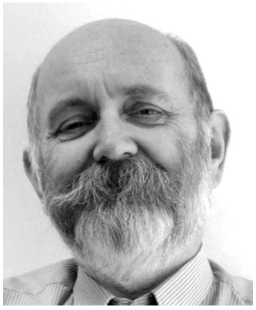
Attending to Individual Students: How student modelling can be used in designing personalised Blended Learning objects



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Summary
This paper reports on research carried out at the University of Hertfordshire over the past ten years relating to how the experience of learning can be personalised for individual learners. This work relates primarily to Computer-Based Learning (CBL), but is not restricted to it, as it encompasses a blended approach, linking on- and off-computer teaching and learning activities. The research reported in this paper relates to the development of psychological and domain-based student models and how they can be used together in a composite student model to assist in the selection and use of Blended Learning objects. It is argued that the needs of individual learners may be attended to in this way. Techniques in user modelling, theories of instructional design and sophisticated methods of evaluation are discussed as being central to this approach.

Introduction

Today in Higher Education, increasing reliance is being placed upon the use of online learning (Dearing, 1997; DfES, 2005). Often such systems are used to manage learning, present information and test learners in an entirely undifferentiated way, all users having exactly the same view of the system. With the development of increasingly large and complex computer applications and greater diversity in learner groups, consideration of individual differences has become an important issue in designing usable and useful applications.

Despite this increasing use, the impact of Information Technology on educational practice is generally less than has been predicted, even after more than fifteen years of investment in research, infrastructure, support and training. In some cases, online learning systems and applications simply reproduce existing paper-based material in textual or simple multimedia format and ignore the need for intrinsic motivation (Crook, 1997). It is often assumed that using computers for learning is motivational *per se.* Interaction between the learner and the learning system in many systems is often about simple navigation between screens and is not directed specifically to learning. There is a need to distinguish between real interaction and simple button pressing. Pedagogy is often overshadowed by system design considerations in the development of online and multimedia learning applications. For interaction to be beneficial to learning, it must involve thinking and engagement.

Another important issue in the design of online and multimedia learning materials is that of making them useful and usable to a wide range of learners. As class sizes grow, this is becoming an increasing problem in traditional face-to-face teaching. A good teacher is able to adapt to the learning needs and styles of the learners they are teaching. The ability to do this well is a great skill and it demands speedy feedback and sensitivity to the characteristics and needs of learners and how these affect teaching strategy. This is difficult with large class sizes, but it might be possible using computers, by means of a range of modelling techniques within the domain of Artificial Intelligence. A computer can learn a great deal about the characteristics, skills and abilities of a user. This information can be made available to teachers or to instructional computer environments. Although such approaches are mediated primarily through learner interactions with computers, information obtained about learners online can be used in a blended approach in other areas and contexts.

1.0 Blended Learning

Blended Learning relates to a learning programme where more than one delivery mode is being used. For example, face-to-face lectures may be supplemented by the use of multimedia or new learning technology, to facilitate interaction between large groups of learners and a teacher. Online-managed learning systems may provide video and audio conferencing facilities for remote learners or networked computers might be used in lectures, for example. The objective of the blended approach is to optimise the learning opportunities and to increase cost-effectiveness. It provides an opportunity for the matching of learning objectives, learning style or preference and delivery mode. It is assumed that this approach by itself will improve teaching and learning (Dean *et al,* 2001), though this has not yet been shown. However, there is an opportunity within a blended approach to use sophisticated information about learners' skills, knowledge and characteristics to provide or configure a learning environment optimised for individual learners, using the techniques of student modelling. We argue that Blended Learning is best when it is planned at an individual level, and information about learners can be used to inform the planning process.

2.0 Student modelling

Student modelling is a form of user modelling, applied to learning. There are several techniques or approaches that all have the following four problems to solve (Fischer, 2001):

- What aspects or characteristics of a user to model;
- How a student model can be represented within an application;
- How to inform and update a student model based on performance within a domain;
- What aspects of the interface to change for individual users.

2.1 Modelling approaches

Psychological user models rely on a set of psychological characteristics, so-called global descriptors, for each user, based upon assumptions about individual characteristics. These may include personality, cognitive skills, motivation, reasoning abilities, perceptual speed, memory, language skills, listening skills, visual skills, intelligence, age, gender and similar personal characteristics. Barker and colleagues (2002) found that it was difficult in their model to know what psychological aspects of a learner to model, how to obtain values for each learner, how to adapt these values based on interactions with the system, and how to configure the system based on the values held in a model for each individual.

