

Seeing is as good as doing

Seeing is as Good as Doing

Magda Osman

University College London

Department of Psychology

University College London

Gower Street

London WC1E 6BT

England

Phone: +4420 7679 7572

Fax: +4420 7436 4276

Email: m.osman@ucl.ac.uk

Abstract

Given the privileged status claimed for active learning in a variety of domains (visuo-motor learning, causal induction, problem solving, education, skill learning), the present study examines whether action-based learning is a necessary, or a sufficient, means of acquiring the relevant skills needed to perform a task typically described as requiring active learning. To achieve this, the present study compared the effects of action-based and observation-based learning on controlling a complex dynamic task environment. Both action- and observation-based learners either learnt by describing the changes in the environment in the form of a conditional statement, or not. The findings show that observational learners are sensitive to the instructional manipulations pursued during learning, in ways that are comparable to the active learning conditions. For both, advantages in performance, accuracy in knowledge of the task, and self-insight were found when learning was based on inducing rules from the task environment.

Seeing is as Good as Doing

Who has better knowledge and skill, the back seat driver, who is learning to drive, or the actual driver, who is also learning to drive, the person watching their friend play a new game on the Sony play station, or the friend who is actually playing the game? Our daily lives frequently involve learning to control complex dynamic environments like those referred to in the question, but how we come to form the relevant skills needed to master such environments remains much debated. Laboratory versions of these tasks, referred to as Complex dynamic control tasks (CDC-tasks) (e.g., See Figure 1: water purification system) typically include several inputs (salt, carbon, lime) that are connected via a complex structure or rule to several outputs (chlorine concentration, temperature, oxygenation). In such environments, people are required to make a series of decisions, often in real time, that each depend on the other, and in an environment that changes autonomously, as a consequence of the person's actions (Brehmer, 1992).

The prevailing view is that skill acquisition in these tasks develops through procedural learning: that is, incidentally and without the mediation of reportable knowledge (Berry, 1991; Berry & Broadbent, 1984, 1987, 1988; Dienes & Berry, 1997; Lee, 1995; Stanley, Mathews, Buss, & Kotler-Cope, 1989). This form of learning produces instance-based knowledge: i.e., Specific actions undertaken whilst interacting with the system become associated with the specific effects that they generate. Through repeated exposure to the same instances, this knowledge is gradually formulated into reportable rules about how the task operates (e.g., Broadbent, Fitzgerald, & Broadbent, 1986; Dienes & Fahey, 1995, 1997; Gibson, Fichman, & Plaut, 1997). In support of this, there is evidence that people can successfully control a CDC-task independently of any reportable knowledge of the rule or causal structure that determines its operation, and without self-insight as to how they are able to perform it (e.g., Berry & Broadbent, 1984, 1987, 1988; Stanley et al., 1989). Another compelling demonstration of dissociations between rule- and instance-based knowledge is

found in the contrasting effects of observation-based and procedural-based learning (Berry, 1991; Lee, 1995). Observation-based learning involves problem solvers watching the actions taken by another problem solver attempting to learn a CDC-task. This encourages the observer to focus on understanding how the system operates (i.e., rule-based knowledge). In contrast, procedural-based learning encourages knowledge of how to operate the system (i.e., instance-based knowledge). When compared, observers show better rule-based knowledge than procedural learners, but poorer control performance.

Others, however, have suggested that successful skill acquisition depends on a combination of rule-based and instance-based knowledge, which develops through hypothesis testing (e.g., Burns & Vollmeyer, 2002; Osman, in press A, in press B; Sweller, 1988; Vollmeyer, Burns, & Holyoak, 1996). By exploring the task and formulating rules about how it operates, the learner is able to update their rule-based knowledge through the instances that they have generated to test them. Through practice, a wider range of instances are experienced, and these enable the learner to form generalizable knowledge that they can transfer to other similar tasks. Evidence for this comes from studies that compare different types of goal instructions during learning. For instance, instructions like “explore the system,” an example of a non-specific goal (NSG), are contrasted with “learn about the system while trying to reach and maintain specific outcomes,” an example of a specific goal (SG). The former instruction is assumed to encourage hypothesis testing, because rules can be generated and tested, whereas, in the latter instruction, learning is constrained by generating instances that fulfill specific criteria. When tested on their ability to control the system to previously trained goals, SG-learners’ performance is equal to that of NSG-learners’ that have not learnt to perform the task to any criteria. Furthermore, for untrained goals, NSG-learners outperform SG-learners. Taken together with evidence that NSG-learners also have superior structural knowledge about the system, this suggests that rule-

