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CHAPTER TWO

Basic Topics and Approaches to the Study of Complex Problem Solving

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INTRODUCTION

Basic research in the area of complex problem solving (henceforth CPS) has been criticized repeatedly for its lack of a theoretical foundation (Funke, 1986, 1991a). As will become apparent, this state of affairs has changed little. There is still a long way to go before a level of theoretical resolution is achieved that is comparable to that of the related areas of learning and memory research. This chapter describes and evaluates important basic research approaches to the study of CPS. Besides being strongly biased toward basic research, the discussion is naturally confined to topics not covered in detail in other chapters.

What follows is divided into four sections. Quite conventionally, a bit of history will make up the first section of the chapter. The historical perspective is useful in sketching what could be considered major trends in CPS research, the discussion of which will be spiced with a number of the area's most aggravating methodological problems. Second, approaches will be presented that try to pin down what CPS is by relating it to constructs traditionally used to describe interindividual differences. Some of this research will be called *deficit oriented*, mostly because of some researchers' conviction that subjects who fail can tell us more than those who succeed. In contrast, the third section will introduce *competence oriented* approaches that focus on determinants of successful learning and control. These approaches typically base their theorizing on formal analyses to the task environments. The final section will try to name and characterize interesting future directions of research in the area.

HISTORICAL AND METHODOLOGICAL ASPECTS

As has been pointed out in the first chapter, research on problem solving—particularly in the German-speaking countries—dates back to the very early days of Experimental Psychology. Basic research that looks at how people interact with complex dynamic task environments did not become possible, however, until new technological advances enabled the simulation of complex systems in laboratories. While this was a necessary precondition for this new line of problem-solving research, the force behind it arose largely from two other, independent sources. One was a sincere discontent with the limitations of the theoretical concepts present at the time which did not seem to be able to explain how people control "buildings, equipment, manpower and consumable supplies" (Broadbent, 1977, p. 192). The second source was a dissatisfaction with a *one-sidedness* of tasks (see Dörner & Reither, 1978, p. 527) used in typical laboratory studies on problem solving such as chess or the disk problem (Ewert & Lambert, 1932; later the problem was referred to as the *Tower of Hanoi*). Such problems were criticized for being too simple, fully transparent, and static, whereas real-world economical, political, and technological problem situations were said to be complex, intransparent, and dynamic. Thus, controlling dynamic scenarios such as simulated economies, cities, and factories would seem to bring real world problems into the laboratory (Dörner, 1981). It is probably not a mere coincidence that such statements emerged at about the same time as Neisser

(1976) published his influential plea asking for ecologically more valid studies in Cognitive Psychology.

However, as should become evident in the reminder of this chapter, although both approaches appear to have been motivated similarly, there are fundamental differences between them in terms of methodology, research strategy, and theoretical development, to name just a few. For instance, Broadbent (1977), in illustrating this point, described a study in which subjects controlled a simple city TRANSPORTATION SYSTEM that was based on two simultaneous linear equations. The number of individuals per bus and the available parking space could be manipulated by altering the time interval between buses entering the city and by altering the parking fees. Broadbent emphasized that the system was deliberately kept simple and mathematically well-defined "to allow an analysis of psychological processes" (p. 192).

The other end of the continuum is occupied by the often-cited LOHHAUSEN study (Dörner, Kreuzig, Reither, & Stäudel, 1983; see also Dörner, 1981, 1987). In this study, subjects were asked to control a small town (named LOHHAUSEN) by manipulating, for instance, the working conditions, leisure time activities, taxes, the housing policy and the like. Overall, the LOHHAUSEN computer simulation comprised more than 2,000 highly interconnected variables, far too many for subjects to digest even within the span of 8 two-hour experimental sessions.[1] The goal for subjects governing LOHHAUSEN was deliberately kept vague. They were simply told to make sure the town would prosper in the future. Each subject interacted with the system indirectly by telling the experimenter which measures to take. The experimenter would then make the appropriate inputs. Also, subjects had to acquire the information they felt to be important by asking questions of the experimenters who, in turn, tried to answer at the level of aggregation of the questions. In sum, the LOHHAUSEN study combined a number of features believed to be relevant in real-life political and economic decision making.

To return to Broadbent (1977), his focus was on the striking disparity between his subjects' satisfactory control performance on the one side and the lack of subjects' ability to answer questions about the system they had learned to control on the other. The fundamental question was which overall cognitive architecture would be capable of explaining such findings. In subsequent studies, Broadbent and Berry and their coworkers were able to pin down a number of factors that appear to influence the development of either control performance or verbalizable knowledge or both (e.g., Berry,

[1]While LOHHAUSEN certainly represents the "tip of the iceberg," the naturalistic task environments used in the *systems thinking* program (Dörner, 1983a) generally tend to be quite large and complex with many interconnected variables—typically about 10–60 (see Funke, 1988, 1991b, for a review and brief characterization of these systems).

statistically significant results (Eyferth, Schömann, & Widwoski, 1986), the systematic variation and control of system properties both helps to detect effects that are unique to a specific task, and it serves to estimate the impact of these properties on processes of knowledge acquisition and knowledge application.

At this point, it is interesting to note that, within the *systems thinking* tradition, a few naturalistic scenarios have become quite popular and are typically referred to by their proper names as if they constituted experimental paradigms in their own rights. A short list of examples includes MORO (Putz-Osterloh, 1985, 1987; Putz-Osterloh & Lemme, 1987; Roth, Meyer, & Lampe, 1991; Strohschneider, 1986, 1991; Stäudel, 1987), FIRE (Brehmer, 1987, this volume; Brehmer & Allard, 1991; Dörner & Pfeifer, 1992; Schoppek, 1991), and the TAILORSHOP (Funke, 1983; Hörmann & Thomas, 1989; Hussy, 1991; Lüer, Hübner, & Lass, 1985; Putz-Osterloh, 1981, 1983b, 1987; Putz-Osterloh & Lemme, 1987; Putz-Osterloh & Lüer, 1981; Süß, Kersting, & Oberauer, 1991).[2] This development most likely is a consequence of the fact that naturalistic scenario's are formally intractable systems with largely unknown properties such that they do not lend themselves to experimental manipulations. Needless to say, simply using a task with largely unknown properties over and over again is not a solution to the problem.

The availability of formal tools to describe the dynamic task environments with sufficient precision provided a first basis for theorizing about how system knowledge could be represented in memory. For instance, Funke (1985, 1986) has suggested a class of dynamic tasks based on linear equation systems. The relations among the variables of these systems can be described by deterministic multivariate autoregressive processes. Consequently, Funke (1985, 1986) hypothesized that a subject exploring and later controlling a dynamic task environment that is based on linear equation systems, gradually constructs a causal model of the task. In a certain sequence, information is added to the model corresponding to the autoregressive processes' parameters (such as the direction and the relative strength of the interconnection between two variables).

The idea of taking the formal model of a task as a starting point for theorizing about its mental representation is perhaps best illustrated by analogy to the role of formal logic in research on deductive reasoning. While early hypotheses discussed in the psychology of reasoning rested on the

[2]MORO is a developing country scenario in which subjects can influence the living conditions of a ficticious nomadic tribe. FIRE is a fire fighting scenario in which fire fighting units must be deployed so as to minimize the impact of fires that emerge unpredictably at various locations of an imaginary terrain. This scenario—with a different semantic embedding—was first used in military contexts. Finally, subjects managing the TAILORSHOP must run a simplistic small company by purchasing raw materials, hiring and firing workers, and the like. Again, these scenarios have been described in detail by Funke (1986, 1988, 1992b).

premise that human inferencing was to be seen in close analogy to formal logic (Beneke, 1833/1877), it appears that the systematic deviations from this premise were particularly interesting cases for both empirical research and theorizing (e.g., Wason & Johnson-Laird, 1972). Very similarly, formal system characteristics, for instance those of linear equation systems, can be used as a starting point for theorizing about the representation of such systems in memory.

