Model-Based Learning and Performance

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Abstract

Model-based learning is both a new and old paradigm of psychology and education. In pedagogy we can find this idea since decades (and until today various conceptions of model-based learning have been developed in the fields of mathematics, physics or geography education aiming at guided discovery and exploratory learning. Traditionally, there are two major approaches of theory and research on model-based learning: A functional-pragmatic approach and a constructivist approach, which is closely related with the theory of mental models. This chapter focuses on both approaches with a particular emphasis on measuring the effects of model-based learning on different performance criteria, such as understanding and problem solving, analogical reasoning, and situation-dependent decision making.

The chapter starts with a description of the theoretical foundation of model-based learning with a particular emphasis on the learning-dependent progression of mental models and its systematic assessment by means of particular diagnostic methodologies. The epistemology and psychology of mental models as the fundamental basis of model-based learning are described whereby models will be separated from cognitive schemas, discussed as the "building blocks" of the psychological understanding of cognition. The impact of mental models on comprehension and problem solving as well as on analogical reasoning and decision making is discussed. Comprehension and reasoning in specific situations necessarily involve the use of mental models of different qualities. Besides the mental model approach, model-building activities have been emphasized in various areas of instructional research aiming at the improvement of learning and problem solving in subject matter domains, such as physics or mathematics. In contrast to the mental model approach, these instructional approaches of model-based learning correspond with functionalist-pragmatic conceptions of model-building activities within the realm of mathematics and physics education. Both approaches of model-based learning have had initiated numerous empirical studies which are summarized and discussed.

Keywords

Mental models • Analogical reasoning • Problem-solving • Knowledge diagnosis • Model-based teaching • Situation awareness • Decision making

Introduction

Model-based learning is both a new and old paradigm of psychology and education. In education this idea has been around for decades (cf. Chapanis, 1961), and a variety of

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conceptions of model-based learning aimed at guided discovery and exploratory learning have been developed in the fields of mathematics, physics, and geography education (cf. Hodgson, 1995; Lesh & Doerr, 2000; Penner, 2001). These conceptions correspond to a large extent to functional and pragmatic approaches of model-based learning, whereas the construct of mental models as it emerged in cognitive science in the 1980s corresponds to a constructivist view on model-based learning (Johnson-Laird, 1983; Seel, 1991).

Although the two movements differ with regard to their epistemological and theoretical foundations, they share a strong instructional impetus insofar as the suggestion has been made that models are constructed from the significant properties of external situations, such as school settings, and the subject's interactions with well-designed learning environments (cf. Lehrer & Schauble, 2010; Norman, 1983). Indeed, learning environments can be designed in such a way that students may be involved in a process of discovery and exploratory learning in which they extract facts from information sources, look for similarities and differences between these facts, and thus develop new concepts (cf. Carlson, 1991). In this context, instruction is oriented toward facilitating model-based learning and providing the students with opportunities to create their own models for solving tasks and problems. Advocates of this approach argue that learning occurs as a multistep process of model building and revision (Lehrer, 2009; Penner, 2001). Similarly, proponents of the mental model approach argue that learning occurs when people actively construct meaningful mental representations, such as schemas and coherent mental models that communicate subjective experiences, ideas, thoughts, and feelings (cf. Seel, 1991). Although these conceptions obviously overlap to a great extent with regard to the impact of instruction on model-based learning and performance, they approach this topic from different theoretical perspectives and research interests, as described in the following sections.

Major Lines of Research on Model-Based Learning

The intentional construction of models has played an important role in mathematics (Schichl, 2004), the philosophy of science (Bailer-Jones, 2009), and psychometrics (Borsboom, 2005) for a long time. However, in this chapter the focus is on model-based learning and performance in various subject matter domains, such as physics and mathematics, where models serve explanatory functions. These conceptions can be classified as functional-pragmatic approaches that go "beyond constructivism" (Lesh & Doerr, 2003). In addition, the chapter also describes the impact of the mental model approach on learning and reasoning. Clearly, this approach goes "beyond pragmatism" and aims at creating epistemological plausibility with regard to the "cognized world" as well as reasoning (Seel, 1991).

Pragmatic Approaches of Model-Based Learning

Pragmatic and functional approaches of model-based learning and performance have played an important role within the realm of instructional psychology since the 1980s, but their origins can be dated back further. The concept of models already played a central role in information science in the 1950s and 1960s, where one can find the idea that the learning consists of the procedures people use to construct *internal models* of their environments (e.g., Steinbuch, 1961). At the same time, Chapanis (1961) classified models into two broad categories: *reproduction models*, such as architects' models that operate with physical objects and diagrams, and *symbolic models* aiming at the representation of knowledge about the world. The various approaches of the 1960s culminated in the advent of a "general model theory" applied to issues of representation and scientific understanding (Stachowiak, 1973; Wartofsky, 1979).

From a pragmatic point of view, talking about *models* always implies asking for the *original* to be modeled. Globes are models of the earth. Naturally, a globe is not a reduced earth but rather it is designed to give answers to questions about the locations of different places or the distances between places. With regard to the chemical composition of the earth, a globe is not relevant. This example illustrates a basic property of models: Every model is constructed in accordance with specific intentions in order to simplify its original in several respects. By virtue of its nature as an idealized reduction to relevant characteristics of its original, *a model may be understood as a concrete*, *comprehensible*, *and feasible representation of nonobvious or abstract objects* of consideration. The representation of the objects' attributes and components comes second to the representation of structural relationships. Evidently, the functions of a model—and in consequence, also the requirements for its structural features—are defined on the basis of the intentions of the model-constructing person. Therefore, in physics as in other disciplines the term *model* is principally used in accordance with functional intentionality:

- Models may serve as means of *simplifying* an investigation to particular and relevant phenomena in a domain.
- Models may serve to help the user *envision* that which is being modeled and make the invisible visible.
- Models are constructed as analogies that identify relationships within an unknown domain to be explained (e.g., quantum mechanisms) with the help of the relationships within a known domain. (e.g., Rutherford's atomic model).

Such models are heuristic hypotheses about structural similarities of different domains. Usually, they are called *analogy models*.

These characteristics of models are also emphasized in various areas of instructional psychology with the aim of improving learning and problem solving in subject matter domains such as physics or mathematics. Stewart, Hafner, Johnson, and Finkel (1992), for example, have summarized the central idea of these instructional approaches by stating that "a science education should do more than instruct students with respect to the conclusions reached by scientists; it should also encourage students to develop insights about science as an intellectual activity" (p. 318). Accordingly, advocates of this approach argue that "given that we wish to involve students in the practices of scientists, we focus primarily on model building" (Penner, Lehrer, & Schauble, 1998, p. 430). In science, an important goal of instruction is to help students develop powerful models for making sense of their daily experiences involving light, gravity, electricity, and magnetism. These models respond to the partial and incomplete models that students are likely to build with regard to phenomena of everyday physics (Clement, 1979, 2000). In order for these preconceptions or misconceptions to be changed, model-based learning in the classroom must correspond to the conceptual models and the constructs of the respective scientific discipline in the curriculum (Etkina, Warren, & Gentile, 2005).

A similar argumentation can be found with regard to the learning of mathematics in the classroom. Mathematizing is considered as a form of modeling and requires the use of specialized formal languages, symbols, graphs, pictures, concrete materials, and other notation systems to develop mathematical descriptions and explanations that often make great demands on students' representation capabilities. Therefore, Hodgson (1995), Lesh and Doerr (2000), and other authors argue that helping students to develop powerful mathematical models should be among the most important goals of math instruction, helping them to understand not only mathematics but also how it can be applied to phenomena of the real world that involve mathematical entities such as directed quantities (negatives), multivalued quantities (vectors), ratios of quantities, changing or accumulating quantities, or locations in space (coordinates). Actually, the "big idea" of those who advocate model-based learning in the math and science classroom is to provide students "with the skills they will need to accomplish this in the real world. This is the objective of mathematical modeling" (Hodgson, 1995, p. 353).

Comparable argumentations concerning the importance of model-based learning, and especially the use of mathematical models, can also be found in the areas of geography (e.g., Guermond, 2008), biology (e.g., Laubichler & Müller, 2007), and chemistry (Heyworth & Briggs, 2007).

Constructivist Approaches of Model-Based Learning

In the 1980s, the theory of mental models emerged and introduced a constructivist approach to modeling into cognitive science and related fields of interest (Gentner & Stevens, 1983; Johnson-Laird, 1983). The theory of mental models is based on the assumption that 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 explaining it to others (Seel, 1991).

