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Chapter 2

SHOULD ACTION BE AWARDED A SPECIAL STATUS IN LEARNING?

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ABSTRACT

The role of action has been strongly emphasized, not only in cognitive research on learning and problem solving, but also in education and instructional psychology. The Constructivism tradition has long asserted that action plays a crucial role for learners in developing their own knowledge. In an educational context, active engagement entails students examining their own ideas, considering alternative explanations for newly taught concepts, and evaluating competing perspectives. Some theorists (e.g., Anzai & Simon, 1979) propose that these processes are found when *learning is by doing*. However, a constructivist perspective implies that instructional formats enable self-monitoring (e.g., Covington, 2000; Pintrich & De Groot, 1990), which includes reflective activities such as describing, explaining, and evaluative thinking (e.g., Covington, 2000; Zimmerman, 1990), which are not exclusive to action. The present article discusses findings that concern two related and thus far, unexplored two questions: How affective is observation-based learning in a complex skill learning task that usually requires processes that involve active engagement with it? How does monitoring affect the transfer of problem solving skills in complex skill learning task?

The first aim of the article is to introduce ways of using common educational tools like the self-observation technique, which involves re-exposing individuals to their own self-generated behaviors, in novel way. This can provide insights into how people use self-regulatory mechanisms like monitoring on internally represented behaviors. The second aim is provide support for the view that in the absence of active learning, learning indirectly (i.e. Observation-based learning) is a practical and, in some cases, necessary method of knowledge and skill acquisition, and does not in turn lead to decrements in

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acquired knowledge and skill. Finally, the article presents the argument that the degree of self-monitoring that takes place may be a mediating factor in preserving the view that action has a special status in knowledge acquisition.

Many believe that without actively engaging with a to-be-learned task we cannot fully learn the essentials of it. This claim seems to be particularly popular in explaining the effectiveness of the acquisition of highly practiced behaviors (e.g., car driving, operating electrical devices – e.g. mp3 players, mobile phones, DVD/video recorders, camcorders) in which a sequence of behaviors is needed to reach a specific outcome. However, there is growing psychological literature (e.g., Bird, Osman, Saggerson, & Heyes, 2005; Osman, in pressA, in pressB; Osman, Bird & Heyes, 2005) that challenges the claim that direct active experience is essential, and that other forms of learning simply fail to extract the essential properties of a task. This chapter discusses findings that have sustained the view that active-based learning has a privileged status over observation-based learning, with specific focus on research that explore learning in complex dynamic problem solving tasks. Next, this chapter introduces related research that has examined the affects on knowledge acquisition when learning is observation-based. The tension generated by these different approaches to knowledge acquisition is the basis for the empirical study that follows. The study aims to address the following questions: What are the differences between action-based and observation-based learning? Do people gain more from performing, or from observing their performance? In so doing, the empirical techniques used in the study, and the findings that are reported, illuminate ways of understanding some of the differences between action-based vs. observation-based learning. Finally, this chapter aims to provide a convincing challenge to the view that action should be awarded a special status in learning.

1. WHY IS ACTION IMPORTANT IN LEARNING?

Several lines of research have proposed that learning-through-doing (i.e. procedural learning) is essential to the acquisition of knowledge. These include implicit perceptual-motor sequence learning (e.g., Kelly & Burton, 2001; Kelly, Burton, Riedel, & Lynch, 2003), memory (Goschke & Kuhl, 1993; Marsh, Hicks, & Bink, 1998; Maylor, Chater, & Brown, 2001; Maylor, Darby, & Della Sala, 2000), causal structure learning (Lagnado & Sloman, 2004; Steyvers, Tenenbaum, & Wagenmakers, 2003; Waldman & Hagmayer, 2001), and developmental, educational and instructional psychology (Anderson, 1987; Resnick, 1983, 1987; Schauble, 1990; von Glasersfeld, 1989). In understanding why direct interaction with a task is crucial to successful learning, it is just as important to examine the kinds of learning environments for which active learning is thought to be necessary. In the following section I introduce a task (Complex dynamic control task) that has often been described as action-based (i.e. procedural), and that in turn is thought to require procedural learning in order for it to be successfully completed.

1.1. Complex Dynamic Control Tasks (CDC-Task)

CDC-tasks have been a popular task environment for examining a host of phenomena including: motivational and affective processes in complex decision making (Earley, Connolly, & Ekegren, 1989; Locke & Latham, 2002; Vancouver, 1997), skill learning in naturalistic decision making (Brehmer, 1992; Kerstholt, 1996; Lipshitz, Klein, Orasanu, & Salas, 2001), memory and attentional processes in problem solving (Burns & Vollmeyer, 2002; Miller, et al., 1999; Vollmeyer et al., 1996), and implicit learning (Berry, 1991; Berry & Broadbent, 1988; Dienes & Fahey, 1995, 1998). Their popularity and range (e.g., car driving, computer programming, air traffic control, medical decision making, business management, mechanical engineering) makes them ideal for studying the acquisition and transfer of skill-based knowledge in a variety of complex interactive environments (Campbell, 1988; Cañas, Quesada, Antoli, & Fajardo, 2003; Funke, 2001). To illustrate, a typical CDC-task includes several inputs that are connected via a complex causal structure or rule to several outputs (See Figure 1). The CDC-task presented in Figure 1 is taken from Burns and Vollmeyer's (2002) task, which was based on a water tank purification plant and will be used in the present study.

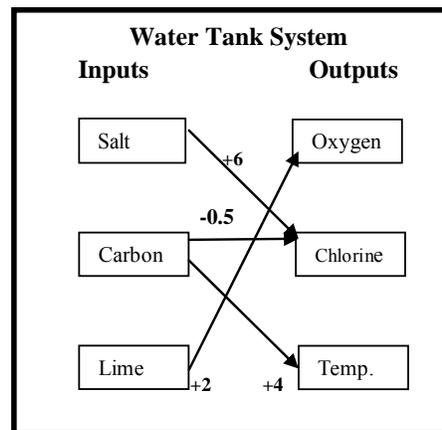


Figure 1. Water tank system with inputs (salt, carbon, lime) and outputs (oxygenation, chlorine concentration, temperature).

The process by which a problem solver learns about the system is revealed by the values of the inputs that they change and the associated changes to the outputs; this is dependent on the strategy that they adopt (e.g., vary all inputs at once, vary one input on each trial, vary one input by one unit on each trial). Through this process, problem solvers acquire knowledge about the underlying structure of the system. That is, by manipulating the input values, problem solvers can then track the effects on the outputs, which enables them to reason from cause (input changes) to effect (output changes), via acquisition of the causal structure or the rule that relates inputs and outputs. To examine problem solvers' knowledge of the system, two types of measures (direct tests, indirect tests) are used. In the learning phase, changes to the inputs are designed to discover the underlying structure of the system. The learning process (procedural learning) also involves learning how to operate and control a dynamic environment: i.e., it is changing as a consequence of the learner's actions. The knowledge that

is acquired is procedural, and represents “knowing how” to perform actions that are tied to specific goals. This is different from declarative knowledge, which is “knowing that” of particular facts about the underlying actions and structural knowledge concerned with the goal itself (e.g. Anderson, 1982). At test, indirect tests of knowledge measure problem solvers’ procedural knowledge (i.e. how successful their changes to the inputs are in reaching specific output goals). In addition to this, direct test of knowledge examine the accuracy of problem solvers’ declarative knowledge (i.e. structural knowledge of the system).

