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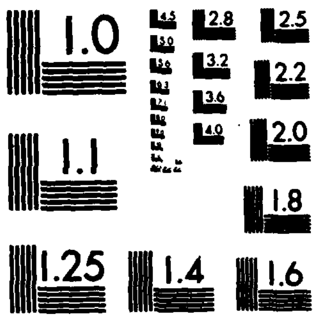

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Applied Cognitive Science

Technical Report No. 2

E.E. Smith and Allan Collins

October 1983

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One focus of modern cognitive science is the interaction between people and complex systems, such as computer and electronic systems. American society is becoming inundated with more and more complex systems. The skills required to design, operate, and fix these systems have become necessary ones for anyone to function successfully in our society. Teaching people to deal with these systems, → over

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APPLIED COGNITIVE SCIENCE

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Applied Cognitive Science

One focus of modern cognitive science is the interaction between people and complex systems, such as computer and electronic systems. American society is becoming inundated with more and more complex systems. The skills required to design, operate, and fix these systems have become necessary ones for anyone to function successfully in our society. Teaching people to deal with these systems, and designing the systems so that they are easy for people to use, are important goals for an applied cognitive psychology. In this paper we present a framework for understanding the research in the cognitive sciences on human interaction with systems, and describe some of the best research carried out in this area.

Some Critical Distinctions

Much of the recent research in cognitive science is concerned with the relation between a person and a system, particularly a computer system. At the most general level, there can be two kinds of relations between a person and a system: either one *replaces* the other, or somehow they *interact*. With regard to replacement, it is always a matter of a computer system replacing people, and the area of research in cognitive science that is concerned with this goes by the name of "expert systems". We shall have little to say about expert systems for our fundamental concern is with the interaction of people and systems. (For a recent review of expert systems, see Feigenbaum & McCorduck, 1983).

In considering how people interact with systems, four domains of inquiry come to mind. Perhaps the most obvious concerns what the person understands about the system. That is, what is the person's representation or model of the system? This question has led to a substantial amount of research under the heading of "mental models". The second kind of question is the reverse of the first, namely, What is the system's model of the person? More precisely, What model of a likely user of a computer system has been incorporated into the programs guiding the system? The area of research dealing with this question is referred to as "user models". The remaining two kinds of questions of interest are consequences of the "model" questions just considered. Specifically, given a deficiency in either a person's mental model of a system, or in the systems's user model of a person, we can change either the person or the system. Changing the person give rise to the third type of question--How can we teach or instruct people to have more correct mental models of the system? The associated area of research will be called "explanation and instruction". Changing the system gives rise to the fourth kind of question--How can we alter the system so that it incorporates a more correct user model of the person? The associated area of research is "cognitive engineering".

The distinctions we have thus far drawn regarding persons and systems are summarized in Table 1. The first distinction is between <u>replacement</u> and <u>interaction</u>. Subordinate to <u>interaction</u>, we have distinguished between <u>models</u> and <u>change</u>, i.e., research on mental models and user models concerns the nature of models, while work on explanation and instruction and on cognitive engineering deals with how to change the models. Orthogonal to the contrast between models and change, there is a distinction regarding who is the focus, either the person in research on mental models and on explanation and instruction, or the system in research on user models and cognitive engineering.

While the structure in Table 1 hardly exhausts all the distinctions that could be drawn, it suffices as a useful starting point for a discussion of possible relations between a person and a system.

Mental Models

In order to operate and repair complex systems such as electronic and computer systems, it is necessary to have a mental model of how the system behaves. These mental models give people the power to simulate how the system will behave if they perform some action or if some component is not functioning properly. There has recently been a large amount of research on this topic in cognitive psychology and artificial intelligence, perhaps best represented by the book on Mental Models edited by Gentner and Stevens (1983). We will try to summarize here some of the key ideas and approaches in that literature.