In a historical review, Johnson-Laird (2004) traced the theory of mental models back to Peirce's (1883) early semiotics as well as to Wittgenstein (1922), and the Gestalt psychologists, such as Wolfgang Köhler (1947), who argued that vision creates an isomorphism between the force fields of the brain and the cognized world. Similarly, information theorists of the 1950s (e.g., Steinbuch, 1961) argued that learning consists in constructing *internal models* that are conceived as a cognitive isomorphism of structured domains or elements of the environment. This isomorphism is considered to be a threshold value, which can be approached by the internal models of a subject but not reached.

In accordance with Peirce's semiotics and the distinction between index, icon, and symbol, cognitive psychology differentiates at the very least between images (picture-like) and propositions (language-like) as forms of mental representation. Johnson-Laird (1983) added mental models as a particular form of representation that mediates between images and propositions. Markman (1998) has illustrated this idea with the following example: "Imagine a situation in which a boy stands at the top of a hill, makes a snowball, and rolls it down the snow-covered side of the hill. A person may never have witnessed an event like this, but one can construct the event and talk about it. One can imagine that the snowball rolls down the hill and gets larger and larger as it rolls, because snow sticks to it. A mental image of this event occurring might be formed … but this situation goes beyond a mere mental image; it requires reasoning about the physics of the situation to determine how the image changes over time" (Markman, 1998, p. 248).

In addition to the argumentation that mental models are a particular form of mental representation, Johnson-Laird (1983, 2004) also referred to the work of Craik (1943), who argued that an individual who intends to give a rational explanation for something must develop practicable methods in order to generate adequate explanations from the available knowledge of the world and his or her limited information processing capacity (Khemlani & Johnson-Laird, 2011). Thus, in order to create plausibility the individual constructs an internal model that both integrates the relevant semantic knowledge and meets the requirements of the situation to be mastered. Accordingly, this model "works" when it fits the subject's knowledge as well as the explanatory need with regard to the concrete situation to be mastered cognitively. More generally, Craik pointed out:

> If the organism carries a 'small-scale model' of external reality and of its own possible actions within its head, it is able to try out various alternatives, conclude which is the best of them, react to future situations before they arise, utilize the knowledge of past events in dealing with the present and the future, and in every way to react in a much fuller, safer, and competent manner to the emergencies which face it (Craik, 1943, p. 61).

By means of an internal or mental model, an individual is able to simulate real actions in the imagination. This means that a "mental simulation runs" envisioning in the imagination the events that would take place in the world if a particular action were to be performed. Thus, mental models allow one to perform actions entirely internally and to judge the consequences of actions, interpret them, and draw appropriate conclusions. Accordingly, model-based reasoning occurs when an individual interacts with the objects involved in a situation in order to mentally manipulate them so that the cognitive operations simulate specific transformations of these objects which may occur in real-life situations. This means that these *simulation models* operate like thought experiments to produce qualitative inferences with respect to the situation to be mastered. Although there were some authors before the advent of the mental model approach (such as Hacker, 1977; Veldhuyzen & Stassen, 1977) who emphasized the importance of internal models in operating with complex technical or physical systems, the idea of conducting simulations with mental models is probably the most important characteristic of the mental model theory. It constitutes the fundamental basis for qualitative reasoning as well (Forbus & Gentner, 1997; Greeno, 1989). Mental models "run in the mind's eye" to produce qualitative inferences with respect to the situation to be mastered cognitively.

The essence of the mental model theory can be described in the words of Johnson-Laird, who proclaimed that "mental models play a central and unifying role in representing objects, states of affairs, sequences of events, the way the world is.… They enable individuals to make inferences and predictions, to understand phenomena, to decide what action to take and to control its execution, and, above all, to experience events by proxy" (Johnson-Laird, 1983, p. 397). However, the question remains of how mental models are constructed.

Another question that repeatedly appears in the literature concerns the distinctiveness of mental models in relation to schemas. Ever since the concept of mental models was introduced into cognitive science it has been criticized by proponents of schema theories, who consider mental models to be mere instantiations of local schemas rather than a discrete theoretical construct (e.g., Brewer, 1987; Rips, 1987). In contrast, the schema concept is not popular in the field of cognitive science. For example, Anderson (1983) and Johnson-Laird (1983) did not operate with the schema concept, and other researchers, such as Brown (1979) and Prinz (1983), have rejected "schemas" as an unnecessary and insufficiently defined construct of cognitive psychology. This is not the place to expound on the arguments of this controversial debate about schemas and mental models and their cognitive functions. Basically, cognitive scientists agree on the point that schemas and mental models serve different cognitive functions: Schemas represent the generic and abstract knowledge acquired on the basis of manifold individual experiences with objects, persons, situations, and behaviors (Mandler, 1984). As soon as a schema is fully developed it can be applied immediately to assimilate information about new experiences. But how do people operate cognitively in the case of novel problems for which no schema can be retrieved from memory? The answer for those who advocate modeling activities is that people construct a mental model of the situation or problem to be mastered. In accordance with this argumentation, the next section of this chapter describes a theoretical model that integrates schemas and mental models into a more comprehensive architecture of cognition with the aim of explaining their mutually compensating cognitive functions.

A Cognitive Architecture of Model-Based Learning and Reasoning

According to Rumelhart, Smolensky, McClelland, and Hinton (1986), people have three essential abilities for processing information and acting successfully in various environments. First of all, people are very good at *pattern matching*. They are obviously able to quickly "settle" on an interpretation of an input pattern. This ability is central to perceiving, remembering, and comprehending. It is probably *the* essential component of most cognitive behavior—and it is based on the activation and instantiation of schemas. Secondly, people are very good at *modeling* their worlds due to their ability to anticipate new states of affairs resulting from actions in the world or from an event they might observe. Both pattern matching and modeling are grounded on building up expectations by "internalizing" experiences and are crucial for making inferences (Seel, 1991). Thirdly, people are good at *manipulating* their environments. This can be considered as a version of man-the-tool-user, which is perhaps the crucial skill for building a culture. Especially important here is the ability to manipulate the environment and to create artifacts as external representations which can be manipulated in simple ways to get answers to very difficult and abstract problems.

As people gain experience with the world created by their actions they internalize their experiences with external representations to develop mental models.

Schemas and Models: Two Sides of the Same Coin?

In order to explain the aforementioned basic capabilities, Rumelhart et al. (1986) divide the cognitive system into two modules or sets of units. One module—called an *interpretation network*—is concerned with producing appropriate responses to any input from the external world, while the other module is concerned with constructing a *model of the world* and producing an interpretation of "what would happen if we did that" with a particular external representation. The modeling part of the cognitive architecture is concerned with generating expectations about possible changes to the world as a result of imagining an external representation and operating on it. The interpretation network receives input from the world and reaches a relaxed mental state by producing relevant cognitive responses, whereas the "model of the world" predicts how the input would change in accordance with these responses.

From a psychological point of view, it can be argued that the interpretation network operates with *schemas*, which help the learner to assimilate new information into cognitive structures and constitute the fundamental basis for the *construction of mental models* of the world as well. In cognitive psychology as well as in PDP models, schemas are characterized asslot-filler structures used to organize concepts, relations between them, and operations with them semantically. However, PDP models do not consider schemas as stored structures of the semantic memory that can be activated when necessary but rather as representations of complex constraint satisfaction networks that trigger the interpretation of input information. Schemas emerge at the moment they are needed to interpret new information. Each schema results from the interaction between a large number of simpler units, which all work together to come to an interpretation of input information. Schemas are implicit in people's knowledge and are triggered by the events that they have to interpret. Clearly, this conception contradicts the conventional belief that schemas are stored in memory. From the point of view of the PDP approach, *nothing stored actually corresponds directly to a schema*; rather, "what is stored is a set of connection strengths which, when activated, have implicitly in them the ability to generate states that correspond to instantiated schemata" (Rumelhart et al., 1986, p. 21). Schemas are active processes but not products. They can be understood as recognition devices which aim at the evaluation of their goodness-of-fit to the data being processed.