1.2. CDC-Tasks, Procedural Tasks?

CDC-tasks like the problem solving example above involve perceptual-motor behaviors that are designed to fulfil a set of constraints in order to achieve a goal. Dissociationists (Berry, 1991; Berry & Broadbent, 1988; Dienes & Berry, 1997; Lee, 1995; Sun et al., 2001) propose that knowledge acquired in CDC-tasks and experience in controlling them is embedded within the interactions problem solvers have with the system (see Osman, 2004 for a review of Dissociationist position). It is because of this that only learning through action can produce successful control behaviors; this involves storing individual instances or exemplars of specific condition-action states (i.e. the state of the system, the subsequent inputs changed and their corresponding outputs). Thus, mastering a control task requires successfully matching the goal and the current situation to previously encountered instances in order to determine the next appropriate response. Moreover, the position of Dissociationists is that knowledge is conscious only to the extent that the response which is appropriate to a given situation can be stated, but what led to that response is unavailable to consciousness (Buchner et al, 1995; Dienes & Berry, 1997; Dienes & Fahey, 1998).

1.3. Evidence for Procedural Learning in CDC-Tasks

The empirical foundation of this position is the phenomenon showing that declarative knowledge is dissociated from procedural knowledge. For example, work carried out by Broadbent (e.g. Broadbent, 1977; Broadbent & Ashton, 1978) is one of the earliest examples exploring dissociations between procedural and declarative knowledge. Procedural knowledge, as demonstrated by good control performance, is unaccompanied by declarative knowledge of the task environment (Berry & Broadbent, 1984; Dienes & Berry, 1997; Dienes & Fahey, 1995), and unaccompanied by self-insight of the processes used to control it (Berry & Broadbent, 1984). In addition, practice can lead to further improvements in the controllability of the system, but not to similar increases in declarative knowledge (Berry & Broadbent, 1988). Implicit learning theorists (Broadbent, Fitzgerald & Broadbent, 1986; Dienes & Berry, 1997; Dienes & Fahey, 1995; 1998) also claim that dissociations are found because the two systems operate over different types of knowledge. Typically in CDC-tasks, the input-output relations are non-salient and therefore difficult to acquire. Rather than abstracting the underlying structure of the system, exemplars (i.e. associations between specific actions and their consequences) are formed. Hence, dissociations between direct and indirect measures occur because similarity is used to match new goal states of a system with previously stored exemplars; this often leads to relevant procedural knowledge facilitating

good control performance, but with no accompanying structural knowledge of the system (Broadbent, et al, 1986; Dienes & Fahey, 1995; 1998). Consistent with this, studies contrasting observation-based and procedural-based learning show that on indirect and direct measures, performance was poorer for observation-based learners (Berry, 1991; Lee, 1995). The strong implications of this are that there is an advantage of action over observation because CDC-tasks are proceduralized tasks in which learning is incidental and results from direct interactions with the system (Berry, 1991; Berry & Broadbent, 1988; Stanley, Mathews, Buss, & Kotler-Cope, 1989; Sun, Merrill, & Peterson, 2001).

2. OBSERVATION-BASED LEARNING

Often, active learning is contrasted with passive or “observation-based learning”, in which the learner acquires knowledge indirectly, usually by watching another perform the to-be-learned task. For example, in a science class, pupils will watch a teacher demonstrate a sequence of procedures that will help them to understanding how the rate of a chemical reaction could be measured. Or in a training course, such as speech therapy training, students learn from video taped sessions of experts and trainee non-experts interacting with clients (e.g., Cox, McKendree, Tobin, Lee & Mayes, 1999).

Many theorists (e.g., Berry, 1991, Kelly & Burton, 2001; Kelly et al, 2003; Lee, 1995) have claimed that without direct manipulation of the variables in a procedural task, the learner has an uphill struggle, both in dealing with the added memory load that is incurred through observation-based learning, and the added inferential processing that is needed to determine what aspects of the task are relevant. However, recent work (e.g., Dandurand, Bowen, & Shultz, 2004; Gonzales, 2005; Osman, in pressA, in pressB) suggests that it is far from clear that contrasting observation with procedural learning is a successful method for uncovering dissociations between declarative and procedural knowledge. There is evidence showing that, through instruction, observational learning can involve hypothesis testing and self-evaluative thinking, which when attenuated lead to poorer control performance and structural knowledge of a CDC-task. This evidence suggests that in problem solving contexts, observation-based learners are sensitive to instructions that affect cognitive activities in the same way as procedural-based learners. To add to this, observation in combination with active learning can improve control performance in CDC-tasks and interactive game problems above and beyond simply physical practice alone – (e.g., Gonzales, 2005; Kohl & Fisicaro, 1996; Shea, Wright, Wulf, & Whitacre, 2000). Additionally, in some cases observational learning can lead to performance that exceeds procedural based learning in problem solving contexts (Dandurand, et al, 2004).

2.1. Specific Examples of Observation-Based Learning in CDC-Tasks

Gonzales (2005) presented learners with an opportunity to learn about a CDC-task from their own mistakes in three ways. After generating each learning trial, the self-exemplar condition were replayed their own trial again, but without any feedback, whereas the feedback-exemplar condition received detailed outcome feedback after being replayed each

trial. However in the expert-feedback condition, after each trial they had generated themselves, they were played the trial of a highly skilled participant. Gonzales (2005) found that in later tests of control performance, the expert-feedback condition out performed both others. Similar findings were reported by Dandurand, et al (2004) using a different kind of problem solving task. They presented participants with a mathematical ball-weighing problem solving task in which they were required to decide how many counters on each side of a balance would be needed to find the lighter counterfeit one. There were three types of training conditions. During learning participants watched variants of the problem being solved by an expert, or were given instructions that described the strategies that the observer group were watching being implemented, or were given feedback on their performance. Participants were then presented with new versions, from that of the training problems, to solve. Dandurand et al (2004) found that the observer group's performance exceeded the other active learners, despite the other participants having interacted with the task. In both these studies, the findings suggest that rather than simply reproducing the observed expert behavior, learners were extracting the relevant strategies from the experts to scaffold their own knowledge of the task.