In a series of papers de Kleer and Brown (Brown, Burton, & Zdybel, 1973; de Kleer, 1977, 1979; de Kleer & Brown, 1982, 1983) have been exploring notions of qualitative simulation and

Table 1

Some Critical Distinctions in Cognitive Science

	Interaction		Replacement
	Focus on Person	Focus on System	
Models	Mental Models	User Models	Expert Systems
Change	Explanation and Understanding	Cognitive Engineering	

envisioning of how systems behave. The key idea in their approach is that you can break down a complex system or device (e.g., a door buzzer) into a set of component models (e.g., switches, coils, etc.). In order to construct a qualitative simulation of the system you must know two things: (1) the topology of connections between the various components (i.e., what is connected to what), and (2) the incremental input-output functions of the various components (i.e., if a particular input to a component goes up, what happens to the output).

de Kleer and Brown (1982, 1983) argue that component models should consist only of statements about local inputs (e.g., the current goes up) and local effects (e.g., the output voltage goes down). That is, the model for a switch or coil in one circuit should be the same as that in another circuit. The only thing that varies from circuit to circuit is the particular connections. By knowing the connections and the component models, one can "envision" how the system will function. In other words, one can construct a mental model of the system, that can then be "run," producing what we think of as seeing the system run in our "mind's eye."

For a mental model to be robust, de Kleer and Brown (1982, 1983) argue that you need to keep out of the structural model of the system all reference to the way the system functions (called the no-function-in-structure principle). If you do not, then the model is only good for understanding an intact system. If any component malfunctions or behaves differently in some way, you have no chance of understanding the functioning of the system. To have a robust understanding you want to be able to replace the intact component model with a faulted component model and envision what happens. But it is very difficult to construct mental models where the function of the system does not penetrate the component models. Nevertheless the principle serves as an important criterion for robust models.

Forbus (1982) has extended the de Kleer and Brown analysis to construct a general language for describing processes in qualitative terms that he calls "qualitative process theory." Qualitative process theory is meant to be a language for describing any person's qualitative understanding of how a system works. It has no specific physics built into it, only assumptions about what are the crucial entities needed for reasoning in a qualitative way about processes. Central to his claims is that understanding the various processes that a system carries out is the core of understanding the behavior of the system.

The five parts to any process description in the theory are shown in Table 2 describing fluid flow. The individuals (source, destination, and path) are the entities involved in the process. Preconditions specify what topological connections must exist for the process to occur: In this case the path must be aligned, i.e., open and connected from the source to the destination. The

Table 2

Qualitative Process Theory Representation
of Fluid Flow (from Forbus, 1983)

```
Process fluid-flow

Individuals:
          s=a contained-fluid (source)
          d=a contained fluid (destination)
          path=a fluid-path(path s d)

Preconditions:
          aligned(path)

Quantity conditions:
          A[Pressure(s)] > A[Pressure(d)]

Relations:
          Let flow-rate be a number.
          flow-rate αQ(A[Pressure(s)] - A[Pressure(d)])

Influences:
          I + (Amount-of(d), flow-rate)
          I - (Amount-of(s), flow-rate)
```

quantity conditions are quantitative relations that must hold for the process to occur: In this case the pressure of the source must be greater than the pressure of the destination. Relations specify what must hold during the process: In this case the flow rate is proportional (α_Q) to the difference in pressure between the source and destination. The influences represent the outcome of the process: In this case the amount of liquid at the destination increases and the amount of liquid at the source decreases, both as a function of flow rate. The key ideas in the theory are that different views of processes like fluid flow can be represented in these terms, and that the notation is adequate to model human reasoning about all the different processes that occur in physical systems.

Stevens and his colleagues (Stevens & Collins, 1980; Stevens & Steinberg, 1981; Williams, Hollan, & Stevens, 1983) have emphasized the different kinds of models people have of systems and how models are refined in the course of learning. Some of the distinctions Stevens and Steinberg (1981) make between different models are:

1. <u>Structural</u> <u>vs</u>. <u>Dynamic</u>. Structural models are used to describe a system in a time-invariant manner and dynamic models to describe changes that occur in the system over time.

2. <u>Componential</u> <u>vs</u>. <u>Topological</u> <u>vs</u>. <u>Geometric</u>. Structural models can be decomposed simply into components, or more usefully into topological configurations where the connections between components are preserved, or geometric configurations where the spatial relations between components are preserved.

3. <u>Behavioral</u> <u>vs</u>. <u>Internal</u> <u>Structure</u>. Among dynamic models, behavioral models describe a system or a component simply in terms of its inputs and outputs (i.e., "black box" models). Internal-structure models, on the other hand, break the system down into the interactions between various components.

4. <u>Aggregate</u> <u>vs</u>. <u>Mechanistic</u>. Internal-structure models can either be aggregate or mechanistic. In aggregate models the components behave in a uniform manner, whereas in mechanistic models each component has a unique behavior.