Basically, Rumelhart et al. (1986) see the emergence of "models of the world" or *mental models* in the same way. A mental model also consists of a network which does not take its input from the external world but rather from the interpretation network, with the aim of specifying the actions that can be carried out in pure imagination. Its product consists of an interpretation of what can happen when actions are performed. Accordingly, the function of the mental model is to simulate actions in the mind, to assess their consequences, to interpret them, and to use these interpretations for making inferences. While the interpretation network takes its inputs from the world, the model-based network takes its inputs from actions of the interpretation network and predicts what changes they will bring about. Therefore, the model-based network can also be considered as an "action network" and constitutes the space for mental simulations. The two networks are related closely to one another and constitute the fundamental basis for mental operations (Seel, 1991).

Schemas and Mental Models as Modes of Assimilation and Accommodation

According to Seel (1991), the cognitive architecture proposed by Rumelhart et al. (1986) corresponds to Piaget's (e.g., 1976) idea that cognition is regulated by the interaction between assimilation and accommodation, which aims at adjusting the mind to meet the necessities of the external world. Assimilation can be considered as the fundamental basis of the interpretation network and is dependent on the activation of cognitive schemas, which allow new information to be integrated into existing cognitive structures. In cognitive psychology, schemas are understood as slot-filler structures that serve central cognitive functions, such as integrating information into cognitive structures, regulating attention, making inferences in the process of acquiring knowledge, and reconstructing it from memory. As soon as learners have consolidated schemas to a sufficient extent through learning and development, they provide them with the cognitive framework for "matching" information from stimuli with content from knowledge memory, thus allowing them to select the information that is consistent with a schema. Anderson (1984, p. 5) captures the essence of these functions of schemas when he remarks: "*Without a schema to which an event can be assimilated*, *learning is slow and uncertain*." Schemas represent the *generic* knowledge a person has acquired in the course of numerous individual experiences with objects, people, situations, and actions. As soon as a schema can be activated, it is automatically "played" and regulates the assimilation of new information in a "top-down" procedure. This allows information to be processed very quickly, a function which is vital for humans as it enables them to adapt to their environment more quickly.

Assimilation is a basic form of cognitive processing, but certainly not the only one. Another basic form consists in

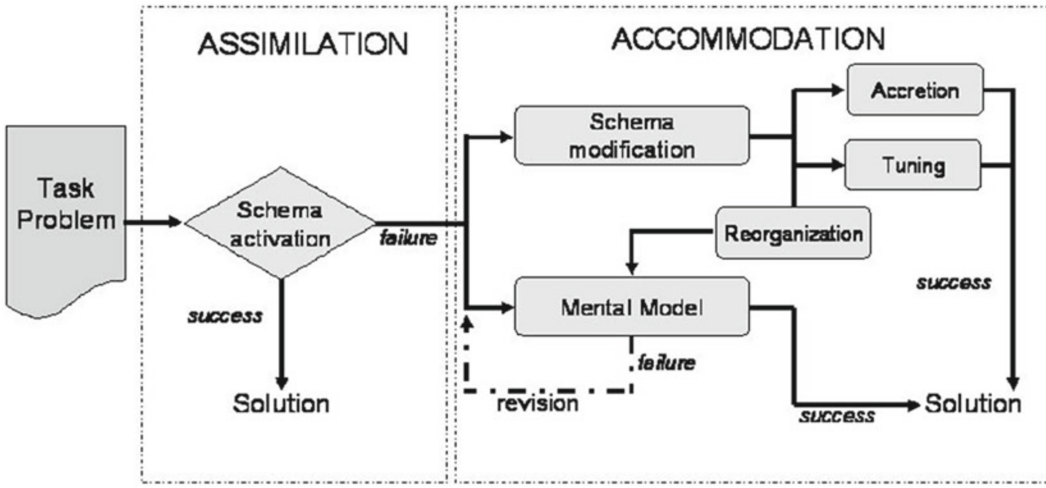

Fig. 37.1 Cognitive functions of assimilation and accommodation

accommodation aiming at restructuring knowledge. Accommodation aims, first of all, at a modification of a schema by means of accretion, tuning, or the reorganization of its structures and content (Norman & Rumelhart, 1978). This kind of accommodation presupposes an adjustment of existing schemas to new but familiar input information. However, if this adjustment of a schema is not possible, i.e., if the accretion, tuning, and/or reorganization of a schema fails—or if there is no schema to be activated at all—the learner either can abandon the cognitive processing or invest mental effort to develop a mental model as a more elaborated form of accommodation. Accordingly, mental models must be seen as products of accommodation (as discussed in Piaget's epistemology) that aim at adjustments of cognitive structures to the environment whenever the subject is not able to activate and modify an appropriate schema (Seel, 1991, 2006). In contrast to schemas, mental models operate from the "bottom up" under the continuous control of consciousness. As long as the information being processed can be assimilated promptly into cognitive structures and as long as schemas can be modified by means of accretion, tuning, and reorganization, there is no need to construct a mental model. This theoretical conception can be illustrated as in Fig. 37.1.

Mental models constitute the fundamental basis for developing "models of the world," discussed here in accordance with Rumelhart et al. (1986), and they may serve as *models for reasoning* as well as *models for understanding* (Mayer, 1989). In both cases, mental models are constructed to meet the specific requirements of situations and tasks the subject is faced with for which the activation and/or modification of a schema fails. While a schema is a slot-filler structure, a mental model contains a set of assumptions that must be justified by observations. This justification of assumptions is closely connected with a *reduction to absurdity* (Seel, 1991), which is a process of testing continuously whether a model can be replaced with a better model. As long as this is not possible, the model is considered suitable.

Models for understanding have their starting point in the tentative integration of relevant simple structures or even single bits of domain-specific knowledge step by step into the coherent design of a working model in order to meet the requirements of the task to be accomplished. Johnson-Laird (1983) considers this process of a stepwise enrichment of models as a "fleshing out" that also refers to the learning-dependent progression of mental models. Mental models for understanding represent the structure of world knowledge because they are generated to structure it and not to reproduce or copy a given external structure. Models for understanding correspond to pragmatic conceptions of modeling. They can be externalized by means of particular symbol systems and generate subjective plausibility with regard to complex phenomena to be understood and explained. However, in contrast to the pragmatic approach of modeling, proponents of the mental model theory agree on the point that mental models are cognitive artifacts which correspond only more or less to the external world since people can also construct pure thought models which bear no direct correspondence to the external world but rather only to world knowledge. This corresponds to the idea of coherence epistemology (Seel, 1991). In general, models for understanding have the following characteristics: (a) They are incomplete and constantly evolving; (b) they are usually not an accurate representation of a phenomenon but typically may contain errors and contradictions; (c) they are parsimonious and provide simplified explanations of complex phenomena; and (d) they often contain measures of uncertainty about their validity that allow them to be used even if incorrect.

Modeling and Reciprocal Emotions

Since its introduction into cognitive science, mental model theory has clearly placed emphasis on cognitive aspects of modeling. However, the integration of schemas and mental models into a cognitive architecture that adapts Piaget's epistemology also allows for the inclusion of emotional aspects of schema activation and model-based learning (Ifenthaler & Seel, 2011).

Emotions are mental responses that arise spontaneously. According to Goetz, Preckel, Pekrun, and Hall (2007), emotions can be divided into *stateemotions* (e.g., "I am anxious while taking this math exam") and *traitemotions* that occur consistently in various situations (e.g., "I am generally anxious"). Kuhl (1983) has introduced a model of emotional emergence in which cognition, emotions and operations reciprocally affect each other. Accordingly, cognitive processes and the reciprocal interactions with emotional states are the basis for goal-directed actions, which are particularly important for mental models.

Naturally, the construction of a mental model and schema modification both presuppose an *assimilation resistance* that provokes not only a cognitive dissonance but also emotional responses that interact reciprocally with cognitive processes. Kuhl(1983) has introduced a model of emotional emergence in which cognition, emotions, and operations reciprocally affect each other. In this model, cognitive processes and the reciprocal interactions with emotional states are the fundamental basis for goal-directed actions (Gross, 1998)—which are particularly important for mental models. Whenever assimilation in a schema fails and corrective attempts are not immediately successful, this schema enters a state of *disequilibrium*, which in turn evokes arousal (Eckblad, 1981; Piaget, 1945). This *assimilation resistance* may have various causes due to the complex, novel, and incongruous objects to be processed, but it always results in varying degrees of disequilibrium and arousal of the cognitive system. The amount of arousal may vary from one point in time to another and from person to person, but according to Berlyne (1971) it always stimulates epistemic curiosity and active stimulus seeking. The role of arousal may be formulated as follows: (1) Arousal is assumed to increase with the degree of incongruity in schemas. (2) High levels of incongruity are innately aversive and associated with negative feelings. (3) It is assumed that the stronger a schema is, the larger will be the effect of incongruity in that schema and the more arousal will be generated. (4) Incongruity occupies processing capacity and stimulates bottom-up processing of information. (5) Arousal and incongruity are to be regarded foremost as two facets of a unitary process, the activation of a schema.

