# 4<sup>th</sup> International Conference on Artificial Intelligence and Education

University of Amsterdam May 24, 25, 26 1989

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	Thursday, M	lay 25 1989 (d	lay 2)
9h00	Invited speaker: Marc Eise	nstadt (AI in (Education in AI))	
0h00	COFFEE / TRANSFER		
	D 009	D 109	C 117
10h30	Twidale Student Models Intermediate representation for student error diagnosis and support.	Shute Cogn. Res. An Investigation of Learner Differences in an ITS Environment: There's No Such Thing as a Free Lunch.	Moyse Teach. Stra Knowledge Negotiation Implies Multiple Viewpoints.
11h00	Beeson	Singley	Nathan
8	The User Model in MATHPERT: An Expert System for Learning Mathematics.	The Algebra Word Problem Tutor.	An Unintelligent Tutoring System for Solving Word Algebra Problems.
11h30	Derry Fuzzy Remedies to Problems in Diagnostic Modelling.	Hall Qualitative Diagrams: Supporting the Construction of Algebraic Representations in Applied Problem Solving.	Sharples The Radiology Tutor: Computer-Based Teaching of Visual Catagorisation.
2h00		LUNCH	
	D 009	D 109	C 217
13h15	Evertsz Student Models	Derry Cogn. Res.	Cumming Teach. Stra
	Refining the Student's Procedural Knowledge Through Abstract Interpretations.	Characterizing the Problem Solver,	Collaborative Intelligent Educational Systems.
13h45	Newman Is a Student Model Necessary? Apprenticeship as a Model for ITS.	Mioduser Student's Representations of Declarative and Procedural Knowledge.	Brecht Planning the Content of Instruction.
4h15		TEA	
	D 009	D 109	C 217
	P y Recognition	Swan Cogn. Res.	Boulet Shells / Too
14h45		The Teaching and Learning of	A Design Task Advisor.
14h45	MENTIONEZH: An I.T.S. about 4 geometry.	Problem Solving Through Logo Programming.	
14h45 15h15	· · · · · · · · · · · · · · · · · · ·	Problem Solving Through Logo	Selker The COgnitive Adaptive Computer Help (COACH) Interface.
	geometry. Greer Incorporating Granularity-Based Recognition into SCENT.	Problem Solving Through Logo Programming. Schröder Instruction-based acquisition of the operational knowledge for a functional, visual programming	The COgnitive Adaptive Computer
15h15	geometry. Greer Incorporating Granularity-Based Recognition into SCENT.	Problem Solving Through Logo Programming. Schröder Instruction-based acquisition of the operational knowledge for a functional, visual programming language.	The COgnitive Adaptive Computer Help (COACH) Interface.



## Instruction-based acquisition of the operational knowledge for a functional, visual programming language

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#### **Olaf Schröder and Klaus Kohnert**

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This contribution deals with instruction-based knowlegde acquisition in a fairly complex but well-defined domain. The domain is the operational knowledge about the interpreter of ABSYNT, a functional, visual programming language which was developed in our project. Runnable specifications of the ABSYNT-interpreter were translated into sets of visual rules, serving as instructional material for students to acquire the operational knowledge. We are concerned with the following questions:

- How do subjects acquire the operational knowledge while simulating the interpreter of ABSYNT under guidance of the Instructional material?
- In what respects and why does the operational knowledge gained by the students (the mental representations they construct) differ from the instructional material?

If the mental representation of the operational knowledge corresponds to the instructional material, then specific hypotheses about performance characteristics in different computation situations can be derived. An experiment was conducted in which pairs of programming novices acquired the computational knowledge for ABSYNT by computing the value of ABSYNT-programs with the help of the instructions, thus simulating the interpreter. The hypotheses were disconfirmed, indicating that there are structural differences between the acquired mental representation of the operational knowledge for ABSYNT and the instructional material. There is evidence that the mental representation of the operational knowledge consists of larger units than the instructional material, leading to the following hypotheses about the acquisition process and the mental representation of the operational knowledge:

- · The operational knowledge is represented as a net of rules.
- The rule net is continuously adapted to novel situations by problem solving methods such as working backward with the help of the instructional material: A new sequence of rules and goals is planned ahead, and then the rule net is modified accordingly.

. The rule net is improved by the chunking of rules due to practise.

A computational model gets currently implemented. Its aim is to reproduce a) the sequence of computational steps produced by a pair of subjects, b) categories of verbalizations prior to each computational step, and c) to enable specific predictions about the acquisition of the operational knowledge. The model currently gets specified by a detailed analysis of the data. Parts of the specifications are implemented by now.

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## The Case for Formalising Student Models (and Intelligent Tutoring Systems generally)

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### John Self

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Intelligent tutoring systems research is at a pre-scientific stage of development. There is no 'theory of ITS' and newcomers to the field may read recent ITS texts (such as Wenger (1987) and Mandl and Lesgold (1988)) assured that they will encounter no formal symbols and the minimum of technical content. The assumption that this state of affairs is unavoidable, perhaps even desirable, is having an unfortunate influence on the methodology and quality of ITS research.

This paper will consider the prospects for (and potential benefits of) formalising aspects of ITSs, in particular, student models.

We will first try to draw some lessons from analogies with other educational and engineering enterprises, and from developments in educational philosophy. The implicit philosophy of ITS - which will be developed by reviewing attempts to specify principles, if not a theory, of ITS (e.g. Hartley (1973), Anderson et al (1986), Ohlsson (1986), Wenger (1987)) - will be seen to be limited. Once a sounder foundation for ITSs has been specified, it becomes possible to identify the elements of a theory of ITS. These elements lie within (formal) AI, in areas such as belief logics, reason maintenance, meta-level architectures, and discourse models - areas from which ITS research has been divorced.

We may then develop a broader notion of 'tutoring' than that implicit in ITS research and one which pays more than lip-service to the view that learning is a process of construction, not accretion. In particular, we will consider the benefits of a genuinely collaborative style of interaction.

Finally, we will consider the evaluation of ITSs. Here is a prime example of the malign influence of the present perceived state-of-the-art. The demand for empirical evaluations in realistic settings may have blinded ITS designers to the view that, in the longer term, these are precisely what they should be designing to avoid. The present experimental strategy has (in apparent paradox) led to the ITS field acquiring an unenviable reputation for the nondelivery of 'working systems'.