5. <u>Causal</u> <u>vs</u>. <u>Synchronous</u>. Internal-structure models can either be causal or synchronous. Aggregate models are inherently synchronous, but mechanistic models break events into causal chains, or treat them as occurring synchronously.

6. <u>Action-flow</u> <u>vs</u>. <u>Information-flow</u>. Among causal models, there are action-flow models where some kind of substance or energy flows through the system, and there are information-flow models, where information flows through the system.

Young (1981, 1983) has compared two different kinds of mental models that people have for electronic calculators. The first kind of model he calls a surrogate model. His prototypical example of a surrogate model is the one provided by Hewlett-Packard for their reverse Polish notation calculator shown in Figure 1. The model specifies four registers, X, Y, Z, and T, as well as what happens to the numbers in each register when a new number is entered, when a unary operation is performed, or when a binary operation is performed. This surrogate model allows one to simulate what will happen for any combination of inputs, as with the incremental qualitative models of de Kleer and Brown (de Kleer, 1979; de Kleer & Brown, 1982, 1983).

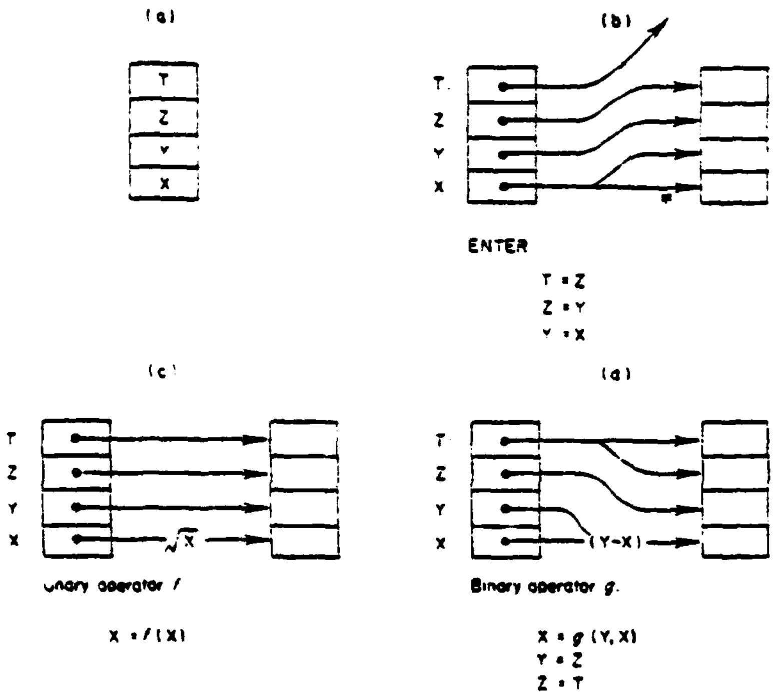

FIG. 1. Stack register model for the RPN calculator.

Figure 1. Surrogate model for the RPN calculator (from Young, 1981).

Young argues that this is not the kind of model people normally use to understand calculators. Instead, he argues that people's understanding of calculators is based on a _mapping_ between the task, in this case doing arithmetic, and the actions necessary to carry out the task. People know alot about arithmetic, and the ease of learning and using most calculators depends on how simple the mapping is between their knowledge of arithmetic and the steps they must carry out with the calculator. For algebraic calculators that let you put in parentheses and give precedence of X and / over + and -, the mapping is particularly straightforward. But for simpler calculators like the four-function calculator he analyzed, the mapping can become quite difficult. For example, to find the quotient for 6/(3+5), it is necessary to type the input sequence "3+5/=6=" which is only obscurely related to the original algebraic expression. For most uses of a calculator it is this _task-action mapping_ model that is crucial, and which should be used to guide design.

Like Young, Gentner (1983; Gentner & Gentner, 1983) argues that people understand new systems by analogy with systems they already understand. She proposes a "structure-mapping" theory of how people map their knowledge about one system (the base) onto a new system (the target). The basic notion is that a structure mapping consists of a 1 to 1 mapping of elements from a base system onto elements of the target system. The mapping preserves relationships between elements but leaves specific attributes of the elements behind. Hence it is a mapping only of the structural relationships between elements rather than a complete mapping of all the properties of elements in the two systems.

