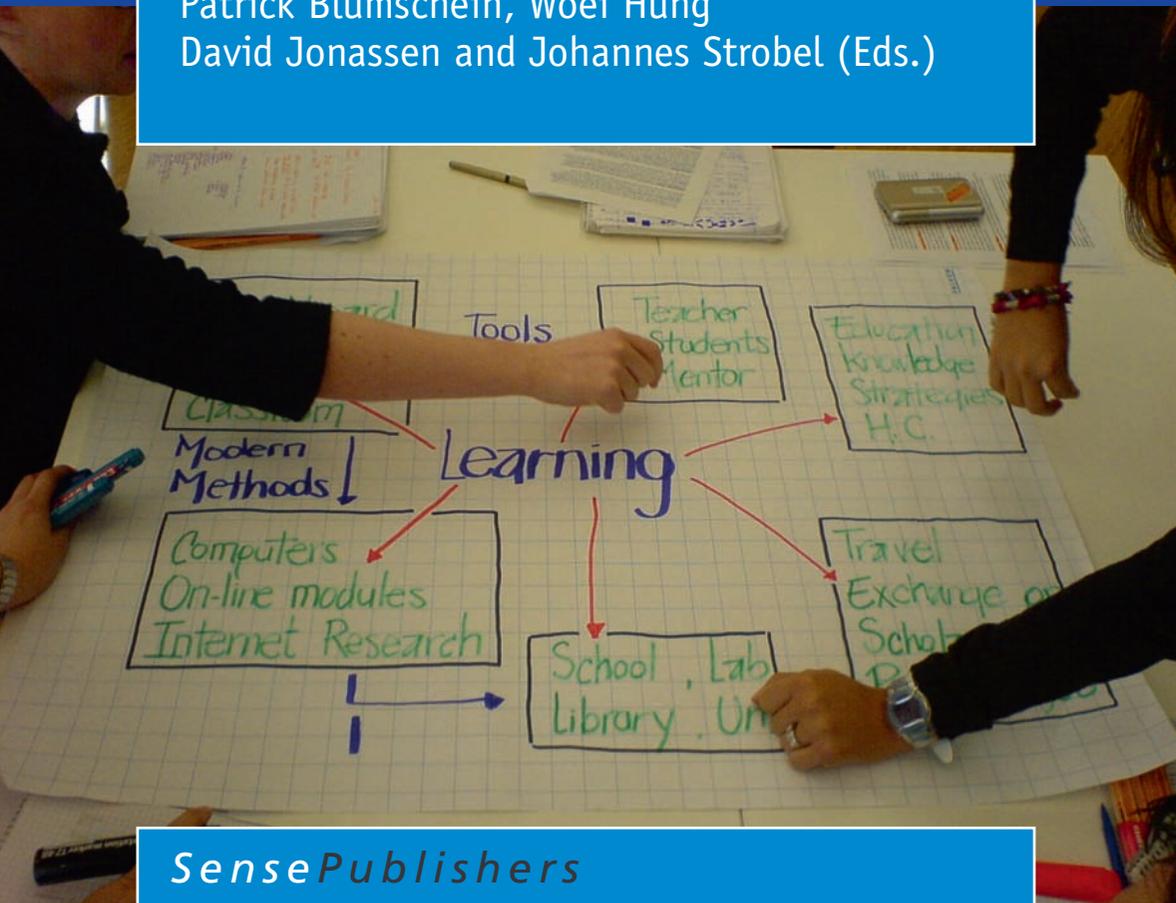# Model-Based Approaches to Learning

Using Systems Models and Simulations to Improve Understanding and Problem Solving in Complex Domains

Patrick Blumschein, Woei Hung
David Jonassen and Johannes Strobel (Eds.)

*Sense*Publishers

MODEL-BASED APPROACHES TO LEARNING: USING SYSTEMS MODELS AND SIMULATIONS TO IMPROVE UNDERSTANDING AND PROBLEM SOLVING IN COMPLEX DOMAINS.

MODELING AND SIMULATIONS FOR LEARNING AND INSTRUCTION

Volume 4

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Scope

Models and simulations have become part and parcel of advanced learning environments, performance technologies and knowledge management systems. This book series will address the nature and types of models and simulations from multiple perspectives and in a variety of contexts in order to provide a foundation for their effective integration into teaching and learning. While much has been written about models and simulations, little has been written about the underlying instructional design principles and the varieties of ways for effective use of models and simulations in learning and instruction. This book series will provide a practical guide for designing and using models and simulations to support learning and to enhance performance and it will provide a comprehensive framework for conducting research on educational uses of models and simulations. A unifying thread of this series is a view of models and simulations as learning and instructional objects. Conceptual and mathematical models and their uses will be described. Examples of different types of simulations, including discrete event and continuous process simulations, will be elaborated in various contexts. A rationale and methodology for the design of interactive models and simulations will be presented, along with a variety of uses ranging from assessment tools to simulation games. The key role of models and simulations in knowledge construction and representation will be described, and a rationale and strategy for their integration into knowledge management and performance support systems will provided.

Audience

The primary audience for this book series will be educators, developers and researchers involved in the design, implementation, use and evaluation of models and simulations to support learning and instruction. Instructors and students in educational technology, instructional research and technology-based learning will benefit from this series.

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DEDICATION

For Anna, Ferdinand, Kaspar, and Katharina
who gave me the power to keep this project on going.
Thanks to Mike Spector and Norbert M. Seel for their confidence.
Patrick Blumschein

For Audrey, who brought me a new outlook on life.
Woei Hung

To Johannes Strobel, student, friend, and teacher
David Jonassen

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J. MICHAEL SPECTOR

FOREWORD

This volume was originally conceived by David Jonassen and two of his former students. Authors were recruited to contribute, but due to missed deadlines and people transferring positions, the initial opportunity to publish was missed. I was one of those original contributors, and I had helped recruit several others. When it was learned that the volume would not be published, several of the authors contacted me and asked if there was something that I could do. Fortuitously, together with Norbert Seel and Konrad Morgan, I had initiated a book series closely related to the topic of this volume with Sense Publishers. Quite naturally, I proposed publishing the work in that series. This would require a slightly different editorial team, so I also proposed Patrick Blumschein as the lead editor, partly because he was located in Europe not far from the publisher and several of the key authors. Peter de Liefde at Sense Publishers and my series co-editors agreed, as did Patrick. I am happy to report that we have managed to keep the work alive.

This volume is important for a number of reasons. In an important sense, it represents the heart and soul of the Modeling and Simulations for Learning and Instruction series edited by Spector, Morgan and Seel for Sense Publishers. While we already have published several volumes in that series, this is the first comprehensive volume to specifically address the core topic of Model-Based Approaches to Learning: Using Systems Models and Simulations to Improve Understanding and Problem Solving in complex Domains.

Among the core issues addressed in this volume are the distinctions between learning from models, learning with models, and learning by modeling. The traditional approach to model-based learning involves prescriptions and guidelines for developing models and simulations in support of various learning objectives. That traditional approach is not abandoned in this volume. Rather, it is supplemented by a cognitive perspective on how people inherently make use of models in interpreting their experiences. Internally constructed representations are one kind of model and they are indeed a critical factor in learning. Additionally, making the creation of external representations – another kind of model – a core learning activity is yet another approach to model-based learning.

Simulations require the existence of an underlying model – an executable mathematical model that can be deployed so that values change with the passage of time and circumstances within the model itself. Interactions with the simulation can help learners develop an understanding of the dynamic relationships and their complexity in a given problem domain. This kind of model-based learning has also existed for some time, but how well and in what ways simulation-based learning can support the internal construction of knowledge and development of skills has not been well explored in the research literature. Nor has it been established

how to construct sequences of learning activities centered around an interactive simulation. These issues are explored herein, and our hope is that this volume will encourage more empirical research of this kind.

In addition to the critical differences among different approaches to model-based learning, this volume explores innovative uses of models in the areas of assessment, feedback and collaboration. Collaborative model-building activities can be an effective form of group learning. Using models constructed in response to problem scenarios also can be an effective assessment methodology. Moreover, individually constructed models as well as group constructed models can be woven into a learning sequence as feedback and prompts for reflection.

The very notion of a model cuts across many dimensions and is especially rich with regard to the potential to support learning. A model may be internally constructed by an individual. A model may be an artifact constructed by one or more individuals. A model may be mathematically articulated so that it can support a simulation. A simulation model may be interactive allowing one or more individuals to input values and make predictions about outcomes. Interactions with a simulation may lead individuals to alter existing internal mental constructs or possibly create new ones. The creation of an external model can deepen one's understanding of a complex domain. Such external artifacts may be used to assess progress of learning and the development of expertise.

The question is not to model or not to model. Humans model instinctively. It is part of our nature to model. We cannot help but created internal representations of things we experience, especially those that are new or confusing. We cannot help but talk about those experiences with others. Both of these natural activities involve models. Humans are model builders and users. It is what we do. It would foolish to overlook this modeling aspect of our nature when it comes to learning and instruction. Models are rich in terms of potential to support learning. This volume is rich in terms of what it offers with regard to model-based learning. We hope that both researchers and educators will benefit from the research presented here.

J. Michael Spector
Tallahassee, Florida
11 February 2008

PATRICK BLUMSCHEIN

PREFACE

This book provides a state-of-the-art review of modeling for learning in complex domains. Topics covered include the foundations of knowledge structures and mental model development, modeling for understanding, modeling for assessment, individual versus collaborative modeling, and examples of the use of simulations to support learning and instruction in complex, cognitive domains. The thread tying these chapters together is an emphasis on what the learner is doing and specifically on having learners engaged in modeling and simulation construction rather than merely interacting with constructed simulations.

If learning is an active self-directed process of human adaptation to environmental circumstances, than instructional designers have to prepare learning environments which enable learners to perform in this regard. Human learning either yields to manage new situations or improve efficacy of known behavior (Piaget, 1977). Besides this assumption the human mind is able to create whole new worlds without any feedback from the outside world – an outstanding human quality (Kierkegaard & Fichte; De Bono, 1968). And to even surpass this, humans are probably the only creatures who can simulate complex scenarios in mind (Seel, 1991). The theory of model-based learning and instruction (Seel 2003; Blumschein 2008) takes most of those assumptions into account, when asking how we model the world. Pretty close to this question Norman (1994) asks what are the *Things That Make Us Smart*? A possible answer to this question is, that we do use tools - mindtools (Jonassen 1996). Usually learners use simulations and other computer-based tools as applications which have been designed by the instructors. The learners don't get insights in the design of the tools itself, that is why they don't understand the functions. These are called black box models. Engaging learners in understanding and building such simulations is a great challenge but crucial for critical thinking. Such models would be called glass box models. The act of modeling in this vein needs to include reflection upon our thinking processes and the function of the tools which we apply for modeling (meta cognition sensu Flavell, 1979). On the one side, mental models could be understood as intra individual thinking tools whereas drawings, texts, and simulations on the other side are external (mind) tools. These external tools can be used to generate models as well. Following this path, Spector mentions in the foreword of this book, "humans model instinctively. It is part of our nature to model". Applying our model - our new knowledge - in the outside world is both crucial to extend our cognitive processing capacity, like embedding a "second level cache", and increasing validity and reliability of the models by testing the hypothesis in the environment. It is of great importance to see all the chapters in this book as contributions to the question how people think, how they learn and how we can support those

phenomenons. The reader finds these roughly unfolded topics in this paragraph discussed in more detail in the following chapters in this book. However, another "analogue model" for a model-based approach to learning and instruction will be layed out in the following paragraph.