To summarize, research on human performance when interacting with complex dynamic systems has been coarsely divided into two different main streams. One approach has been to use naturalistic scenarios in order to bring everyday problems into the laboratory, and to try to identify interindividual differences in how subjects control a dynamic system. In contrast, the other approach has been to use formally well-defined systems with known properties and to systematically manipulate features of the task environment to test assumptions about how people acquire and use knowledge in interacting with these tasks. Each approach appeals to a different part of the research community.

Of course, the distinction between the two lines of research is not quite as clear-cut as has been portrayed here. For instance, researchers employing naturalistic scenarios do in fact manipulate *some* features of their tasks—features that do not require any knowledge of formal system properties such as the semantic context of the system (Hesse, 1982a) or the degree to which the system variables' interrelations are made transparent to subjects (Putz-Osterloh & Lüer, 1981). Nevertheless, the bisection appears useful in that it captures the general trends in the field. With this in mind, it is now appropriate to go into more detail and look at some of the major empirical and theoretical developments in the area.

THE SEARCH FOR INDIVIDUAL DIFFERENCES

A number of diverse constructs have been used as determinants of interindividual differences in system control performance. Among them, we find constructs that are known to have a psychometric background, such as test intelligence or motivation. In addition, a number of concepts have been coined rather ad hoc to describe *phenomenologically* what distinguishes good from poor system controllers. As mentioned previously, poor controllers have been said to be unable to understand the concept of exponential growth, to reason in causal chains rather than in causal nets, and to exhibit a tendency towards "intellectual emergency reactions" (see Dörner, 1981, p. 167). It is important to keep these two major classes of concepts separated because the former, but not the latter, are psychometrically founded as of yet. This, of course, must not be understood as a prejudice about the theoretical value of constructs from the one or the other class.

Intelligence, Learning Potential, and Motivation

One of the most startling results of early research on how people controlled dynamic systems was the lack of a correlation between subjects' intellectual abilities as assessed by Raven's (1965) Advanced Progressive Matrices or other standard tests of intelligence, and control performance—at least not when the problem was intransparent, as many real-life problems were said to be (Dörner, 1979; Putz-Osterloh, 1981; Putz-Osterloh & Lüer, 1981). These findings seemed rather plausible at the time, given the pertinent dissatisfaction with *static* and *artificial* standard tests of intelligence combined with the idea that naturalistic scenarios would somehow be more ecologically valid. This may help to explain, among other things, the popularity of control tasks in personnel selection (see U. Funke, this volume) despite warnings of experts in the field against this practice (Kluwe, Schilde, Fischer, & Oellerer, 1991). However, the patterns of correlations between measures of test intelligence and measures of control performance in subsequent studies have been much less clear, and their interpretation is subject of an ongoing debate (for details see Beckmann & Guthke, this volume). For a theory of how people control dynamic systems, however, the most promising way seems to go beyond simply correlating global test intelligence scores with control performance measures. Rather, it seems more interesting to try to single out components of intellectual ability that contribute to control performance under different experimental conditions. In other words, a purely *psychometric* approach is probably not sufficient if anything of theoretical relevance is to be gained.

Consider, for instance, the study by Hussy (1989) in which several variants of a relatively simple dynamic system were employed. Subjects' task was to control a LUNAR LANDER—its speed, heat, fuel resources, and height above the moon surface—and bring it to ground safely. The nonlinear problem is mathematically tractable (Thalmaier, 1979). The average deviation of a subject's intervention from what would be the optimal input served as performance measure. As in a number of studies before, Hussy (1989) manipulated how transparent the problem was for subjects. In the transparent condition, numerical information was provided about the effects of different slow-down maneuvers, and subjects received feedback about some of the system states. This information was not available in the intransparent condition due to "inoperative gauges." All subjects' intellectual abilities were assessed using scales from the Berlin Intelligence Structure Model (Jäger, 1982). According to this model, *operative factors* such as speed of processing, memory, or processing capacity with respect to verbal, figural, and numerical information processing must be distinguished. Among other things, Hussy (1989) found processing capacity to be the single most predictive operative factor, regardless of the experimental condition. However, in the intransparent condition, figural memory, but not verbal or numerical memory, predicted control performance. This finding fits the assumption that intransparent systems place particularly high demands on subjects' ability to generate and maintain mental models of the task for successful control.

Hörmann and Thomas (1989) used the same tasks to measure intelligence, but their subjects controlled the TAILORSHOP, a 24-variable scenario intended to simulate a small company that subjects were asked to run for 12 fictitious months. Hörmann and Thomas's results differed from those of Hussy (1989) in that control performance—the amount of capital accumulated over the 12 months—correlated with indicators of intelligence only under the transparent presentation condition. The authors also assessed subjects' system knowledge in terms of how many relations between variables subjects were able to reproduce correctly after the control trials. Hörmann and Thomas (1989) argue that this measure, in contrast to the control performance index, reflects how well subjects understood, and learned about, the complexity of the entire system. System knowledge correlated highest with the processing capacity operative factor. In the intransparent condition, the memory factor correlated with performance. The latter findings parallel those of Hussy (1989; see also Süß et al., 1991), but it should be kept in mind that the systems used appear to differ greatly (although we have no means to analyze exactly *how* they differ). Another problem is that the two studies rely on different dependent measures (in fact, the amount of capital accumulated in running the TAILORSHOP is a rather arbitrary, idiosyncratic measure of performance). Nevertheless, both studies seem promising for a future theory in that they combine a component-oriented view of what constitutes intelligence with theoretically meaningful experimental manipulations of system properties. In other words, studies on the relation between intelligence and the control of dynamic systems seem interesting to the degree to which they can contribute to answering the question which cognitive faculty is demanded by which property of the task.

A very recent development is to relate not static intelligence but rather subjects' learning potential to performance on dynamic control tasks (Guthke, 1993a; for details see Beckmann & Guthke, this volume). Both types of tasks seem to involve learning from feedback about success and failure which is not true for traditional tests of intelligence (Guthke, 1993b). Beckmann (in press) has provided interesting evidence pertaining to this presumption. He investigated the relation between both control performance and system knowledge on the one side, and learning potential performance on the other. Subjects interacted with a dynamic scenario based on linear equation systems. The same underlying system was either presented as an abstract MACHINE with three different dials as input variables and three gauges as output variables, or as a concrete CHERRYTREE with water supply, light, and warmth to be regulated, and the number of cherries, leaves, and insects on the tree as output variables. As it turned out, subjects learned nothing when interacting with the CHERRYTREE, and there was no relation between control performance and either of two learning potential tests. Presumably, the semantic context provided by the CHERRYTREE labels prevented subjects from acquiring new information. Rather, they maintained their inadequate prior knowledge. In contrast, however, subjects showed significant learning when interacting with the structurally identical MACHINE system, and there were indeed substantial correlations between learning about the system and performance on both learning potential tests. These results validate Guthke's (1993b) assumptions and show that it is rather promising to further explore what is or is not shared in terms of cognitive processes between interacting with complex dynamic tasks and the construct of learning potential.