We can illustrate these ideas in terms of Gentner's analysis of Bohr's classic analogy between the solar system (the base) and the atom (the target) shown in Figure 2. In the analogy the sun maps onto the nucleus of the atom and the planets map onto the electrons. The properties to be mapped across are not the specific attributes of the sun or planets, such as their color, size, or temperature, but rather the relationships between them: the nucleus is much more massive than the electrons, just as the sun is much more massive than the planets; the electrons revolve around the nucleus, just as the planets revolve around the sun, etc. Of course, any analogy invites incorrect inferences as well. For example, one might incorrectly infer that the nucleus is hotter than the electrons, since the sun is hotter than the planets, or that the electrons attract each other, since the planets attract each other. Thus Gentner's theory specifies how people understand new systems by analogy, and how analogy can lead to systematic errors in understanding.

In summary, the research on mental models centers on how people represent knowledge about systems and their individual components. People often infer how a system will behave by propagating the behavior of the individual elements for different input conditions. Furthermore, people construct mental models of new systems by analogy with their knowledge of other systems.

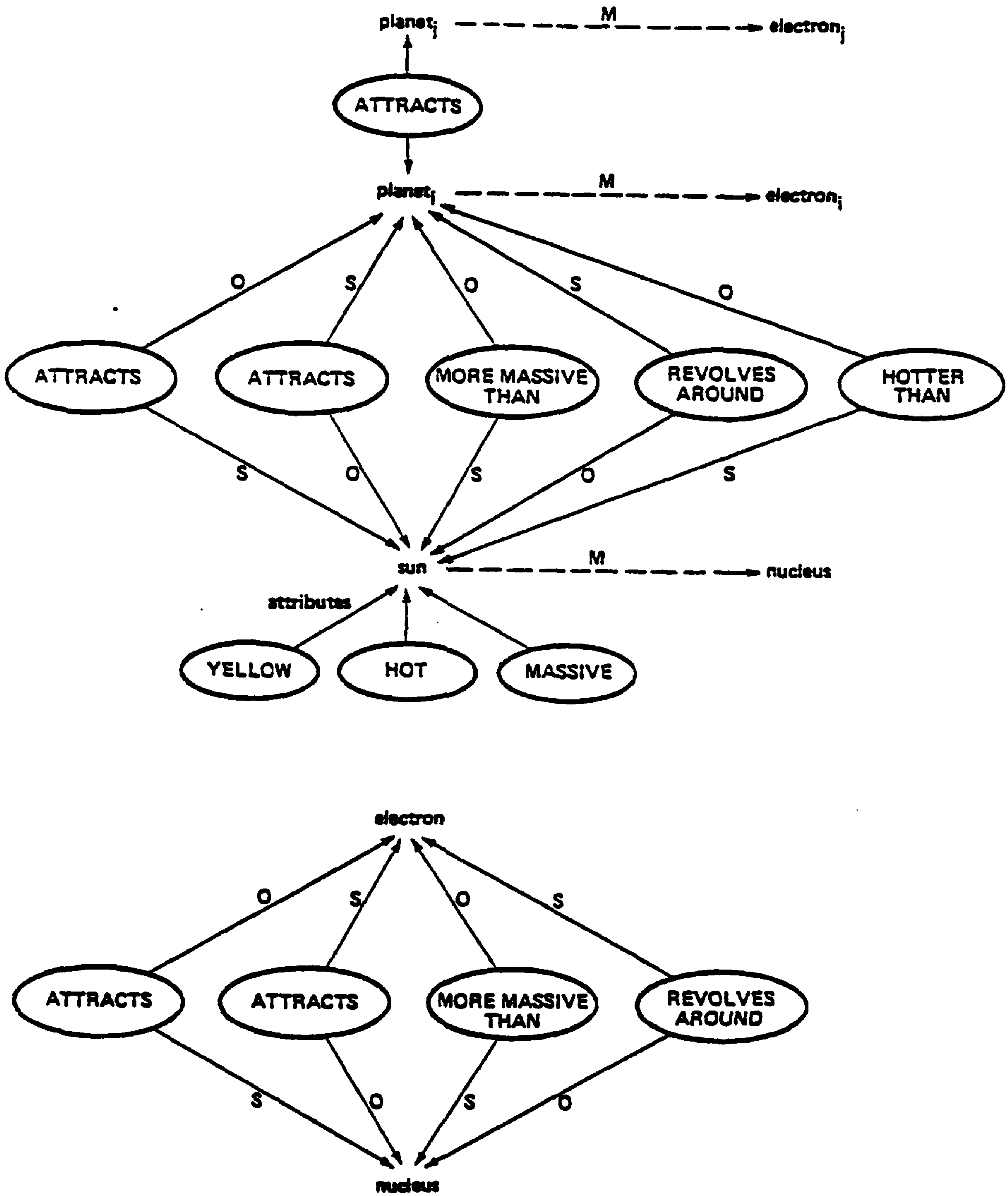

Figure 2. Representations of knowledge about the solar system and the hydrogen atom, showing partial identity in the relational structure between the two domains.

Explanation and Understanding

As society requires more and more interactions with technical systems, there is a growing concern about how best to teach people such systems. Recent work on this problem has been much influenced by the research on mental models just reviewed, and by related work on "schemas." We will consider two sample trends in this recent work, one dealing with the use of analogies to convey models of technical systems, and the other dealing with the role of models or schemas in understanding instructions for assembling and operating technical systems.

Educators have long suspected that analogies play a substantial role in students' understanding of science and technology. As mentioned in the previous section, people often tend to try to construct a model of a novel technical domain by analogy to some domain they already know about. Recently, cognitive psychologists have tried to directly study this learning-by-analogy process. Gentner and Gentner (1983), for example, were interested in the consequences of using analogies to teach the basics of electricity. They used two different analogies--(1) current in a circuit is like water flowing through pipes, and (2) current in a circuit is like a crowd of people moving through a corridor--which should eventuate in two different models of electricity. For the group of subjects taught the "water-flow" analogy, current was mapped onto water, a wire was mapped onto a pipe, a battery was mapped onto a pump, and a resistor was mapped onto a constriction in a pipe. For the group