Several approaches following this cognitive and model-based vein of learning and instruction can be found in educational science in the last decades (for a overview: Forbus & Feltovich, 2001; Lajoie, 2000). One very famous and well known is the approach of the CTGV people: The Cognition and Technology Group at Vanderbilt (CTGV, 1997). The most prominent model out of this group is probably the one called Anchored Instruction. Starting with a mean theory of human cognition (Bransford, 1989; Bransford et al., 2004) the group developed video-based learning scenarios, which engaged students in situated problem-solving environments. Over the years the approach has been further developed. This lead to the development of more and more tools fostering learner's thinking processes (Adventure Player, STAR.legacy, SMART). As you can imagine, computers do play a crucial role within this approach as multifunctional tools. Actually the Teachable Agents (Biswas et al., 2001) is the most prominent product emanated from the Anchored Instruction concept. In the first designs of learning environments in the early 1990th students were solely animated to solve, for instance distance-calculation problems shown in the video. All other activities of problem-solving took place in the social arrangement of the school classroom with quite some support by the teachers and their material. Nowadays, in the Teachable Agents model, the student works with an agent. This radically changes the role of the learner from "learning by doing" to modeling "learning by teaching". In this specific scenario "Betty" is the teachable agent who has to solve the problems (Crownover, 2007). Thereby several tools help the student to assess data and check for valid solutions. As a theoretical foundation Biswas and Schwartz (Blair et al., 2006) developed 4 design principles for the Teachable Agents: (1) Use explicit and well-structured visual representations, (2) enable the agent to take independent actions, (3) model productive learner behaviors, and (4) include environments that support teaching interactions. This also goes along with the postulates of designing effective learning environments that fosters critical thinking and problem-solving (Pellegrino, 2007; Bransford et al., 2000). First is said that learning environments need to be learner centered. Therefore taking into account what the very learner brings in to the educational setting is evident. The most prominent factors for that is the prior knowledge and prior experience (Ausubel, 1968; Bransford et al., 2004). Learning environments need also to be knowledge centered, which means they need well-organized bodies of knowledge – possibly in form of expert models. Last but not least, learning environments should focus on assessment. Students need qualified feedback in their learning processes to be able to understand how they perform and to find out if they are still on the right track to reach the goal. Summing up the research and development of the CTGV they have had a great emphasis in building learner models, teaching models, assessment models and modeling learning environments (Pellegrino, 2007). This book deals with all of these focal points from the perspective called learning by system modeling and it

therefore provides an extension to the glass-box approaches: The book explores the learning impact of students when constructing models of complex systems.

All the authors of the 15 chapters in this book have certainly a great emphasize on human learning processes from a model-based perspective. However, we find several focal points. Therefore the book is divided in three sections. In the first section we have several authors dealing with theoretical fundamentals of modeling, simulation, assessment and problem-solving. In the second section we gain insights to the meaning of learning by modeling, and last but not least we unfold possibilities to learn how to model for both, students and instructors. In addition we introduce several tools for modeling. In the afterword we discuss where we can go from there to open the road for further perspectives of model-based learning and instruction. In the remainder of this section we shortly overview the chapters of the book to display the red line in more detail.

The first part of the book provides a theoretical introduction to model-based approaches to Learning. Seel and Blumschein start with the topic of model-based learning with simulations from a learning psychology perspective. The authors also discuss how emergent technologies immerse in learning and instruction. For that reason new media and new means of technology open at least a two fold challenge. First, new technology changes our daily live dramatically, which compel people to adjust and create appropriate competencies to deal with that. Second it opens new ways for educational purposes. In every respect simulations play a crucial role for educational purposes like enhancing dynamic thinking and operating in abstract domains, which where inaccessible before. However it's a matter of cognitive processing that enables a learner to act successful. Mental models may be generated, elicited or adjusted, improved and tested with system modeling. Exploring system modeling and simulations for learning environments may enhance direct and qualified feedbacks for learning processes, as claimed by educational psychologists all times. With these topics the chapter of Seel and Blumschein opens up the field of system modeling and simulations discussed in this book.

In chapter 2 Seel, Ifenthaler and Pirnay-Dummer show different techniques to diagnose mental models. As mental models are theoretical constructs of how human cognition works in the state of problem-solving, they are not observable straightforward. Several researchers yet have applied procedures to diagnose mental models like think aloud protocols, structure formation techniques, concept-mapping, causal diagrams and more recently the DEEP methodology (Spector in this book). All of them are described in the light of mental models in this chapter. Seel et al further-on show how their own tools SMD and MITOCAR can help to diagnose not only a concept of a mental model but also the progression of mental models in thinking and learning processes. With these techniques the authors carry forward both traditions in problem-solving research, the US American one and the European perspective. Two major questions from this type of research are: How can we describe and compare the difference between expert models and novice models? How can novices proceed to become expert problem-solvers? Another interesting research question is: Can an artificial system provide expert-like models

to aid novices learning processes? Even so it still remains difficult to gain a high validity by diagnosing mental models, the suggested methods by the authors of this chapter show highly automated procedures for these types of diagnosis which can at least make assessments ways faster.

Hung shows in chapter 3 how system modeling can be a tool for enhancing students' development of conceptual understanding of a domain. Therefore he argues for integrating systems modeling into instruction. The common practice of demonstration of worked examples is not helpful per se to understand system processes behind the surface of a problem. Instead system thinking should be taught to help students create adequate mental models. Such models have to represent the problem space of a problem. Students can represent such a problem space when they are able to understand the conceptual framework of the problem. Hung argues that system modeling evolves students' problem solving competences, because it displays relationships and interactions of elements, the non linearity of processes and shows the formalisms and mechanisms of a problem. Applying system modeling further-more helps students to articulate their cognitive processes and thereby validate concepts through communication with others. System modeling therefore helps students to become effective problem solvers.

Part two of the book deals with how people learn by modeling. In chapter 4 Jonassen discusses systems modeling tools to construct models of cognitive processes and shows how modeling software like STELLA can be used to help students building such models and reflect upon their thought processes. He reports a case study where students built models of motivation and through running the built simulation they could test their assumptions and also compare their model with those developed by other student groups. He also highlights the importance of comparing one's own conceptions with those of other groups for meaningful learning. In addition Jonassen discusses how systems modeling software can help to assess students' models and help to compare them with expert's models. Limitations of systems modeling like high demands on working memory, the necessity of learning the tool versus focus the conceptual change process, and critical representation of "real" world processes through modeling seem to be yet unsolved problems.

In chapter 5 Carney, Forbus, Il and Fisher are asking how modeling can foster analogical reasoning. Underlying Gentners (1989) theory of structure mapping, the authors describe analogical reasoning as alignment, comparison, transfer, and creation of abstract knowledge. Modeling can help students understand different phenomena when using the same modeling logic or providing representational building blocks in a learning environment. Carney et al use Vmodel, a product from the Qualitative Reasoning Group at Northwestern University, which is based on Forbus' (1984) Qualitative Process Theory to provide such a modeling environment. A case study with 7th grade students shows how modeling in this environment works. The starting point of this research was that resources like gasses, water or energy are finite. In the following the instructor asked the students to model what would happen to a mouse sitting in a sealed bell jar over time. After introducing them concepts of plants and photosynthesis, they were again asked to

implement this knowledge in their model. In an final interview the instructor asked what would happen to a candle in such an environment. To solve this problem, students had to draw analogies of burning and breathing. The reported interviews demonstrate very authentic how thought processes of the subjects are related to the model environment.

In chapter 6 Reimann and Thompson suggest using more agent-based modeling systems and show how this software can be applied in the field of environmental education. The Authors compare system dynamics modeling with agent-based modeling to see how external representations can be helpful for problem solving. System dynamics have a strong representational advantage as they use a graphical language which is easy to use. However, they hardly allow users to describe systems on multiple levels. On the other hand agent-based systems offer the chance to combine social and physical systems, including the role of the individual. Yet, they need to be extended from a pedagogical point of view to more effectively serve the needs of learning and instruction. The authors show the pros and cons of these approaches, provide criteria for decision making, and suggest a concept of learning complex environmental systems. A case study shows how this could be realized.

In chapter 7 Hillen and Gonzales suggest to use dynamic stories to compensate the weakness that most people involved in problem solution processes can hardly understand system dynamic models. The authors suggest stories like Schank (1993) introduced them to learning a while ago. Matching stories and systems dynamic models elicits dynamic stories. Dynamic stories are generated out of a systems dynamics model. With an example from an oil platform they show how dynamic stories can be developed and applied. Three parts of dynamic stories are discussed as situation, problem, and solution episodes in such stories. Users will be able to better understand different decision scenarios based on the simulation model underlayed of the stories.

Spector introduces "The DEEP Mehodology for Assessing Learning in Complex Domains" (Spector & Koszalka, 2004) in chapter 8. Experts and Novices were asked to mark things in a given text which are helpful for a given problem scenario. Further more they should also explain their items and develop a problem solution. In addition, other possible solutions should be displayed as well. Expert conceptualizations were mark able different to novices', experts identified more factors, and were more detailed in their description. The Deep tool shows how Experts and Novices behave in different domains, and what their typical problems are like. Unlike think-aloud protocols DEEP can highly efficient serve as a diagnosis tool for a large amount of individuals.

In chapter 9 van Borkulo, van Joolingen, Savelsbergh and de Jong have developed a test to access knowledge of dynamic systems, higher-order reasoning and domain specific knowledge. The authors are especially interested in analysing learning outcomes depending on different instructional designs. In this vein they distinguish between modeling, learning with simulation, and expository learning. Further-on a framework is presented to capture learning outcomes in terms of reasoning processes, complexity, and domain specificity. This leads to 12 cells in

the framework, which are: apply, create, and evaluate reasoning processes. With each of them assigned to simple, complex, domain specific or general. The chapter exemplifies the 12-cell framework with the content of global warming for pre-university students. And in this way it shows how the framework can be helpful to design a systematic design of instruction by modeling.

The third part of the book focuses on the learning to model perspective. In chapter 10 Alessi recurs to the gadget "you learn something best when you teach it". His chapter deals with the didactical design of model-based learning environments, focussing on learning by teaching and pilot testing to improve quality of instructional systems development. As a starter he first reports some critical points responsible for the only moderate success of system modeling learning environments in schools (e.g. Mandinach&Cline, 1994; Spitulnik, Krajcik & Soloway, 1999). Alessi sums up that students have problems to activate appropriate cognitive structures, miss qualified discussions of the models and need much more time to deal with the new environment and curricula. Alessi therefore suggests a three step model to generate more successful environments. First, make models accessible to naïve learners, second, pilot test these models with naïve learners, third, revise the models accordingly. The crucial point in this approach is that students first have to understand the processes, then create a model of such, check their hypothesis' and make the model accessible for naïve learners after. Testing with naïve learners, as a kind of end-user testing, makes students to rethink their approaches and model creation. Alessi however states that pilot testing is just one aspect of feedback to revise a model. But it elicits best qualified communication about the model and the understanding of naïve users. This finally helps students to improve their learning processes with model simulation environments better than traditional teaching.

In chapter 11 Nicolaou, Nicolaidou and Constantinou mention that natural sciences in schools needs well educated teachers and quite a bit of technological background. Especially international comparative assessment studies brought light into such kinds of needs (e.g. OECD 2004). The authors therefore follow the task to enhance teacher education programs in natural sciences, by improving scientific reasoning. They observe a lack of modeling skills in teacher education, which also affects K-12 education. For these circumstances the authors show how modeling tools can be applied and effect teaching quality. Nicolaou et al apply Stagecast Creator™ in a WebCT™ learning environment. Within the inquiry-based curriculum student's task was to observe moon phases and construct a series of successive models of the moon phases and share their results with others and improve it afterwards.

In chapter 12 Harrer, Bollen and Hoppe show how the two worlds of web-based learning and face-to-face scenarios can merge together, of course with some benefit. The authors use a computer supported cooperative workspace CSCW and implement an interactive simulation feature comparable to Jonassen's famous mindtools (Jonassen, 1996). The idea is to get the benefit of face-to-face learning in terms of collaborative learning with using cognitive tools into a web-based environment. Harrer, Bollen and Hoppe call this "collaborative mindtools" (Harrer,

2001). The research group present Cool Modes and FreeStyler as examples for collaborative mindtools and describe how these tools can be applied for several learning scenarios. Usually models are stored as graphical representations via the above mentioned software to a sever. The authors further show possible applications for their tools in schools with the example of the famous birthday paradox and with an scientific experiment with a water tank (stock and flow). Also different forms of didactical designs are presented to show how web-based learning and modeling simulations can increase the value not only of distance learning scenarios but also of face-to-face learning scenarios in class. Harrer, Bollen and Hoppe in this sense continued and enhanced the work of Scardamalia and Bereiter from the 1980th.

In chapter 13 Scheutz approaches simulation-based learning from a human-robot interaction point of view. He therefore presents his SimWorld agent-based artificial life simulation environment, which enables students to develop and discover models of real-world systems. In his chapter he shows how students can develop a model of the phonotactic behavior of female frogs in a swamp when they are listening to the calls of male frogs and approach them. The chapter introduces how the agent-based environment has been developed technically and which open source software can be applied for these purposes. Further more he discusses several agent-based software tools in means of its instructional usefulness.

