technologies in education

Regardless of philosophy, psychology or any other academic consideration, it is undoubtedly the case that the new technologies increasingly being applied to education have stimulated some of the trends discussed above. For example, the advent of high-fidelity multimedia and virtual reality systems naturally leads to its enthusiasts arguing for the merits of learning through 'immersion in a situation', which is a variation of the situationist's view. Similarly, the availability of high-speed networks permits a degree of distributed, collaborative working which was previously unattainable and this leads to discussions about the intrinsic virtues of 'social learning' mediated by technology.

This review is concerned specifically with the role of AI in education and hence we will not discuss the technical details of new technologies but only the potential relevance of AI to them.

At the moment, the current excitement with the new technologies owes nothing to AI. However, as the history of educational innovation shows, new technologies tend not to deliver all that they promise and it is quite predictable that as the limitations of the new technologies become clearer so AI techniques will be adopted to help overcome them. For example:

- The successful use of multimedia interfaces requires models not only of the media themselves, but of the user, task and discourse (Maybury, 1994), aspects that have long been studied in conventional AI-ED research. No doubt existing work on, for example, student modelling and discourse management will not be immediately applicable and will need to be adapted but this is clearly work with an AI orientation.
- The effectiveness of virtual reality as a learning environment depends fundamentally on the relation between learning and social and perceptual experience, a relationship which is central to AI research. Even at the technical level, preliminary experiments have already shown the need for surrogate 'co-learners' and other intelligent agents in the environment (Shute and Psotka, 1994).
- According to Katz and Lesgold (1994), the demand for computer-supported collaborative learning environments for workplace training can best be met by adapting the coached practice environments, such as SHERLOCK (Lesgold, Eggan, Katz and Rao, 1992), originally developed for individual learning. If so, present AI-ED research can be seen as the basis from which the new theories required for these environments will evolve.

Whatever the future, recent technological advances have radically changed AI-ED systems. A few years ago, a review such as this would be profusely illustrated with screen images to show student-system interactions, usually involving natural language-like typed communication (see, for example, the illustrations in Wenger (1987)). Now, with graphic interfaces and multimedia, it is virtually impossible to capture on paper the richness and immediacy of such interactions.

Measures of effectiveness

The evaluation of any educational innovation, including AI-ED systems, is inherently difficult (Mark and Greer, 1993; Winne, 1993). However, because of the expense of AI-ED system implementation, the demand for successful evaluations is quite reasonably made. It is only recently that AI-ED research has been able to respond to the challenge by carrying out large-scale empirical studies which show the benefits of AI-ED systems in real educational settings, for example, the evaluations of:

- The Geometry tutor, as mentioned above (Schofield, Evans-Rhodes and Huber, 1990).
- SMITHTOWN, a discovery world that teaches scientific inquiry skills in the context of microeconomics (Shute and Glaser, 1990).
- SHERLOCK, where twenty hours using the system were judged to be as effective as two years 'on the job' (Nichols, Pokorny, Jones, Gott and Alley, 1993).
- A STATICS tutor, where the instructional design effort per hour of instruction time was about 85 hours, compared to 100-300 hours for traditional CAI (Murray, 1993).
- A VCR tutor (Mark and Greer, 1991).
- The Space Shuttle Fuel Cell tutor, where NASA trainers were so convinced of its superiority over alternatives that it was adopted without need for a formal evaluation (Duncan, 1992).

These evaluation studies, however, use educational techniques with AI-ED products but do not themselves use AI techniques. Rather more relevant to this review is the possible use of AI for evaluative purposes.

Any AI-ED system is an implementation of a (usually implicit) theory of learning and instruction. If the theory were sufficiently explicit it could be expressable in executable form and thus the outcomes from the AI-ED system could be predicted by running the system with 'simulated students'. VanLehn, Ohlsson and Nason (1994) consider the possible uses of simulated students to support teaching training, to enable an AI-ED system to act as a collaborative partner, and to permit formative evaluations. In the last case, for example, one can imagine using a failure-driven subtraction learning procedure to determine which of the following examples is more likely to promote learning:

$$\begin{array}{r} 85 \\ - 27 \\ \hline \end{array} \qquad \begin{array}{r} 745 \\ - 127 \\ \hline \end{array}$$

The example on the right might lead to the generalisation that borrowing should be from the column immediately to the left; the example on the left might also lead to the generalisation that borrowing should be from the left-most column. Thus the theory would predict (in contrast to standard textbooks) that the example on the right is better since it is potentially less confusing to an impasse-driven learner.

Thus an AI-ED system itself may be used for formative evaluations before being used with real students. This is, of course, standard practice in other fields of computer use, but its usefulness in AI-ED may be doubted because of our lack of faith in the soundness of the theories of learning concerned. The principle, however, seems sound.