Overlay models compare the user performance within a domain to some standard measures of performance, such as that of an expert user (the Expert model), and configure the presentation of information or remedial action accordingly (Brusilovsky, 1996). Another approach, using stereotype models, also known as Canonical models, assigns users into one or more stereotypic groups (e.g. novice, intermediate, advanced, and expert). In this way, all the members of the group share and inherit the same properties of their stereotype (Crow & Smith, 1993). We argue that a combined approach is able to overcome many of the limitations inherent in each of the above methods.

3.0 Constructivist approach to learning

Since early times there have been many attempts to understand how humans learn. No doubt these attempts will continue long into the future. In the early part of the last century, emphasis was placed on the most effective ways of providing instruction for learners, based upon ideas from the behaviourist school of psychology. The ideas put forward at that time were based upon theories derived from experimental work with animals, where changes in behaviour in response to external stimuli were seen as the most important outcomes of training. Behaviourist approaches have been employed extensively in the design of tutoring systems for humans from the 1950s to the present day (Crowder, 1960; Patrick, 1992).

In more recent times, psychologists have emphasized the importance of the human mind in so-called cognitive approaches to learning. Important classes of cognitive approaches are the constructivist theories of learning (Collins & Adams, 1977). These are based on the assumption that learning is an individual internal process that takes place in various external contexts. Constructivist approaches include such aspects of learning as:

- Personal autonomy and control over learning
- Active involvement and engagement with tasks
- Learning by doing rather than watching
- The importance of motivation in learning
- The importance of the learner as an individual with personal skills and motivations to learn

- Personal responsibility for learning
- Attention to the process of learning, rather than simply the content of learning
- Integration of new knowledge with existing
- Collaboration with others and the social aspects of learning
- The importance of situating learning tasks into a real context
- Attention to personal growth and development of learners.

There is a great deal of evidence that constructivist approaches are useful and important in the design and delivery of teaching and learning (Jonassen *et al,* 1999), especially with computers. It is probably true to say that learning materials and approaches based on instructivist theories are easier to develop, produce and evaluate than those based on constructivist ideas. The former simply require a plan for the delivery of content and a system of feedback. The latter require attention to individual needs, context and the development of personal strategies for learners. In these cases, learners following the same course may have very different experiences of learning, following different routes through their learning. It was important that the appropriate balance between instructivist and constructivist approaches to learning for each individual could be obtained in our modelling approach.

4.0 Intelligent tutoring systems and learning objects

Intelligent Tutoring Systems (ITS) are systems that adapt the delivery of teaching and learning based on the individual requirements of their users. The systems developed are often based on overlay type student models, although there are examples where global description models have been used in ITS (Barker *et al,* 2002).

There is a great potential for ITS to provide an individualised constructive learning environment that is able to employ features of overlay models and instructivist approaches as well as more constructivist approaches based upon a psychological student model. The development of such a system, based upon Learning Objects is described in the next section. In this approach, a composite student model was developed which was intended to combine features of instructivist and constructivist learning theories into a single application.

4.1 Learning objects

Learning objects are reusable objects, often multimedia and computer-based (but not always), that can be used in the design of learning programmes and courses. They may range from simple text or audio pieces, video and interactive applications, assessment objects and tasks, through to large group assignments and exercises. They are slotted together to produce learning systems. It is often claimed that they are, or at least should be, reusable and suitable for delivery in more than one module. Learning objects may be linked together by tutors to produce a recommended structure for learning, or can be seen as opportunities for learners to browse and select the most appropriate set of objects for their individual needs. It is claimed that the learner is able to gain benefit from this approach, leading to greater freedom, motivation, empowerment and differentiation as well as self-paced and constructive learning. Learning objects may also be efficient due to their potential re-use. Creating structured multimedia applications is expensive. They are often limited in the scope of their use to a few situations and rapidly go out of date with even small changes to modules. Learning objects can be modified or replaced as necessary in a course, without affecting the underlying structure of a module.