Chapter 14 deals with model simulation software in the agricultural domain. Johnson, Bryden and Refsgaard have developed a systems model called TOP MARD, which can analyse how the various functions of the agricultural sector in any given territory affect the sustainable economic development and quality of life and how different policies influence these relationships. The authors used STELLA to create this model with 29 partners of 12 European countries. This had several reasons, like a high transparency, openness, and to be designed for learning and improving system thinking. The model consists of 8 sectors with complex relationships: resources, agricultural production, tourism, regional economy, quality of life, demography, policy, and outcome indicators. This Case study shows how difficult and intricate the development of such a far reaching project can be and how helpful a systems dynamic approach can support the goals.

In chapter 15 Johnson and Sikorski unfold a different perspective on system modeling when they have taken up and refined the ideas of automated instructional design processes (e.g. Spector et al., 1993). The authors focus on modeling and simulating training system development to gain insights in impacts of specific factors in learning and instruction. They suggest walking through 5 phases of instructional design to finally develop such a model. These 5 phases are selecting an instructional strategy and learning model, select the representative learning and performance tasks, select the key input factors, conduct an empirical study, and develop a training algorithm and a model. Johnson and Sikorski introduce IMPRINT (Improvement Performance Research Integration Tool) as a software tool to model the human performance system. In their chapter the authors demonstrate the system modeling in the domain of technical maintenance training at the US army (balancing a tyre, change a shock absorber, repair an automatic

transmission). Modeling training systems as shown here by the authors can help training decision makers find critical factors in trainings like mental effort, task difficulty, prior experience and how instructional strategies influence the expected output. Comparing the results of an empirical study of such interactions with the modeling simulation in IMPRINT helps to validate the instructional strategy.

In the afterword of this book Hung and Blumschein discuss possible ways for learning by modeling, learning to model, and the development of the tools for modeling.

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PART I: INTRODUCTION AND FOUNDATIONS

Mental model and problem representation are the two main focuses of Part I – the conceptual framework of modeling-based learning. All system modeling processes start with a rough, simple, unsophisticated, and perhaps, inaccurate problem representation that is based on the modeller's prior mental model about the knowledge domain. The problem representation is further refined through the conceptualization of elements and properties, the interrelationships among them, and then model testing and modification processes. The refinement of the problem representation resulting from the cognitive processes involved in the system modeling process is reflected in the individual's mental model for later use. Therefore, understanding what role mental model and problem representation play in the system modeling process as well as the nature of the cognitive processes involved is necessary for laying the theoretical groundwork for the second part of the book – the effective use of system modeling as a cognitive and instructional tool.

OVERVIEW OF THE CHAPTERS OF PART I:

NORBERT M. SEEL AND PATRICK BLUMSCHEIN

MODELING AND SIMULATION IN LEARNING AND INSTRUCTION: A THEORETICAL PERSPECTIVE

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ABSTRACT

The goal of this chapter is to provide a theoretical background for the understanding of the various aspects of model-based simulations and their infusion in instructional fields of application. Therefore the potential of computer simulation to enhance student learning and problem-solving, defined as a change in a student's mental model, is described. Mental models, conceptual models and simulations are distinguished. Further-on modeling technologies are discussed with regard to glass-box and black-box models. A crucial question is how instructional design can integrate simulation technologies and the evoked cognitive processes into instructional planning. The chapter closes with perspectives for future development.

INTRODUCTION

About 20 years ago Greenfield (1984) discussed possible effects of new information and communication technologies on children's learning and behavior. In contrast with other scholars she addressed the emerging technologies as cultural artefacts which demand complex cognitive skills from the people who use them, and these skills and the related knowledge that come from using them are not obtained in instructional contexts like schools, but are acquired informally. Since this time, the overall situation has changed significantly: Schools have begun to use computers and improve the students' technological fluency. However, parallel with changes in the class informal experiences with information and communication technology have become more common for children and young people. Actually, today's students are exposed to multimedia in all aspects of their lives, from MTV to the World Wide Web. Multimedia is also finding its way in to computer simulation. Students get excited about commercially available entertainment programs such as Microsoft's Flight Simulator and Maxis' SimCity which contain realistic detailed simulations. Not to speak about the s*imulation games* and *adventure games* that appeared on home computers in the late 1970s (Provenzo,

1991). To date life simulations, virtual worlds, and web-based games will probably gain more and more popularity. Second Life, a massively multiplayer online role-playing game, already counts more than 1.5 million users today (Clariana & Stroebel, 2008, Steinkuehler, 2008).

Information and communication technologies have evolved to the point where they do have important and unique roles to play in learning. These roles have to do with creating environments, whether simulated or virtual, which students can explore freely or within varying constraints required by guidance in order to construct knowledge and practice problem-solving methods on their own. The key to the success of this application of media is not so much in how the "message" itself is presented, but in the degree to which students can work out for themselves ways to reduce the dissonance between what the environment presents to the user and the knowledge and experience the user brings in when he or she enters the environment. An extended use of the computer as a tool to expedite the processes of problem solving may help shift the focus from the end product and from the pure acquisition of facts to cognitive processes like manipulation and under-standing which then encourages curiosity and creativity. In this sense various features of emerging technologies may help students become better problem solvers: (a) the new technologies are interactive systems, (b) the "locus of control" is shifted to the learner, (c) the computer can simulate experiments and model real situations, (d) immediate feedback is given to student responses, and (e) in several cases the computer can perform operations, for example simulations, that are impossible or impractical on alternative media (Seel & Dijkstra, 2004). Indeed, the status of computer technology today makes nearly all other media in the technical sense of the word obsolete and useless. Moreover, the technology is able to produce all the forms of representation on which students can operate. Actually, recent developments in interactive software, and the emergence of systems thinking provide a unique opportunity to create interactive model-based simulations that address student learning. Computer simulation programs encourage students to explore complex and realistic systems. The interactive environment and graphic capability of these programs provides instant feedback to the students. In addition to dynamic simulation capabilities, many of these programs allow the user to incorporate animation into the simulation.

Simulations are computer programs aiming at modeling complex systems' behaviors. They allow a learner to explore a system in a controlled way in order to better understand how the system components interact, and how alternate decisions can affect desired outcomes. In meteorological education and training, for example, simulations may model atmospheric processes (e.g. COMET simulations have modelled physical processes such as mountain waves, gap winds, aviation icing conditions, and convective storms; Bar-Nun, 1991), or forecast process systems (e.g. Weather Event Simulations). In the future, these types of simulations might merge to create even more intelligent instructional simulation systems. Such simulations could provide a rich level of fidelity along with sufficient instructional support, and include some degree of artificial intelligence that can adapt the fidelity, difficulty, and support to an individual learner's needs.

This book provides a new perspective called learning by system modeling and an extension to glass-box approaches of simulations: The book explores the learning impact of students when constructing models of complex systems. In this approach students are building their own models and engaging at a much deeper conceptual level of understanding of the content, processes, and problem solving of the domain. Research from the area of mindtools suggests that students' conceptual understanding and application of knowledge is much deeper and advanced when they are involved in learning by modeling (Jonassen, 1999).

The objective of this introduction is to provide a theoretical background for the understanding of the various aspects of model-based simulations and their infusion in instructional fields of application. It describes the potential of computer simulation to enhance student learning, here defined as a change in a student's mental models.

SIMULATION AND MODELING

At a first glance, a simulation seems to be an imitation of some real thing, for instance a complex system, a state of affairs, or a process. However, a simulation is a computer program that attempts to simulate the reality by operating with an abstract *model* of a particular physical or social system and its characteristics in order to gain insight in the functioning of the system. Talking about models implies to ask for the original to be modeled. Globes are models of the earth. Naturally, a globe is not a reduced earth but rather it shall give answers to questions asking for the locations of different places or for the distances between places. With regard to the chemical composition of the earth, a globe is not relevant. This example illustrates: Every model is constructed in accordance with specific intentions in order to simplify its original in several respects. Clariana and Strobel (2008) point out that the question of the nature of relationship between the model and what is modeled (i.e. the original) is as old as modeling itself. From an epistemological point of view, there are two general conceptions concerning the nature of modeling. The first conception emphasizes the *representational* character of modeling – the model represents reality, it is a *model of* something (Wartofsky, 1979); the other conception considers the *model as a cognitive artefact* which is constructed intentionally in order to create subjective plausibility with regard to the original (Seel, 1991; 2001).

In cognitive psychology, both conceptions of modeling are captured by the theoretical concept of mental models. When people learn to interact with a system it means they construct a particular representation about its operations and the structural relationships between its components. Researchers have called this representation the "mental model" of the system (Norman, 1983). Cognition takes place in the use of mental representations in which individuals organize symbols of experience or thought in such a way that they effect a systematic representation of this experience or thought, as a means of understanding it, or of explaining it to others (Seel, 1991). Learning occurs when people actively construct meaningful representations from presented information, such as coherent *mental models* that

represent and communicate subjective experiences, ideas, thoughts, and feelings (Mayer et al., 1999). The function of a mental model is twofold: On the one hand it serves the mental representation of something (e.g., a complex system) that is called the original. Due to an idealized reduction to relevant characteristics of its original *a model is a concrete, comprehensible, and feasible representation of non-obvious or abstract objects or phenomena*. The representation of the objects' attributes and components comes second to the representation of structural relationships. On the other hand, mental models constitute the fundamental basis for qualitative reasoning (Johnson-Laird, 1983). Model-based reasoning occurs when an individual mentally manipulates an environment in order to simulate (in the sense of a thought experiment) specific transformations of the system which may occur in real-life situations. Then, mental models "run in the mind's eye" to readily produce qualitative inferences with respect to the situation to be cognitively mastered (Forbus & Gentner, 1997).

When we consider the basic understanding of model-based simulation we have to distinguish between the model on which a computer simulation is based and the model that is constructed by the learner in order to understand the computer simulation and its underlying model. In order to avoid conceptual confusion a distinction can be made between *mental models* and *conceptual models* (Norman, 1983; Kluwe & Haider, 1990). A mental model is a subjective internal model related to a complex system of the real or imagined world. It is idiosyncratic by nature and represents a particular cognitive artefact of an individual. Conceptual models, on the other side, are "objective" models developed, for example, by scientists in the basis of their subjective mental models. *Conceptual models* can be considered as shared mental models which represent the knowledge of a scientific community. Clearly, a computer simulation can be based on a mental model of the developer of the simulation or on widely accepted conceptual models of a discipline. However, the model on which a computer simulation is based corresponds usually to an instructionally designed model that implies – in addition to the conceptual model of the system to be modelled – interfaces (learning tasks, manuals, tools) in order to guide the learners' construction of mental models and problem solving.

Both functions are included in the model on which a computer simulation runs. In other words, the core of each computer simulation consists of a (conceptual) *model of the system* to be modelled and no simulation can be better than the underlying model. In addition to the *model of* the system a simulation program must also include a *model for* reasoning in order to simulate the transformations of the system. Then, a simulation can be used to show the possible real effects of alternative conditions and courses of action. In other words: A simulation is a computerized version of the model of a system that runs over time and is iterative by nature with regard to the underlying model: A model of the system must be constructed, then the computer program simulates the model, learns from the simulation, revises the model, and continues the iterations until an adequate level of understanding is developed. The conceptual model is the focal point of each simulation. All activities either converge upon or emanate from the conceptual

model. All structures, through mappings either into or out of the conceptual model, must be to some extent compatible with it.

MODEL-BASED SIMULATION AND SYNTHETIC LEARNING ENVIRONMENTS

Modern computer systems are offering increasingly effective means for the *simulation of complex systems* with many independent variables which may be manipulated. As a consequence of this development, simulation has become a widely used tool for research on human interaction with complex environments. Generally, two different kinds of simulation are used for different purposes: First, simulation is used to create task environments in which experiments can be made with subjects to study their cognitive behavior within a training context, which involves simulation of some well-structured systems or of a more loosely coupled environment (such as the activities of the citizens of a fictitious town). This kind of simulation can be conceived of as an extension of traditional experimental psychology since it seeks to verify hypotheses about human behavior in the accomplishment of cognitive tasks. In fact, studies in which subjects interact with simulations of complex task environments offer a suitable combination of the advantages of performance analysis in the complexity of real-life scenarios and in well-controlled laboratory experiments. The second kind of simulation serves to validate comprehensive models of human cognition, and thus includes tests of hypotheses about which cognitive operations and processes will be used in a complex setting (see, for example, Kieras, 1990). This is clearly an extension of the previous verification simulation and it presupposes that such a simulation was successful. Closely related with the first approach of research with the help of simulations is their use in various instructional settings where computer simulations serve as a learning environment or are embedded in a more comprehensive learning environment in order to facilitate model-based learning (de Jong & van Joolingen, 2008).