and instance-based knowledge combined is more effective than instance-based knowledge alone (e.g., Burns & Vollmeyer, 2002; Osman, in press A; Vollmeyer et al., 1996).

Given these conflicting views, this article asks: Is procedural learning necessary to ensure skill acquisition in a complex dynamic environment? To address this, the present study included six conditions [Active (generate)-Instance, Active (generate)-Instance + Rule, Active (replicate)-Instance, Active (replicate)-Instance + Rule, Observe-Instance, Observe-Instance + Rule], across which the involvement of procedural learning was gradually attenuated. If procedural learning is necessary for skill development in CDC-tasks, then active conditions will consistently show superior control performance compared with observers, but poorer rule-based knowledge. If instead, instance- and rule-based knowledge combined are necessary for control skills to develop, then, regardless of action- or observation-based learning, both kinds of learners will show superior knowledge relative to those acquiring only instance-based knowledge.

Method

Ninety-six students from University College London volunteered to take part in the experiment, and were paid £4 for their participation. Participants were randomly allocated to one of six conditions, with sixteen in each. Participants were tested individually and were presented with a fully automated version of Burns and Vollmeyer's (2002) water purification system, which was run on Dell Optiplex computers.

Materials & Procedure

All participants were presented with a CDC-task (See Figure 1), in which they were told to imagine that they worked in a water purification plant, and that their job was to inspect the water quality of the system. The system was operated by varying the different

levels of salt, carbon, and lime (inputs), which then changed the three water quality indicators: oxygenation, temperature, and chlorine concentration (outputs). The CDC-task was divided into two phases, the learning phase (40 trials divided into 4 blocks of 10 trials), and the test phase with two control tests (each test 10 trials).

In the learning phase, all participants received the same goal-specific instruction (i.e., the following output values in the system must be reached and maintained: Oxygenation = 50, Chlorine Concentration = 700, Temperature = 900), which was identical to that of Control Test 1. Each condition also received additional instructions. The Active (generate)-Instance condition was required to generate input values to achieve and maintain the output values specified. In addition to this, the Active (generate)-Instance + Rule condition was instructed that, at the end of each trial, they were to verbally describe the input and output changes in the form of an ‘if____, then____’ statement (e.g., if input salt is changed to 10 units, then the output value of carbon is 516). In the Active (replicate)-Instance condition, participants were required to change the inputs according to a trial history: i.e., A pre-specified set of trials were presented to each participant, in which the input/inputs that had to be changed and the values they had to be changed by were listed for every trial.¹ In addition, the Active (replicate)-Instance + Rule condition described the input and output changes in the form of an ‘if____, then____’ statement. In the Observe-Instance condition, participants’ job was to carefully track the changes to the inputs and outputs on each trial, which changed according to the same trial history presented in the active-replicate conditions, and to assess how successfully the output values met the criteria output values. In addition, the Observe-Instance + Rule condition described the input and output changes in the form of an ‘if____, then____’ statement.

The test phase was the same for all conditions. The criterion values participants had to reach and maintain in Control Test 1 were Oxygenation = 50, Chlorine Concentration = 700, Temperature = 900, and in Control Test 2 the values were Oxygenation = 250; Chlorine

Concentration = 350; Temperature = 1100. The output criteria in Control Test 2 were unfamiliar to all six conditions, since this control test involved a goal that they had not been trained on, and provided a test of the generalizability of their control skills.