Focusing on *nonintellectual* aspects of problem solving, Hesse, Spies, and Lüer (1983) investigated the influence of motivational factors on how well subjects controlled the spread of an epidemic in a small town. These authors based their study on a state-trait concept of motivation. The trait component—success versus failure orientation—was assessed by a questionnaire, while the state component was manipulated experimentally by describing the disease as rather, or not very disastrous; one group of subjects was told to fight smallpox, the other group fought influenza. The underlying system was identical for both groups. The smallpox, but not the influenza group, was assumed to show high degrees of *personal involvement.* A rather complex combination of the values of several system variables served as performance criterion. The results were rather clear; subjects in the smallpox group showed more personal involvement, took more time, and were better at controlling the spread of the disease than subjects in the influenza group. In addition, better performance for the smallpox problem was observed for subjects classified as success oriented. More detailed analyses with respect to the state component of motivation revealed, among other things, that highly involved subjects showed more signs of self-reflective and analytical cognitive activity which resulted in a better understanding of the system and a selection of more effective measures to control the spread of the diseases. Also, the trait-component of motivation resulted in better performance primarily because success-oriented, but not failure-oriented subjects *sustained* their initial levels of self-reflective activities.

This study is interesting not only because it helps to integrate problem-solving research with other research areas, but also because the authors took a step toward analyzing in more detail how relatively stable and relatively transient aspects of motivation influence the way people attempt to understand and control a dynamic system.

A number of other personality traits have been related to control performance with varying success. For instance, self-confidence and a questionnaire of *cognitive control* were found to correlate substantially with a summary performance score in the LOHHAUSEN task (Dörner, Kreuzig, Reither, & Stäudel, 1983; Kreuzig, 1981). One major problem is, however, that these assessments have taken place *after* the control task. Funke (1986) was able to show that post hoc correlations between control performance and the questionnaire of *cognitive control* were much larger than a priori correlations, suggesting that the questionnaire was capturing people's memory of having been successful or unsuccessful at the task rather than predicting success. In addition, the fact that subjects governing Lohhausen had to interact with the experimenter to retrieve system information and to make system interventions, may account for the role of self-confidence in control performance in this particular task.

Certain features of spoken language (e.g., use of words classified as *dogmatic* such as *all*, *always*, or *must*) were also related to poor control performance (Roth, 1985, 1987). Unfortunately, these results could not be replicated (Roth et al., 1991), and the theoretical connection between control performance and linguistic features remains unclear. Finally, eye movement patterns have also been found to covary with control performance. Lüer, Hübner, and Lass (1985) compared the best and worst subjects in their sample and found that less successful subjects showed unsystematic strategies of collecting information from the display.

Experts Versus Novices

Another typical approach to analyze how a task is performed is to look at what distinguishes experts from novices. Reither (1981) found that, in line with assumptions about differences between good and poor controllers (Dörner, 1981), novices were more likely to reason in causal chains as opposed to causal nets, and also more likely to ignore side effects when interacting with a scenario simulating "the climatic, ecological, and ethnic conditions of a region similar to Upper Volta in West Africa" (Reither, 1981, p. 126; translation by the author). Experts were economic aid professionals with 6 to 8 years of experience in Third World countries, and novices were postgraduates who were just about to start an economic aid career.

Putz-Osterloh (1987) compared seven economics faculty with a sample of 30 "unselected" students on their interactions with, first, the *economic* scenario TAILORSHOP and, later, the Third World *ecological* scenario MORO. Dependent measures were derived from subjects' control performances and from thinking aloud protocols. For both systems, Putz-Osterloh found that the experts were better than the student sample with respect to knowledge acquisition and verbalized intervention strategies. In contrast, experts' control performance was better at the economical scenario TAILORSHOP than at the ecological scenario MORO. In particular, when controlling the TAILORSHOP, experts, but not novices, were able to take into account *conflicting goals* such as simultaneously having to increase the company's revenues and the workers' wages. This was interpreted to show that experts have an advantage over novices because they can use their domain-specific knowledge to control the economic system, whereas their generalizable heuristic knowledge about how to operate complex systems shows up in better system knowledge and more adequately verbalized strategies in both systems. A replication of the previous study (Putz-Osterloh & Lemme, 1987) compared 24 graduate students in business administration who served as experts to 28 students from non-business areas. This time, experts were better at controlling both MORO and the TAILORSHOP. However, both groups of subjects were indistinguishable with respect to strategic knowledge.

Unfortunately, the pattern of results of these few studies on expert-novice differences is inconsistent and, so far, relatively uninformative for a theory of CPS. Future investigations should place more emphasis on defining and assessing in greater detail what knowledge and skills experts have that novices don't (see Funke, 1992b). Ideally, these differences should be explicated a priori on the basis of thorough task analyses and the cognitive processes the tasks involve, and not by simply observing how *apparent* experts perform at tasks that semantically appeal to the experts' professional designation. This, of course, is useful only if one believes that expertise in controlling complex dynamic systems is more than just the conditioned application of "grandmother's know-how" (Dörner & Schölkopf, 1991)

Self-Reflection, Heuristic Competence, and the Need to Gain Control: The Regulation of Actions

It seems highly plausible that self-reflection should be helpful in controlling complex dynamic systems. In particular, attempts to cope with critical situations of a system should both stimulate and benefit from self-reflective activities (Dörner & Schölkopf, 1991). Indeed, post-hoc analyses of subjects' verbalizations when interacting with complex dynamic systems have indicated that there might be a difference between *good* and *poor* controllers with respect to self-reflective activities (Dörner, 1981; Dörner, Kreuzig, Reither, & Stäudel, 1983; Reither, 1979). As we know from the study by Hesse et al. (1983), highly motivated subjects show more signs of self-reflection, and success-oriented subjects sustain their initial levels of self-reflective activities relative to failure-oriented subjects. Also, when the *matching familiar figures* test is used to distinguish between self-reflective subjects (more hits, longer latencies) and impulsive subjects (fewer hits, shorter latencies), better control of the LUNAR LANDER is observed with those classified as being self-reflective (Hussy & Granzow, 1987).

In addition, it has been shown that experimentally induced self-reflection is effective in improving performance on items taken from a standard test of intelligence (Hesse, 1982b). Putz-Osterloh (1983b) attempted to test empirically whether induced self-reflection also increases control performance when interacting with the TAILORSHOP. After subjects had made their interventions, they were to answer a number of questions (adapted from Hesse, 1982b) pertaining to their past interventions and to the possibilities to improve their interaction with the system. These manipulations had no effect on control performance. In a subsequent study, Putz-Osterloh (1985) investigated whether in the previous experiment the focus of subjects' self-reflection could have been too *general* to yield results that could be turned quickly into concrete interventions. One group of subjects practiced *specific* self-reflection while working on a training problem. Typical self-reflection questions were "Do I have a precise goal?" or "Do I have enough information?" Subsequently, subjects controlled the MORO system. In addition to control performance, system knowledge was assessed by recording the number of variables and their interrelations as they surfaced in subjects' think aloud protocols. Again, the group that had practiced self-reflection did not perform better at controlling the system nor at verbalizing system knowledge than the group with no self-reflective practice. Thus, induced self-reflection—with both rather general and relatively concrete foci—does not seem to have an influence on control performance. In the light of the present evidence, earlier conclusions based on correlational results that self-reflection is instrumental in improving learning about, and control of, complex dynamic systems, have to be interpreted with caution. As of yet, there is no evidence for a *causal* role of self-reflection in controlling complex systems.

Another trait-like concept that has been assumed to play a role in system control is subjects' so-called *heuristic competence* (Dörner, 1982; Dörner, Kreuzig, Reither, & Stäudel, 1983; Dörner, Reither, & Stäudel, 1983). Heuristic competence has been defined as "the confidence of a person in his or her abilities to cope successfully with novel situations" (Stäudel, 1988, p. 137; translation by the author). Heuristic competence is assumed to be relatively stable and to change only in the long run through accumulated experiences with novel problems. The construct is conceptually related to the *locus of control* (Rotter, 1966) and *self-efficacy* (Bandura, 1977) constructs. Indeed, the need to gain and maintain control is thought to be the *primary motive* that underlies subjects' interactions with complex dynamic systems (Brehmer, 1989; Dörner, 1983b; Dörner, Kreuzig, Reither, & Stäudel, 1983). A questionnaire has been developed that measures the construct of *heuristic competence* (Stäudel, 1988).