  Instructional researchers apply computer simulations in order to create "synthetic learning environments" for instructional purposes. Cannon-Bowers and Bowers (2008, p. 318) define a synthetic learning environment as a learning environment characterized in terms of a particular technology (e.g. a simulation or game), subject matter, learner characteristics, and some leading pedagogical principles. That is to say, a particular task simulation has been designed to model some specific domain of reality with which students can interact. From an instructional point of view it is necessary to state that the particular model of the reality that constitutes the core and scope of the simulation represents both the subject matter as well as the "conceptual models" of a subject. A simulation is a method of teaching/learning or evaluating learning of curricular content that is based on an actual situation. The simulation, designed to replicate a real-life situation as closely as desired, has students assume roles as they analyze data, make decisions, and solve the problems inherent in the situation. As the simulation proceeds, students respond to the changes within the situation by studying the consequences of their decisions and subsequent actions and predicting future

problems/solutions. During the simulation, students perform tasks that enable them to learn or have their learning evaluated. A well-designed simulation simplifies a real world system while heightening awareness of the complexity of that system. Students can participate in the simplified system and learn how the real system operates without spending the days, weeks, or years it would take to undergo this experience in the real world.

Computer simulations of this kind are increasingly considered to be innovative learning environments which are consistent with how people learn: Variables can be limited to a manageable level and structure and direction for learning can be provided, real-world problems can be addressed, and students can take control and responsibility for their own learning progress. Classroom simulations motivate students by keeping them actively engaged in the learning process through requiring that problem-solving and decision-making skills be used to make the simulation run. As the simulation runs, it is modeling a dynamic system in which the learner is involved and plays a role. Thus, participation in simulations enables students to engage in systems thinking and enhances their understanding of systems as well as of social science and/or science concepts. Thus, a learning environment which contains computer simulation facilities may support knowledge acquisition as well as problem solving as an application from the known to the unknown. Actually, learning initiated by computer simulation involves explorative thinking, inductive, and analogical reasoning. These skills put high cognitive and metacognitive demands on students, who must generate hypotheses and test them by accomplishing learning tasks actively as well as performing experiments in the simulated environment. Accordingly, computer simulations of complex environments often require *complex problem solving*, which can be characterized as follows (Funke, 1992): (1) A simulation exists which represents a particular domain with variables to manipulate; (2) learners operate overtly with this system; (3) multiple answers are demanded to accomplish provided tasks and more than one hypothesis concerning a possible solution is available. Furthermore, interactions with simulation programs require (4) cognitive processes with more than one or two iterative steps of "trial-and-error" as well as (5) an increased time to complete the tasks.

As pointed out above complex problem solving, especially in computer-simulated task environments, depends to a great extent on the *mental models* subjects are able to construct in order to understand the structure of the simulated system and to mentally simulate transformations of the system. Since student mental models are built upon assumptions that evolve over time as a result of experiences and prior learning, the simulation environment gives students a chance for "playing" with their assumptions, testing various beliefs, and seeing the response of the system to their inputs. Authentic tasks are required that enable the learners to explore the environment in dynamic interaction with the context as if they were really there. Furthermore, embedded supports and scaffolds can be provided to assist novice problem solvers in operating within the learning environment.

Computer simulations have become a useful part of mathematical modeling of many natural systems in physics (computational physics), chemistry and biology,

human systems in economics, psychology, and social science and in the process of engineering new technology, to gain insight into the operation of those systems, or to observe their behaviors. Other contexts include simulation of technology for performance optimization, safety engineering, testing, training and education. Regularly they entail particular modeling technologies.

MODELING TECHNOLOGIES

In general, models as the central component of a computer simulation can serve different functions:

– Models serve the *simplification* of the relevant phenomena in a closed domain.
– Models also serve the *envisioning* in order make visible the invisible (e.g. Rutherford's atomic model).
– Models can serve the construction of analogies by mapping a well-known explanation (e.g. Rutherford's atomic model) onto an unknown domain (e.g. quantum physics). The idea of analogy models can be illustrated by an example provided by Holyoak and Thagard (1995): "… our knowledge of water provides us with a kind of internal model of how it moves. Similarly, our knowledge of sound provides us with a kind of model of how sound is transmitted through the air. Each of these mental models links an internal representation to external reality. But when we consider the analogy between water waves and sound propagation, we are trying to build an isomorphism between two internal models. Implicitly, we are acting as if our model of water waves can be used to modify and improve our model of sound" (p. 33).
– Finally, models serve the purpose of qualitative reasoning which occurs when an individual mentally manipulate states of the model in such a way that operations simulate specific transformations of these states which may occur in real-life situations. These *simulation models* operate as thought experiments to produce qualitative inferences.

Taking into account that the capability of users to understand a computer simulation depends, to a large extent, on their ways of thinking modeling technologies and tools are used in order to serve either the exploration of a complex phenomenon or the construction of mental models in order to provide a subjective understanding of the simulation model. Basically, two broad categories of modeling technologies and tools can be distinguished: (a) Tools which serve the exploration of a model, and (b) tools which can be used for the construction of models (Clariana & Strobel, 2008).

In the case of *model exploration* simulations are generally distinguished in accordance with the differentiation between "black-box models," in which the computations are hidden and relationships between the variables of the system can only be inferred and "glass-box models" which overtly display all mechanisms and functions of the system being modelled.

Most of the simulation games on the market are black-box models, as it is one of the teasing things to hide the strategy behind the surface. Good examples of such games are Myst/Riven®, Simcity®, War Craft®. In Myst® or Riven® you are the

hero who starts the game with absolutely no clue about what to do. The challenge is, exactly to find out what it is all about and then try to understand all the machines and worlds you have to pass. Sometimes know-how about the laws of physics helps, sometimes not. However, you have no access to the construction behind it. Also flight simulators, the most prominent simulation games ever, are black-box models, when the user has no prior knowledge about the system. Just playing with it, will crash any helicopter in a few seconds, and one has no chance to understand why. But this will change when the user switches his role to be a learner instead and well prepared. So this example shows how difficult it is to distinguish between black-box and glass-box models. Also the grade of complexity of a model also determines the black-box model. One could say that a given simulation consisting of a huge amount of processes and mathematical formulas which interact, but this model is so complex to understand, no human soul can handle such a complexity in a given time in a simulation (this is the case in flight simulators). The EPICS game (Brown, Rawley & Jatoi, 1997) is a role play to simulate dynamic decision making in the domain of educational planning. It is a black-box model for two reasons. First, the different roles are played by humans, who are always uncontrollable. Second, the users have no access to the rules behind the game, as it is a major goal to practice educational decision making under time pressure and with very little resources. We will come back to EPICS later on. In general in black-box models, what goes on "under the hood" of a simulation has been hidden from the user, who is led to infer how the simulated system functions only indirectly from its behavior in reaction to user input. Sometimes this leads students to misinterpret the behaviors of simulations and to build faulty mental models of the systems they represent. Winn et al. (2006) describe an example of how misconceptions arose from the opacity of a simulation of ocean processes.

By contrast, *glass-box simulations* (Tanimoto, 2005) are visible to users, who can reify and directly inspect the mathematical and logical models that underlie them. Very popular examples of glass-box models are Java-Applets for physics lessons in school. Most of these simulations are very restricted to a specific goal. Building a electric circuit with a battery, a switch, a bulb, an adjustable resistant and a voltage meter. Students can raise the current until the bulb bursts. With the voltage meter they measure the voltage level and with an additional ammeter they can figure out how huge the power was which the bulb busted. As this all follows Ohm's law students can learn the process and understand the simulation and repeat it how often they want without any damage or costs. Also the discussed models in this book are glass-box models, as they have the intention to teach people, which necessarily implies to give access to the "hidden" rules.

A new movement of glass-box models entails the use of animated personal agents that drive simulated training environments (Baylor & Ryu, 2003). There is substantial empirical evidence pointing toward the potential value of educational agents as a virtual "coach." When systems have a social interface, participants can rely on standard interaction skills (such as interpreting agents' facial expressions or taking into account eye contact), making the interaction with the computer much

smoother (Dehn & van Mulken, 2000). However, a careful design of the agent persona or "role" within the environment is critical to establish credibility, believability and reasonable expectations from the student.

Alternatively to model explorations there are modeling technologies and tools which allow the user to construct his/her own models. Clariana and Strobel (2008) call this application "*model building*." Students operate with particular tools which allow them to construct their own models. These tools can be *variable-based or agent-based*.

STELLA, Powersim, and Model-it are popular examples of *variable-based modeling tools* and operate with a formalized language for qualitative modeling. The resulting models are called "*system dynamics models*" whose variables have no attributes but change dynamically based on the mathematical models and equations that define the relationships within the system. In such system, at least two variables at two different times are related: $Y(t) = f (Y(t-1), ..., Y(t-k))$. The system's dynamics is attributed to the fact that states and interventions at a former time affect the state of Y at the time t. Based on this assumption, for instance Model-It allows the learner to make qualitative models of cause and effect relationships. Through this technology, the user creates objects with which he or she associates measurable, variable quantities called factors and then defines relationships between those factors to show the effects of one factor upon another. Relationships can model immediate effects or effects over time. Model-It provides facilities for testing a model and a "Factor Map" for visualizing it as a whole. Students define objects, factors and the relationship between factors' qualities. The student is facilitated in this modeling process by a variety of scaffolds. These scaffolds include features which (a) allow for multiple linked representations, (b) options which hide additional complexity, (c) learner guidance through subtasks and (d) prompting for explanations for constructed relationships. There are numerous studies that indicate the effectiveness of the application of STELLA, Model-it and other variable based model-building tools (Hannon & Ruth, 2001).

The other broad class of emerging model-building tools puts *agent-based modeling* at the center of development and research. An agent based model consists in a collection of autonomous agents (or simply agents) which interact between themselves ruled by some simple characteristics that are modelled from the observation or analysis of real world entities in order to simulate their more complex characteristics. Agents can be considered as computational entities that can conceptually incorporate in a natural way some human mechanisms such as perception, action selection, autonomy, etc. Clariana and Strobel (2008) have pointed out that in agent-based modeling tools the agents possess different attributes and their behavior changes in accordance with a pre-defined set of rules to respond to the situational demands of a simulated environment. Actually, the virtual or simulated environment with its spatial dimensions provides the space where the agents move, interact and pursue their goals. Thereby, the agents *mimic* the behavior of real people in a real environment. Agent-based simulation tools have been widely used in geography (da Silva et al., 2004), social sciences (Tobias & Hoffmann, 2004), and construction management (Rojas & Mukherjee, 2005;

Wattkins & Mukherjee, 2008). Another very interesting approach is Dörner's (2003) PSI model of emotion, personality and action. PSI is an attempt to create a body-mind link for virtual agents. It aims at the integration of cognitive processes, emotions and motivation. Emotions become apparent when the agents interact with the environment and display expressive behavior, resulting in a configuration that resembles emotional episodes in biological agents. The agents react to the environment by forming memories, expectations and immediate evaluations. The agents are virtual creatures that act according to motives that stem from physiological and cognitive urges. They build representations of their environment based on interaction. Their cognition is modulated according to perceived situations and performance, and thus they undergo emotional states. PSI agents are able to adapt to different circumstances in the environment. Up to now, the PSI theory has been applied to different virtual agent simulations in different types of environments and has proven to be a promising theory for creation of biologically plausible agents.

Beyond these modeling technologies and tools we can find in the related literature the far-reaching idea to integrate these tools into more comprehensive learning environments that also promote collaboration and group processes. A good example to illustrate this approach consists in the game *Educational Policy Simulation EPICS* from Brown, Rawley and Jatoi (1997). In this simulation learners interact with each other in a game with different roles to play, and the model-based simulation only computes the decisions made in the group. EPICS was developed to model and simulate the dynamics of educational planning and decision making in a low income country, and it necessitates complex problem solving. EPICS provides a fictitious but realistic environment in which fundamental economic concepts and issues in planning for educational improvement at different levels can be experienced and experimented with. EPICS thus allows to explore the scope of strategic planning and related decision making in a complex task environment. The simulation is complex to reflect the complexity of the educational system. This corresponds with the argumentation of Alessi (1988) who has recommended low fidelity in simulations for novice learners with an increase in fidelity to support transfer for more advanced learners. More specifically, it is recommended that the complexity of the learning environment should reflect the complexity expected for performance in real-world settings.