The implications of the findings from studies examining the acquisition of knowledge via observation, is that observation-based and procedural-based learning engage similar cognitive processes responsible for planning and control of complex skills. Moreover, as well as learning through observation, people are able to accommodate the knowledge of experts in such a way as to improve, through error detection and correction, their performance.

2.2. Why might Observation-based Learning be Important?

Observation based learning is an important technique used for teaching and training many skills (e.g., piano playing, syntax parsing, speech therapy techniques, statistical skills). It is practical, not only because the learning situation might incur a degree of danger, or injury requires that certain skills be relearned, but also because it helps to reduce the amount of physical practice needed to reach proficiency (Newell, 1981; Schmidt, 1988). Clearly, such examples show that observation based learning is a successful method by which declarative knowledge is acquired, and used to perform procedural based skills. Much of the research on acquisition of motor skills also suggests that both procedural and declarative representations are activated during observation-based learning. This may also explain why it is that in many of these studies an association between these types of knowledge is reported (e.g., Dandurand, et al, 2004; Gonzales, 2005; Osman, in pressA, in pressB). Moreover, studies of observational learning suggests that, people are likely to employ self-evaluative behaviors that enable them to track their own knowledge, and this can in turn lead to the successful uptake of relevant task knowledge.

Bandura's (1986, 1988) Social cognitive theory places at the heart of human cognition self evaluative processes that regulate motivation and actions. Pursuing a goal is guided by selectively attending to qualitative and quantitative aspects of ongoing behavior, which enables people to evaluate the status of their behavior in relation to a goal (Bandura & Locke, 2003; Karoly, 1993). In this way, monitoring or self-regulatory mechanisms track goal-relevant information, modulate motivation, and trigger self-reflective judgments. One of the mechanisms that occupy a central role in the regulation of motivation and action is that of

perceived self-efficacy. This refers to people's beliefs in their ability to exercise control over environmental events, and with this people regulate motivational (e.g., Litt, 1988), affective, (e.g., Bandura & Cervone, 1986; DeShon & Alexander, 1996; Elliot & Dweck, 1988) and decisional processes (e.g. Earley, Connolly & Ekegren, 1989; Kanfer, et al., 1994; Tversky & Kahneman, 1974). For instance, perceived self-efficacy is shown to mediate problem solving in such a way that it produces poor performance irrespective of people's actual capabilities (Bandura & Wood, 1989; Bouffard-bouchard, 1990; Wood & Bandura, 1989). As compelling is evidence showing that increasing people's belief in their self-efficacy guides attentional and cognitive processes so that, in problem solving tasks, peoples accuracy in analyzing their solutions to problems can be radically improved (e.g., Bouffard-bouchard, 1990). Studies of expertise show that self-regulatory systems (Bandura, 1991) are critical in the acquisition of complex behaviors; ranging from athletic and musical performance, to managerial decision making and stock-broking, (Bandura, 1991; Bandura & Locke, 2003; Ericsson & Lehman, 1996; Karoly, 1993; Rapoport, 1966; Rossano, 2003; Stanovich, 2004). Selecting relevant information that bears on a solution depends on keeping an internal status check of ongoing performance through error detection and correction (Bandura, 1991; Bandura & Locke, 2003; Karoly, 1993; Lehmann & Ericsson, 1997; Rossano, 2003). Additionally, through judgments of self-efficacy experts advance their behavior towards achieving increasingly more and more difficult goals, thus extending their knowledge and experience (e.g., Bandura & Wood, 1989; Bouffard-bouchard, 1990; Wood & Bandura, 1989).

2.3. Self-Monitoring in Education

Not only is monitoring relevant in studies of expertise, this kind of self-regulatory mechanism has been implicated in the achievement of goals in school performance (Covington, 2000; Dweck, 1986; Pintrich & De Groot, 1990; Zimmerman, 1990). In classroom settings, self regulatory mechanisms are revealed in a number of ways: 1) active engagement in their own learning, 2) analyzing the achievements of their school assignments, 3) planning for and marshalling their resources to meet these demands, 4) monitoring their progress towards completion of those assignments (e.g., Pintrich, 1999; Zimmerman, 1990). In the latter case, accurate monitoring facilitates accurate self-evaluation by enabling students to periodically check the status of their behaviors relative to the goals they plan on achieving, and modify their behaviors accordingly (Baker, 1989; Jacobs & Paris, 1987). What this implies is that, one's achievement goals are thought to influence the quality, timing, and appropriateness of cognitive strategies that, in turn, control the quality of one's achievements. Research supporting this conclusion (e.g., Cross & Paris, 1988; Brown & Palincsar, 1989) shows that self-regulatory mechanisms improve performance in a number of ways: 1) increasing the allocation of attentional resources more appropriately, 2) increasing the use of existing strategies, 3) increasing awareness of comprehension breakdowns. Taken together, there are good grounds for claim that high level executive functions, such as monitoring, are necessary in tracking the consequences of our behaviors, and a means of enabling us to regulate our actions in order to progress and learn.

2.3. Self-Observation Based Learning

Our capacity to learn vicariously (Bandura, 1986, 2002) also means that self-regulatory mechanisms can modulate behaviors learnt from observed as well as active experience. The self-observation technique involves re-exposing individuals to their own self-generated behaviors: In so doing, the technique enables a comparison of subjective experiences with objective representations of them. Usually this involves showing individuals past generated behaviors through a host of media (e.g., video recordings, photographic stills, point light displays [videos of people making movements are reduced to lights on the joints]). For example, developmental studies (Fireman & Kose, 1991, 2002; Fireman, Kose, & Solomon, 2003; Fosnot et al., 1988) report improvements in children's ability to solve the Tower of Hanoi (TOH) task through video-tapped presentations of their previous solutions. In Fireman et al 2003 study, children completed the TOH task and were then shown their own moves, or another child's previous inefficient moves, or another child's correct completion of the task. Following this, they were then presented with another TOH task. Children benefited most from observing their previous inefficient problem solving strategies than the behaviors of other children.

The technique works because self-correcting procedures allow individuals to detect and improve on previously generated behaviors (e.g., decision making, meta-perception; motor learning). This is also why it is used as an educational tool (e.g., Covington, 2000; Pintrich & De Groot, 1990; Zimmerman, 1990), and as a therapeutic aid in clinical environments (e.g., Bailey & Sowder, 1970; Dowrick, 1983; Giesler, et al, 1996; Hung & Rosenthal, 1978). One problem with studies using the self-observation technique is that they have focused on the accuracy of detecting self generated behaviors and the improvements that might follow. They show self-regulatory mechanisms operating over veridical representations, but this provides little insight into how people use these mechanisms on internally represented behaviors. To shed light on this, the present study examines self-regulatory mechanisms and their effects on later transfer of skilled control behaviors by re-exposing problem solvers to products of their own strategic thinking (e.g., decision-making and hypothesis testing behavior) rather than actual visual (i.e. video) presentations of their actual selves performing. In this way it is possible to empirically control the information that people's self-regulatory mechanisms are operating on, as well as examine how this later impacts on the transfer of their control behaviors.