In accordance with this argumentation, Eckblad (1981) has proposed a cognitive theory of affect that integrates assimilation resistance and emotional responses (see Fig. 37.2).

Eckblad's theory contends that affects are mediated by cognitive schemas which match input information. Performance is intimately linked to the moving edges of assimilated variation and assimilated complexity along two

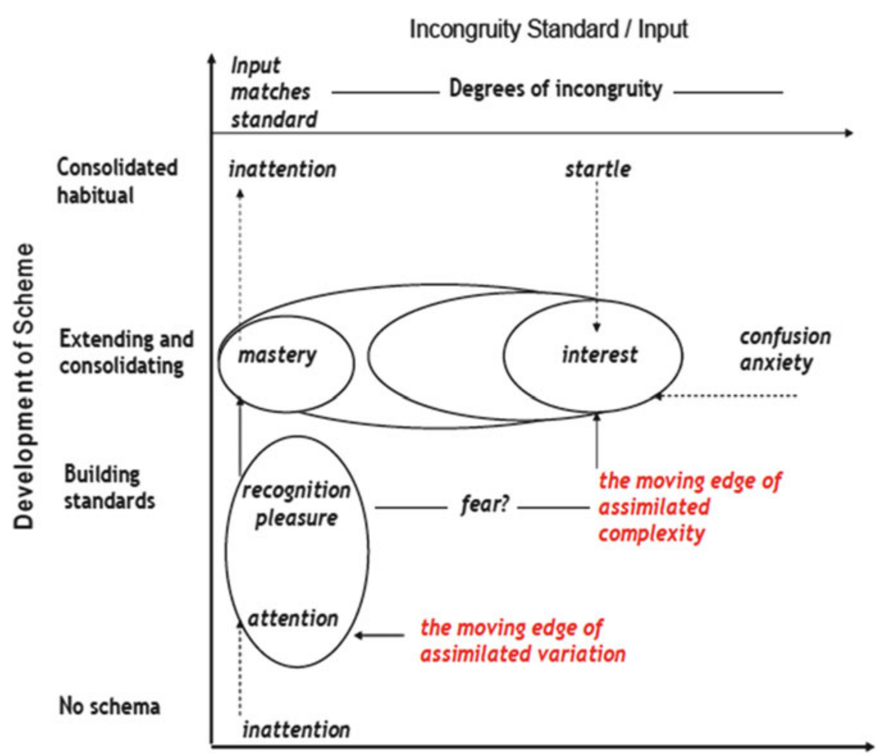

Fig. 37.2 Eckblad's (1981) cognitive theory of affect (Eckblad, 1981, p. 39)

dimensions, namely the development of schemas and the degree of experienced incongruity. With regard to the first dimension, inattention results if there is no schema available or if a schema corresponds to a consolidated habit. Between these poles, the development of schemas is associated with building standards as well as with extending and consolidating the standards (discussed in terms of slot-filler structures). Depending on the degree of assimilated variation of the input to be processed, attention moves to recognition and then to mastery. According to Eckblad, recognition is connected with pleasure. Varying degrees of incongruity between the input and schemas may result in different emotions as the schemas develop. While incongruity in the phase of building standards may result in fear, it may evoke interest in the phase of consolidation. However, when incongruity becomes stronger during the consolidation phase, the interests move to confusion and anxiety.

From Eckblad's theory one can conclude that assimilation in general goes along with pleasure and interest, whereas assimilation resistance and the need for accommodation goes along with confusion and anxiety. Accordingly, it can be argued that the successful activation of schemas is accompanied by positive emotions whereas the construction of a mental model starts with negative emotions. Positive emotions may increase the learner's optimism and confidence and thus facilitate the application of available schemas. Indeed, recent experimental research has consistently shown that *positive state emotions* are more likely associated with the productive use of schemas as generic knowledge structures and related with top-down processing. In contrast, *negative state emotions* are more likely associated with bottom-up processing and a more systematic gathering of information, as well as with paying more attention to the details of the tasks to be mastered (e.g., Fiedler, 2001; Schwarz, 2000). According to the schema- and model-based approach as discussed in this article, positive emotions seem to promote the activation of schemas whereas negative emotions seem to promote the construction of mental models. According to the *mood repair hypothesis* (Krohne, Pieper, Knoll, & Breimer, 2002), people with negative emotions spend more time collecting information in a systematic manner in order to cope effectively with situational demands, which are considered to be a cause for negative emotions. Similarly, Fiedler's (2001) *affect-cognition theory* postulates that positive and negative emotions have a strong impact on the modality of information processing and motivation: "While negative mood supports the conservative function of sticking to the … facts and avoiding mistakes, positive mood supports the creative function of active generation, or enriching the stimulus input with inferences based on prior knowledge" (Fiedler, 2001, p. 3). Interestingly, Fiedler also refers to the Piagetian terms *accommodation* and *assimilation*. In his view, negative emotions facilitate accommodation and can be related with model-based learning, whereas positive emotions support assimilation and can be related with schema-based learning.

Fields of Application of Model-Based Learning and Performance

Although the idea of model-based learning and performance has a long past, it has a short history. Schichl (2004) and Johnson-Laird (2004) have traced the roots of modeling back to the cultures of the Ancient Near East (Babylon, Egypt) and Ancient Greek philosophy. These authors delineate the two major lines of argumentation. Schichl focuses on the use of mathematical models to represent the real world through mathematical objects (or a formalized mathematical language), whereas Johnson-Laird emphasizes the concept of internal models as a particular format of mental representation. Clearly, there has been a continuous tradition of modeling in physics, biology, chemistry, geography, economy, architecture, and other disciplines throughout the centuries. However, modeling seems to have been taken for granted in these sciences and did not become a matter of educational concern until the 1950s and later. Since this time, modeling has been increasingly recognized as a powerful tool for promoting students' understanding of a wide range of mathematical and scientific constructs. Today, teaching students to develop powerful models is regarded as among the most significant goals of mathematics and science education (Clement, 2008; Lesh & Sriraman, 2005).

The theory of mental models struck a chord in the 1980s independently of this movement and became one of the most prospering fields of research in cognitive science. Due to the particular emphasis on language and reasoning in Johnson-Laird's (1983) seminal textbook, the theory of mental models and related research focused on text and discourse processing (Rickheit & Habel, 1999) and deductive reasoning (Evans & Over, 1996) for over two decades. Furthermore, the theory of mental models became prominent in the areas of human–computer interaction, system dynamics and simulation, spatial cognition, developmental and cultural psychology, and educational psychology.

Generally, both approaches to model-based learning and performances center on several basic functions of models, such as explaining complex phenomena of the physical and social world, making predictions and decisions, and communicating knowledge. Accordingly, we can distinguish the following fields of application of model-based learning (Seel, 2003).

- Models for understanding complex phenomena
- Models for reasoning
- Models for making predictions and decisions
- Models for communicating knowledge

Models for Understanding Complex Phenomena

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. Jacobson (2000) and other authors, such as Seel (2006) or Clement and Rea-Ramirez (2008), have pointed out that unusual or complex phenomena like the structure of the lungs or cells, molecular structures and reaction mechanisms in chemistry, or causes of current flow in electricity are notoriously difficult to learn and can only be made sense of through the construction and application of a (mental) model. Thus, a mental model can be seen as an ad hoc construction a person uses to explain something and to create subjective plausibility with regard to complex world phenomena.

According to Schichl (2004), most of the theories developed in physics have started with models for understanding: Newton's mechanics, thermodynamics, Einstein's theory of relativity, quantum mechanics, the Standard Model of particle physics, and many more. However, models for understanding also play an important role in biology (e.g., predator–prey models or epidemiological models), geography (e.g., avalanche models), and economics (e.g., inflation models). Indeed, it seems that most people can cope effectively with a complex phenomenon or system by constructing and maintaining a mental model that provides them with enough understanding of the system to control it. In this sense, the notion of mental models is not only interrelated with the explanation of complex phenomena but also with complex problem solving, which usually provides a unique challenge for learning and instruction (cf. Seel, 2006).