MODEL-BASED SIMULATION IN THE CLASSROOM OF THE FUTURE

Rapidly evolving information and communication technologies have pervaded all sectors of the industrial and everyday world, and they have driven changes in industrial production and business practices. Parallel with this development emerging technologies also have influenced the classroom and the practice of instruction because with all technical innovations it was supposed that their use would improve learning and instruction. Although some predictions concerning the impact of new information and communication technology on learning and

instruction revealed as too optimistic it is evident that information technology has significantly changed the classroom inside and outside schools.

Nowadays we can find new tools of information technology, such as weblogs, RSS, screen casting, video blogging, pod casting, social bookmarking, tagging (Asmus et al., 2005) that will transform the web into a fully interactive space (WEB 2.0). In addition, so called learning management systems (LMS) have been developed to support students in their learning. Aiming at adapting the instruction to the needs, background, interests and goals of learners, researchers have begun to use the various possibilities existing in the field of Artificial Intelligence to provide adapted responses to learners. In this vein "intelligent Learning Management Systems" are addressing the problem of effective adaptive learning. Closely related to this approach is the idea of affective tutoring and affective user modeling. Beyond personal and pedagogical agents aiming at supporting learners in operating in interactive learning environments (Johnson et al., 2000) vision-based human affect analysis is an active research area for development of intelligent and interactive affective computing systems (Conati, 2002; Cowie et al., 2001).

Another promising approach is Augmented Reality technology which enables instructors to develop, with moderate efforts, new instructional practices and curricula to bring scientific and cultural contents to school classes in an easy to comprehend way. A major assumption is that using 3D presentations and supportive interaction techniques may lead to a better understanding of scientific and cultural content coupled with high student motivation. The students have the possibility to interact together with the virtual objects in a virtual shared space provided by an Augmented Reality display system and thereby perform learning by doing and experimenting. The Augmented Reality framework allows students to interact with the teaching material in 3D and at the same time it supports a team-oriented approach in school classes. It raises the level of understanding of complex processes with the students through immersion and self-experience. Actually, the idea of immersive learning is currently very popular in the field of medical education and is considered as a bridge between classroom learning and real-life clinical experiences. This includes the use of *simulation and modeling* technologies in order to replace or amplify real experiences with "artificial" experiences, often immersive in nature, that evoke or replicate substantial aspects of the real world by means of model-based simulations. Advocates of Augmented Reality technology postulate a *classroom of the future* which contains several kinds of simulators, in addition to textual and visual learning tools. In the same way that the use of periodic flight training assists airline pilots, simulations will become an integral part of the practice of subjects, such as medicine or engineering. The capability for this exists today, although the level of effort is high. In the future, tools might exist to facilitate intelligent simulation development, making it easier to justify the costs of such approaches for appropriate areas of job performance.

A review of literature indicates a lack of good overviews of the approaches to system design of simulations in Intelligent Computer Assisted Instruction. Though single systems have to some extent been evaluated with regard to their performance, an organized evaluation, especially a comparative evaluation of the systems that

have been created within the field is lacking. What is necessary is to analyze the design of model-based simulations and its implications for the other parts of an instructional system. This book intends to provide the reader with an overview about most recent trends of model-based simulations inside and outside the classroom.

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MENTAL MODELS AND PROBLEM SOLVING: TECHNOLOGICAL SOLUTIONS FOR MEASUREMENT AND ASSESSMENT OF THE DEVELOPMENT OF EXPERTISE

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ABSTRACT

In this chapter we focus on the progression of mental models in performing complex problems within a given subject domain. We begin with a short review of two major lines of problem solving research, namely the North American and European lines. We then discuss the functions of mental models and complex problem solving, which provide a unique challenge for researchers in the field of learning and instruction. From the perspective of mental model theory, we argue that complex problem solving requires iterative steps of hypothesis testing, which involves the construction and reorganization of appropriate mental models. If our instructional goal is to facilitate the progression of mental models, we have to assess the learning-dependent progression of mental models. However, one central problem of mental model research is the diagnosis of the progression of mental models. The analysis of different approaches for measuring change in mental models leads to a unique approach for a systematic diagnosis of the progression of mental models. The chapter concludes with a discussion of different formats and representations for the diagnosis of mental models.

INTRODUCTION

Research on problem solving has a long tradition in both psychology and education. Cognitive psychologists agree that people have abilities that are essential for processing information and acting successfully in different environments. According to Rumelhart, Smolensky, McClelland, and Hinton (1986), one of these abilities is that humans are very good at pattern matching. They are evidently able to quickly "settle" on an interpretation of any input pattern. This ability is central for perceiving, spontaneous remembering, and comprehending. It is probably *the* essential component for most cognitive behavior and is based on schemata, defined here as generic knowledge structures. Secondly, humans are also very good at

modeling their worlds. That is to say that they can anticipate the new state of affairs resulting from actions or from an event they observe. This ability is based on building up expectations by operating on experiences and is crucial for inferential learning and reasoning. Thirdly, humans are good at manipulating their environments. This can be considered as a version of man the tool user and is perhaps the crucial skill in forming a culture. Especially important here is the ability to manipulate the environment so that it comes to represent something by means of artifacts of technology. Rumelhart et al. (1986) argue that these abilities are dependent on two interacting modules or sets of units of the cognitive system. One module – called an "*interpretation network*" – is concerned with the activation of schemata, and the other one is concerned with constructing a "model of the world." It takes as input some specification of the actions we intend to carry out and produces an interpretation of "what would happen if we did that." Part of this might be a specification of what the new stimulus conditions would be like. Thus, the interpretation network (i.e. an activated schema) takes input from the world (to be explained) and produces relevant cognitive (re-)actions, whereas the second module, i.e. the "model of the world," predicts how the input would change in response to these reactions. In cognitive psychology it is common to speak of a *mental model* that would be expected to be operating in any case, insofar as it is generating expectations about the state of the world and thus "predicting" the outcomes of possible actions. However, it is not necessary for world events to have really happened. In the case that they have not, the cognitive system replaces the stimulus inputs from the world with inputs from the mental model of the world. This means that a "mental simulation runs" to imagine the events that would take place in the world if a particular action were to be performed. Thus, mental models allow one to perform entire actions internally and to judge the consequences of actions, interpret them, and draw appropriate conclusions.
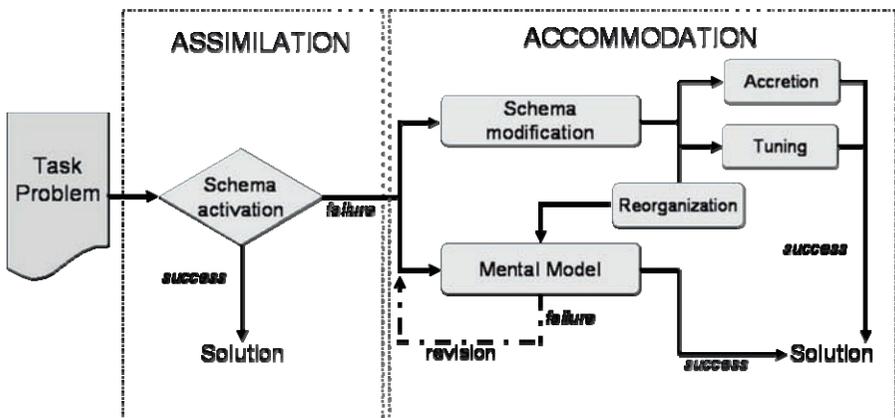

Figure 1. Cognitive functions of assimilation and accommodation

This cognitive architecture described by Rumelhart et al. (1986) corresponds to a great extent with Piaget's epistemology and the basic cognitive functions of assimilation and accommodation (Seel, 1991). Assimilation is dependent on the availability and activation of cognitive schemata, which allow new information to be integrated into cognitive structures.

Schemata (or frames, scripts) can be defined as coherent slot-filler structures of the human mind that provide an individual with cognitive structures which allow a prompt interpretation of new information. If a schema does not fit immediately with the requirements of a new task it can be adjusted to meet the new requirements by means of accretion, tuning, or reorganization. However, if accretion or tuning is not successful or if no schema is available, accommodation must take place in order to reorganize and structure an individual's knowledge concerning the construction of a mental model. In accordance with Piaget's epistemology, the idea of mental models is based on the assumption that an individual who intends to give a rational explanation for something must develop practicable methods to generate appropriate explanations on the basis of both principally restricted domain-specific knowledge and a limited capacity for information processing. Mental models represent the structure of the world because they are generated to structure it and not to assimilate a given external structure. The individual constructs a model that integrates the relevant bits of domain-specific knowledge into a coherent structure step by step in order to meet the requirements of a phenomenon to be explained.

In this chapter we are concerned with the development of mental models and their influence on learning and problem solving. More specifically, we focus on the learning-dependent progression of mental models in solving complex problems within a given complex domain – as advocated in the mental model hypothesis (Seel, 1991). First, we will discuss two major fields of research on problem solving: the North American and European lines. Secondly, we will summarize the processes of mental model construction involved in solving complex problems. Thirdly, we will briefly discuss some methods for observing changes in mental models, followed by a more detailed discussion of the systematic diagnosis of the progression of mental models. We will conclude with a final summary.

MAJOR LINES OF RESEARCH ON COMPLEX PROBLEM SOLVING

The nature of human problem solving has been studied by psychologists over the past hundred years. Beginning with the early experimental work of the Gestalt psychologists in Germany (e.g. Duncker, 1935; Wertheimer, 1959), and continuing through the 1960s and early 1970s, research on problem solving typically operated with relatively simple, laboratory tasks (e.g. Duncker's famous "X-ray" problem; Ewert & Lambert's 1932 "disk" problem, later known as "Tower of Hanoi") that appeared novel to participants (e.g. Mayer, 1992). Various reasons account for the choice of simple, novel tasks: they had clearly defined optimal solutions, they were solvable within a relatively short time frame, researchers could trace participants' problem-solving steps, and so on. The researchers made the underlying assumption

that simple tasks such as the Tower of Hanoi (see below) captured the main properties of "real world" problems, and that the cognitive processes underlying participants' attempts to solve simple problems were representative of the processes they engaged in when solving "real world" problems. Thus, researchers used simple problems for reasons of convenience and thought it would be possible to generalize their findings to explain how people solve more complex problems. Perhaps the best-known and most impressive example of this line of research is the work by Newell and Simon (1972). This research was linked with the paradigm shift known as the "cognitive revolution" (Bruner, 1990), which focused on sequential information processing, the decomposition of problems, and the application of analogies. Whereas Gestalt psychologists maintained that problem solving is based on "restructuring" a problem in order to gain "insight" into its solution, cognitive psychologists such as Newell, Simon, and Dörner agreed on the point that problem solving should be considered as information processing. Accordingly, these researchers progressively questioned the simple laboratory tasks of problem solving research because many empirical findings could not be generalized to more complex, real-life problems (Funke & Frensch, 1995). Evidently, empirical findings and theoretical concepts derived from simple laboratory tasks did not generalize to more complex, real-life problems. Even worse, it appeared that the processes underlying problem solving in different domains differed from each other.

Cognitive psychologists propose that the first thing a person does when confronted with a problem is to try to construct a mental representation of its relevant features. This internal representation of a problem is termed a *problem space* – and if its construction has been successful the problem space will consist of information about the initial and goal state of the problem as well as information about the operators which can applied to solve it. Generally, a problem occurs if a person does not know how to proceed from a given state to a desired goal state. Thus, a problem is described by three components: (1) a given initial state s_α; (2) a desired final state s_ω; and (3) a barrier which hinders the solution of the problem, i.e. to come s_α from to s_ω. A helpful classification of problems and the barriers involved in them has been provided by Dörner (1976), who argues that the type of a problem depends on the transparency of the goal criteria and how familiar the means of solving it are (see Table 1).