After every 10 trials in the learning phase, and after each control test in the test phase, all participants were presented with a structure test, consisting of a diagram of the system shown on screen, and were asked to indicate which input was connected to which output. On completion of the experiment, participants were presented with a record of three different trial histories from the learning phase: one that they had actually experienced during the learning phase, and two randomly selected alternatives from the Active (generate) conditions. They were asked to decide which of the three they had experienced, and what formed the basis of their judgment: i.e., did they recognize specific trials? Did they rely on a sense of familiarity? Did they guess?

Scoring

Structure test performance was based on computing the proportion of input-output links correctly identified for each test. A correction for guessing was incorporated: 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 could be made). The maximum value for each structure score was 10. Successful performance is indicated by an increase in structure scores.

Control Tests 1 and 2

Control performance was measured as error scores, and was calculated in the same way for each test. Error scores were based on calculating the difference between each target's output value (i.e., the criterion according to the 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 participant for each trial, to minimize the skewedness of the distribution of scores. All analyses of error scores are based on participants' mean error,

averaged over all 10 trials, across all three output variables. Successful control performance is indexed by the difference between the achieved and target output values, thus lower error scores indicate better performance.

Results

Test of Control Skills

The mean error score of all six conditions presented in Figure 2 suggests that, in all three Instance + Rule-based conditions, control error scores decreased (indicating good performance) in both tests, compared with the three Instance only based conditions. To analyze this, a 2x2x3 ANOVA was carried out using test (Control Test 1, Control Test 2) as within subject variables, and knowledge (Instance, Instance + Rule) and learning format (Active (generate), Active (replicate), Observe) as the between subject variables. The analysis showed a significant main effect of test: $F(1, 90) = 4.87$, MSE = 0.13, $p < 0.05$, $\eta^2 = 0.05$. There was also a significant main effect of knowledge: $F(1, 90) = 59.22$, MSE = 1.56, $p < 0.005$, $\eta^2 = 0.39$. No other main effects or interactions were significant. Because there was no interaction between knowledge and test, the control error scores for each condition were collapsed across tests. The significant increase in control error scores (impaired performance) in the Instance conditions compared with the Instance + Rule conditions for the Active (generate), Active (replicate), and Observe conditions, was confirmed by a planned comparison for error scores: $t(15) = 2.75$, $p < 0.05$, $d = 1.42$, $t(15) = 5.05$, $p < 0.05$, $d = 2.61$, and $t(15) = 8.78$, $p < 0.005$, $d = 4.53$, respectively.

Test of rule-based knowledge: The mean error scores were collapsed across phase for each of the six conditions and are presented in Figure 2. The figure suggests that, in the three Instance + Rule-based conditions, structure test scores increased (indicating good performance) compared with the three Instance only based conditions. To analyze this, a 2x2x3 ANOVA was carried out using phase (Learning, Test) as within subject variables, and knowledge (Instance, Instance + Rule) and learning format (Active (generate), Active

(replicate), Observe) as the between subject variables. The analysis showed a significant main effect of phase: $F(1, 90) = 4.561$, MSE = 0.18, $p < 0.05$, $\eta^2 = 0.48$. There was also a significant main effect of knowledge: $F(1, 90) = 29.58$, MSE = 4.18, $p < 0.0005$, $\eta^2 = 0.24$. No other main effects or interactions were significant. Because there was no interaction between knowledge and test, the structure test scores for each condition were collapsed across phase. Planned comparisons confirmed the significant increase in structure test scores (improved performance) in the Instance + Rule conditions, compared with the Instance conditions for the Active (generate), Active (replicate), and Observe conditions: $t(15) = 2.65$, $p < 0.05$, $d = 1.37$, $t(15) = 3.19$, $p < 0.01$, $d = 1.65$, and $t(15) = 4.37$, $p < 0.001$, $d = 2.26$, respectively.