Models for Reasoning

From the very beginning, one of the major fields for the application of mental models has been logic, i.e., deductive and inductive reasoning. Coming from a syntactical approach, Johnson-Laird (1983) emphasized the specific role of mental models especially for deductive reasoning. Although this approach did not remain uncriticized and was contrasted with schema-based approaches of deductive reasoning, the application of mental models can be considered as one of the most complete theories of human reasoning, as Evans and Over (1996) and Wilhelm (2004) have stated. Schema-based reasoning and the application of pragmatic judgment schemas are considered as the fundamental basis of *semantic or pragmatic approaches* that constitute mental logic theories. Proponents of mental logic theories (e.g., Braine, 1990; Cheng & Holyoak, 1985; Evans, 1982) argue that individuals apply schemas of inference when they reason. Errors in reasoning occur when pragmatic reasoning schemas are not retrievable or cannot be applied successfully.

The theory of mental models, on the other hand, argues that reasoning is primarily a matter of constructing mental models of the premises (for instance, of a syllogism) that enable mental "leaps" in the establishment of truth values and operate only with the premises which are consistent with the conclusion. Thus, mental models make it possible for people with minimal information to reach correct conclusions since they test the truth value of only premises which are subjectively plausible and do not contradict the conclusion when combined with one another. Comparing the schema-based and model-based approach of reasoning, Wilhelm (2004) concludes that the mental model theory covers a broader range of phenomena than mental logic theories do. According to the *mental model theory* of logical thinking, humans are capable of making deductive inferences of a certain degree of complexity without having knowledge of or applying the rules of logical reasoning. The theory of mental models states that a person who goes about solving a syllogism first "translates" the propositions included in the premises into an internal analogous representation on the basis of his or her semantic knowledge, then tests whether various possibilities of interpreting the premises are consistent with a conclusion, and finally modifies, if necessary, the model he or she constructed at the outset until the premises and the conclusion are "suited" to each other.

As with deductive reasoning, some authors (e.g., Holyoak & Thagard, 1995; Johnson-Laird, 1994; Seel, 1991) also emphasize the importance of mental models for inductive reasoning. Induction enables cognitive systems, on the basis of only a few examples, to progress from given evidence to more general propositions. According to Holland, Holyoak, Nisbett, and Thagard (1986), creating analogies (or analogy models) is an especially effective inductive mechanism. In order to understand or explain an unknown phenomenon (target domain) a person refers to available knowledge about similar phenomena (base domain) and creates an analogy model for both. On the basis of the structural similarities between the models of the base and target domain, the person reaches a conclusion by analogy, integrates both models into a unified solution model under the assumption that they are similar, and tests whether it is possible to create an alternative solution model which then could replace the former model. Holyoak and Thagard (1995) have exemplified this mechanism of inductive reasoning as follows: Our general knowledge about water enables us to create a mental model of how water moves. In the same way, our knowledge about sounds enables us to create a mental model of how sound is transmitted through the air. Each of these mental models links a representation with a phenomenon in the physical world. Now, when we create an analogy between waves in the water and the spreading of sound through the air, we build an *isomorphism* (i.e., a structurally compatible map) *between two mental models*. This means that we assume we can use our model of water to progressively modify and improve our model of sound. In the end, we must validate this explanation by testing whether the analogy between the two analogy models has helped us to achieve a better understanding of the transmission of sound in the physical world. Thus, analogy models may be understood as heuristic hypotheses of a structural similarity between different domains. Another way of making inferences through inductive reasoning is by constructing and applying what Gigerenzer, Hoffrage, and Kleinbölting (1991) refer to as a *probabilistic mental model*. This type of mental model is not the product of long contemplation, but rather of the spontaneous creation of plausibility. Probabilistic mental models generate inductive inferences by associating the specific structure of a problem with a probable structure of the natural surroundings one is familiar with. Although the theory of probabilistic mental models has had an important influence on research on probability judgment (e.g., Betsch & Fiedler, 1999) it has also been criticized as psychologically implausible (Dougherty, Franco-Watkins, & Thomas, 2008).

Models for Making Predictions and Decisions

One of the most intriguing features of mental models is that they can be used for mental simulations. In addition to the practice of making inferences, there are two major fields of mental simulations: (1) making predictions about the future development of a phenomenon and (2) making decisions.

The predictive power of mental models has been investigated since the 1980s (e.g., Kurland & Pea, 1985) and is currently one of the most promising fields of research in various fields of interest, such as dynamic systems forecasting (Wang, 2007), the forecasting of the effects of global climate changes (Stott et al., 2006), and the prediction of water availablity and water quality by means of watershed modeling (Chaplot, Saleh, & Jaynes, 2005). It is noteworthy that the current research on model-based predictions goes beyond the mental model approach, operating instead with mathematical models and algorithms (e.g., Hu, Si, & Yang, 2010).

Another important application of model-based simulations is *decision making*, especially under risk. This is closely related with the field of naturalistic decision making in everyday situations. Decision making under risk (e.g., in fire fighting, military, rescue) is in general characterized by dynamically changing conditions, the challenge to respond immediately to these changes, ill-defined tasks, time pressure, and far-reaching personal consequences in the case of mistakes. Several analytical methods of decision making, such as the Expected Utility Theory or the Prospect Theory (Kahneman & Tversky, 1979), have traditionally been referred to in the literature, but Klein and Calderwood (1991), Stewart, Chater, Stott, and Reimers (2003), and others argue that analytical methods of decision making under risk eventually fail because they take too much time and lack the flexibility to allow the decision maker to respond to rapidly changing conditions of situations. In accordance with the idea of schema theory, it can be argued that the activation of a schema brings about enormous time advantages for the mastery of challenging situations if they are similar and belong to the same category (Falzer, 2004; Marshall, 1995). However, in the case of novel phenomena and problems, the available schemas are usually inappropriate and must be replaced by mental models. Indeed, the theoretical approach of mental models emphasizes cognitive processes of generating plausibility and of probabilistic reasoning (Gigerenzer et al., 1991) that are involved in decision making under risk. Therefore, natural decision making on the basis of mental models can be considered as an effective alternative to schema-based decision making.

This kind of natural decision making is at the core of Klein's (1989) *Recognition Primed Decision* (RPD) model, which contains aspects of problem solving and decision making for natural decisions. The fundamental basis of this model consists in an action of the decision maker that is based on the identification of a situation as known or prototypical. The decision maker apprehends a situation in terms of familiarity with former experiences. The evaluation of familiarity with a set of known cases results in the recognition of accessible objectives, relevant evidence, expectations, and plausible behaviors. The decision maker creates a possible option and evaluates it by means of a mental simulation in order to check whether there are any pitfalls which could prevent it from being realized. If it is possible to avoid these pitfalls the option will be strengthened. Otherwise, it will be rejected. If there are no barriers or pitfalls the option will be realized. This argumentation corresponds to the theory of mental models (Kieras, 1985)—especially with regard to its emphasis on mental simulations of options for action. In addition, the RPD model includes the concept of *situation awareness*, which has been popular in the areas of military and rescue since the 1980s (e.g., Craig, 2001; Klein, Calderwood, & Clinton-Cirocco, 1986; Sparkes & Huf, 2003). Situation awareness "is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and projection of their status in the near future" (Endsley, 1995). Due to obvious similarities in argumentation, situation awareness and mental models have been integrated into the theoretical concept of the *situation model* (Endsley, 2000), which is a mental

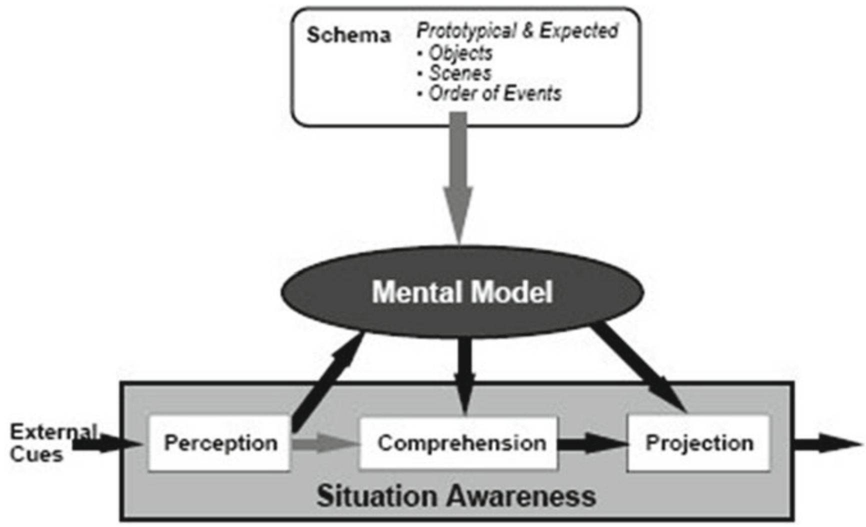

Fig. 37.3 Situation models as a combination of mental models and situation awareness (Endsley, 2000, p. 2)

model enriched by situation awareness. This is illustrated in Fig. 37.3.