Table 1. Classification of problems in accordance with both the clarity of objectives and certainty of resources (Dörner, 1976)

		Clarity of Objectives	
		high	*low*
Certainty of Resources	*high*	**Interpolation Barrier**	**Dialectic Barrier**
	low	**Synthetic Barrier**	**Dialectic & Synthetic Barrier**

In the case of a problem with an interpolation barrier, both s_α and s_ω are known – e.g. if you want to travel from Tallahassee to Syracuse. The problem consists in the interpolation, i.e. the effective order of the necessary transformations of states of time and space. The solution requires the correct combination or order of known operations. In the case of a problem with a synthetic barrier the set of operations aiming at the transformation from s_α to s_ω is not closed. That means that the individual knows after several trials of problem solving that the available means and operations are insufficient. A good example is the task of producing gold from straw: s_α and s_ω are known, but both the effective combination of operations and the necessary operations are unknown. Therefore, the problem consists in finding the effective operations and their correct combination. Accordingly, the major task consists in the synthesis of an inventory of effective operations. With reference to our example, we know that such an inventory does not exist because we can produce all sorts of things from straw but not gold. In the case of problems with a dialectic barrier the problem solver knows that a given situation s_α must be changed, but only global criteria for the desired change are known. For example, a young lady wants to have an apartment which is more attractive than her previous one, but she doesn't know how this can be achieved (combination of colors, style of furniture, etc.). Although it may be easy to find comparative criteria we can assume that the subjectively satisfying solution to this problem can be found in a dialectic process. Accordingly, a first sketch will be evaluated with regard to both external consistency (e.g. concerning the requirements of the environment) and internal consistency. This sketch must probably be modified or revised and will then be evaluated again. And so on. Another example for a dialectic process of problem solving is the production of a master's thesis.

The type of barrier evidently depends on the prior knowledge and the applicable skills of the problem solver. If, for example, an individual does not know anything about chemistry then the production of ammonia will be a problem with a synthetic barrier, whereas it will only be a problem with an interpolation barrier for a chemist. Moreover, a complex problem may contain not only one barrier but possibly all kinds of barriers. The experience of a barrier motivates problem solvers to varying degrees to grapple with a problem and leads them to test different solutions.

Problems also vary in terms of how structured they are. Jonassen (1997) classifies problems on a continuum from *well structured* to *ill structured*. This differentiation corresponds with the distinction between *well-defined* and *ill-defined problems*, which has its origins in the specification of components of a problem space. Well-structured problems have a well-defined initial state, a known goal state or solution, and a constrained set of known procedures for solving a class of problems. In other words, they require the application of a limited and known number of concepts, rules, and principles (e.g. means-ends analysis) being studied within a restricted domain. In contrast, the solutions to ill-structured problems are neither predictable nor convergent because they often possess aspects that are unknown. Additionally, they possess multiple solutions or solution methods or often no solutions at all. Jonassen (1997) points out that structuredness often

overlaps with complexity: Ill-structured problems tend to be more complex, especially those emerging from everyday practice, whereas most well-structured problems tend to be less complex. Problems vary in complexity. The complexity of a problem is determined by the number of issues, functions, or variables it involves; the degree of connectivity among these variables; the type of functional relationships between these properties; and the stability of the properties of the problem over time (Funke, 1991). Simple problems, like textbook problems, are composed of few variables, while ill-structured problems may include many factors or variables that may interact in unpredictable ways. For example, international political problems are complex and unpredictable. Finally, problems vary in their stability or dynamicity. More complex problems tend to be dynamic; that is, the task environment and its factors change over time. When the conditions of a problem change, people must continuously adapt their understanding of the problem while searching for new solutions, because the old solutions may no longer be viable. For example, investing in the stock market is often difficult because market conditions (such as demand, interest rates, or confidence) tend to change, often dramatically, over short periods of time. Static problems are those in which the factors are stable over time. Clearly, ill-structured problems tend to be more dynamic, whereas well-structured problems tend to be fairly stable.

Although cognitive psychologists on both sides of the Atlantic generally agree on the point that problem solving should be considered as information processing, different lines of research emerged in North America and in Europe. In *North America*, initiated by the work of Herbert Simon researchers began to investigate problem solving separately in different natural knowledge domains – such as physics, writing, or chess playing – thus relinquishing their attempts to extract a unique and comprehensive theory of problem solving. The North American line focused on the investigation of problem solving within specific domains such as reading, calculating, political decision making, and personal problem solving (Funke & Frensch, 1995). Newell, Shaw, and Simon (1959) introduced the General Problem Solver (GPS), which simulates human problem-solving behavior. This computer program was proposed to provide an essential set of processes to solve a variety of different problems. Accordingly, the GPS solves distinctive formally described problems or tasks by itself and with a specific analogy to human problem-solving performance (Ernst & Newell, 1969), which presupposes the sequential transformation of knowledge structures. During a problem-solving process, mental operators generate the shift from an initial knowledge state to the desired final state. An example of such serial information processing is the *Tower of Hanoi* problem. Although the GPS was expected to be a general problem solver, it clearly was limited to "well-defined" problems, such as word puzzles, chess, or the proving of theorems in logic. Nevertheless, the GPS provided a basis for a wide range of common problems in different domains. Whereas the GPS was concerned with solving any given problem in any domain, expert systems (ES) were domain specific to a high degree.

While the GPS attempted to represent the process of decision making and thus went to the core of the understanding of reasoning under the assumption that there

was more or less only one single process, ES imply different reasoning processes and attempt to represent the expert knowledge as well. But ES are no longer the instances that *make* the decisions, they only *support* human decision making, which is a very important difference on the theoretical level and even more important when we think in terms of mental model building. A very famous ES which influenced most of the younger systems is MYCIN (Buchanan & Shortliffe, 1984). Many other ES were developed on the basis of MYCIN and other early ES – the inferential component of MYCIN was developed further into the content independent system-shell EMYCIN. Since then, ES have improved in the fields of knowledge representation, human-computer interfaces, and the logic driving their inferential engines, inspired for instance by non-monotonic reasoning and default logic (Reiter, 1980). In addition to the rules and knowledge bases, later systems are empowered by probability networks in order to strengthen the heuristic modules (Rödder, 1991). However, ES were developed to aid in decision making and to present results in a well-founded manner to the expert who makes the final decision. But human decision making is not based on individual constituents, even if they are well founded. Due to a lack of systematic empirical research, the effectiveness of ES could not be clarified.

While the North American line focused successfully on the implementation of problem solving in computer systems, the European line focused on the simulation of complex environments to empower human problem solving and decision making within complex domains. Two approaches surfaced, one initiated by Donald Broadbent (Berry & Broadbent, 1984, 1988; Broadbent, 1977) in the United Kingdom and the other by Dietrich Dörner in Germany (Dörner, 1976; 1987; Dörner & Wearing, 1995). The two approaches have a common emphasis on relatively complex, semantically rich, computerized laboratory tasks constructed to resemble real-life problems. The approaches differ somewhat, however, in their theoretical goals and methodology. The tradition initiated by Broadbent emphasizes the distinction between cognitive problem-solving processes that operate under awareness versus outside of awareness and typically employs mathematically well-defined computerized systems. The tradition initiated by Dörner, on the other hand, is interested in the interplay of the cognitive, motivational, and social components of problem solving and utilizes very complex computerized scenarios that contain up to 2,000 highly interconnected variables (e.g., the Lohhausen project of Dörner, Kreuzig, Reither, & Stäudel, 1983; Ringelband, Misiak, & Kluwe, 1990).

Both approaches focused on laboratory tasks with complex structures which were computerized and analogous to real-life situations. Broadbent's experimental research emphasized the distinction between cognitive problem solving processes in explicit and implicit modes (Berry & Broadbent, 1995). These experimental approaches helped to categorize expert problem solving further, thus strengthening the understanding that there is nothing like *one single problem solving skill* or deterministic algorithm which accurately describes human problem solving and that each of the categories comes with different sets of knowledge and skills.

On the other hand, Dörner developed complex computer environments with more than 2,000 variables that emphasized the interactions between motivational,

social, and cognitive factors of complex problem solving (Dörner, 1986; Dörner et al. 1983). The experimental results revealed typical errors which occur when one works with complex systems (Dörner, 1989). The computational models were no longer used to *simulate* (or imitate) the problem solving process but to *stimulate* them. Instead of trying to compute the problem solving process (as in GPS) or support the decisions (ES), Dörner developed research instruments for a better understanding of problem solving and at the same time provided environments to train problem solving skills. On the computational level, the environments of course still have to be deterministic in order to be implemented. But due to the many variables it was not possible for subjects to understand all of their effects. Having models which are fully available to the researcher (or to the instructor) and yet unable to be disclosed to the subjects led to a better understanding of the problem solving process. These insights still provide us with opportunities to train human complex problem solving. The approaches to general problem solving or general decision making may have turned out to be incomplete (or even inefficient), but the chance to simulate complex environments helps in understanding and training expert human decision makers.

Interestingly, research on complex problem solving coincides with mental model research insofar as researchers such as Funke (1992) agree on the point that complex problem solving necessarily presupposes the process of mental model building. In addition, Krems (1995) investigated differences in the domain specific knowledge, strategies, and cognitive flexibility of experts and novices in complex problem solving situations. Accordingly, the interrelation between mental models and complex problem solving provides a unique challenge for research in the field of learning and instruction (Jacobson, 2000).

MENTAL MODELS AND COMPLEX PROBLEM SOLVING

How does the immune system respond to constantly changing bacterial and viral invaders? How do birds achieve their flocking formations? Can a butterfly influence the weather? Why do traffic jams form and how can traffic flow be improved? How do galaxies form? These questions, asked by Jacobson (2000), focus on phenomena that may be regarded as complex systems. They present unique challenges for people because with increasing complexity it becomes very difficult to understand such systems and to operate effectively with them. Therefore, the process of coping with complex systems such as power plants or industrial systems is closely related to problem solving. As stated above, mental models *represent* the subject's knowledge in such a way that even complex phenomena become plausible. In other words, comprehension and reasoning in specific situations necessarily involve using mental models of different qualities to understand the world (Greeno, 1989; Seel, 1991). The learner makes a mental effort to understand complex systems and in doing so constructs appropriate mental representations to model and comprehend these systems. Certainly, this kind of learning may also involve the accumulation of domain-specific knowledge, but its main purpose consists in the construction of causal explanations with the help of

appropriate mental models as a central means of cognitive accommodation. Clearly, there is no need for a mental model as long as the learner can assimilate a new situation or new learning material into retrievable cognitive structures and schemata. This means that a substantial *resistance to assimilation* is a prerequisite for constructing a mental model, and the degree of this resistance depends greatly on the complexity and unfamiliarity of the topics to be learned.

Evidently, most learning tasks and well-structured problems, such as Duncker's x-ray task and the Tower of Hanoi task, can be solved by means of activating and/or modifying an available schema (for example, see Sweller, 1988), whereas *ill-structured problems* regularly possess aspects that are unknown. Additionally, such problems might have multiple solutions, various solution methods, or even no solutions at all. Ill-structured problems often require learners to make judgments and express personal opinions or beliefs about the problem and presuppose the construction of mental models. In contrast to well-defined problems, the initial state, the desired end state, and the barriers are all complex and change dynamically during the process of problem solving (Seel, 2006). For instance, policy making is just such a dynamic, complex problem; that is to say that the task environment and its factors change over time and don't "wait" for a solution as they do, for instance, in the case of a chess problem. When the conditions of a problem change, the solver must continuously adapt his or her understanding of the problem while searching for new solutions because the old solutions may no longer be viable. For example, investing in the stock market is often difficult because market conditions, such as demand, interest rates, or confidence, tend to change, often dramatically, over short periods of time. All of this cannot be done by means of schemata which can be activated from long-term memory but rather demands the construction of a mental model. Complex problem solving is guided by explanatory mental models designed with a specific end in mind. The problem solver explores these models by developing hypotheses and then varying input parameters to investigate how well his or her conjectures align with the models. More generally, problem solving presupposes that people actively construct meaningful representations, such as coherent *mental models*, that represent and communicate subjective experiences, ideas, thoughts, and feelings. By means of such representations an individual is also able to simulate real actions in imagination (in the sense of thought experiments) in order to solve a complex problem. In this context, mental models fulfill several functions: (1) They guide the comprehension of the system as well as the concrete operations with it; (2) they allow the system's states to be explained; and (3) they allow predictions about the system's behavior and the effects of intervention in the system to be derived (Greeno, 1989; Young, 1993). Complex problem solving requires iterative steps of hypothesis testing as well as an increased time for constructing *appropriate* mental models (Funke, 1992). This constitutes a problem in itself because mental models are regularly incomplete and constantly evolving. They are usually not an accurate representation of a phenomenon but rather typically contain errors and contradictions. However, mental models are parsimonious and provide simplified explanations of complex

phenomena; they often contain measures of uncertainty about their validity that allow them to be used even if they are incorrect.