3. PRESENT STUDY

The first objective of the study is to examine the affects on performance in CDC-tasks when learning was action-based or observation-based. The second objective was to adapt the self-observation technique so that participants would be able to re-experience prior self-generated learning behaviors. To this end it would be possible to compare whether participants would benefit from their past learning experiences when being exposed to them again via observation, or re-experiencing them again first hand by re-enacting them. In the following study participants performed two CDC problem solving tasks each of which was composed of a learning phase and control test phase. All participants solved the first problem

in the same way. The critical manipulations concerned the contents of the learning phase in the second problem, participants either observed the learning phase in the second task (Observe-self, Observe-other), or they actively interacted with the task (Act-on-self, Act-on-other). The adaptation of the self-observation technique is as follows. In ‘self’ labelled conditions participants were exposed to their own learning phase from the first problem again in the second problem. In addition, the study included a further elaboration of the self-observation technique. In ‘other’ labelled conditions participants were yoked to a participant in the corresponding ‘self’ condition, and so were exposed to that individual’s learning phase in the second problem.

If procedural learning is necessary for good performance in control tasks, then the performance of observation-based learning conditions would be compromised compared to the performance of action-based learning conditions. If however, participants are sensitive to the content of the learning phase, and engage in evaluative thinking whilst learning procedurally as well as observationally, then performance for both action-based and observation-based conditions should be equivalent. Additionally, if self-evaluative and monitoring behaviors are involved, then, during the learning phase, people will be sensitive to the kind of information presented (i.e., the source of the second learning phase), not its presentation format (observation-based, action-based). In this case, participants will demonstrate knowledge of the difference in the source of the second learning phase.

Method

Participants

Forty-eight students from University College London volunteered to take part in the study and were paid £6 for their involvement. They were randomly allocated to one of the four conditions (Observe-self, Observe-other, Act-on-self, Act-on-other) with twelve in each. Participants were tested individually. The order of presentation of the two dynamic control tasks (i.e. the Water tank system, Ghost hunting task) was randomized for each participant.

Design and Materials

The present study used a mixed design that included two between subject variables comparing re-exposure to self-generated learning instances vs. exposure to other-generated learning instances (i.e. Self vs Other), and the effects of learning format on transfer of control performance (Observation, action). There were also two within subject variables, one examining the transfer of control performance between two CDCTs in two tests of transfer (Control Test 1, Control Test 2), and one examining the transfer of causal structural knowledge between two CDCTs in four tests (Structure Test 1, Structure Test 2, Structure Test 3, Structure Test 4). Each participant was required to solve two CDCT problems, and the order of presentation of the two problems was randomized for each participant. For each problem, there was a learning phase, consisting of 12 trials in which participants were given an opportunity to learn about the control system. After the 6th and 12th trials, participants were presented with a direct test (Structure Tests 1, Structure Test 2) of their knowledge of the underlying structure of the system. Participants were then presented with two indirect tests (Control Test 1, Control Test 2) which measured their ability to control the system to specific

criteria. Control Test 1 consisted of 6 trials, followed by another structure test (Structure Test 3). Control Test 2 consisted of 6 trials, followed by another structure test (Structure Test 4).

The critical manipulation was the contents of the learning phase that participants received in the second problem. All participants generated their own learning experiences in the learning phase of the first problem, but, in the second, half of the participants re-experienced their original learning phase (observe-self, act-on-self), and the other half experienced a different learning phase to the one they had generated (observe-other, act-on-other).

CDCTs

The design and underlying structure of the two CDCTs (Water-tank control system, Ghost hunting control system) that were used were based on the Water tank system (as shown in Figure 1). The only differences between the two problems were the visual layout of each system as presented on screen and the cover story (see Osman, in pressB for full details of the CDC-tasks used). In the Water-tank control system participants were told that they were a worker from the water purification plant and that it was their job to inspect the new system that was being used. The system worked by varying the different levels of salt, carbon and lime (inputs), and this in turn changed oxygenation, temperature and chlorine concentrations (outputs) which are indicators of how pure the water is. In the Ghost hunting control system participants were told that they were newly recruited ghost hunters, and that they had returned from a field experiment. It was their job to learn the relationship between three pieces of equipment that had been used in the field, and the phenomena that each machine detected. The three machines (i.e., GGH Meter, Anemometer, Trifield Meter) represented the three inputs, and the three phenomena that were detected (Electro Magnetic Waves, Radio Waves, Air Pressure) represented the three outputs. The control element of the task was to modify the levels of the readouts of the phenomena by manipulating the dials on each machine.

For each problem at the start of the learning phase, and at the beginning of each control test, the input values were set to 0, and the output levels were set as follows: Output 1 (Water tank= Oxygenation, Ghost hunting= Radio Waves) = 100; Output 2 (Water tank = Chlorine concentration, Ghost hunting = Electro Magnetic Waves) = 500; Output 3 (Water tank = Temperature, Ghost hunting = Air Pressure) = 1000.

Procedure

Participants were told that they would be taking part in a problem solving task. On completion of the first problem, participants were then told that they would be required to solve a second problem, but at no stage were they informed that the two problems were structurally the same.

First Problem: Learning phase. In the first problem, in the learning phase, participants were presented with a computer display (see Figure 2) with three input variables and three output variables. The underlying structure that connects the inputs and outputs is presented in Figure 1.