Currently, there is some evidence linking high heuristic competence to successful control of the MORO system (Stäudel, 1987), but there is also other evidence of no relation between heuristic competence as assessed by Stäudel's (1988) heuristic competence questionnaire and control performance with a relatively simple "cold-storage depot" (Reichert & Dörner, 1988).

Beyond the more *traditional* personality traits, *poor controllers*, that is, subjects who fail to gain control over a complex and intransparent task, are assumed to be distinguishable from *good controllers* by the typical errors they make (Dörner, Schaub, Stäudel, & Strohschneider, 1988). Over the years, quite a few of these errors have been extracted from observations and described in a number of studies conducted in Dörner's laboratory (Dörner, 1981, 1983b; Dörner & Pfeifer, 1992; Dörner & Reither, 1978; Reichert & Dörner, 1988). These errors are said to demonstrate, better than anything else, how cognition, emotion, and motivation interact in system control tasks. As an illustrative example, consider the feeling of loosing control over the system which may result in a "cognitive emergency reaction" (Dörner, 1981), a state in which subjects (a) reduce their self-reflective activities, (b) increase their tendency to react quickly, (c) entertain more and more reductive and rigid hypotheses about what is going on in the system to be controlled, and, (d) formulate increasingly global and abstract goals. As this example shows, errors may occur at four different stages: (a) in the area of self-organization, (b) when making decisions, (c) when framing hypotheses, and (d) when defining action goals.

Based on an analysis of poor controllers, Dörner et al. (1988) have presented an *action regulation* model of how the tendencies to commit errors such as the "cognitive emergency reaction" may develop. Even more, the model is designed to serve as a "general structure for the explanation of human behavior in complex dynamic systems" (p. 217; translation by the author). The model is based on a memory structure composed of interconnected sensory, motivational, and motor components for storing information about facts, needs, and actions, respectively. At the heart of the model, and central for the control of actions, are *intentions*. Intentions are *ephemeral* units consisting of *temporarily structured* information from memory. Each intention is assumed to comprise information about initial and final states, the past history of the system, the importance of the intention, its *temporal perspective* (i.e., the beginning and end of actions associated with the intention), the intention's *success probability*, and the competence to act according to the intention. Further, the model has four *information processing units*. One unit *generates intentions* from information available about the systems' needs and the current environment. Another unit *selects intentions* from information about the situation and the intentions currently active in some sort of intention working memory (combining the weighted importance of an intention with its associated success probability much like an expectancy-value model would predict). A third unit *promotes intentions*, either by activating automated action sequences or by initiating controlled planning activities. The final unit *perceives the environment in light of the currently active intentions*, delivering information about the space-time coordination of the system. Figure 2.1 graphically depicts the information processing units (in rectangles), together with the data structures (in ovals) they operate on.

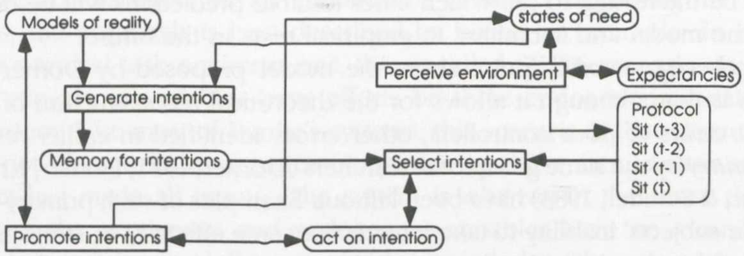

FIG. 2.1. Graphical illustration of the basic components of Dörner's model of action regulation. Information processing units are represented as rectangles and the data structures they operate on are represented as ovals (Dörner et al., 1988; see text for details).

As mentioned previously, this conceptual framework can be used to describe errors typical for poor controllers. For instance, if the intentions selected for processing change repeatedly, then the unit responsible for promoting intentions is under time pressure and works less well. In turn, the system's competence is reduced, a new intention (designed to find the causes for the failure) is added to the intentions working memory and competes with other *active* intentions. In addition, the weights of all active intentions have to be adjusted. Thus, the selection unit will change the intentions to be processed even more often, resulting in even worse processing of the intentions, and the associated states of need accumulate. At the end of the vicious circle we may find a "cognitive emergency reaction."

The model is designed to be implemented as a computer simulation (see Dörner & Wearing, this volume) and as such has a number of advantages over more vague earlier formulations (e.g., Dörner, 1982). Nevertheless, Funke (1992b) has criticized the model for being too weak to provide testable predictions, and also for presenting as causal hypotheses what are simply a priori truths to the competent language user (e.g., the importance of an intention is said to increase if the underlying state of need increases, see Dörner et al., 1988, p. 222). More precision is perhaps achieved easiest by incorporating in greater detail the theories the model capitalizes on in its current state. For instance, the operation of the unit that selects intentions might be specified according to existing expectancy-value theories (e.g., Feather, 1982). In addition, the concept of competence implied by the representation of each intention could be specified by incorporating assumptions from self-efficacy theory (e.g., Bandura, 1977).

However, it is granted that not all aspects of the theory can be open for empirical tests, and some tests of the action regulation model might indeed be possible. For instance, according to the model, higher competence should result in better overall performance but, as mentioned above, the evidence for this assumption is contradictory (Reichert & Dörner, 1988; Stäudel, 1987).

It will be interesting to see which other testable predictions will be derived from the model and submitted to empirical tests in the future.

Another noteworthy point about the model proposed by Dörner et al. (1988) is that, although it allows for the theoretical reconstruction of some typical errors of poor controllers, other errors identified in earlier research as *primary* by the same group of researchers (Dörner, 1981; Dörner, Kreuzig, Reither, & Stäudel, 1983) have been left out. Examples of such primary errors include subjects' inability to take into account side effects (i.e., subjects have been said to be reasoning in causal chains rather than in causal nets), or their lack of understanding of exponential trends. In the present model of action regulation, the focus appears to have shifted from looking at *why* subjects fail in terms of the cognitive processes involved to what happens *during the process* of failing.

The obvious alternative is, of course, to take a closer look at how subjects *learn* about a system and analyze what it takes to arrive at *successful control*. The approaches described in the rest of this chapter take this perspective and shall thus be referred to as *competence-oriented*. As will become clear, a competence-oriented perspective quite naturally leads not only to different research questions, but also to a different sort of model. The interest is primarily in the forms of learning, knowledge representation, and knowledge use when subjects interact with complex dynamic systems, and the focus is on the impact of the task's properties on these cognitive processes.

APPROACHES BASED ON FORMAL TASK ANALYSES

In order to determine the influence of task properties on learning and memory, one must be able to manipulate the task environment systematically. This, in turn, requires that the relevant task properties can be pinned down formally. The straightforward way to accomplish this goal is to search for an established formalism that can be used to describe interesting task environments and see how far one can go with it.

Linear Equation Systems

Funke (1985, 1986, 1992a, 1992b) has developed a theory that combines, in one homogeneous framework, three essential aspects of research on how people interact with complex dynamic systems: the formal description of the task environment, assumptions about learning and knowledge representation, and the diagnostic methods to assess what has been learned.