taught the "moving-crowd" analogy, current was mapped onto people in the crowd, a wire was mapped onto a corridor, a battery was mapped onto a loudspeaker "imploring the people to move faster," and a resistor was mapped onto a gate in a barrier. Gentner and Gentner hypothesized that the moving-crowd analogy is better than the water-flow analogy in providing a good model of how resistors work. This is because in the moving-crowd analogy a resistor is viewed as a gate (rather than as an obstruction), which permits the inference that two resistors in parallel should allow more current to flow than would one resistor.

To check this prediction, Gentner and Gentner gave all subjects problems to solve after they had presumably mastered their analogy. Each problem involved a complex circuit -- either two batteries or two resistors connected in series or in parallel. The subjects' task was to compare current and voltage at several points in the circuit with that of a corresponding point in a "simple" circuit, i.e., a circuit with only one battery and one circuit. As expected, subjects who had learned the moving-crowds analogy gave more accurate answers about circuits with parallel resistors than did subjects who learned the water-flow analogy. Interestingly, on other kinds of problems the groups taught different analogies did not differ in performance. Hence, it is not a simple matter of one analogy providing a better model of electricity than the other. Rather, the different analogies induce somewhat different mental models of electricity, and in some circumstances one model may be superior to the other, while in other circumstances this ordering of the models may reverse.

Turning now to the role of models in instructions, the basic idea is that in order to operate or assemble a system, it is not enough to follow specific instructions; one must also have a model of how the system works, or will work once assembled. This idea is illustrated by the work of Smith and Goodman (1982) on understanding assembly instructions. They had people assemble a simple electrical circuit that included as major components a battery, an on-off switch, and a bulb. Some subjects were given only the instructional steps, while others were given the steps plus some explanatory material. The explanatory material concerned either the structure of the circuit (e.g., each major component of the circuit and how it can be decomposed into minor components), or the function of the circuit (e.g., the flow of electricity through conductors).

Both kinds of explanatory material offered schemas of the circuit (though only the functional material may have offered a true model), and both had widespread beneficial effects on performance. An instructional step was read faster and executed more accurately when it was preceded by explanatory material than when it was not; in addition, the inclusion of explanatory materials improved subjects' memories for the instructional steps as well as their ability to troubleshoot a faulty version of the circuit. It seems, then, that explanation fostered a schema of the circuit, which in turn benefited reading, execution, memory, and problem solving.