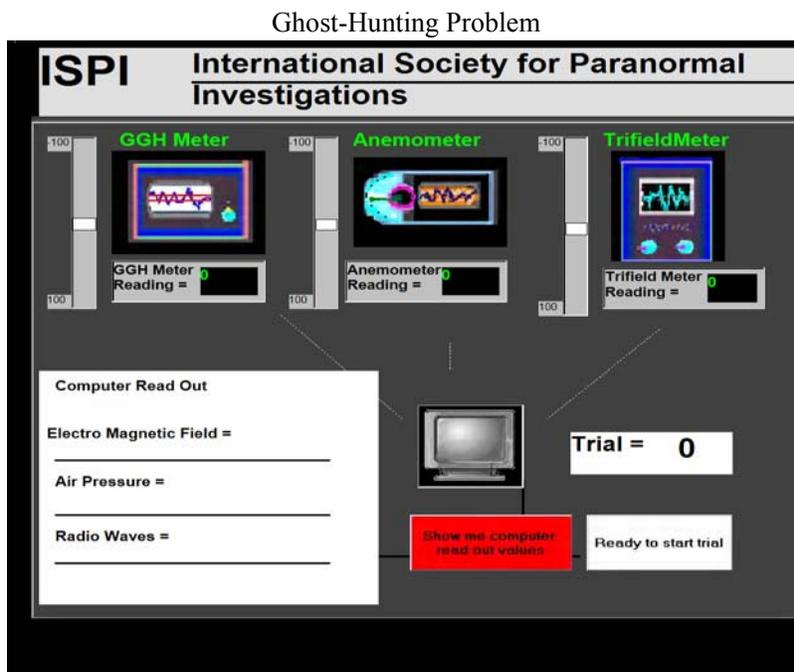
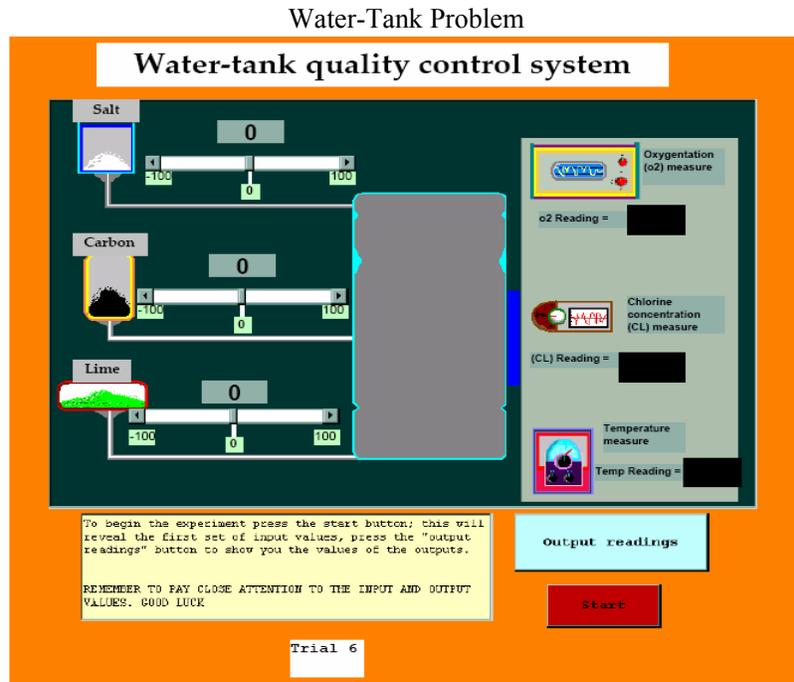


Figure 2. Screen Shots of Water-Tank and Ghost Hunting tasks

The learning phase comprised 12 trials, which were divided into two blocks of 6 trials. Each trial consisted of participants changing the value of any number of inputs, by using the slider corresponding to each. Each slider ranged on a scale from -100 to 100 units. When participants were satisfied with their changes to the inputs, they clicked on a button labeled

“output readings,” which revealed the values of all three outputs. When they were ready to start the next trial, they clicked a button “next trial,” which hid the output values from view. On the next trial, participants made their changes to the inputs, and these affected the output values from the previous trial: thus, the effects on the outputs were cumulative from one trial to the next. After the first block of 6 trials, participants were presented with a structure test that was designed to index knowledge of the causal structure of the control system. A diagram of the system was shown on screen, and participants were asked simply to indicate which input was connected to which output. The direction of the input-output connection was implicit in the way that participants interacted with the CDCT, and was also indicated in the instructions to the task, and so it was not necessary to examine the directionality of the input-output relations, only which connections existed. After this, they began the next set of 6 trials, followed by a second structure test: at the beginning of the first trial of the second block, the input values were set to 0 and the outputs were also reset to their respective starting values.

Control Test 1. After the learning phase and Structure Tests 1 and 2, participants were tested on their ability to control the system. In this phase, all participants were required to change the input values in order to achieve, and then maintain, set output values. In the first and second problems, the criterion values they had to achieve were the same, and only the labels of the outputs were different: Output 1 (Water tank = Oxygenation, Ghost hunt = Radio Waves) = 50; Output 2 (Water tank = Chlorine concentration, Ghost hunt = Electro Magnetic Waves) = 700; Output 3 (Water tank = Temperature, Ghost hunt = Air Pressure) = 900, for the course of 6 trials. On completion of this phase, participants were presented with a structure test (i.e., Structure Test 3). *Control Test 2.* In this phase, all participants were required to change the input values, in order to achieve and then maintain a different set of output values to Control Test 1. In first and second problems, the criterion values they had to achieve were the same, and only the labels of the outputs were different: Output 1 (Water tank = Oxygenation, Ghost hunt = Radio Waves) = 250; Output 2 (Water tank = Chlorine concentration, Ghost hunt = Electro Magnetic Waves) = 350; Output 3 (Water tank = Temperature, Ghost hunt = Air Pressure) = 1100, for the course of 6 trials. On completion of this phase, participants were presented with a structure test (i.e., Structure Test 4).

Second Problem Observation-based learning phase: In the second problem, for half of the participants the learning phase was observation-based. With the exception that participants themselves could not manipulate input values during the learning phase, but were instead replayed their learning phase from the first problem or yoked to the learning phase of a participant in the Observe-self condition, the observation-based and action-based versions of the learning phase were identical. Observers began by clicking a button to reveal the input values generated by the model for the first trial. (No time limit was imposed on the time spent studying the input values or output values on each trial.) For example, if the model changed the input Salt by 50 units on Trial 1, this would in turn change the output value of Chlorine Concentration to 556 (i.e., Chlorine Concentration starting value = 500 units, + Salt value change = 50 units, + constant added noise on input-output connection = 6 units). The observer would also see the input Salt change by 50 units. Then, when they were ready, participants clicked a second button to reveal the corresponding output values for that trial: in this case, the starting values of the outputs Temperature and Oxygen remained the same, but the corresponding output Chlorine Concentration changed to 556 units. As soon as they were ready, participants clicked a button to indicate that they were proceeding to the next trial: the button hid the output values from view. Participants then repeated the process of seeing the

input values, and then the corresponding changes to the output values. As in the action-based version, after Trial 6, and after Trial 12, participants were presented with a Structure test.

Second Problem Action-based learning phase: For the remaining participants the learning phase of the second problem was action-based. In the Act-on-self condition, participants' learning phase from the first problem was logged: This included a trial history of the inputs that were changed, and the values that they were changed by. At the start of the learning phase participants were instructed to change the system by following the trial history sheet. This indicated which inputs to change and the corresponding values they should be changed by. The Act-on-self condition were presented with a trial history which was of their own learning phase from problem one, and the Act-on-other condition were presented with the trial history of a participant from the Act-on-self condition.

Post-test question. After completing the second problem, participants were informed that the experiment they had taken part in consisted of one key manipulation in the learning phase of the second problem which was described to them (i.e., exposure to self-generated learning, or exposure to other-generated learning). They were then asked which of the two manipulations they had experienced. This question served as an index of self-insight, and examined whether participants could accurately detect whether the learning phase, which they had experienced in the first problem, was the same as or different to their own learning phase in the second problem.