It is argued that the unstructured use of learning objects will move the burden of educational system design from the teacher or software developer to the learner and produces a motivating constructive learning opportunity. The experience of using and developing learning objects does not entirely agree with this view. Rather than interesting and constructive objects that a learner is able to engage with and integrate into his or her own learning, learners are sometimes presented with a mismatch of instructional bits and pieces that are delivered without planning, design or structure. Difficulties include deciding the relevance of objects to modules, academic level and context of use, structure of instruction or presentation, framework for delivery, granularity of objects, instructional intentions and learning objectives and the lack of a theory to guide their use. The use of a composite student model to structure and deliver appropriate learning objects that may be used instructively or constructively as the need arises within an ITS framework is the goal of the research reported here.

5.0 Components of the composite model

Our research in this area over the past few years has led to the development and testing of two student models, a domain based overlay type model and a psychological model, both intended for use in ITS applications. A composite student model, based on these ideas is proposed that employs features of both these approaches. The domain based model we developed was based upon work undertaken with colleagues into the use of Computer Adaptive Testing (CAT) (Lilley *et al,* 2004a, 2005). The psychological model is related to work with colleagues into the use of mental models in student modelling (Barker & Adisen, 2004, 2005; Adisen *et al,* 2004). In the next sections I will explain these two modelling approaches.

5.1 An overlay model based on Computer Adaptive Testing.

Two limitations of overlay models are difficulties in generalising to other domains and their reliance on instructivist learning theory. An overlay model based on CAT has the potential to overcome the first of these limitations. Traditional computer-based tests (CBTs) are not tailored towards individual learners, as the same fixed set of questions is administered to all students regardless of their proficiency levels within the subject domain. Such a static approach often poses problems for some learners, given that questions that might be too difficult, and therefore bewildering, for one learner might, at the same time, be too simple, and thus unchallenging, to another learner. By contrast, in a CAT the level of difficulty of questions is interactively selected to match the estimated proficiency level of individual learners. In summary, a CAT usually starts with a question of average difficulty. Correct responses will usually cause a more difficult question to follow. Conversely, an incorrect response will trigger a less difficult question to be administered next. An adaptive algorithm based on the 3-PL Model from Item Response Theory (IRT) was employed to select the questions to be administered to each individual learner. A detailed description of IRT is beyond the scope of this paper and the interested reader is referred to Lord (1980). The student model is based on a representation of the most probable proficiency level within a subject domain exhibited by the learner. Knowledge on students' proficiency levels is obtained and updated by unobtrusively monitoring and evaluating student performance during assessment of their knowledge in a domain (Lilley & Barker, 2003). One of the central elements of the 3-PL Model is the level of difficulty of the question database. In our CAT applications, subject experts were employed to rank test questions in order of difficulty. Question databases are also adapted and updated automatically, based on user performance over time. A calibration method based on Bloom's taxonomy of cognitive skills (Bloom, 1956) was employed as shown in Table 1.

The proficiency level obtained in this way is useful as a measure of performance in a subject, and because it provides additional information. The use of Bloom's taxonomy provides a link between performance on a test and a learning theory related to students' cognitive skills and understanding within a domain. An outcome of each test is the generation of a student profile based on a topic area within the subject domain, which is related to Bloom's taxonomy. We have argued that a CAT level uniquely identifies an important boundary between what a learner knows and does not know in a subject area. This boundary identifies not only ability in the domain, but also provides an estimation of cognitive skills. It identifies the unique boundary between what is challenging and motivational, what is too difficult at the current stage and what is too easy (Lilley & Barker, 2003). At this level a learner is challenged and not overwhelmed, or de-motivated by too simple tasks.

We have shown our CAT approach to be an efficient, useful and fair method of testing (Lilley & Barker, 2003; Lilley *et al,* 2004a, 2005). Our recent work has shown that the student model derived from CAT tests can be used to provide personalised automatic differentiated feedback for learners (Lilley *et al,* 2004b). An overlay model based on CAT is ideally suited to control the selection of the level and identity of learning objects for delivery to a learner in an ITS. In order to attend to the style of presentation and interaction, a psychological student model can be used in addition to the CAT profile to assist in such decisions.

5.2 A psychological model based on a student's mental model

A mental model has been described as: "The mediating intervention between perception and action. It provides a representation of functions, systems and processes which in turn, provide the means to interpret, to remember, to communicate information and to control performance" (Getner & Stevens, 1983).
A mental model plays a role in all phases of the use of a computer application. In such applications users rely upon a mental model for task planning and task delegation, taking actions, receiving and interpreting the system's reactions for both expected or the unexpected results. The success in using a system depends both on how well the mental model represents the system and on how well the system can adapt to a learner's natural mental models. It is likely, therefore, that building and

Table 1: Level difficulty (b) and its correlation with Bloom's taxonomy of cognitive skills.