Similarly, we can imagine applying the student modelling component of AI-ED systems to assist in the thorny problem of assessment (Martin and VanLehn, 1993). Most AI-ED systems which are not entirely exploratory environments maintain some kind of student model, that is, some representation of what it is believed the student has understood. This student model may be used for many purposes within an AI-ED system, e.g. to determine appropriate problems to set, to provide remediative feedback, etc. Many techniques have been developed to build student models (Dillenbourg and Self, 1992b), some derived from well-known AI techniques such as:

- discriminative concept learning (Langley and Ohlsson, 1984), where the aim is to induce the student's problem-solving procedure from observations of his correct and incorrect results;
- resolution from computational logic (Costa, Duchenoy and Kodratoff, 1988), where the technique is used to suggest and prove hypotheses about a student's beliefs;
- neural networks (Mengel and Lively, 1991), where the network is trained to simulate a student's cognitive processes;
- fuzzy logic (Derry and Hawkes, 1993), to provide an approximate diagnosis, recognising that a student's behaviour is not entirely consistent and induction from it is risky;
- Bayesian belief networks (Katz, Lesgold, Eggan and Goldin, 1992), also to provide a less precision-oriented approach to student modelling;
- model-based diagnosis (Self, 1993), to cast the student modelling problem in the terms of general diagnosis in AI;
- belief revision (Kono, Ikeda and Mizoguchi, 1994), to keep the model consistent with observations;
- logic meta-programming (Beller and Hoppe, 1993), to reconstruct hypothetical solution paths to check against constraints associated with correct solutions.

The need for, and success of, these methods remains a controversial topic within AI-ED research (Lajoie and Derry, 1993; Spada, 1993). But to the extent that these techniques are successful and so provide a useful evaluation of an individual student (useful in the sense that it may support individualised interactions) they may be used for assessment purposes. Educationalists must argue about the ethics of computer-based assessment and about whether what can be reliably assessed in this way is in fact what should be assessed, but again the principle seems sound: many AI-ED systems aim to build student models and to the extent that this is possible it may form a basis for assessment of the student and hence an evaluation of the system's effectiveness in helping that student to learn.

On-going debates

Education has been a controversial topic for two millenia at least: AI has been equally controversial for rather less long. AI in Education is bound to provoke debate. After two decades, a body of techniques has been developed which are beginning to be standardly re-applied in new systems. Some early AI-ED concepts are now routinely used in off-the-shelf computer-based learning systems: for example, a 50-dollar typing tutor uses a student model with a bug catalogue to generate new practice lessons as needed. Some larger-scale AI-ED systems have been shown to be effective within larger organisations such as the military (as discussed above).

But still there is considerable argument about AI-ED research. Some of the arguments have been touched upon above. We conclude by mentioning some more general questions:

- Is AI a dangerous metaphor for education? For some critics AI is seen as supporting a rather behaviouristic approach to learning, in that it aims to adapt the learner to conform to the knowledge embedded in the AI system. As we have indicated, this is a simplistic characterisation of only a sub-class of AI-ED systems.
- Can AI-ED systems support student autonomy and open learning? The more that intelligence is put within AI-ED systems the more the temptation may be to apply it to control and direct the student's interactions with the system. However, the range of AI-ED systems includes much more than overbearing tutoring systems.
- Will AI-ED systems ever be used in real educational settings? Of course, this depends on what is understood by a 'real educational setting'. The traditional school classroom is perhaps not a very promising setting for many systems. But the organisation of classrooms is changing rapidly and it also seems likely that more learning will occur outside the official classroom as access to computer technology improves and individuals learn at home or at work, for their own interest or career development.
- What will be the impact of new educational technologies and what role will AI play within them? At the moment we are in a phase where the radically different nature of the new technology has side-lined AI. Eventually, however, there will be a merging of the more software-oriented AI focus with the more hardware-oriented new technology focus.
- Will AI-ED research continue to progress through the rather unprincipled implementation of demonstration systems, or will some theoretical basis for AI-ED system design be developed? Currently only certain components of AI-ED systems are amenable to any kind of theoretical analysis and no comprehensive 'theory of AI-ED systems' is likely in the near or medium-term future.
- Do AI-ED systems reflect a reasonable view of the nature of knowledge and learning? This brings us full circle. As we have discussed, there is no consensus within AI-ED research about these issues and we can find examples of systems which reflect many different

philosophies. Apart from the perception of AI-ED research as a field oriented towards producing practically useful systems, AI-ED may also provide a more technical contribution to such fundamental debates.

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For those readers requiring more detail than is possible in a short review, a list of recent AI-ED books is given below. No general book on AI in Education has been published since Wenger (1987), which reviewed all the significant research up to 1987. Nearly all the AI-ED books published since then are edited collections of papers (with the remainder describing a particular project). Thus none of the recent books gives a balanced and comprehensive picture of the field. Relevant research is also published in the following journals: *Journal of Artificial Intelligence in Education*, *Journal of the Learning Sciences*, *Interactive Learning Environments*, *International Journal of Human-Computer Studies*, and *Instructional Science*.

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