Scoring

Structure scores. The scoring scheme used to score performance on structure Tests 1-4 involved computing the proportion of input-output links correctly identified for each test. A correction for guessing was incorporated, and was based on the same procedure used by Vollmeyer et al. (1996), which was simply correct responses (i.e., the number of correct links included, and incorrect links avoided) – incorrect responses (i.e., the number of incorrect links included, and correct links avoided) / N (the total number of links that can be made). The maximum value for each structure score was 1.

Control Tests 1 and 2. Control performance was measured as error scores in Control Tests 1 and 2. Error scores were based on calculating the difference between each target's output value (i.e., the criterion according to the control test) and the actual output value produced by the participant for each trial of the transfer test. A log transformation (base 10) was applied to the error scores of each individual participant for each trial, to minimize the skewedness of the distribution of scores. All analyses of error scores for Control Test 1 were based on participants' mean error, averaged over all 6 trials across all three output variables. The error scores for Control Test 2 were calculated in the same way. Success in control performance on transfer tasks is indexed by the difference between the achieved and target output values, and therefore the lower error scores indicate better performance.

Results

This section first analyzes initial differences between conditions, then control performance, then structural knowledge in each CDC-task. Correlation analyses examine the potential association between control performance and structural knowledge. Finally, responses to the post-test question are analyzed.

The control performance of the four conditions in the first problem was initially compared, to rule out any possibility of initial group differences influencing any later main effects. A 2x4 ANOVA with control test (Control Test 1, Control Test 2) as a within subject variable, and condition (Observe-self, Observe-other, Act-on-self, Act-on-other) as a between subject variable, was conducted on mean error scores. The analysis did not reveal significant findings suggesting that there were no initial differences between the different conditions.

Control Test Scores

Figure 3 shows that overall error scores in Control Test 1 appear to be lower than error scores in Control Test 2. Figure 3 also indicates that for Control test 1 and Control test 2 the error scores of the Observe-self and Act-on-self appear to have decreased in Problem 2 compared to Problem 1. In contrast, the error scores of the Observe-other and Act-on-other conditions appear to be stable across Problem 1 and 2. To examine the possible interaction between the diversity of learning experiences and control performance across Problem 1 and 2 the following analyses were conducted.

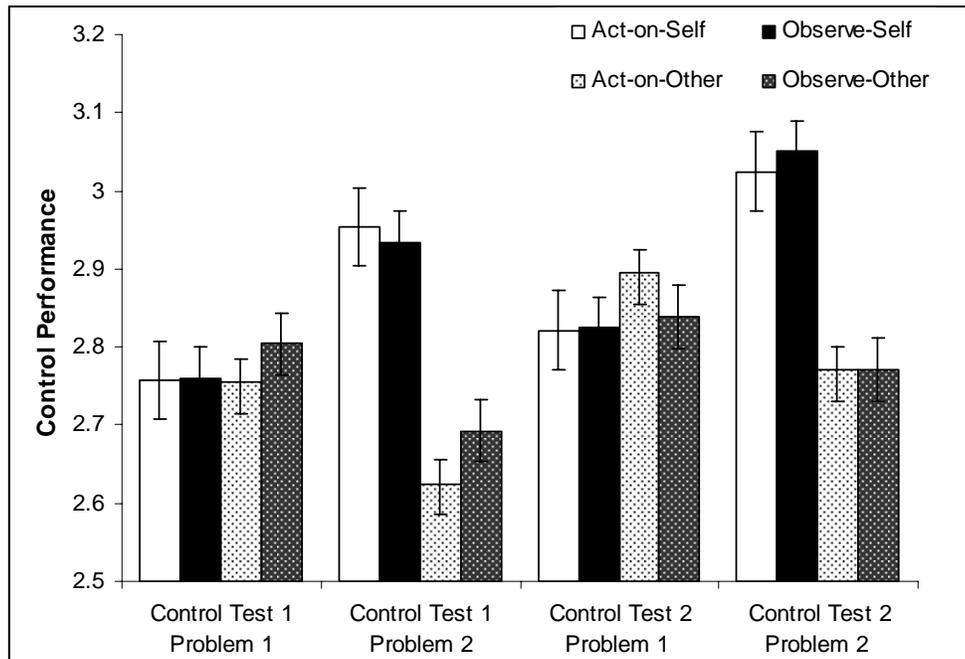


Figure 3. Mean Error scores (\pm SE) at Control Test 1 and Control Test 1 for each condition. Successful performance is indicated by *lower* mean error scores

The following analyses were conducted on the mean error scores calculated for each participant. A 2x2x2x2 ANOVA was carried out with Control Test (Control Test 1, Control Test 2) and Problem (1st Problem, 2nd Problem) as the within subject factors, and learning phase (Self, Other) and learning format (action, observation) as between subject factors. The analysis revealed a significant main effect of Control Test, $F(1, 44) = 11.561$, $MSE = 0.39$, $p < 0.002$. There was also a significant main effect of learning phase on error scores $F(1, 44) = 7.06$, $MSE = 0.72$, $p < 0.05$, and a significant Learning phase x Problem interaction $F(1, 44) =$

21.08, $MSE = 1.14$, $p < 0.0005$. No other analyses were significant. To locate the source of the interaction, tests of simple main effects were carried out. Because learning format was not found to have a significant effect on error scores, error scores were collapsed across Observe-self and Act-on-self conditions, and across Observe-other and Act-on-other conditions. The significant increase in error scores across problems for the experience *self* conditions was confirmed by planned comparisons of error scores in Control Test 1 $t(23) = -23.23$, $p < 0.0005$, and Control Test 2 $t(23) = -17.77$, $p < 0.0005$. The decrease in error scores across problems for the *other* conditions was not statistically confirmed by planned comparisons of error scores in Control Test 1 $t(23) = 1.91$, $p = 0.067$, and Control Test 2 $t(23) = 1.98$, $p < 0.061$, although both tests approached significance. Thus, the evidence suggests that the difference in the patterns of transfer of control performance across both problems was the result of the content of the second learning phase, and not its presentation format. There was negative transfer of procedural knowledge in the Observe-self and Act-on-self conditions, and a positive transfer in the Observe-other and Act-on-other conditions.

Structure Test Scores

For each participant, the scores from Structure Tests 1-4 were averaged across the first problem, and again for the second problem. The averages of these scores from each of the four conditions are presented in Figure 4, which indicates that, for the Observe-self and Act-on-self conditions, structure scores increased in the second problem compared to the first. For the Observe-other and Act-on-other conditions, structure scores decreased in the second problem compared to the first.