Difficulty parameter *(b)*	Cognitive skill	Skill involved
$-3 \leq b \leq -1$	Remember	Ability to recall taught material
$-1 < b < +1$	Understand	Ability to interpret and/or translate taught material
$+1 \leq b \leq +3$	Apply	Ability to apply taught material to novel situations

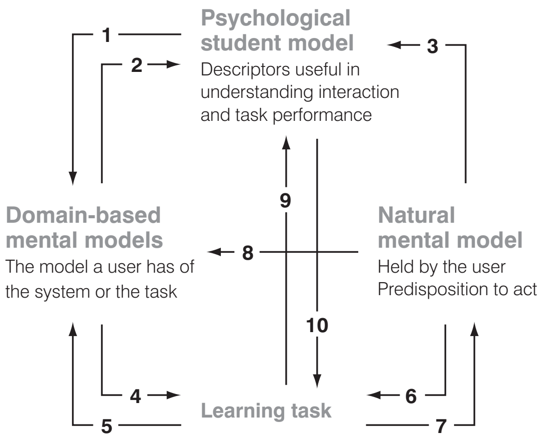
adapting a student model based on a student's psychological characteristics will be useful in terms of creating an appropriate model for a learning system. Two approaches present themselves when using such models:

- Adapt the system in consideration of a student's current mental model of a situation or task
- Adapt the student's interaction strategy in consideration of the current task or application

The second approach has been applied previously by traditional Artificial Intelligence (AI) approaches, such as adapting the students' mental model to the mental model embedded into the system. This will depend on performance in domain-specific environments, offering help and support customised to the student's problem solving state (Corbett *et al,* 2000).

Attempts may be made to change or adapt a student's mental model to those offered by the system. It is likely that students will better understand the attributes and behaviours of a system if it is the one based on their existing mental model, rather than using a different or inappropriate mental model (Webb, 1994). A possible approach is to combine these two approaches to psychological modelling. This strategy is shown Figure 1 and is an attempt to describe the relationship between tasks, the domain model (model of the system), the natural mental model (model held by the student) and psychological student model as a student performs a learning task within a given domain. The direction of primary interactions is shown by the arrows. See Adisen *et al* (2004) for more details of the model.

Our current research into psychological student models and their relationship to mental



1. The Psychological student model informs the Domain model.
2. The Domain model updates the Psychological student model.
3. The Natural mental model updates the Psychological student model.
4. Domain model influences the Task performance.
5. Tasks change the Domain model.
6. The Natural mental model influences the Task performance.
7. Task influences the student's Natural mental model.
8. Domain-based mental models are derived or based on Natural mental models.
9. Task performance updates the Psychological student model.
10. Psychological student model is used to assist the task performance.

Figure 1: The relationship between models and the system

models can be summarised as follows:

- Understanding the characteristics of mental models and the ways they can be obtained.
- Development of psychological student models related to mental models, including identifying and obtaining the psychological descriptors.
- Implementation of a student model in an adaptive learning application in a real context.
- Assessing the efficacy of the approach in such adaptive systems compared to other approaches.

The identification of psychological descriptors for our modelling approach has yielded interesting results related to verbal and visual skills profiles. These hold great promise as easily measurable and adaptable components of the model. We have also developed language testing tools that will provide a measure of language skills in learners. Learning styles and cognitive styles have been studied as potential components (Barker *et al,* 1997, 1999, 2000, 2002), though results from these and more recent studies have been less promising. The use of co-operation to obtain and to adapt values for psychological descriptors, despite some limitations, is likely to be important in this approach (Barker *et al,* 2000, 2002).

6.0 Composite student model

The components of the composite student model, described in the previous sections, have been implemented and tested. The next stage is to integrate the domain-based and psychological approaches into a single modelling approach and to implement and test the composite student model in real contexts. Figure 2 sets out our current composite model and shows how the components of the model relate to each other and how they will be used in the development of individualised Blended Learning objects.

This model is composed of parts of the psychological and the domain models and involves aspects of co-operation, mediated through an agent who may be human or computer-based. The purpose of the model is to inform the selection and presentation of learning objects as part of a learning task or a module. The selection of the object is based on four factors:

a) the student characteristics (psychological model or profile)
b) the student performance in the domain (the domain model based on CAT)
c) the current tasks to be performed
d) the set of learning objects available.