User Models

People have different interests and backgrounds. As computer systems become more sophisticated, they will take these differences in knowledge into account in the way they interact with people. One thrust of research in the cognitive sciences has been to develop more sophisticated models of users in systems. To illustrate the notion of user models we will describe three approaches to building such models that different researchers have taken: (1) Rich's (1979) GRUNDY, which models a user's interests in order to recommend books, (2) Collins, Warnock, and Passafiume's (1975) model of a student's knowledge about South American geography for the SCHOLAR computer-aided instruction system, and (3) Burton & Brown's (1979) model of student's strategies in playing the Plato arithmetic game, "How the West Was Won." These are perhaps the three most sophisticated user models developed to date, and they exemplify the potential of this kind of development.

GRUNDY (Rich, 1979), which plays librarian, uses stereotypes (or prototypes) to try to build a model of what kinds of books are interesting to a person, in order to recommend new books to them. The stereotypes in GRUNDY are schema-like (Minsky, 1975; Rumelhart & Ortony, 1977) data structures representing, for example, the characteristics of a "sports person" or a "religious person". The stereotype for "sports person" indicates they like excitement, tolerate violence, and do not like romance. Book descriptions are stored in terms of their appeal to different types of people (e.g., sports person, religious person).

When a person first starts to use GRUNDY, he is asked for descriptive words about himself (e.g., religious, likes sports), from which the system constructs an initial model of the person. This model consists of a set of characteristics (e.g., likes excitement) and estimated strengths for the characteristics. These are derived from the stereotypes it has stored that the input descriptions triggered. For example, if the person says he likes sports, this triggers the "sports person" stereotype, from which GRUNDY concludes that the person probably does not like books concerned with romance or education and probably does like books concerned with excitement, violence, and suffering. Of course these inferences may be incorrect, and GRUNDY may have to revise them later.

GRUNDY then discusses specific books with the user. If the person has read, but did not like, a particular book that GRUNDY thought he would like, it revises its model of the person based on what the person did not like about the book. If the person has not read a particular book that GRUNDY thinks he would like, it describes the book and asks whether the book sounds interesting. If not, it tries to pin down what aspect of the book does not appeal to the person in order to further refine its model of the user. In this way GRUNDY slowly accumulates a better model of the user, so that its book recommendations come closer and closer to the person's interests.

Collins, Warnock, and Passafiume (1975) approached the problem of user modeling in terms of how a computer tutor can estimate what knowledge a student has or does not have. The context of their work was the SCHOLAR CAI system, which tutored students on South American geography. Unlike Rich, who simply tried to build a user model in GRUNDY, Collins et al. studied how human tutors model their students in order to simulate human tutoring strategies in SCHOLAR. They found that human tutors partially order each piece of information they know about a topic, such as South America, in terms of how important it is (or equivalently, how likely anyone is to know that piece of information). Based on the student's answers to questions, the tutor then can estimate what level of knowledge the student has about the topic with respect to that partial ordering.

The tutor decides how to present new pieces of information based on his estimate of the student's knowledge as shown in Table 3 (from Collins et al., 1975). The tutor skips over the most important information, because he assumes the student knows it. The next most important information he asks about because the student may or may not know it. Less important information he tells the student on the assumption the student does not know it, but can learn it. Still less important information is skipped over, because the tutor assumes it is too much to learn. The examples from Table 3 reflect the model of the student from one actual teaching dialogue. Another more sophisticated student was handled differently: The tutor skipped over more information on the assumption that the student knew it, and each of the categories of information in the table was shifted accordingly. Collins et al. subsequently built a version of this strategy into the SCHOLAR system.

Burton and Brown (1979) built another kind of student model into the Plato arithmetic game called "How the West Was Won." The game board is shown in Figure 3. The object of the game is to get to "Home" before the other player. Each player moves by forming an arithmetic expression using three random numbers generated by the spinners in the upper right hand corner. The player can form any expression with the three numbers using plus, minus, times, divide, and parentheses. There are also special moves in the game: if you land on any town, you move forward automatically to the next town; if you land on a shortcut (such as 5 in Figure 3), you move forward to the end of the shortcut (i.e., 13); if you land on your opponent, he moves back two towns. In order to play the game successfully, the student has to consider whether it is possible to make any of these special moves given the three numbers. The major limitation on performance in the original Plato game was that students often locked onto a single strategy, such as multiplying the two

Table 3

The Different Categories of Information that Determine What Questions are Asked and What Information is Presented