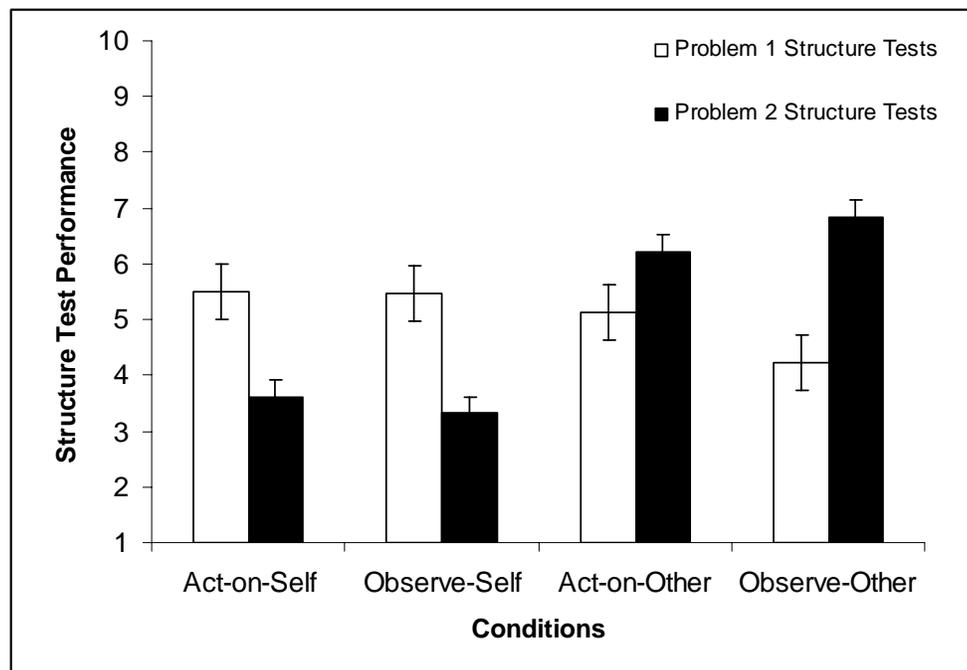


Figure 4. Structure test scores ($\pm SE$) averaged across Structure Test 1, 2, 3, and 4 for each condition in Experiment. Successful performance is indicated by *higher* structure scores.

The reverse trend is indicated for the Observe-other and Act-on-other conditions. This was analyzed using a 2x2x2 ANOVA over averaged structure test scores, using problem (1st Problem, 2nd Problem) as a within subject variable, and condition (self, other) and format (observation, action) as the between subject variables. There was a significant Condition x Problem interaction, $F(1, 44) = 13.70$, $MSE = 56.16$, $p < 0.001$. No other analyses were significant. Because learning format was not found to have a significant effect on error scores, error scores were collapsed across Observe-self and Act-on-self conditions, and across Observe-other and Act-on-other conditions. The significant decrease in structure scores across problems for the *self* conditions was confirmed by planned comparisons of structure scores between Problem 1 and Problem 2 $t(23) = 3.67$, $p < 0.001$. The increase in structure scores for the *other* conditions across problems indicated in Figure 4 was also confirmed $t(23) = -3.33$, $p = 0.005$. Thus, the evidence suggests negative transfer of declarative knowledge in the Observe-self and Act-on-self conditions, and a positive transfer in the Observe-other and Act-on-other conditions.

Correlation between Control Performance and Structural Knowledge

A correlation analysis was carried out on control error scores (averaged across Control Tests 1-2), and structure test scores (averaged across Structure Tests 1-4) from the first and second problems. A significant negative relationship was found between structure test scores and control test error scores in the first problem, $r(48) = -0.47$, $p < 0.001$, and in the second problem, $r(48) = -0.48$, $p < 0.001$. These findings strongly indicate that, for both types of learning phase (observation-based, procedural-based), there is a relationship between control performance and structural knowledge.

Post-Test Question

Ninety-two percent of participants in the Observe-self condition and 67% in the Act-on-self condition reported accurately which of the two conditions they were in. Seventy-five percent of participants in the Observe-other condition and 83% in the Act-on-other condition answered correctly. Pearson's chi-squared analysis revealed no significant difference in correct and incorrect response by condition

DISCUSSION

The aim of the study was to offer insights into the following questions: What are the differences between action-based and observation-based learning? Do people gain more from performing, or from observing their own self-generated behaviors?

In response to the first question, the evidence from the study suggests that successful transfer of control performance was found to be independent of the format of the learning phases of each problem. Structural knowledge and control performance were also found to be associated in both problems. This further suggests that the uptake of knowledge is not

impeded when learning is observation-based compared to action-based, and that in both modes of learning, associations, rather than dissociations are found. In addition, participants' accurate self-insight enabled them to correctly identify the source of the second learning phase. In response to the second question, there was positive transfer of structural knowledge and control performance in Observe-other and Act-on-other conditions, and negative transfer in Observe-self and Act-on-self conditions. Taken together, the evidence indicates that procedural knowledge and declarative knowledge in CDC-tasks are associated.

Although inconsistent with dissociationists' claims, the findings indicate that monitoring mediates the transfer of control behaviors. For both theories, monitoring serves a regulatory function, because it tracks and selects out relevant information bearing on a desired outcome. This is through evaluation of either skilled behaviors (Bandura, 1986), or of the hypothesis testing strategies developed during learning (Burns & Vollmeyer, 2002). The study also revealed that monitoring mediated the transferability of control behaviors, and this was based on the content of the second learning phase. The usefulness of this was retrospectively evaluated from participants' control performance in the control test phase of the first problem. Both *self* conditions appear to have judged negatively their own learning phase, and so, assuming it to be less effective, failed to transfer relevant knowledge that would have enabled them to successfully control the system in the second problem. Both *other* conditions, in contrast, appeared to have judged the learning phase of the second problem positively. These evaluations may have been the result of having identified the learning phase as not their own, and thus assuming that it provided a new opportunity to learn. Consequently, they transferred relevant knowledge gained from the first problem to the second, thus facilitating positive transfer of control skills.

Action-Based Vs. Observation-Based Learning

The prevailing view, that of Dissociationists, is that control skills in CDC-tasks are procedural, and their transferability is limited because procedural knowledge is perceptually bound and inflexible (e.g., Berry, 1991; Berry & Broadbent, 1988; Dienes & Berry, 1997; Lee, 1995; Sun et al., 2001). This claim is supported by findings that control skills are transferred only if the transfer task itself is perceptually and structurally similar to the original (Berry & Broadbent, 1988), and that if learning in both is procedural-based (Berry, 1991; Berry & Broadbent, 1988). Moreover, the transfer effect is eliminated when information that hints at the similarity of the transfer task to the original is presented (Berry & Broadbent, 1988). The strong implication from these and other studies of dissociations (Berry & Broadbent, 1984; Dienes & Berry, 1997; Dienes & Fahey, 1995) is that, when invoked during the acquisition, application, and transfer of control skills, declarative knowledge leads to decrements in measures of procedural knowledge.