Correlation between control performance and structural knowledge. The following correlation analyses were carried out on control error scores (averaged across Control Tests 1-2), and structure test scores (averaged across Structure Tests 5-6 in the test phase). Scores were collapsed across the four active conditions, and then again for the remaining observation conditions. Correlation analyses revealed a significant negative relationship between structure test scores and control test scores: $r(64) = -0.31$, $p < 0.05$, and, $r(32) = -0.47$, $p < 0.01$, respectively.

Test of self-insight. Table 1 indicates that more correct identifications of the learning trials experienced were made in Instance + Rule conditions than in Instance conditions. A Chi-squared analysis, collapsing responses across action-based conditions, and comparing accuracy of responding in Instance and Instance + rule conditions, confirmed the trend indicated in Table 1: $\chi^2 (3) = 8.78$, $p < 0.05$. Furthermore, Table 1 suggests that more participants relied on specific instances to identify their learning phase in Instance + Rule conditions than in Instance conditions, whereas the Instance-based conditions relied more on guessing. This was also confirmed using a Chi-squared analysis: $\chi^2 (3) = 9.47$, $p < 0.05$.

Discussion

The target question asked in this article asked: Is procedural learning necessary to ensure skill acquisition in a complex dynamic environment? The evidence from this study shows that procedural learning is sufficient for the successful uptake of relevant knowledge, but not necessary, given that observational learning produced patterns of performance equivalent to those of the active learning conditions.

Implicit learning theorists (e.g., Berry, 1991; Berry & Broadbent, 1988; Sun et al., 2001) have maintained that the knowledge required to control CDC-Tasks is embedded within the interactions problem solvers have with the system. Furthermore, knowledge is conscious only to the extent that the response that is appropriate to a given situation can be stated, but the knowledge used to support that response is unavailable to consciousness (Buchner et al., 1995; Dienes & Berry, 1997; Dienes & Fahey, 1998). Similar claims are made in other tasks considered to be procedural learning tasks, or called, alternatively, implicit learning tasks (e.g., artificial grammar learning, Reber, 1989; sequence learning, Nissen & Bullemer, 1987; Willingham et al., 1989). The study is the first of its kind to provide clear evidence that explicitly thinking about the relationship between events and outcomes as rules leads to superior knowledge about how a CDC-task works, how to operate it, how to transfer control skills to an untrained goal, and self-insight into what one does to learn about how to operate it.

The findings converge with previous evidence suggesting that instructions designed to encourage hypothesis testing and other similar meta-cognitive processes (e.g., monitoring-tracking one's online goal-directed behaviors) do not interfere with the uptake of skilled knowledge, as some have claimed, and may even enhance skilled performance (e.g., Berardi-Coletta et al., 1995; Osman, in press A, in press B). Thus, the present study shows that hypothesis testing, rather than the active engagement with a procedural task, is necessary for

Seeing is as good as doing

the successful uptake of knowledge, and its application to mastering a complex control system.

Footnote

1. The trial histories for the Active (replicate-instance), Active (replicate- Instance + Rule), Observe (Instance), Observe (Instance + Rule) conditions, were based on the learning phase generated by one of the participants from the Active (generate – Instance + Rule) condition. Participant was selected on the basis of their control performance in the test phase, which was closest to the mean across both Active (generate – instance) and Active (generate – Instance + Rule) conditions. This was favored instead of a full yoking procedure, because the source of any differences in these conditions was carefully controlled, and was likely to result from the instructional manipulations during learning, rather than from the trial history itself.