The development and successful application of a mental model often requires quite a lot of time and mental effort due to basic processes of analogical reasoning. Evidently, this goes far beyond the conception of cognitive load (Sweller, 1988; Paas, Renkl, & Sweller 2004) and necessarily presupposes a *long-term working memory* (Kintsch et al., 1999), without which solving complexity would never be possible for the human mind.

First, the development of a mental model is closely related to the process of "fleshing out" (Johnson-Laird, 1983), which involves the successive completion of a model: The person creating the model constructs an initial solution model by selecting only a few attributes from a known base domain and then mapping them to the target domain. If this process leads immediately to an acceptable conclusion by analogy, the procedure can be finished. But this situation should arise relatively infrequently since it is not usually easy to construct a mental model to explain an unknown phenomenon on the basis of previous experiences with similar phenomena. The justification of a conclusion by analogy presupposes an unsuccessful *reduction to absurdity* (Seel, 1991). This is a process of continuously testing whether a model can be replaced with an alternative model or not. To illustrate this, we can refer to the metaphor of a gold digger who is continuously washing away the sand to find the gold nugget. A model is "true" as long as we cannot find a better one. This process corresponds to Popper's (1966) falsification principle.

Both complimentary iterative processes – "fleshing out" and reduction to absurdity – are closely related with learning experiences stored in a person's memory system. The psychological literature suggests that accumulated learning experiences that we store in long-term memory can take on two basic forms: declarative and procedural. Various types of cognitive structures are used to store declarative and procedural knowledge – such as lists, associations, plans, scripts, schemata, and mental models, too. Accordingly, the learning-dependent progression of mental models in the course of instruction, as well as their possible transitions to schemata, is of central importance for instructional psychology, because it can be argued that the application of a schema will be more efficient and less faulty (Brewer, 1987; Rips, 1987). Despite the central importance of mental models for complex problem solving, instruction generally aims at the development of schemata, with which a person can *quickly* settle on learning and problem solving.

In complex contexts mental models have to adapt to represent each new state of the problem due to world changes over time. Since mental models are ad hoc representations, they show their benefits in situations where no schema is applicable. Being able to monitor changes to mental models over time would provide us with the necessary insight into complex problem solving – and into the representations of complex problems. Among others, two types of change are of special interest. The first has to do with how experts adapt their models within complex problem solving processes. The second is about how novices become experts over time, how their general and domain-specific model building skills develop during this process, and how their models change.

MEASUREMENT OF MENTAL MODELS

As pointed out above, humans need mental models to solve problems that they have never confronted before. During the solution process they don't have a reliable path to the solution – they first have to find it. However, inferences which are valid at one point in time might not be valid anymore a short time afterwards due to a change of the problem space. Politics offers many good examples of this – just think of something complex like the public health system. Up to now it can be argued that individuals successfully operate in such dynamic systems on the basis of mental models that must map the dynamics of the system. Actually, the question of a valid and reliable measurement of change is one of the central problems of mental model research (Seel, 1997). Mental models are theoretical constructs which are not observable. Therefore, individuals have to externalize their mental models, and changes in these externalizations are interpreted as changes in the underlying mental models, i.e. researchers can only learn about mental models if individuals communicate their mental models (Hanke, 2006; Seel, 1991).

The psychological and educational diagnosis of models presupposes repeated measurements of mental models in the course of problem solving processes. In the following section we discuss some selected methods for the assessment of mental models. We focus on (1) Thinking-Aloud Protocol, (2) Structure-Formation Technique, (3) Concept-Mapping Tools, (4) Causal Diagrams, and (5) the DEEP methodology.

Thinking-Aloud Protocol

The *Thinking-Aloud Protocol* method requires for a person to be able to verbalize the cognitive processes while solving a problem (van Someren et al., 1994). The dual requirement of both solving a complex problem and verbalizing the cognitive processes represents an unfamiliar situation for the test person. Therefore, the test conductor has to ask for detailed information about the test person during the experiment. Training in verbalizing cognitive processes is often realized before the actual experimentation. The method is usually realized as a single-subject study along a standardized schedule with four phases. The first phase serves to make the test person familiar with the situation of an experiment. The second phase is the observation part, where the test person verbalizes solutions for the problem. The third phase includes an interview of the documented audio and/or video recordings. The fourth phase completes the method with an analysis and interpretation of the data. The data collected represents only a small amount of the cognitive processes which occur when one solves a complex problem. One problem with the *Think-Aloud Protocol* method is the insufficient and imprecise verbalization of the test person. Furthermore, the quantification of the collected data and the explicit relation of verbal data to cognitive processes call the validity and reliability of this method into question (see Nisbett & Wilson, 1977). However, Chi (1997) and Ericsson & Simon (1980) have developed practicable procedures for quantifying verbal data.

Structure-Formation Technique

Scheele and Groeben (1984, 1988) developed a *Structure-Formation Technique* (SLT) to represent the subjective theories of a test person using concepts and named relations. The SLT method is used in different variations for the diagnosis of knowledge structures. One essential distinction of these variations is whether the concepts and named relations are provided by the test conductor or can be chosen by the test person freely. The SLT is realized in two phases. In the first phase, the test person collects concepts of the problem to be solved and writes them down on paper cards. The second phase serves to structurally connect the concepts with named relations. The final product of the experiment is a network of concepts which are structurally connected with named relations. The individual network of a test person can be compared with expert networks. Although the time consuming method requires for the test person to have persistent cognitive ability and high motivation, the networks can be analyzed with regard to their content and their structural shape.

Concept-Mapping Tools

The purpose of computer-based *Concept-Mapping Tools* is the diagnosis of a person's individual structural and semantic knowledge (Mandl & Fischer, 2000). According to the SLT method, a concept map consists of different concepts which are connected with named relations. The collected data of a *Concept-Mapping Tool* can be processed directly for further analysis. The use of the computer enables test persons to easily reconstruct the individual concept maps during the experimentation. The following research groups are working on the development and evaluation of computer-based *Concept-Mapping Tools*:
– IHMC Cmap Tools 4.03 (cmap.ihmc.us)
– Inspiration 8 (Inspiration Software, Inc., 2006)
– COMASOTO (Weber & Schumann, 2000)
– CCMap (Reiska, 2005)
– MaNET (MannheimResearchCompany, 2002)

Causal Diagrams

The procedure of causal diagrams was first applied by Funke (1985), and they have been combined with the SLT (Scheele & Groeben, 1988) by Seel (1999) and Al-Diban (2002). Causal diagrams are considered as re-representations of the test persons' mental models. From a methodological point of view, there are three criteria for evaluating the causal diagrams produced by test persons. (1) The "Goodness of Causal Diagrams" measures the quality of structural knowledge involved in mental models. (2) The "Depth of Connectivity" within a causal diagram is the quotient of the number of relations n_{pf} (or arrows) and the number of concepts n_{beg}, and (3) the "Complexity" of a causal diagram is its causal depth. These three criteria allow one to measure the observation of change in causal

diagrams, defined as external representations of mental models. The *Test for Causal Diagrams* has been found in tests to be satisfactory in terms of objectivity, reliability, and validity (Al-Diban, 2002). However, the data collection is very time consuming.

The DEEP methodology

The *Dynamic Evaluation of Enhanced Problem-solving* (DEEP) methodology was developed as a web-based knowledge mapping technique for problem-based assessment (Spector, 2004). The test persons are provided with a problem scenario in which they are asked to represent their models of the problem space. Spector (2004, 436) reports five steps for constructing these models:
– Listing key facts and causal factors influencing the problem situation
– Documenting each factor – what it is and how it influences the problem
– Constructing a graphical depiction of how these factors are linked
– Making annotations of each node and link
– Indicating other considerations or approaches

The *DEEP methodology* identifies gaps between novice and expert decision making in complex domains. Spector et al. (2005) discuss their initial findings with the *DEEP methodology* in three different problem domains – engineering design, environmental planning, and medical diagnosis. The findings show that the *DEEP methodology* enables researchers to identify differences between novice and expert thinking and problem solving.

The five methods discussed above show that a measurement of change in mental models requires precise and well-defined indicators. From a methodological point of view, the measurement of change includes latent person variables that cannot be observed directly. Accordingly, we must construct and use reliable and valid indicators to assess mental models over a defined period of time with several measurement points (Seel, 1999). Furthermore, the observation of change in mental models requires a systematic diagnosis.

SYSTEMATIC DIAGNOSIS OF THE PROGRESSION OF MENTAL MODELS

The progression of mental models has been of central interest from the beginnings of mental model research (Johnson-Laird, 1989; Seel, 1991). This has been discussed by Johnson-Laird (1989, p. 485) as follows: "What is at issue is how such models develop as an individual progresses from novice to expert, and whether there is any pedagogical advantage in providing people with models of tasks they are trying to learn."

Accordingly, the diagnosis of the progression of mental models has to assess the mental models of novices and their transition to more appropriate mental models at several stages of the learning process (Seel, 1999). Therefore, we argue that the progression of mental models is a specific kind of transition between pre- or misconceptions (the initial state of learning; defined as a novice model) and causal explanations (the desired end state of learning; defined as an expert model).

The systematic diagnosis of the progression of mental models requires at least eight principles. The diagnosis
– is embedded in a complex problem situation,
– is applied in different subject domains,
– allows the construction, modification, and reorganization of mental models,
– collects mental model data in a longitudinal design,
– indicates the successive model construction and completion from novice to expert models,
– considers characteristics of expert models,
– provides valid and reliable quantitative data, and
– enables a methodologically straightforward analysis and interpretation of the data collected.

Taking into account these eight principles, we developed the SMD TECHNOLOGY (Ifenthaler, 2006) and MITOCAR (Pirnay-Dummer, 2006) for a systematic diagnosis of the progression of mental models.

The SMD TECHNOLOGY (**S**urface, **M**atching, **D**eep Structure) is a new method for assessing the learning-dependent progression of mental models. Individual models (in terms of externalized mental models) are assessed on three different levels.
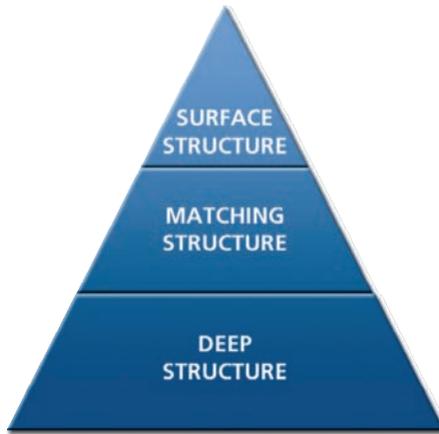

Figure 2. The three levels of the SMD-Technology

The first level constitutes the *Surface Structure*, on which a rapid and economically graphical and/or optical assessment is made possible. The *Surface Structure* θ is defined as the sum of all propositions P in an individual model.

$$\theta = \sum_{i=0}^{n} P_i \qquad (1)$$

The assessment of the structural properties of the externalized models is realized on the *Matching Structure* level. The *Matching Structure* μ is defined as the quantity of relations R of the shortest path between the most distant nodes K.

$$\mu = \max_{i,j}\{d(i, j)\} \tag{2}$$

The third level is defined as the *Deep Structure*, on which the models are assessed in terms of their semantic structure. The *Deep Structure* δ is calculated as the similarity (Tversky, 1977) between a domain-specific expert model M_{ex} and the individually assessed model M.

$$\delta = \frac{f(A \cap B)}{f(A \cap B) + \alpha \cdot f(A - B) + \beta \cdot f(B - A)} \tag{3}$$

We conducted three experimental studies within different subject domains (ecology and geophysics), and the findings show that it is possible to identify the learning dependent progression of models on the three levels of the SMD TECHNOLOGY (Ifenthaler, 2006). The findings are consistent with the assumption that models progress from initial preconceptions to causal explanations (Ifenthaler & Seel, 2005; Seel, Al-Diban, & Blumschein, 2000).