To explain the disparity between the dissociationist position and evidence from the present study, the following discussion considers the issues in terms of Bandura's Social Cognitive theory. Common to studies that reveal dissociations in a CDC-task is that hypothesis testing behaviors are prevented during learning (e.g., Berry, 1991; Berry & Broadbent, 1984, 1987, 1988; Broadbent et al., 1986; Dienes & Fahey, 1995, 1998; Marescaux et al., 1989; Stanley et al., 1989). Another common pattern is that dissociations are found when measures of declarative knowledge are taken after, rather than during,

learning (e.g., Berry, 1991; Berry & Broadbent, 1984, 1987, 1988; Dienes & Fahey, 1995, 1998; Marescaux et al., 1989). Taking multiple measurements of declarative knowledge during learning prompts participants to keep track of their knowledge whilst updating it. Moreover, the knowledge tapped at this stage is more accurate because it coincides with the time at which it was acquired (Burns & Vollmeyer, 2002; Sanderson, 1989; Sanderson & Vicente, 1986; Voss, Wiley & Carretero, 1995).

Common to studies of CDC-tasks that encourage hypothesis testing is evidence of associations between declarative knowledge and procedural knowledge (e.g., Burns & Vollmeyer, 2002; Gonzalez et al., 2003; Gonzales & Quesada, 2003; Sweller, 1988). Hypothesis testing focuses the learners' attention on both relevant properties of the CDC-task: i.e., the rule and instance space. This is because it involves exploration of the system, which is refined as the learner develops systematic ways of generating and testing hypotheses. As long as learners can explore the system in this way, they will develop insights into the structure of CDC-task (declarative). Correspondingly, they will also have an understanding of the procedures needed to control the task (procedural), and conscious access to these different forms of knowledge (self-insight). Importantly, the Social Cognitive theory asserts that monitoring enables learners to track their hypothesis testing strategies, and continually update their knowledge of the input-output relations of the CDC-task. This provides a means of relating their understanding of the structure of the system to their experiences of how it operates. Monitoring serves a regulatory function, because it tracks and selects out relevant information bearing on a desired outcome. In the present study, the conditions for learning were ideal for hypothesis testing. By monitoring their knowledge of the system whilst hypothesis testing, learners in the present study were able to transfer their knowledge across perceptually similar and different CDC-tasks, demonstrate associations between declarative and procedural knowledge, acquire skilled knowledge under both observation and procedural-based learning conditions, and demonstrate self-insight.

NEGATIVE TRANSFER EFFECTS

Although rare, demonstrations of negative transfer in studies of problem solving and rule learning do exist (e.g., Chen & Daehler, 1989; Lee & Vakoch, 1996; Luchins, 1942; Novick, 1988; Woltz, Bell, Kyllonen, & Gardner, 1996; Woltz, Gardner, & Bell, 2000). In many of these studies, negative transfer of skilled learning is taken as an indication of expertise. The studies show that well rehearsed memories, for sequences of operations, make it difficult for people to prevent transfer to contexts similar to conditions in which they were acquired. For example, in studies of rule learning (Luchins, 1942; Woltz, Bell, Kyllonen, & Gardner 1996; Woltz, Gardner, & Bell, 2000), participants trained in the discovery and application of rules to specific tasks tend to over-generalization to novel instances in which they are not applicable. Additionally, as expertise in the use of rules increases, or as exposure to the learning environment in which they were acquired increases, so too does the inability to detect and self-correct the errors made, and the ability to discover new solutions (Lee & Vakoch, 1996; Woltz, Bell, Kyllonen, & Gardner, 1996; Woltz, Gardner, & Bell, 2000).

Whether transfer errors reflect retrieval of prior problem solutions that guide solutions of similar problems, or the application of skilled memory representations, both are shown to be

examples in which prior experience inhibits the search for alternative solutions to those previously acquired. The findings from the present study are the antithesis of this, because negative transfer reflects a failure to capitalize on prior learning experience, and this then prompts the search for alternative solutions. This disparity can be explained by the fact that, in previous studies, participants were sufficiently skilled in problem solving or rule learning, whereas in the present study there was little opportunity for participants to develop highly skilled control behavior. For this reason, in previous studies, transfer is an index of strong memory of prior learnt instances, whereas in the present study transfer is an index of the effects of re-exposure to actual or believed self-generated learning instances.

SELF OBSERVATION

Developmental studies (Fireman & Kose, 1991, 2002; Fireman, Kose, & Solomon, 2003; Fosnot et al., 1988) of problem solving have reported improvements in the performance of children's ability to solve the tower of Hanoi task through video-tapped presentations of their earlier solution strategies. One reason why the present study was unable to find similar benefits is that assisted improvements in performance via self-observation may be dependent on actual visual presentation of earlier problem solving behavior. In addition, the tower of Hanoi task is an example of a task that is solved by means-end analysis, and does not involve hypothesis testing behavior. Since it is a simpler task to perform than the CDC-task used in the present study, it may be that self-observation is effective only in simpler tasks. Taken together, these differences may have interfered with the kinds of beneficial effects of self-observation reported in previous developmental studies of problem solving.

However, the negative transfer effect reported in the present study is compatible with findings from clinical studies using the self-observation technique. Early examples (Bailey & Sowder, 1970; Hung & Rosenthal, 1978) show that patients suffering from depression negatively distorted self-related information, and applied the same interpretive bias to presentations of their own behavior. Conway, Singer, and Tagini (2004) suggest that autobiographical memory is mediated by later evaluation of self-generated behaviors, and clinical studies provide examples in which the mediation can become distorted by biased and inaccurate self-assessments (e.g., Giesler, Josephs, & Swann, 1996). Similarly, Dowrick (1983) claims that the self-observation technique can make people aware of their past failings, and inhibit their ability to accurately adjust their behaviors accordingly. Consistent with this, in the present study it has been argued that the evidence shows biased self-assessments of the effectiveness of previous learning experiences, and this leads to selective hypothesis testing behavior.

CONCLUSION

Consistent with many fields of research, Educational and Instructional psychology asserts that action plays a crucial role for learners in constructing their own knowledge (Anderson, 1987; Resnick, 1983, 1987; Schauble, 1990; von Glasersfeld, 1989). This follows from the *learning by doing* tradition (e.g., Anzai & Simon, 1979). Studies of CDC-tasks also show that

comparing one's own learning to that of another individual during the acquisition phase of a complex problem has facilitative affects on performance (Gonzales, 2005; Sengupta & Abdel-Hamid, 1993). However, this involves learning from an expert. The present study suggests that there are facilitative affects if one is comparing one's own behavior to that of a peer, and that these affects are transferable. In addition, the evidence shows that action does not have a special status over observation in the acquisition of skilled control behaviors (Osman, in pressA; Osman & Heyes, 2005). Even within the *learning by doing* tradition expertise develops as a result of self-monitoring (e.g., Covington, 2000; Pintrich & De Groot, 1990), which includes reflective activities such as describing, explaining, and evaluative thinking (e.g., Covington, 2000; Zimmerman, 1990), and these need not occur through action.

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