	Categories of Information	Examples from A Student Dialogue
1.	Information the tutor regards as very important which he assumes the student knows, and so does not ask about.	South America is a continent. South America is south of North America.
2.	Information the tutor regards as important, which he thinks the student may or may not know, and therefore asks about.	The Andes are the major mountain range in South America. The Amazon is a large river in South America.
3.	Information the tutor regards as somewhat less important, which he thinks the student probably does not know, so he presents the information to the student.	The Parana is a large river in South America. The highest mountain in the Andes is Aconcagua.
4.	Information the tutor regards as still less important and too much beyond the student's level of sophistication to be worth presenting.	The Paraguay River is a tributary of the Parana River. Manaus is a port halfway up the Amazon River.

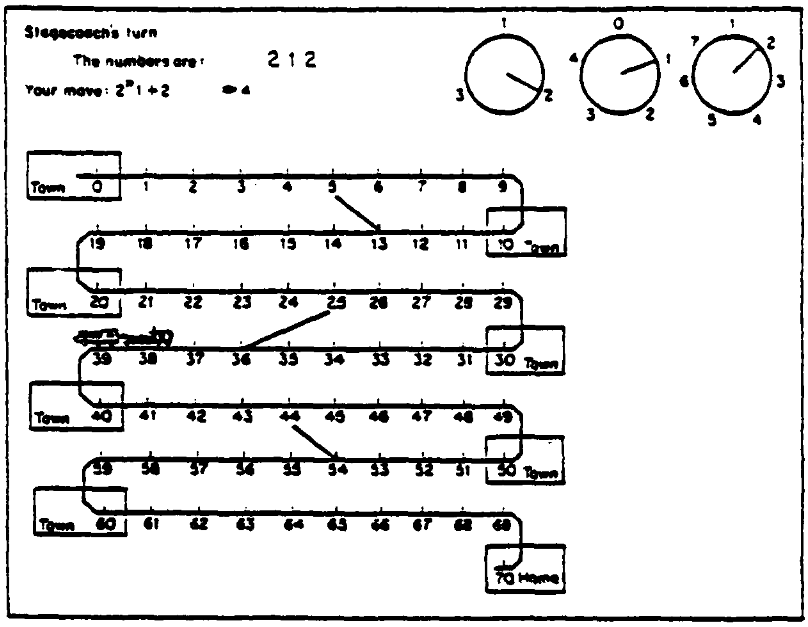

Figure 3. Game board for "How the West Was Won" (from Burton & Brown, 1979).

largest numbers and adding the third, so that they never considered different possible moves.

In order to encourage students to play strategically and thereby practice their arithmetic skills, Brown and Burton developed a coach that builds a model of the individual student by watching him play a series of games. The coach watches to see if the player uses parentheses, subtraction, multiplication, division, and the three special moves. It rank orders each possible move in terms of how far ahead of your opponent it puts you. If a student consistently does not use parentheses or fails to land on a town when it would benefit him to do so, then the coach infers that the student does not understand that strategy very well. When a move occurs where using a particular strategy like landing on a town would improve his position substantially, then the coach interrupts after the student has made his move. It then points out how he could have done better by making an alternative expression that would have landed him on a town. It also gives him a chance to take his move over. The coach is programmed not to interrupt too often so that it doesn't become a nuisance. Of course, if the student is playing close to optimally, he'll never be interrupted by the coach.

These three examples illustrate the power of user models in computer systems. As we build more sophisticated machines that are interacting on a day to day basis with people, we expect that these kinds of user models will become commonplace.

Cognitive Engineering

In attempting to incorporate a better model of people into computer systems, researchers have not only incorporated knowledge about typical users (as in the above cases), but also have sought principles that characterize human information-processing capacities so that these principles could be considered in the design of the system. The search for these principles has made use of several different strategies, two of which are illustrated in what follows.

One strategy in cognitive engineering involves analyzing the errors that people make when interacting with a system, and then accounting for these errors in terms of known psychological principles of human information processing. Norman (e.g., 1981, 1982) has recently used this strategy, and a number of his examples or cases are worth mentioning. One case is "mode" errors, where people act as if the system were in one state when in fact it is in another. Such errors are particularly prevalent in systems that do not provide feedback about their current state, which fits with the widely agreed upon information-processing principle that people need extensive feedback in monitoring complex processing.