The psychological student model is based upon a set of descriptors for each learner, held in a user database. It is updated by user interaction with the interface and co-operatively, possibly mediated interactively, using an agent. In some cases, the agent could be a tutor, but normally would be a computer-based personality-type agent, or sometimes an invisible agent.

Psychological descriptors such as language ability, learning style and personal skills profile as described previously, as well as academic approaches adopted, are used primarily to help decide upon the style and nature of learner interaction with the interface and the presentation strategy for the material. The domain model is based on Computer Adaptive Test profiles, obtained either by testing during the application, or read from student profiles held in the databases. The domain model is used to inform the selection of learning objects based on their complexity and level.

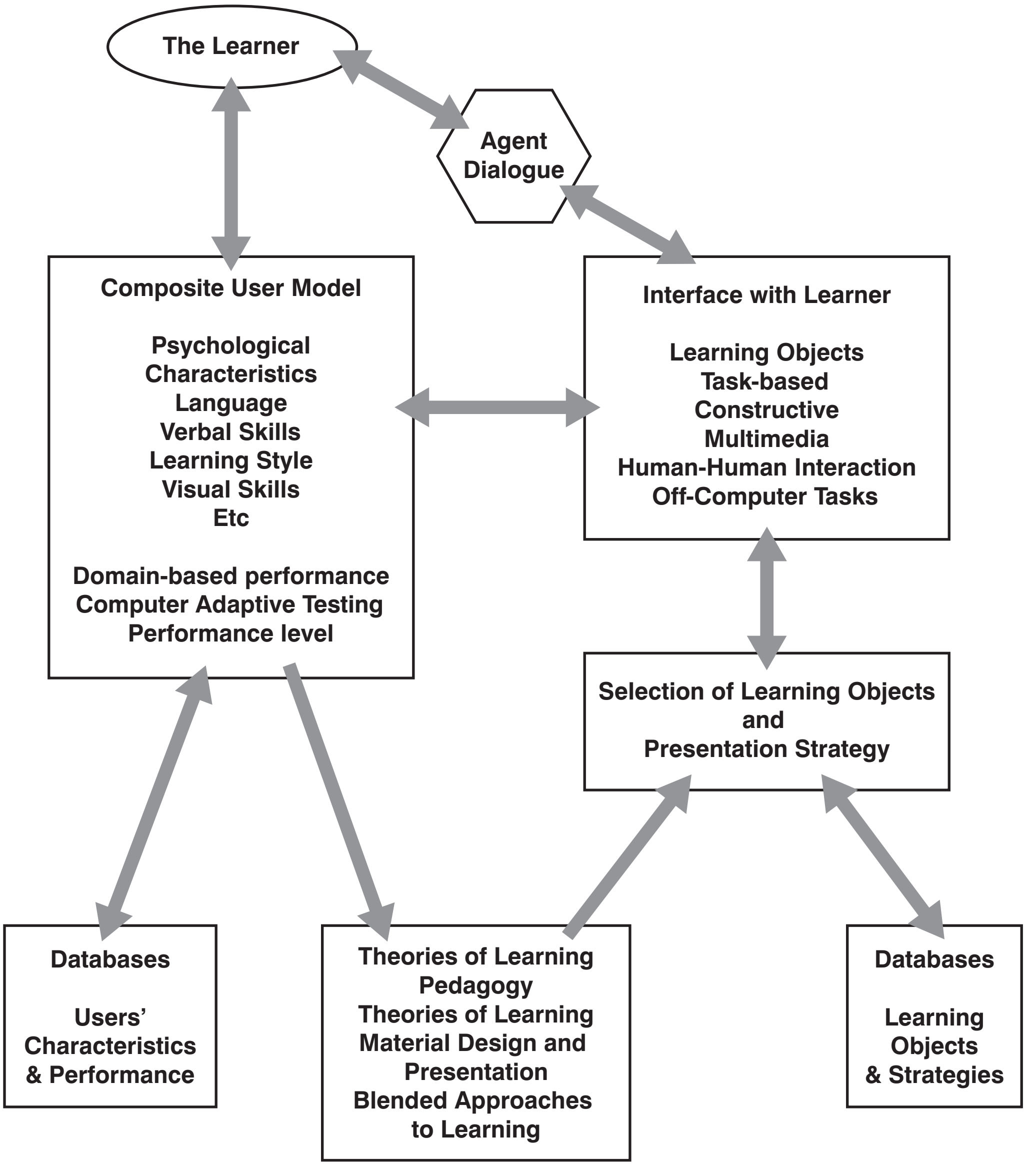


Figure 2: The current composite student model

7.0 A blended theory of design

It is hoped that the selection of appropriate learning objects for an individual at a particular stage in their learning will be useful in providing an individual learning experience. If this is to be a beneficial experience, it is important to move from theories of learning to theories of instructional design. This is perhaps the most difficult stage in the process. Given a set of individual characteristics for a learner, what is the best learning environment to provide on their behalf? Questions such as what features of the model are relevant in a given situation; what mix of constructive and instructive strategies should be used; what materials (multimedia, paper, web-based etc.), what delivery mode (online, face-to-face, tutorial etc.) have yet to be answered (Merrill, 2005). At present, such decisions about how to provide learning in complex blended environments are being made continuously by educators who establish and use these environments without the benefit of such detailed knowledge of their learners at an individual level. We are currently engaged in designing and testing a whole range of learning objects, from simple, fine-grained objects intended to deliver one or two ideas, to complex objects that include face-to-face meetings and group activities (Doolan & Barker, 2003, 2004) and individualised feedback (Lilley & Barker, 2004b). We are developing applications, based on similar ideas to Intelligent Tutoring Systems, that implement our composite student model to inform selection and presentation of these objects. Our experience has shown that it is possible to understand a great deal about the needs of individuals and to help configure learning opportunities according to these needs. It will be important to use a range of