In the first step of this approach, we develop graphical approaches such as concept maps, causal diagrams, the DEEP methodology, and partially SMD TECHNOLOGY in order to re-represent knowledge of idiosyncratic individuals, which of course leads to great difficulties in comparing different drawings or maps between whole groups. Secondly, we choose whether to give the subjects a set of prescribed content (e.g., concepts) which, however, wouldn't be their own knowledge any more, or to collect many different codings, which would lead to a very large and incomprehensible map when we try to aggregate the data. The same goes for the researchers' interpretation while trying to aggregate the data qualitatively. This wouldn't allow an assessment of the subject's representation anymore either. Thirdly, natural language provides its users with a sufficient amount of convention – despite its well-known ambiguities, language works well enough in most everyday cases. The users of graphical representations, however, are rarely well trained and can never be trained as well as in their native language, which is a surprisingly old assumption, leading us back even to the Stroop test (Stroop, 1935). Although it is very well possible to recode the data a posteriori by interpreting synonyms, we still put in intolerable amounts of subjective interpretation, which leads to the conclusion that only an expert can diagnose another expert's knowledge. At least one expert has to be present when one is interpreting different synonyms of single concepts. The inherent difficulties which come with these approaches are obvious. No one knows if the interpreting expert (or even group of experts) overlays the aggregation process. If we don't aggregate we still only have isolated model

representations. When we come to this point, we could still interpret and compare the surface structures and draw conclusions concerning the deep structure, the deep domain. But what, for example, would a similarity between surface structures of completely different domains tell us? This might tell us only that mental models are always similar up to some point. The aggregation problem can of course be solved if the subjects use the highest conventional symbols available, which clearly are to be found in their natural language – and if we have the proper set of tools to transform natural language into model re-representations. To do so, we use technologies from *parsing* and *corpus* linguistics.

Thus, a central part of the SMD TECHNOLOGY was the development of a set of tools called MITOCAR (Model Inspection Trace of Concepts and Relations), which provides a solution to the problems of graphical approaches discussed above (Pirnay-Dummer, 2006). In MITOCAR, subjects go through two different rounds. In the first round they only provide natural phrases (source phrases) about their specific subject matter. Before the second round, the parser extracts the most frequent concepts from the text corpus of the group and connects them to pairs of concepts. In the second round the subjects rate how close the concepts are and how different and how certain they are about their assessment. In addition, the subjects rate the plausibility of their fellow group members' source phrases. This data allows one to derive models and even graphical models (Fruchterman & Reingold, 1991; Ganser & North, 1999) which can be compared in both traditional and new ways.

MITOCAR first builds up the model without having any subject to draw graphical representations (which are interpretations). It uses sentences of natural language and a built-in parser to extract the concepts from the sentences which are relevant for the model. Figure 3 shows an example of a re-representation of MITOCAR.
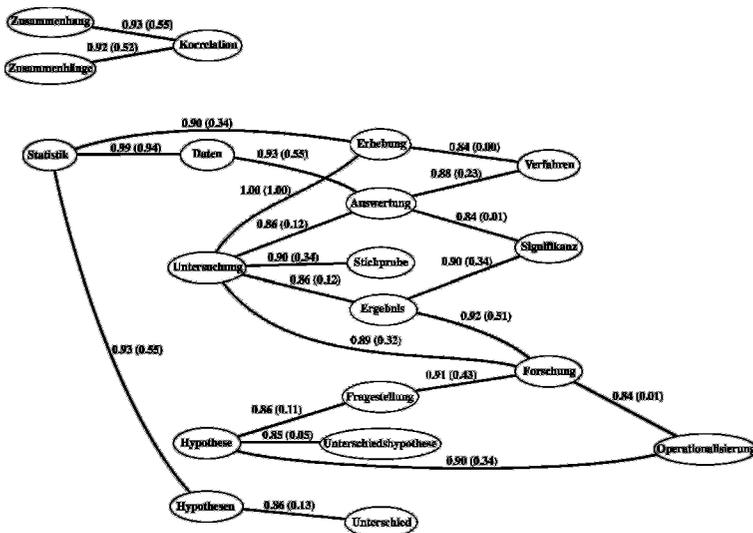

Figure 3. MITOCAR example. Re-representation of a main group model

MITOCAR was used in three subsequent experiments, each containing three different types of expertise. The experiments were conducted within the domain of economics, general didactics, and statistics. MITOCAR has proven to be powerful and also very fast in assessing and comparing shared group models. The first round takes approximately half an hour and the second round takes about an hour for any group of experts (Pirnay-Dummer, 2006). MITOCAR uses different steps of inferences to come from the natural language sentences to the model. The inferential modules of MITOCAR provide a variety of analyses to rebuild the models, to test their boundaries, to test the homogeneity and the multidimensional scaling of the data, and to perform all the necessary statistical tests which compare the semantic, structural, and combined models between groups automatically. The results are automatically reported and interpreted by the MITOCAR software.

Today, the described modules of MITOCAR can also be used in additional fields of application. For instance, they can be used with tracking navigation in learning environments (Dummer & Ifenthaler, 2005) or in the assessment of team performance (O'Connor & Johnson, 2004), and they can also be combined with the DEEP methodology (Spector, 2004). For diagnostic purposes, MITOCAR combines the right set of model structure, assignments of values and variables, and evaluation function. Since the *elements* (components) of mental model building can generally be described as semantic sentences – which obviously still include simple concepts – the structure for the mental models has to combine such sentences in order to allow the cognitive system to draw conclusions.

To trace the structures we can go straight back to both Expert Systems (ES) and the metaphor of the General Problem Solver (GPS). A reconstruction of the traces of expert knowledge on Bayesian Networks has already been conducted successfully (e.g., Janetzko, 1996). An interpretation in psychological terms can be made with reference to the European line of problem solving provided by Dörner and Broadbent. Mental models often contain circular references which cannot be represented by acicular directed graphs (which are needed to build up Bayesian Networks). Although it is possible to work around this by introducing specific rules about what the system should do if a circular reference occurs, circular references are – in the same way as we found in ES (Rödder, 1991) – very common and even desired when building mental models (Seel & Schenk, 2003). Thus, the circular case is no rare exception. The best way to improve this is to use methods for circular graphs. The inferential modules of MITOCAR contain such methods, which combine strategies from causal networks (Pearl, 2000) and similarity measures (Tversky, 1977).

If we have a fairly large number of single user models we need automated strategies to assess the models with regard to the needed time and effort. MITOCAR first builds up the causal network for each single model and then for each group model – while building up but ignoring circular traces – and then uses a combination of both structural and conceptual comparison by Tversky-Similarity.

We use this technique to compare model structures and concepts from different expert groups and novices on the same topic. Tverksy-Similarity also allows us to combine both dimensions, which leads to an automated identification of SMD

Structures. This can be used to measure distances between different types of experts quantitatively. In our case the three groups under study are novices, usability experts, and classical experts. They have disjunctive semantics and structures as shown in the distance graph in figure X (Pirnay-Dummer, 2006):
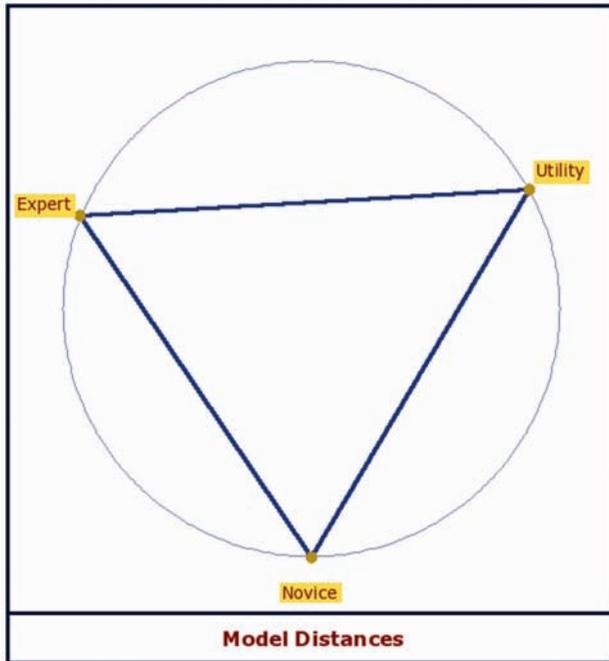

Figure 4. MITOCAR example. Comparing different groups on the same topic

SUMMARY

In this chapter we discussed the development of mental models and their influence on learning and problem solving. More specifically, we focused on the learning-dependent progression of mental models in solving problems within a given complex domain – as advocated in the mental model hypothesis (Seel, 1991). An expanding field of complex systems is a main characteristic of the modern world (e.g. in industry and policy making). This increase in complexity is placing a greater burden on cognitive operations because interaction with complex systems requires higher-level cognitive processes such as problem solving. People have to deal effectively with a multitude of interacting and dynamically changing variables that require the integration of different types of knowledge as well as the construction of mental models. Indeed, we argue that humans need mental models to solve problems that they have never confronted before. During the solution process they don't have a reliable path to the solution – they first have to find it.

However, inferences which are valid at one point in time might not be valid anymore a short time afterwards due to a change in the problem space. It can be argued that individuals successfully operate in such dynamic systems on the basis of mental models that must map the dynamics of the system. Accordingly, the learning-dependent progression of mental models is considered a central component of the development of expertise within a domain (Glaser, 1988). In accordance with this author's argumentation, instruction should support the development of relevant knowledge structures that allow learners to effectively integrate and access task-relevant knowledge in order to solve problems.

Because knowledge structures are often directly related to accurate learning (discussed here in terms of knowledge acquisition) we have to assess the development of structural knowledge as instruction and learning proceeds (Royer, Cisero, & Carlo, 1993). Accordingly, the question of a valid and reliable measurement of knowledge has been one of the central problems of research on learning and problem solving over the past decades. Although there has been substantial methodological progress in assessing knowledge structures in the course of instruction and training (Birenbaum & Dochy, 1996; Nichols, 1994) the assessment of the higher-level cognitive operations involved in complex problem solving by means of mental models still constitutes in itself a complex problem for instructional psychology today.

The definitions of mental models may vary in the literature, but most authors agree that mental models should be considered as well-organized and integrated constructions of the human mind used to comprehend a given phenomenon (Johnson-Laird, 1983; Seel, 1991). Mental models are theoretical constructs which are not observable. Therefore, individuals have to externalize their mental models, and changes in these externalizations are interpreted as changes in the underlying mental models, i.e. researchers can only learn about mental models if individuals communicate their mental models (Hanke, 2006). Accordingly, thinking-aloud protocols and several graphical approaches have been applied successfully to assess mental models. In particular, the technique of using diagrams is considered an appropriate tool for measurement. Actually, the use of graphical methodologies for knowledge assessment has a long history (Ferguson, 1977), and numerous studies demonstrate that diagrams may aid in the overall understanding of complex information. However, this effect is evidently dependent on the nature of the task (e.g. Hegarty & Just, 1993; Mayer & Gallini, 1991; Seel et al., 2000). Indeed, several studies have found that diagrams facilitate performance on knowledge elaboration, and theories positing the role of mental models have been developed to account for these finding (Kieras, 1988; Kieras & Bovair, 1984; Mayer, 1989). In general, we can conclude from this research that diagrams and more complex graphical approaches such as concept maps, causal diagrams, the DEEP methodology, and partially also the SMD-technology are effective methods for the assessment of mental models. However, research that directly assesses mental models in order to reveal how diagrams impact their development is still lacking (Fiore, Cuevas & Oser, 2003). Furthermore, graphical approaches meet with great difficulties in comparisons of different drawings or maps made by the same people over time.

Due to the fact that complex tasks are made up of different types of knowledge (declarative, procedural) there is no single method for measuring them. Thus, reliance on a particular method of assessment is likely to produce an incomplete representation of the learner's knowledge and how it is involved in mental modeling. By using multiple measures to assess the acquisition of knowledge, we may be able to better assess the effectiveness of mental models in complex problem solving. That is why we developed and applied MITOCAR – a language-like format of representation.

Our argumentation is that research on mental models, knowledge representation, and reasoning always has to deal with the diagnosis of knowledge at different points in the learning process. Actually, the formal methodology might not seem to provide the easiest access to this kind of investigation. But since this methodology is consistent with model theory it is likely to help us to find answers to some of the questions about mental models that are still at hand – and doubtless there are quite a few. Furthermore, it is a practicable first step towards the automatization of the diagnostic process and can thus help us to carry out diagnoses faster and more efficiently than is possible with the classical methods. The knowledge garnered from the diagnosis of mental models, model representations, and reasoning will in return be more precise when we need it to design instruction on complex problem solving.

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