As a second example, consider "capture" error, where a capture error tends to occur "...when there is overlap in the sequence required for the performance of two different actions, especially when one is done considerably more frequently than the other. In the course of attempting the infrequent one, the more common act gets done instead." (Norman, 1982). Norman illustrates with an example from a particular text editor, where "w" means to write a file, "q" quits the editor, and the combined sequence "wq" writes then quits. The combined sequence is used very frequently (people regularly use it to finish a day's session), and consequently sometimes when people mean to type just "w" they type "wq" instead. The information-processing principle that accounts for capture errors is well known: frequent actions require less activation for their initiation than do infrequent ones. The remedy for capture errors is to minimize the overlap between the sequences for frequent and infrequent actions.

As a third example of Norman's error analyses, consider the case where a person performs an incorrect action because the triggering conditions for the correct action are widely separated in time. These errors are likely due to the limited capacity of active memory, one of the best-known aspects of human information processing. The remedy for such errors is to insure that the "space" between the initial and final triggering conditions for an action does not exceed the span of active memory.

As a last example of error analysis, consider the errors that result from faulty learning of command names, where these names are neither meaningful in themselves nor transparently related to the functions they denote. Here, the relevant principle seems to be that information that cannot be related to meaningful material is rapidly lost from long-term memory. The remedy for this kind of error is to insure that the relation between the name and the function is transparent, which will make the name meaningful (see Black & Sebrechts, 1983, for an extension of this line of research).

A second strategy in cognitive engineering involves an in-depth analysis of a particular task, where the task is a frequent instance of a person-system interaction. Thus, if one is interested in how people interact with a text editor, one can study this experimentally like any other psychological task. Card, Moran, and Newell (1980; 1983) have done just this. In the text-editing task they studied, a user sits before a computer terminal, which has a keyboard for input and a CRT display for output. In the computer is a file that contains a text, and the user is to update this text file by looking at a printout of the text file marked with modifications and effecting each of these modifications. Card et al. provide a model of the text-editing task that involves the user's goals and the operators available to him to effect these goals.

As in other problem-solving situations, many of the goals are hierarchically structured. The top-level goal might be to edit the manuscript, while one level down the goal might be to determine the next correction in the manuscript that has to be done, while at the next level down the goal might be to locate the exact line in the manuscript that contains the modification. The operators are elementary motor or information-processing acts, such as "get-the-next-page" or "verify-edit" (i.e., check that what actually happened is what was intended). Thus, the operators satisfy the lower-level goals, and concurrent satisfaction of a number of these lower-level goals constitutes a condition that satisfies a higher-level goal (e.g., having satisfied the goals of "locate the next correction" and "replace one letter with another," one has satisfied the higher-level goal of "make the next correction").

This kind of model can successfully predict various aspects of performance, including the time needed to accomplish various text-editing tasks. Such a model can also be used to determine what are the most difficult components, or bottlenecks, in text editing. For example, Card et al. found that more time was consumed by mental operations than by manual ones, suggesting that practice at just the manual aspects of the task may not offer the best means of improvement.

In another example of this in-depth-analysis strategy, Rumelhart and Norman (1982) have provided a detailed account of skilled typing, where a typewriter is a simple system that users typically interact with. Their model rests heavily on the notion of schemas. First, the perceptual system matches each word to a word-schema. The word-schema then activates letter-schemas for all its constituent letters. The schema for "very", for example, activates the four letter schemas for "v", "e", "r", and "y". Each letter schema is in part a motor program, as it specifies the target finger position in a keyboard coordinate system. According to the model, the schemas corresponding to the letters in a word can all be active at once. How, then, does the person come to type the letters in temporal sequence? Because each letter schema inhibits the activation of all letter schemas that follow it. Again, this kind of analysis can be used to explain basic performance data (e.g. various kinds of errors), with a particular emphasis on determining the major bottlenecks in performing the task.

Concluding Comments

Our brief review has merely scratched the surface of research in the cognitive sciences on how humans interact with systems. Current work on mental models, for example, is concerned not only with technological systems, but also with different scientific systems (say, naive models of physics--see some of the papers in Gentner & Stevens, 1983). And the application of this work on mental models of science is likely to have implications for how we instruct students in science courses. Similarly, work on user models is expanding to new domains (e.g., use of a computer system to design electronic circuitry--see Card et al., 1983), and presumably this work will further stimulate research in cognitive engineering. In short, the applications of cognitive science are just beginning to emerge.

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