quantitative and qualitative evaluation strategies and techniques to assess the effectiveness of this approach. Earlier work (Barker & Barker, 2001) has shown that it is possible to understand the most complex interactions that take place when people learn, provided that the context of learning is clearly described. It is our goal that the skills and attributes of each learner will be known to the system and that this information will be used to assist the learner in selecting the most appropriate blend for their needs in their own context.

References

Adisen, A., Barker, T. & Britton, C. (2004) ‘Investigating the potential of mental models in adaptive user modelling’, *Proceedings of HCI 2004: Design for Life,* Leeds Metropolitan University, September 6-10. Volume 2, 161-163.

Barker, T. & Barker J., (2001) *Proceedings of the 4th International Conference on Cognitive Technology: Instruments of Mind, Lecture Notes In Computer Science;* Springer-Verlag London, UK Vol. 2117, 203-213.

Barker, T., Jones, S., Britton, C. & Messer, D.J. (1997) ‘The development of task-based differentiated learning materials for students with learning difficulties and/or disabilities’. *Proceedings of CAL-97 conference,* University of Exeter, March 1997.

Barker, T., Jones, S., Britton, C. & Messer D.J., (1999) ‘Report of a pilot study of an individually configurable multimedia learning prototype based on a co-operative student model of learner characteristics’. *Proceedings oft ALT-C99,* University of Bristol, September 1999.

Barker T., Jones S., Britton C. and Messer D. J., (2000) ‘The use of a co-operative student model of learner characteristics to configure a multimedia application’, *Technical Report, University of Hertfordshire, Division of Computer Science,* August 2000.

Barker T., Jones S., Britton C., Messer D. (2002). ‘The Use of a Co-operative student model of learner characteristics to configure a multimedia application’. *User Modeling and User Adapted Interaction* **12**: 207-241

Barker, T. & Adisen, A. (2004) ‘Visual Skills Analysis and Riding’s Cognitive Style’. *Proceedings of the European Learning Styles Information Network Conference,* University of Durham.

Barker, T. & Adisen, A. (2005) ‘Experiments on Visual and Verbal Skills: The development and testing of a skills profile’, *Proceedings of the European Learning Styles Information Network Conference,* University of Surrey.

Bloom, B.S. (1956) *Taxonomy of Educational Objectives.* Book 1, Cognitive Domain, New York: David McKay Company, Inc.

Brusilovsky, P. (1996) 'Methods and techniques in adaptive hypermedia'. *User Modeling and User-Adapted Interaction,* **6** (2-3), 87-129.

Collins, A. & Adams, M.J. (1977) 'Comparison of two teaching strategies in: Computer Assisted Instruction'. *Contemporary Educational Psychology,* **2**, 133-148.