Basically, the concept of situation models corresponds to a large extent to the theory of mental models, which are situation-dependent ad hoc constructions of the mind that can be used to create subjective plausibility with regard to problems to be solved by means of probabilistic reasoning.

Models for Communicating Knowledge

An important aspect of models is that they can be used to communicate knowledge. In math education, for example, modeling activities may help students to externalize their understanding of situations by helping them to develop models to conceptualize mathematical ideas and processes (Lesh & Doerr, 2000). In terms of Rumelhart et al. (1986) models for communicating are the same as *external representations* (of mental models). External representations play an important role in human learning in general. Hiebert and Carpenter (1992) have pointed out that there are close relationships between external and internal representations of knowledge. More specifically, the form of external representation with which students interact affects how their knowledge is represented internally, and in turn, the form of an external representation is dependent on the internal representation of knowledge and its structures.

Norman's (1983) comments on mental modeling have led theorists to make a distinction between mental models and conceptual models. A *conceptual model* is an external representation (of a mental model) created by teachers or scientists in order to facilitate the comprehension of something to be learned or to communicate the scientific knowledge shared by a community. These external representations can be mathematical formulations, analogies, graphs, or physical objects. An example of an object could be a water pump, which is sometimes used to model a battery in an electric circuit. Conceptual models express and communicate the shared knowledge of a discipline. Nevertheless, like all models they are simplified and idealized representations of real objects, phenomena, or situations.

The idea that conceptual models represent the shared knowledge of a scientific community externally has occasionally been modified to form the concept of so-called *shared mental models*, which are created in teams (Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000). Shared mental models are designed to enable teammates to perform their tasks better by combining their shared knowledge, skills, attitudes, and facilities (Cannon-Bowers, Salas, & Converse, 1993; Druskat & Pescosolido, 2002). Although it seems plausible to assume a close relationship between a shared mental model and successful team performance, it remains unclear how a shared mental model can be generated from multiple external representations of the teammates' individual mental models (Mohammed, Klimoski, & Rentsch, 2000). Furthermore, there has not been much consideration of the factors of shared mental models that can show a causal relationship between them and team performance.

As the case may be, the communication of professional knowledge is generally considered to be a key activity for today's specialized workforce, where knowledge communication problems between experts and nonexpert decision makers (Eppler, 2007) often occur. In order to master these problems, some authors suggest the application of *mental models interviewing* for more effective communication, aiming at the detection and mutual understanding of the mental models of specialists and nonspecialists (Cone & Winters, 2011). Accordingly, mental models interviewing is concerned with the generation of shared mental models between specialists in a particular subject (e.g., teachers) and individuals who are not specialists in that subject (e.g., students). The technique of mental models interviewing has been successfully applied in the area of risk communication (Morgan, Fischhoff, Bostrom, & Atman, 2002). However, not only can communication between experts and nonexperts be difficult but also that between people with comparable knowledge and levels of expertise. Haig, Sutton and Whittington (2006) have proposed the application of a technique called SBAR (Situation, Background, Assessment, and Recommendation) which aims at generating shared mental models for improving communication between clinicians. These approaches all agree on the point that the key to success in communication is learning all one can about others' models and thinking just by listening to them. Accordingly, the intended externalizations of mental models are based on verbal or written communications that can be more or less structured, for example by semi-structured interviews. This emphasis on language-based forms of externalizations in mental models corresponds to Seel's (1991) view that language may be considered the most important "medium" for expressing thoughts, ideas, and feelings. However, language-based external representations can be enriched with illustrations and graphs visualizing a phenomenon. Indeed, *visualization* is the graphical display of information that provides the individual a visual means of information processing—often in combination with texts aiming at successful dual-code processing (Mandl & Levin, 1989; Schnotz, 2002). Due to the basic assumption of cognitive psychologists that representations of knowledge are connected to form (graph-like) networks of knowledge (Hiebert & Carpenter, 1992), external representations of mental models often appear as causal diagrams, concept maps, or semantic networks. Jonassen (2000) calls these forms of external representation *mindtools* and describes them assemantic organization tools which help learners to analyze and organize what they know or what they are learning. Mindtools are computer applications that assist learners in representing what they know and how they think. Certainly, semantic organization tools are helpful devices for externalizing mental models, but maybe more relevant are dynamic modeling tools (such as Stella or Model-It) that help learners to represent the dynamic relationships among ideas (Jonassen & Cho, 2008). In principle, two broad categories of dynamic modeling mindtools can be distinguished: (a) tools which help with the exploration of a model and (b) tools which can be used for the construction of models (Clariana & Strobel, 2008). Both categories have been disseminated widely in education and instruction.

Empirical Research on Model-Based Learning and Performance

Since the emergence of the mental model approach in the 1980s, an abundance of research articles and book chapters (possibly more than 2,000) emphasizing model-based learning and performance has been published. In addition to the pragmatic approach of modeling, the constructivist approach of mental models has also proved to be one of the most productive fields of basic and applied research in cognitive science and education. From the 1980s until the present, research on model-based learning has focused particularly on the functions of mental models in narrative comprehension (Bower & Morrow, 1990), language and text processing (e.g., Garnham, 2001), text and picture processing as well as learning from multiple representations (Schnotz & Bannert, 2003). Another area of extensive research on mental models is human–computer interaction and system dynamics (Groesser, 2012). In view of the multitude of research on model-based learning it is nearly impossible to describe all of the lines of research and their results in detail here. Therefore, I'll focus in the next sections on what we have learned from past research and what we still have to learn from future research.

Lessons Learned from Research on Model-Based Learning

With regard to the aforementioned fields of application of model-based learning and performance one can state that each field has been studied extensively in the past. However, whereas pragmatic approaches have focused primarily but not exclusively on models for understanding and the use of external representations, the mental model approach has focused additionally on deductive reasoning in particular and the predictive power of mental simulations in general. Clearly, the mental model approach has attracted many more scientists from various disciplines than the more pragmatic approach with its emphasis on subject-matter oriented model-based learning. Nevertheless, both approaches have contributed significant findings on the impact of models on understanding and problem solving, but they differ with regard to their theoretical foundations and preferred research methodologies.

Some Methodological Considerations

The pragmatic line of research is characterized by the reference to the traditional use of models in subject-matter domains such as mathematics, physics, chemistry, and others (e.g., Lesh & Doerr, 2003; McClary & Talanquer, 2011; Pearson et al., 2006). Typically, this line of research situates model-based learning in the classroom and aims at systematically observing the emergence of students' qualitative models of phenomena to be explained. In sum, this research provides really impressive examples of modeling activities in the classroom (e.g., Penner, Giles, Lehrer, & Schauble, 1997;

Lehrer, Kim, & Schauble, 2007; Lehrer & Pritchard, 2002), and it shows that even young students invent models of their own, which, however, often prove to be partial, incomplete, and false (Clement, 2000; English & Watters, 2005). Changing these students' ways of thinking about mathematical and scientific concepts demands strong instructional efforts to challenge and test these qualitative models. Research on subject-matter oriented model-based learning is regularly, but not exclusively, related to a clear preference of qualitative research methods, such as collecting verbal data from think-aloud protocols, observational data, and videotape analyses (e.g., Lehrer et al., 2007). In addition, some researchers feel obliged to do design-based research and consider model-building in the classroom as a testing ground for design experiments (e.g., Cobb et al., 2003; Lehrer & Pritchard, 2002; Schorr & Koellner-Clarke, 2003). This is not the place to describe the methodology of design experiments in detail. What can be said is that it provides strong ecological and external validity but poor internal validity (Seel, 2009; Shavelson, Phillips, Towne, & Feuer, 2003) and that it is not suitable for causal inferences concerning treatments or instructional interventions. Finally, it is noteworthy that proponents of the model-building approach in subject-matter domains often avoid the theoretical term of mental models (Lehrer & Schauble, 2003), and sometimes they even attack the underlying constructivist paradigm (e.g., English, 1997). However, there are examples that show how meaningful and fruitful it can be to adapt the concept of mental models to reach a theoretically sound foundation of model-building activities in the classroom (e.g., Clement, 2008).