As a formalism for describing dynamic task environments, Funke suggests the theory of multivariate autoregressive processes, AR_k, where k is the degree of temporal dependency between the input of an exogenous system variable and its effect on an endogenous variable.[3] Bypassing the formal details, the approach is best described by giving an example. In one of Funke's typical task environments, the so-called SINUS scenario, inputs at three exogenous variables have effects on three endogenous variables of the system. Like most of Funke's systems, this scenario is time discrete and does not change states autonomously, that is, the system waits until the subject has made all inputs. The system is *abstract* in the sense that the labels of the exogenous and endogenous variables have no meanings in order to minimize the influence of prior knowledge (the approach is also applicable to semantically rich domains such as ecological systems, see e.g., Funke, 1985). Figure 2.2 presents the system in graphical form, and the simultaneous difference equations governing the system behavior are given in (1).

$$
\begin{aligned}
y_{1,t+1} &= 1.0 * y_{1,t} + 10.0 * x_{1,t} \\
y_{2,t+1} &= 1.0 * y_{2,t} + 0.2 * y_{3,}t + 3.0 * x_{3,t} \\
y_{3,t+1} &= 0.9 * y_{3,t} + 2.0 * x_{2,}t + 0.5 * x_{3,t}
\end{aligned} \tag{1}
$$

where $y_{i,t+1}$ represents the state of an endogenous variable i at time $t+1$, $y_{i,t}$ represents the state of an endogenous variable i at time t, and $x_{i,t}$ represents the state of an exogenous variable i at time t.

The SINUS scenario is only one instance of an infinitely large class of scenarios that are based on simultaneous difference equations. Actually, a software shell exists to generate new scenarios following this formalism. The precision and simplicity of the formalism makes it very easy to manipulate particular features of the task environment such as time delays, variable connectivity, et cetera. Also, goal states can be defined precisely, and for any current system state, it is possible to specify an optimal intervention. From a methodological point of view, these are major advantages over naturalistic scenarios (see also Kluwe et al., 1989; Ringelband et al., 1990).

Funke developed a theory of how people learn and represent what they have learned when interacting with systems of this sort. Basically, subjects are assumed to built a causal model of the task, to which the input and output variables and then the parameters of the AR_k-processes describing the system behavior are added in a certain sequence. Hypotheses about the relations between exogenous and endogenous variables are built in the order of their numerical strengths in the system, provided the user manipulates the particular x_i-y_j-relation by making an input at the exogenous vari-

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[3]Hübner (1989) has argued that mathematical system theory may be a more adequate formalism to derive system properties. However, Funke's approach is preferred here because it implies both a representational theory and a method for constructing rational diagnostic procedures.

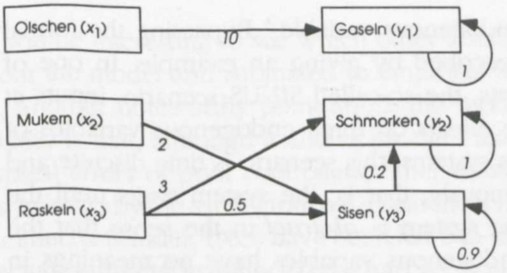

FIG. 2.2. Causal structure of the standard SINUS system (Funke, 1992b). Numbers next to the arrows represent the weights of the influence. Left of the figure: three variables that can be manipulated independently; Right, three variables that have to be controlled.

able. Relations with time-delays (i.e., $k \geq 2$) are built up later and more slowly. Relations open to direct manipulations (i.e., x_i-y_j-relations) are included before indirect relations (i.e., y_i-y_j-relations which result in *side-effects* for any direct influence on y_i). Providing a semantic context has the effect of adding parameters to the model before learning starts which means that some relations may not have to be explored. Relations set a priori are resistant to learning which is why providing a semantic context has detrimental effects if it induces false parameters. Finally, forgetting is also assumed to occur.

Hypotheses about relations are built up from data about current and memorized system states and interventions. According to Funke (1991b, 1992b), hypotheses about system relations can be represented in terms of the following quadruple:

$$H := \langle V_1,\ V_2,\ R,\ C \rangle \tag{2}$$

where V_1 and V_2 are the variables between which a relation R is assumed with confidence C. R comprises all forms of relations a subject may know, including qualitative information, quantitative information, and time delays. C is obviously conceived of in close analogy to the idea of the subject operating as an intuitive scientist.

Finally, Funke and his coworkers have also developed the diagnostic instruments suitable for assessing subjects' task-relevant knowledge in their paradigm (Funke, 1992a, 1992b; Müller, 1993). They distinguish between knowledge relevant to control performance and structural knowledge, a rather straightforward and common distinction (De Kleer & Brown, 1983; Kluwe & Haider, 1990).[4] Control performance, *CP*, is assessed as the distance of the endogenous variables to their goal states. More precisely, control performance is measured by

[4]This distinction appears similar, but is not identical to the distinction made by Berry and Broadbent and their coworkers (Berry & Broadbent, 1984, 1987, 1988; Broadbent et al., 1986; Hayes & Broadbent, 1988). For instance, Funke does not make any assumptions about the location of subjects' knowledge along the explicit-implicit continuum that is central to the work of Berry and Broadbent (see Berry & Broadbent, this volume).

$$CP = \frac{\sum_{i=1}^{n_y} \sum_{t=1}^{n_T} \ln | y_{ij} - g_i |}{n_y * n_T} \tag{3}$$

where n_y is the number of endogenous variables, n_T is the number of trials the system has to be controlled, g_i is the goal value for the endogenous variable i, and y_{it} is the empirical value of variable i at time t. The logarithmic transformation in assessing control performance reduces the influence of extreme deviations.

In order to assess subjects' structural knowledge, the *causal diagram analysis* was developed. Essentially, subjects receive a diagram similar to the one depicted in Figure 2.2. They are asked to fill in the relations they assume to be present in the system. Subjects may do this at one of three different levels of precision. They may simply state that a relation between two variables is present, they may add the relation's direction, or they may specify the relation's numerical value. A summary score is then computed from this information indicating subjects' structural knowledge.

Of course, other methods are possible to assess different aspects of subjects' knowledge about the task. For instance, Müller (1993) has explored the usefulness of reaction time analyses in a yes/no recognition task adapted for the paradigm. However, the advantage of the structural diagram analysis lies in the close relation between representational theory and diagnostic procedure. It is obvious that indices for control performance and structural knowledge can be dissociated. For instance, subjects may build up an *initial action base* (Kluwe & Haider, 1990) when first interacting with the system which may be too fragile and vague to be picked up by the structural diagram analysis. Also, even formally inadequate and fragmentary subjective models of the system structure may lead to considerable control performance (Ringelband et al., 1990). Haider (1992) has pointed out that such a constellation may look like a dissociation between *explicit* and *implicit* system knowledge. However, for his tasks, Funke assumed that subjects first built up structural knowledge which is then turned into successful control performance.

A number of experiments have been stimulated by the theory, examining how properties of the task environment affect the acquisition of structural knowledge and control performance. In these experiments, subjects typically explore the system for a number of trials before they are asked to control it. For instance, the basic SINUS system was manipulated to have either no, one, or two y_i-y_j-relations that result in side effects. Structural knowledge should become worse as a function of the number of y_i-y_j-relations present in the system, and control performance should be a function of structural knowledge. A path-analytic evaluation confirmed this prediction. A similar result was not found for y_i-y_i-relations (i.e., the effect of one variable at time

t on its state at time t+1 resulting in autonomous *growth* or *decline*). Structural knowledge and control performance did not depend on whether no, one, or two y_i-y_i-relations were present (Funke, 1992a, 1992b). Higher degrees of "connectivity" (more x_i-y_j-relations to be included into the model) resulted in both lower control performance and less structural knowledge (Funke, 1985).

If the semantic context of a scenario activates prior knowledge, some parameters are added to the subjects' model of the task before learning starts. This may have beneficial and detrimental effects on learning, depending on whether the actual system structure corresponds to subjects' pre-exploration model of the task or not. Funke (1992a, 1992b) has developed a simple eight variable *ecological* linear equation system according to recommendations provided by environmental experts. In a pilot study, 32 subjects were asked to draw causal diagrams of the system without having interacted with it. Each relation implemented in the scenario was assumed by at least 72% of the pilot subjects, confirming that the system corresponded to subjects' knowledge about the domain. In the subsequent experiment, half of the subjects explored and later controlled this system, while the other half interacted with a system in which the sign of two (out of five) x_i-y_j-relations had been changed. This relatively small change resulted in substantial decrements in both control performance and structural knowledge, showing that activating prior knowledge can effectively impair learning by exploration (see also Beckmann, in press).