Corbett, A., McLaughlin, M. & Scarpinatto, K. C. (2000) 'Modelling Student Knowledge: Cognitive Tutors in High School and College'. *User Modeling and User Adapted Interaction,* **10**, 81-108.

Crook, C. K. (1997) 'Making hypertext lecture notes more interactive: undergraduate reactions'. *Journal of Computer Assisted Learning,* **13**, 236-244.

Crow, D. & Smith, B. (1993) 'The role of built-in knowledge in adaptive interface systems'. *Proceedings of Intelligent User Interfaces,* 97-104.

Crowder, N.A. (1960). 'Automatic tutoring by means of intrinsic programming', in A.A. Lumsdaine and R. Glaser (Eds.) *Teaching Machines and Programmed Learning,* Washington DC: National Education Association.

Dean, P., Stahl, M., Sylwester, D., & Pear, J. (2001) 'Effectiveness of Combined Delivery Modalities for Distance Learning and Resident Learning'. *Quarterly Review Of Distance Education,* **2**(3), 247-254.

Dearing, R (1997) *Higher Education in the learning society: Report of the National Committee of Inquiry into Higher Education,* London: NCIHE Publications (HMSO).

DfES (2005) The Department for Education and Skills e-Strategy, *'Harnessing Technology: Transforming learning and children's services'.*

Doolan, M.A. & Barker, T. (2003) 'Measuring The Effectiveness of StudyNet In The Context Of Online Learning Environments', in *Proceedings of the Computer Aided Learning (CAL) 2003 Conference,* April 8-10, Belfast.

Doolan, M.A. & Barker, T. (2004). 'Evaluation of the use of "StudyNet" a Managed Learning Environment to support collaborative working and collaborative learning'. *Proceedings of 10th International Conference on Technology Supported Learning & Training, Online Education,* Berlin 2004.

Fischer, G. (2001) 'User Modeling in Human-Computer Interaction'. *User Modeling and User Adapted Interaction,* **11**, 65-86.

Gentner, D. & Stevens, A.L. (1983) *Mental Models.* Lawrence Erlbaum, Hillsdale, NJ.

Jonassen, D.H., Peck, K.L. & Wilson, B.G. (1999) *Learning with Technology: A Constructivist Perspective.* New Jersey: Merrill, Prentice Hall Inc.

Lilley, M. & Barker, T. (2003) 'Comparison between computer-adaptive testing and other assessment methods: An empirical study', in *Research Proceedings of the 10th Association for Learning and Teaching Conference.* The University of Sheffield and Sheffield Hallam University, United Kingdom, pp.249-258.

Lilley, M., Barker, T. & Britton, C. (2004a) 'The development and evaluation of a software prototype for computer adaptive testing'. *Computers & Education Journal,* **43**(1-2), 109-123.

Lilley, M., Barker, T. & Britton, C. (2004b) 'The generation of automated student feedback for a computer-adaptive test', in *Proceedings of the 8th Computer-Assisted Assessment Conference,* Loughborough University, United Kingdom.

Lilley, M., Barker, T. & Britton, C. (2005). 'The generation of automated learner feedback based on individual proficiency levels' in *Proceedings of the 18th International Conference on Industrial & Engineering Applications of Artificial Intelligence & Expert Systems, Lecture Notes in Artificial Intelligence* **3533**, pp.842-844.

Lord, F.M. (1980) *Applications of Item Response Theory to practical testing problems.* New Jersey: Lawrence Erlbaum.

Merrill, M.D. (2005) 'First Principles of Instruction: Instructional Design', in C.M. Reigeluth & A. Carr (Eds.) *Instructional Design Theories and Models III.* New Jersey, Lawrence Erlbaum.

Patrick, J. (1992). *Training, Research and Practice.* London, Academic Press.

Webb, M.E. (1994) 'Beginning computer based modeling in primary schools;. *Computers in Education,* **22**(1-2), 129-144.

Biographical notes

Trevor Barker has been a lecturer in Computer Science at the University of Hertfordshire for about eight years. He obtained his Ph.D. in Computer Science at this university for research into student models and multimedia learning applications. He has Master of Science degrees in applied physics and in scientific & numerical computing and a first degree in science. At present Trevor is supervising six research students in the area of educational technology, student and user modeling and computer interfaces and Blended Learning.