Unlike pragmatic approaches of model building, the approach of mental models seems to be more dedicated to experimental (and quasi-experimental) research and to the application of quantitative methods of data collection. Of course, there are also numerous examples of operating with qualitative methods (e.g., Clement & Steinberg, 2002), but most mental model research, especially in the area of deductive reasoning, is of a quantitative nature and aims at testing hypotheses derived from the theory of mental models. This also holds true for mental model research within the realm of educational research, where model-based learning is involved primarily with understanding and problem solving (Seel, 2006). As with the pragmatic line of research, the instructionally motivated research on mental models conducted in the past 30 years has resulted in a comprehensive and unique view on model-building activities under the condition of instruction.

Lessons Learned from Research on Models for Understanding and Problem Solving

In the article "Models for understanding," Mayer (1989) hypothesized that students given model instruction might be more likely to build mental models of the systems they are studying and to use these models to generate creative solutions to transfer problems. Similarly, Johnson-Laird (1989) argued that "what is at issue is … whether there is any pedagogical advantage in providing people with models of tasks they are trying to learn" (p. 485).

Hundreds of studies indicate that it is effective and efficient to provide students with model-relevant information before or during learning in order to help them to construct adequate models for understanding (Mayer, 1989; Seel & Dinter, 1995). Clearly, mental models are not fixed structures that can be retrieved from memory but are constructed when needed to master the specific demands of a new learning situation. Students dynamically modify and restructure their initial mental models when they evaluate externally provided information as being more plausible and convincing than their prior knowledge. This can be interpreted as an indicator of the learners' semantic sensitivity with regard to relevant information from the environment (Seel, 2012). Thus, the learning environment serves as an information resource from which the learners extract the information they need to construct an explanatory model. Model-based learning evidently depends on the learner's retrievable domain-specific knowledge structures, the nature of the material to be learned, and the modality in which the content to be learned is presented by media (Seel, 1986). Actually, it is often easier, especially for a novice learner, to assimilate an explanation provided through a conceptual model than to develop a model of one's own. The provided conceptual model can easily be incorporated into cognitive structures, and related information can be progressively integrated into the adapted model. In contrast, self-organized *discovery learning* aimed at helping students to invent their own models is practicable only if the learner possesses adequate meta cognitive skills to guide the model-building process. As a matter of fact, this approach can be a rather challenging affair which even an expert might sweat over sometimes (Kirschner, Sweller, & Clark, 2006). For most novice students, self-organized discovery learning is often closely associated with learning by trial and error and increases the probability of producing false models (Briggs, 1990; Seel & Dinter, 1995). A substantial conceptual change does not occur, and relatively stable intermediate states of understanding often precede the intended conceptual mastery.

From an instructional point of view, providing students with relevant information in order to help them to construct adequate models might be an efficient method, but most probably it is not appropriate for problem solving or for investigating individual processes of model building and revision. Although research within the realm of the pragmatic approach of model building provides some excellent examples of discovery-based modeling in the math and science classroom (e.g., Doerr, 2006; English & Watters, 2005; Lehrer et al., 2007; Lesh, 2006; Penner et al., 1997), this line of instructional research on model building is still in its infancy. Accordingly, the question of how discovery-based model building can be facilitated by means of particular instructional support has not yet been investigated sufficiently either.

Lessons Learned from Research on the Learning-Dependent Progression of Models

Model-based learning focuses on the construction of mental models of the phenomena under study. In accordance with the aforementioned cognitive architecture of model-based learning, it can be argued that when a mental model is used successfully, it is reinforced and may eventually become a precompiled, stable conceptual model, or even, after many repetitions, a schema (Halford, Bain, Maybery, & Andrews, 1998). If the model is not satisfactory, it will be revised or rejected in the further progression of learning. Changing mental models constructed by students to make them more complete, complex, and dynamic is one of the primary goals of instructional interventions. Or as Johnson-Laird (1989) says: "What is at issue is how such models develop as an individual progresses from novice to expert" (p. 485).

Ifenthaler and Seel (2005) identified the learning-dependent progression of mental models as a specific kind of transition that mediates between preconceptions or misconceptions, which describe the initial states of the learning process, and causal explanations, which are considered as the desired end states of learning. Alternatively, it can be argued that model building consists in progressing through a series of tentative models that will be tested and revised until a model issufficiently stableto function—at least temporarily—as a "conceptual model" (Schaffernicht, 2006). According to this conception, the process of modeling begins when assimilation resistance occurs and ends with a conceptual model or even with a schema. If learning was what caused the model to change, then the differences between the various versions of the model in progress are considered to be the result of the learning (Schaffernicht & Groesser, 2011).

In addition to early studies that focused on the development of children's and students' mental models (e.g., Clement & Steinberg, 2002; Halford, 1993; Kurland & Pea, 1985; Oliver & Hannafin, 2001; Vosniadou & Brewer, 1992), the investigation of the learning-dependent progression of mental models has also been at the core of my own research for the past twenty years (e.g., Darabi, Nelson, & Seel, 2009; Ifenthaler & Seel, 2005, 2011). According to Seel and Ifenthaler (2012), the learning-dependent progression of a mental model is a dynamic process with changes at discrete points in time. Learning can be represented as a sequence of events where each event occurs at an instant in time and marks a change of state in the cognitive or behavioral system. The process of learning can be expressed in the form $y(k) = fy(k-1), \ldots, y(k-ny),\ u(k-d), \ldots, u(k-\mathrm{d}-nu), e(k-1), \ldots, e(k-ne)) + e(k)$, where $y(k)$ is the system output, $u(k)$ the input, $e(k)$ is a zero-mean disturbance term, d is the relative degree, and $f()$ is some nonlinear function. This model allows the process of learning to be seen as a stochastic process that moves in a sequence of phases through a set of states. Although the probability of entering a certain state in a certain phase is not necessarily independent of previous phases, it depends at most on the state occupied in the previous phase. This is known as the *Markov property*. Accordingly, the change of mental models is conceived as a discrete learning process with the Markov property. The whole process involves the following steps: construction of an initial working model which relies upon the individual's generic semantic knowledge, interpretation of the model in terms of plausibility, revision of the initial model, generation of a second model which is again tested with regard to plausibility, followed by a revision of the model that leads to the next test and revision, and so on. Based on this continuous sequence of constructing, testing, and revising models, the learning process will finally reach a state of equilibrium at which the mental model merges into a stable model or even a schema (Halford et al., 1998; Seel, 1991). From that point on, there should only be a slight variation in performance.

The results of the various studies show a relatively consistent and coherent picture. There is no evidence for a transition of a mental model to a schema in any of them, even if there were ten or more tasks to be accomplished and corresponding points of measurement during the learning process (Ifenthaler & Seel, 2011). Although a tendency towards a stabilization of mental models was observable insofar as they were not constructed independently of each other at various points of measurement, their structures were regularly different. Obviously, it was cognitively less demanding for the students to construct a new model at each point of measurement than to remember and stabilize previously constructed models. Across the various studies, mental models proved not only to be highly situation- and task-dependent but also relatively independent of each other, and they showed only a minor tendency to become stabilized as general models. From this observation one can conclude that mental models are, to a large extent, singular formats of representation and usually do not form schemas, although they have a tendency to stabilize increasingly during extended learning. However, more research is necessary to find out how many tasks or situations are necessary for the emergence of a stable conceptual model or even a schema.

Assessment of Model Building and Mental Models

The research on mental models in the 1980s and 1990s highlighted several complexities and consistencies. One consistency was concerned with the development of a new methodology for assessing the construction and learning-dependent progression of mental models. The principles of this methodology include embedding the diagnosis of mental models in a complex problem situation, collecting data in a longitudinal design, providing valid and reliable quantitative data, and enabling a methodologically straightforward analysis and interpretation of the data collected (Seel, 1999).