If the effects of subjects' inputs are delayed (i.e., x_i-y_j-relations represent AR_2 rather than AR_1 processes), structural knowledge also suffers (Funke, 1985). Similar results have been reported by Brehmer and Allard (1991) and by Dörner and Preussler (1990). Dörner and Preussler (1990) confronted subjects with a relatively simple predator-prey system and asked them to adjust the predator variable so as to keep the prey population at a certain level. The authors manipulated a number of independent variables, but the one manipulation that impaired performance most was feedback delay. Brehmer and Allard (1991) used a variant of the FIRE FIGHTING scenario (see Footnote 2). This system is naturalistic in that it tries to model how a "fire chief" would make decisions about the deployment of fire fighting units. Nevertheless, Brehmer and Allard (1991) agree that in order to be useful for experimental research, certain features of the task must be open for experimental manipulations. Therefore, they developed a simulation system that allows to manipulate six different features of the scenario. In a first exploratory study, the authors varied two of these features, feedback delay and task complexity. Feedback about the fire fighting units' activities was either delayed by one or two time units or it was not delayed. In the low complexity condition, all units were equally effective whereas in the high complexity condition, some units were twice as effective as others. While the complexity manipulation had little effect, the feedback delay clearly impaired subjects' control performance. However, it is unclear whether subjects did not detect the delay or whether they were unable to include the delay into their model of the task.

Funke and Müller (1988) hypothesized that active intervention should be an important factor in learning to control a system. They manipulated whether subjects could actively control the SINUS system or simply observe the effects of interventions, and whether or not subjects were required to make predictions about the next system state after each intervention. Observers were yoked subjects in that each of them attended to the interventions and system states produced by an active control subject. In a final phase, all subjects had to control the system. As expected, active control resulted in better control performance, but making predictions had an unexpected negative effect on structural knowledge.

Berry (1991), using the SUGAR FACTORY scenario (Berry & Broadbent, 1984) further explored the role of active intervention. She found that, for instance, neither making decisions about the next intervention nor typing inputs according to another person's decisions alone had a positive effect on subsequent control performance relative to normal interaction with the system. Also, Hübner (1987) found that learning from an example how to control a technical system was drastically more efficient after some experience of active control. Thus, it appears plausible that both the process of generating an intervention from a given state and a desired next state and the experience of the contingency between one's intervention and the next system state are necessary for efficient initial learning. However, motivational effects may help to explain differences in performance: As we know from the study by Hesse et al. (1983) discussed earlier, personal involvement accounts for considerable differences in control performance. It might therefore be argued that active and uninfluenced interaction with the system simply creates higher personal involvement which then, in turn, plays a mediating role by stimulating other processes necessary for successful control.

To summarize, variations in task properties have noticeable influences on people's knowledge acquisition while interacting with dynamic systems. One of the advantages of Funke's approach is that it allows for the systematic variation of well-known task properties. In addition, the approach includes a theory of what and how people learn when exploring dynamic systems, and it includes rational methods for assessing this knowledge. The combination of these three aspects in one homogeneous framework contributes to the fruitfulness of this line of research.

Of course, the approach also has its limitations. First, the price of the formal lucidity of the task environments is the limited set of task properties that are available for manipulation. Although exponential behavior can be simulated with linear equation systems (one simply sets the weight of a

y_t-y_t-relation to a value larger or smaller than one for exponential growth or decline, respectively), other interesting behaviors such as sinusoidal or s-shaped trends and ramp-like or step-like developments are beyond the limits set by the formal basis. Second, and related to the first point, few if any real-world systems will have the exact properties of linear equation systems. The framework therefore does not have the ecological validity that appeared so important in the development of this research area. Nevertheless, real-world systems can at least be approximated (as in Funke's ecological scenarios) which is, after all, what naturalistic simulation systems do, too. Third, by its very nature, the framework places a heavy emphasis on task properties as determinants of human learning to control a system. This is, of course, a problem only if it leads to the neglect of other relevant variables. Funke (1992b) was aware of this possible shortcoming, and has suggested a taxonomy for further theorizing that includes not only task variables but also person variables (cognitive, emotional, and motivational states and traits) and properties of the situation (how the system is presented physically, and what the instructions define as the task to be performed).

Finite State Automata

A framework that shares some of the basic principles with the linear equation systems approach makes use of elementary concepts of the theory of finite state automata (see Buchner & Funke, 1993; Funke & Buchner, 1992 for details). Again, the theory serves as a tool for formally describing the dynamic task environment, it is used as a starting point for hypothesizing about how such systems are represented mentally, and it allows to derive rational methods for assessing these representations. First, as before, it will be necessary to introduce some of the basic concepts used in the approach. Then assumptions about learning and knowledge representation will be presented, and finally the diagnostic methods to assess what has been learned will be discussed.

A deterministic finite state automaton is defined by a finite set of input signals, a finite set of output signals, a finite set of states, and two mapping functions. To illustrate, input signals of a technical device could be buttons and dial positions that can be selected as input at a certain point in time. Output signals are all possible display settings. It is assumed that the system works on the basis of a discrete time scale. At each point in time, the automaton is in a certain state in which it receives one *input signal* (e.g., on a video recorder, the "fast forward" button is pressed). The system then moves to the *next state* which is determined by the *transition function* δ (e.g., the video recorder starts to wind the video tape). Subsequently, the device emits exactly one *output signal* which is determined by the *result function* λ as a consequence of the current state and the input signal (e.g., the "fast forward" arrows on the video recorder's front display are highlighted). As with the linear equation systems approach, a software shell exists to generate arbitrary scenarios following this formalism.

As a concrete example, consider the SUGAR FACTORY as used by Berry and Broadbent (1984, this volume) and by others (Marescaux, Luc, & Karnas, 1989; McGeorge & Burton, 1989; Stanley, Mathews, Buss, & Kotler-Cope, 1989) to investigate different modi of learning while interacting with a dynamic task environment. The system operates according to a simple equation which states that the sugar output at time t+1, S_{t+1}, is determined by the most recent sugar output S_t and the present input I_t, the number of workers employed by the subject:

$$S_{t+1} = 2 * I_t - S_t \tag{4}$$

where $1 \leq I \leq 12$ and $1 \leq S \leq 12$. The values of I are multiplied by 100 and the values of S are multiplied by 1,000 to represent the number of workers and the sugar output in tons, respectively, at time t. (In addition, a random component is usually added such that on two-third of the trials, the system changes, at time t, to a state that is one unit above or below the correct state according to the system equation. I ignore this random component here.)

A convenient way to describe a finite state automaton is by a state transition matrix. In its cells, the matrix contains the automaton's state at time t+1 (S_{t+1}, the next sugar output) given a specific state at time t (S_t, the current sugar output) and a specific input signal at time t (I_t, the number of workers employed). In each column, it contains the *function* of an input signal, whereas the rows reflect possible next states given a certain current state. The SUGAR FACTORY can easily be described in such terms of a state transition matrix (for more details, see Buchner, Funke, & Berry, in press).

As with the linear equation systems framework, the formal descriptions of automata provide not only the background for precise descriptions of task properties such as system complexity (McCabe, 1976), but they also serve as a starting point for hypothesizing about how people might learn to control automata and how what is learned might be represented. It is assumed that users' knowledge about a system can be described in terms of those parts of the transition matrix that are represented in memory and available for guiding system interventions. This is called the person's individual transition matrix (ITM) which may, of course, deviate from the automaton's transition matrix.

When confronted with a previously unknown automaton, learning must begin at the level of individual state transitions, composed of a previous state, an intervention, and a next state. A person's experiences of these transitions while exploring the automaton constitute the *entries* for the ITM.

At that level, a simple associative learning process is assumed to operate on states, interventions, and next states experienced by the exploring subject.

As learning proceeds, people will shift from using knowledge about individual state transitions to clustering state transitions. First, *routines* may be developed to get a system reliably from one particular state to a distant state. This can be referred to as the formation of *horizontal chunks* of state transitions. For example, the state transition sequence S_t-I_t-S_{t+1}-I_{t+1}-S_{t+2}-I_{t+2}-S_{t+3} may be reduced to the form S_t-[I_t-I_{t+1}-I_{t+2}]-S_{t+3}, where the interventions necessary to get from state S_t to S_{t+3} form one single component of a compound state transition and the user no longer needs to attend to the intermediate output signals (Anderson, 1981; Frensch, 1991; MacKay, 1982). Second, state transitions can be combined across a specific intervention or a specific state, given the intervention or the state can be identified as the source of a specific form of invariance. This process can be referred to as the formation of *vertical chunks* of state transitions. An example could be an intervention to change the mode of operation of a device (in the most simple case an on/off switch).

The formal descriptions of finite state automata also serve as tools for developing rational methods to assess system and control knowledge. For instance, state transitions consist of a given system state at time t (S_t), an intervention at time t (I_t), and a next system state at time t+1 (S_{t+1}). These elements can be used to generate *cued recall tasks* to assess what has been retained about a system by presenting two of the elements as cues for the third one (requiring predictive, interpolative, and retrognostic judgments if the missing element is S_{t+1}, I_t, and S_t, respectively). In all these tasks, the basic idea is to take *samples* from the ITM.

One can also expose subjects to entire state transitions that are either possible or impossible for a given device, and measure the speed and accuracy of the verification judgment. For instance, Buchner and Funke (1993) presented sequences of state transitions taken from an explored automaton for verification. If the second of two state transitions was a transition that, in the chronology of system events, had occurred after the first transition, reaction times were faster than when the second transition had actually occurred first, or was unrelated to the first one.

Further, a criterion for optimal control performance which is lacking for most naturalistic scenarios is readily available within the finite state automata approach. Given a present state of a discrete system and an arbitrarily defined goal state, it is always possible to specify whether there exists a sequence of interventions to reach the goal state and, if so, how many and which steps constitute an optimal sequence of interventions (i.e., a sequence involving a minimal number of steps). Subjects' exploration behavior (i.e., the way they approach the knowledge acquisition task) may be an interesting basis for additional dependent variables. A readily available indicator of exploration behavior is the number of different state transitions that are explored relative to all states in the state transition matrix of the system. The more different state transitions subjects explore, the more they should learn about the system. In a recent study (Buchner et al., in press), it has been shown that this may be one reason for negative correlations between control performance and so-called verbalizable knowledge (Berry & Broadbent, 1984). Note that "good controllers" reach the target state more frequently and, thus, experience a smaller area of the system's state transition matrix than *poor controllers.* On the other hand, verbalizable knowledge was assessed by items which probed subjects for the next system state given an old work force value, a current state of the system, and a new intervention. These items can be conceived of as samples from the state transition matrix. Consequently, good controllers who know less about the system's state transition matrix should be worse at these items, resulting in a negative correlation between control performance and verbalizable knowledge.

The associative learning mechanism assumed to be important in early learning about a new system has also been under examination. The basic idea has been that if an associative learning mechanism is at work, then one should be able to observe transfer interference similar to that known from the paired associative learning paradigm (Martin, 1965). After initially interacting with a *source automaton* (a simplified radio with a built-in alarm device), several groups of subjects tried to control different *target automata.* The state transition matrices underlying the target automata were identical for all groups but were completely different from that of the source automaton. However, the target automata differed with respect to the labeling of their input and output signals. For instance, in one condition, these labels were entirely new, whereas in a different condition, the original labels had been preserved. The latter case corresponds to the A-B, A-Br situation in paired associate learning (stimuli and responses from the first list are preserved in the transfer list but they are repaired) which is known to produce considerable negative transfer. In contrast, the former case corresponds to the A-B, C-D situation in which a completely new list is learned. Indeed, knowledge of state transitions, as assessed with predictive cued recall items, was worst for the "new automaton, old labels" condition, and was best for the "new automaton, new labels" condition.

Indirect measures have also been used to assess system knowledge (Buchner, 1993). In one experiment, subjects interacted with an automaton that was constructed such that it "understood" sentences generated by the finite state grammar used in typical implicit learning experiments (Reber, Kassin, Lewis, & Cantor, 1980). One group of subjects memorized sequences of inputs while another group made predictions about the next output signal. Output signals were patterns of 5 black squares in a 5×5 grid. In a subsequent phase, subjects were again instructed to make sequences of inputs. This time, an output signal was occasionally masked after a very brief display interval which previously had been adjusted for each subject's perceptual threshold. Subjects were asked to indicate which of a number of possible output signals they believed to have seen. The output signal actually presented was either the correct signal given the previous system state and the required intervention, or an incorrect signal. Both groups of subjects were better at identifying the output signal if it was correct than if it was incorrect. Moreover, when the output signal was incorrect, subjects did not choose the signal that would have been correct at that position in the sequence more often than would have been expected under conditions of guessing. This latter finding indicates that subjects indeed treated the test as an indirect test.

In recent experiments (Müller, Funke, & Buchner, 1994), the focus has shifted from singular associations to chunking processes. Subjects were trained on twelve element input sequences that were arranged on a structured display such that the first four and the final four elements of the sequence each took place in a different display structure. It was hypothesized that the display structure would induce a clustering of the elements into two *horizontal chunks*. In a transfer phase, subjects learned new input sequences in which four elements of the original sequence were retained. These four elements could either be the final *chunk*, or adjacent elements from both chunks, or four disconnected elements. As predicted, the chunk structure transferred and subjects in the first condition made significantly less errors than subjects in the other two conditions.

Finally, the finite state approach has also been fruitful in applied settings. Funke and Gerdes (1993) analyzed the standard manual of a popular video recorder brand. They asked whether the information contained in the manual was appropriate for building up an adequate ITM of the device. A typical inadequacy was, for instance, a lack of descriptions of output signals (essential for diagnosing what state the device is in). On the basis of this analysis, the authors developed an improved version of the manual designed to facilitate learning how to operate the video recorder. Subjects were asked to perform a number of *timer programming* tasks (i.e., they programmed the video recorder such that a certain TV show would be automatically tape-recorded). Subjects trying to program the video recorder with the old manual needed 27 minutes to perform the tasks as opposed to only 18 minutes for subjects who had received the improved version. The improved manual also resulted in higher accuracy scores. In addition, subjects in the improved manual group were significantly better at responding to interpolative cued recall items (given S_t and S_{t+1}, which input I_t is appropriate?).

This latter example demonstrates that the finite state automata framework can be useful not only for basic research on how people interact with complex dynamic systems, but also for questions of applied psychology. However, the major drawback of the finite state approach is that it becomes impracticable with large-scale systems (although some of the concepts developed within the approach seem transferable to larger systems). Nevertheless, many technical systems we deal with in everyday life are adequately described within the formalism provided by finite state automata theory. Examples include, besides video recorders, computer programs, TV sets, digital wrist watches, banking machines, and so on. Thus, the first point to be made here is that, in drawing upon a well-developed formalism for constructing dynamic task environments, one does not automatically loose ecological validity. One can have it both, ecologically valid task environments and the methodological advantages of well-defined task properties. In fact, the successful research of Funke and Gerdes (1993) shows this empirically rather than simply appealing to the ideal of ecological validity by constructing tasks that look natural.