From its very beginnings, research on model building was concerned with the problem of an appropriate assessment of models and their learning-dependent change. Language is of great importance for human communication about thoughts, and various methods of overt verbalizations have thus always played a central role in the diagnosis of mental models. Many studies have used think-aloud protocols, verbal explanations, speculations, and justification as means to assess knowledge and cognitive artifacts like mental models (Halford, 1993). Some authors (e.g., Garrod & Anderson, 1987; Sasse, 1991) have emphasized the method of *constructive dialogue* between individuals communicating their mental models at comparable levels of expertise (Cone & Winters, 2011). However, methods of verbalization have been criticized by several authors due to their psychometric weaknesses. As a consequence, researchers have applied traditional tests for assessing model-based performances, questionnaires and rating scales, the time needed for learning or the accomplishment of model building, drawings, and other measurements (e.g., eye fixations during task accomplishment) (Seel, 1999). However, these methods for organizing, representing, and mapping mental models were designed, first of all, to assess stable states of mental models and to localize their errors rather than to measure changes in them. It was therefore necessary to develop new methodologies for measuring change in mental models (Doyle, Radzicki, & Trees, 2008; Ifenthaler, Masduki, & Seel, 2011).

Over the past fifteen years, there has been some discussion of several possible methods for the diagnosis of mental models, most of them technology-based, that can be characterized as graphical and language-based approaches. Graphical approaches include the structure formation technique (Scheele & Groeben, 1984), causal diagrams (Al-Diban, 2008), pathfinder networks (Schvaneveldt, 1990), and mindtools (Jonassen & Cho, 2008). Language-based approaches include verbal data from thinking-aloud protocols, "mental model interviewing" (Cone & Winters, 2011), cognitive task analyses (Kirwan & Ainsworth, 1992), and several computer linguistic techniques (Seel, Ifenthaler & Pirnay-Dummer, 2009). In view of the rapid progress in the area of knowledge diagnosis, one can conclude that the problem of the diagnosis of mental models and their change has been solved (Ifenthaler, Pirnay-Dummer, & Seel, 2010). Indeed, one can choose from among a variety of assessment methods which meet psychometric standards. Interestingly, there are also some technology-based approaches which integrate various assessment practices and tools into a comprehensive methodology, such as HIMATT (Pirnay-Dummer, Ifenthaler & Spector, 2010). They can be applied to measure changes in the structure of external representations of mental models as well as similarities between models.

Fields of Interest for Future Research

Model-based learning and performance is probably one of the best and most extensively investigated fields across several disciplines, especially due to the efforts in the area of mental model research. Nevertheless, there are still some issues that demand more research.

One area of future research is the use of models for reasoning, even though an abundance of studies have investigated the role of mental models in deductive reasoning. According to the theory of mental models, individuals are capable of making deductive inferences of a certain degree of complexity without having knowledge of or applying the rules of logical reasoning. Rather, most people make inferences on the basis of mental models (Johnson-Laird, 1983). Although this theoretical approach has been contrasted with schema-based approaches of deductive reasoning, the theory of mental models can be considered as the most influential and pervasive theory in the area of logical thinking. As with deductive reasoning, numerous authors also emphasize the importance of mental model theory for inductive reasoning (Johnson-Laird, 1983; Seel, 1991) as well as for abductive reasoning (Magnani, 2009). Up to now, however, only little empirical research has been conducted on the function of mental models for inductive and abductive reasoning. In accordance with the concept of the learning-dependent progression of mental models, solving inductive or abductive reasoning tasks can be understood as a process of sequential interpretation and integration of task-relevant information and hypotheses for solutions into a mental model of the situation. This "situation model" serves as the context for interpreting new observations, generating new hypotheses, and drawing inductive or abductive inferences. This prediction was confirmed in a series of experiments by Johnson and Krems (2001) and Ifenthaler and Seel (Ifenthaler et al., 2011; Ifenthaler & Seel, 2011). Nevertheless, in comparison with the abundance of empirical research on model-based deductive reasoning, the research on model-based inductive and abductive reasoning is still in its infancy. This also holds true with regard to model-based reasoning by means of analogy models, as several authors (e.g., Lehrer & Schauble, 2006) have shown for subject matter learning in the classroom.

A second field of future research on model-based learning and performance is related to *model-based decision making*. There are two major fields of application: (1) the role of mental models for decision-making within the realm of management and organization and (2) the role of mental models for decision making under risk, necessary in the fields of fire fighting, military, and rescue. The importance of mental models for organizational issues was stressed by Senge (1990) and has been adopted in studies on so-called team mental models (e.g., Christensen & Olson, 2002; Mohammed et al., 2000; Steiger & Steiger, 2009) but more systematic research on this issue is still needed. Basically, this also holds true for decision-making under risk by means of situation models, defined as a combination of mental models and situation awareness.

A third promising field of future research on model-based learning and performance is the area of *system dynamics research*. Dynamic modeling presupposes functional intentionality in the construction and use of mental models for simulating transformations of states of a system. These simulation models allow a learner to explore a dynamic system in a controlled way to understand how the system's components interact and how alternate decisions can affect desired outcomes. Mental models provide a rationale for operating effectively with the complexity of dynamic systems. Accordingly, one can find more and more studies in the area of system dynamics research that work on the basis of mental model theory (Groesser, 2012; Schaffernicht & Groesser, 2011). However, dynamic modeling provides a new perspective called learning by system modeling and an extension to approaches of simulations: When students are involved in learning by modeling, they build their own models and engage at a much deeper conceptual level of understanding of the content, processes, and problem solving of the domain. There are also indications that operating with models of dynamic systems and simulations can be considered as an important future field of instructional research on understanding and problem solving in complex domains (Blumschein, Hung, Jonassen, & Strobel, 2009).

Finally, a new field of research on model-based learning focuses on reciprocal emotions in the process of model building. As mentioned above, model-based learning has attracted many scientists from different disciplines and the idea of mental models has been examined in various fields, such as management, marketing, information systems, consumer behavior, psychology, education, and neuroscience. However, most scientists have limited their focus to cognitive processes, neglecting the interactions of these processes with emotions and feelings. Only very little research has explicitly taken into account both cognitive and emotional aspects of mental models. However, there is some empirical evidence that there are reciprocal interactions between emotions and model building and related cognitive processes (Ifenthaler & Seel, 2012), but this line of research on mental models and model-based learning is only beginning to be explored.

Conclusion

In comparison with other fields of research, model-based learning and performance can be seen as one of the most prospering areas of research across several disciplines, such as cognitive science and education. In view of many hundreds of studies it is nearly impossible to give justice to the variety of research issues and results. Therefore, this chapter's focus was on what we have learned from previous research and what not.

Traditional views on model building activities in the classroom have been contrasted with the mental model theory that emerged in the 1980s as a central theoretical construct to capture situated cognition and pragmatic reasoning. Actually, the metacognitive psychologists who consider mental models to be the best organized representations among declarative learning results (Glaser, 1990). More specifically, it has been argued that comprehension and reasoning in specific situations (e.g., in schools and real-life situations) necessarily involve the use of mental models of different qualities (Greeno, 1989). Most people can cope effectively with a complex phenomenon or system by constructing and maintaining a mental model that provides them with enough understanding of phenomenon or the system to control it. In this sense, the notion of mental models is interrelated with the investigation of problem solving in complex systems, which provides a unique challenge for research in the field of learning and instruction. In consequence, mental models in particular and model building activities in general are closely related with the discussion on higher-order instructional objectives concerning problem-solving and discovery learning in the classroom. Several scholars, such as Lesh and Doerr (2003) encourage the pursuit of higher-order objectives and argue that helping students to develop their own "explanatory models" should be among the most important goals of math and science education. A recommendation often made in recent learning theory and research is to involve students, either individually or in groups, in actively working on challenging problems. If it is true that knowledge about complex systems poses a special learning challenge for students, it seems likely that students should experience difficulties when given problem-solving tasks involving phenomena in complex systems.

When we take the major fields of research on model-based learning and performance into closer consideration, we find a tension between strong theoretical assumptions that lead to precise conclusions and weak assumptions that lead to less precise conclusions. Strong assumptions are helpful when the assumptions apply, but they often do not apply, which then invalidates the conclusions prescribed by the theory. Weak assumptions are less helpful in creating specific instructional systems and learning activities, but they are more generally applicable and less likely to be invalidated. Finding the right balance is the challenge for professional practitioners. They can learn a lot from experimental research on mental models as it is based on strong theoretical assumptions.

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