The second point is that, contrary to widespread assumptions, learning to control complex dynamic tasks might not be fundamentally different from learning and memory as investigated in more traditional research paradigms. Rather, it appears that fundamental cognitive processes as investigated in traditional learning and memory research are also involved in people's interactions with dynamic task environments. Of course, it would be grossly inadequate to claim that there is nothing more involved in controlling a technical device than there is in memorizing lists of paired words. However, at a certain level, the two tasks seem to involve similar learning processes. This suggests that, besides emphasizing the uniqueness and novelty of the dynamic task environments paradigm (Dörner, Kreuzig, Reither, & Stäudel, 1983; Dörner & Reither, 1978), it might also be useful to consider the potential contributions of established theories of learning and memory for a theory of how people successfully perform in complex dynamic tasks.

CONCLUDING REMARKS AND FUTURE PERSPECTIVES

In this chapter, I have tried to provide an overview of the major lines of basic research on how people interact with complex dynamic tasks. Two different ways to approach the topic have been described. On one side, some researchers favor *naturalistic* scenarios as tasks, and they search explanatory constructs based on interindividual differences. On the other side, some researchers exhibit a strong preference for *well-defined* task environments and a focus on knowledge acquisition processes modulated by features of the tasks. Recent developments in basic research on how people control complex systems point to at least three different directions.

First, those interested in interindividual differences in CPS now try to move beyond the *psychometric* approach of simply correlating state or trait variables with ad hoc measures of control performance. Also, it is realized that much can be gained if the task environments used to assess control performance provide rational performance measures and are open to experimental manipulation. Beckmann's (in press) work on the relation between learning potential tests and system control is a good example of the progress already made in this area.

Second, some researchers involved in the *systems thinking* program moved towards action theory. They believe that cognitive, motivational, and emotional processes should not be analyzed separately if one wants to get a complete and realistic picture of how people come to control complex dynamic systems. One problem here is that the inclusion of theoretical terms from action theory such as intention (conceptually an action constituent requiring a deliberately acting person) into a (mechanistic) cognitive framework characterized by information processing units and knowledge structures as in Dörner et al. (1988) will result in the mixing of incompatible theoretical languages. On the surface, one finds semantically queer theoretical formulations (e.g., a processing unit is said to be *responsible* for generating intentions, see Dörner et al., 1988, p. 223), but more serious is that both precision and testability of such a theory will suffer. Another point is that, because there is no such thing as an unique action theory, one should make explicit the underlying perspective (Brandtstädter, 1985) to help clarify which theoretical relations are empirical and which are simply analytical.

A third approach is to search for interesting frameworks to adequately describe the formal basis of the task environment, to hypothesize about the systems' mental representation, and to derive rational measures of control performance and system knowledge. This approach is limited to the types of systems that can be formalized within a particular framework, and it does not take into account noncognitive processes that may be involved in controlling complex systems (although it is of course granted that such processes may play important roles). One of the more problematic aspects here is that focusing on formalizeable task properties, one tends to neglect subjects' prior knowledge. In fact, a number of studies using formally well-described systems have sometimes tried deliberately to exclude the influence of prior knowledge by avoiding meaningful labels of input and output variables (Buchner & Funke, 1993; Funke, 1992b). This *Ebbinghaus approach* to controlling dynamic task environments obviously has its merits in terms of rigorous experimental control, but it also has its limitations, and we do not necessarily have to go back to Bartlett (1932) to see those. Very likely, subjects virtually never control a real-world dynamic task without recourse to some sort of prior knowledge. According to Funke (1992a), the development here should be to focus more on the *interaction* of person, situation, and system influences, rather than on the *main effects* alone. This would include an explicit consideration and assessment of subjects' prior knowledge that is relevant to the simulation's domain. In addition, on the person side, Funke demands that the deficits in diagnosing *heuristic* knowledge be overcome.

Future research will also have to turn to questions that are currently ignored. For instance, the importance of real-time decisions for human system control has been pointed out repeatedly (e.g., Brehmer, 1989, this volume; Brehmer & Allard, 1991), but basic research has largely ignored this variable. Note that decisions can be real-time in a dual sense. First, subjects may have to plan and execute interventions under time pressure. This can be investigated with any of the available dynamic task environments by simply requiring the control task to be completed within a certain temporal limit (e.g., Dörner & Preussler, 1990). Reduced performance should result because the mental processes involved would terminate earlier than under normal circumstances. Second, the system subjects interact with may change autonomously as a function of time. Here, the time pressure is not set externally but is inherent in the task. In addition, subjects must deal with a special type of state change, namely autonomous state changes that are presumably quite different from the ones initiated by subjects' self-generated interventions. We know from the research of Funke and Müller (1988) and of Berry (1991) that learning is severely impaired when both the decision and the active intervention components are missing—which is what characterizes autonomous state changes.

The FIRE task used, for instance, by Brehmer and Allard (1991), is a major exception to the rule that virtually all scenarios employed so far—even the most complex and naturalistic ones—do not require real-time decisions under autonomous state change conditions. Here, we have a fundamental difference to applied research on process control (Bisseret, Figeac, & Falzon, 1988; Strížnec, 1980; Van Daele & De Keyser, 1991) where most complex systems people interact with require decisions in real time. Both the linear equation systems approach and the finite state automata framework can be adapted to incorporate the temporal dimension. For instance, in a finite state automaton one could simply add a separate column to the transition matrix analogous to a new input signal. This new column would contain, for each state, as parameters both the next system state S_{t+1} and the length of the time interval after which the specified state transition will occur, provided the user did not select a different intervention before the end of the time interval.

Another aspect currently ignored, but relevant from an *ecological* point of view is that professionals frequently cooperate with others in process control and decision making. Thus, as we learn more about the cognitive processes involved in an individual's interactions with complex dynamic systems, basic research should also move towards investigating process control embedded in group processes (Schmidt, 1991; Wærn, 1992). A related real-world area is the question of whether skills relevant for successful system control can be taught effectively (e.g., Sonntag & Schaber, 1988). For instance, if one of the primary errors people make when interacting with complex systems really is to reason in causal chains as opposed to causal nets, then teaching how to analyze feedback structures might help to remedy the problem. It is rather ironic that, as with dynamic task environments as tools to select personnel, the real world is again ahead of basic cognitive research in recommending "network thinking" as a "new instrument for tomorrow's successful business executives" (Probst & Gomez, 1991, Foreword; translation by the author).

Finally, the chapter has concentrated on psychological approaches embedded in empirical work rather than on the numerous formal modeling attempts such as *task action grammars* that claim *ex cathedra* to represent user's mental models of a task (e.g., De Haan, Van der Veer, & Van Vliet, 1991). In their current states, these models specify, at most, what the expert user must know to perfectly operate a device such as a computer program (e.g., De Haan & Muradin, 1992). However, it might be useful to explore whether attempts of formal modeling can be utilized for cognitive theories in the future. To repeat the basic idea again, the methodological advantages to be gained from precise formal analyses of the task environments cannot be overestimated, and the question of ecological validity is orthogonal to the question of whether or not a particular scenario has a naturalistic look. However, as with finite state automata and linear equation systems, such formalisms are useful only to the degree to which they can be used to develop theories about knowledge acquisition and knowledge use in dynamic task environments, and to create rational measures for assessing knowledge and control performance. The idea is always to take the formal model of a task as a tool to stimulate theorizing about the task's mental representation, knowing that, beyond a certain point, it will be the deviations from this conceptualization that will turn out to be interesting. This is, of course, an old idea: "By pushing a precise but inadequate formulation to an unacceptable conclusion we can often expose the exact source of the inadequacy and, consequently, gain a deeper understanding" (Chomsky, 1957/1971, p. 5).

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