References

- Berardi-Coletta, B., Dominowski, R., Buyer, S., & Rellinger, E. (1995). Metacognition and problem solving: A Process orientated approach. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 21*, 205-223.
- Berry, D. (1991). The role of action in implicit learning. *Quarterly Journal of Experimental Psychology, 43*, 881-906.
- Berry, D., & Broadbent, D. E. (1984). On the relationship between task performance and associated verbalizable knowledge. *Quarterly Journal of Experimental Psychology, 36*, 209-231.
- Berry, D., & Broadbent, D. E. (1987). The combination of implicit and explicit knowledge in task control. *Psychological Research, 49*, 7-15.
- Berry, D. C., & Broadbent, D. E. (1988). Interactive tasks and the implicit-explicit distinction. *British Journal of Psychology, 79*, 251-272.
- Brehmer, B. (1992). Dynamic decision making: Human control of complex systems. *Acta Psychologica, 81*, 211-241.
- Broadbent, D., Fitzgerald, P., & Broadbent, M. H. P. (1986). Implicit and explicit knowledge in the control of complex systems. *British Journal of Psychology, 77*, 33-50.
- Buchner, A., Funke, J., & Berry, D. (1995). Negative correlations between control performance and verbalizable knowledge: Indicators for implicit learning in process CDCTs. *Quarterly Journal of Experimental Psychology, 48*, 166-187.
- Burns, B. D., & Vollmeyer, R. (2002). Goal specificity effects on hypothesis testing in problem solving. *Quarterly Journal of Experimental Psychology, 55*, 241-261.
- Dienes, Z., & Berry, D. (1997). Implicit learning: Below the subjective threshold. *Psychonomic Bulletin & Review, 4*, 3-23.
- Dienes, Z., & Fahey, R. (1995). Role of specific instances in controlling a dynamic system. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 21*, 848-862.

- Dienes, Z., & Fahey, R. (1998). The role of implicit memory in controlling a dynamic system. *Quarterly Journal of Experimental Psychology, 51*, 593-614.
- Lee, Y. (1995). Effects of learning contexts on implicit and explicit learning. *Memory and Cognition, 23*, 723-734.
- Osman, M. (in press A). Observation can be as effective as action in problem solving. *Cognitive Science*.
- Osman, M. (in press B). Positive transfer and Negative transfer/Anti-Learning of Problem Solving Skills. *Journal of Experimental Psychology: General*.
- Stanley, W. B., Mathews, R. C., Buss, R. R., & Kotler-Cope, S. (1989). Insight without awareness: On the interaction of verbalization, instruction, and practice in a simulated process CDCT. *Quarterly Journal of Experimental Psychology, 41*, 553-577.
- Sun, R., Merrill, E., & Peterson, T. (2001). From implicit skills to explicit knowledge: A bottom-up model of skill learning. *Cognitive Science, 25*, 203-244.
- Sweller, J. (1988). Cognitive load during problem solving: Effects of learning. *Cognitive Science, 12*, 257-285.
- Vollmeyer, R., Burns, B. D., & Holyoak, K. J. (1996). The impact of goal specificity and systematicity of strategies on the acquisition of problem structure. *Cognitive Science, 20*, 75-100.

Acknowledgements

Preparation for this article was supported by Economic and Social Research Council ESRC grant RES-000-27-0119. The support of the Economic and Social Research Council (ESRC) is gratefully acknowledged. The work was also part of the programme of the ESRC Research Centre For Economic Learning and Human Evolution.

Figure Captions.

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

Figure 2. Mean Control Test error scores (\pm SE) at Control Test 1 and Control Test 2 for each condition. Successful performance is indicated by *lower* mean error scores.

Figure 3. Mean Structure test scores (\pm SE) averaged across the learning phase and again for the Control test phase for each condition. Successful performance is indicated by *higher* structure scores.

Table 1. Frequency of responses to questions concerning the identification of the trial history experienced during the learning phase, and the basis for making that response by condition.

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

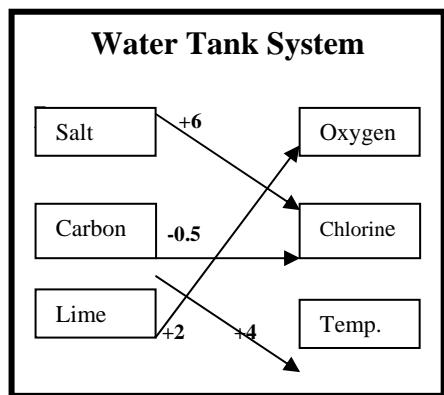


Figure 2. Mean Control Test error scores (\pm SE) at Control Test 1 and Control Test 2 for each condition. Successful performance is indicated by *lower* mean error scores.

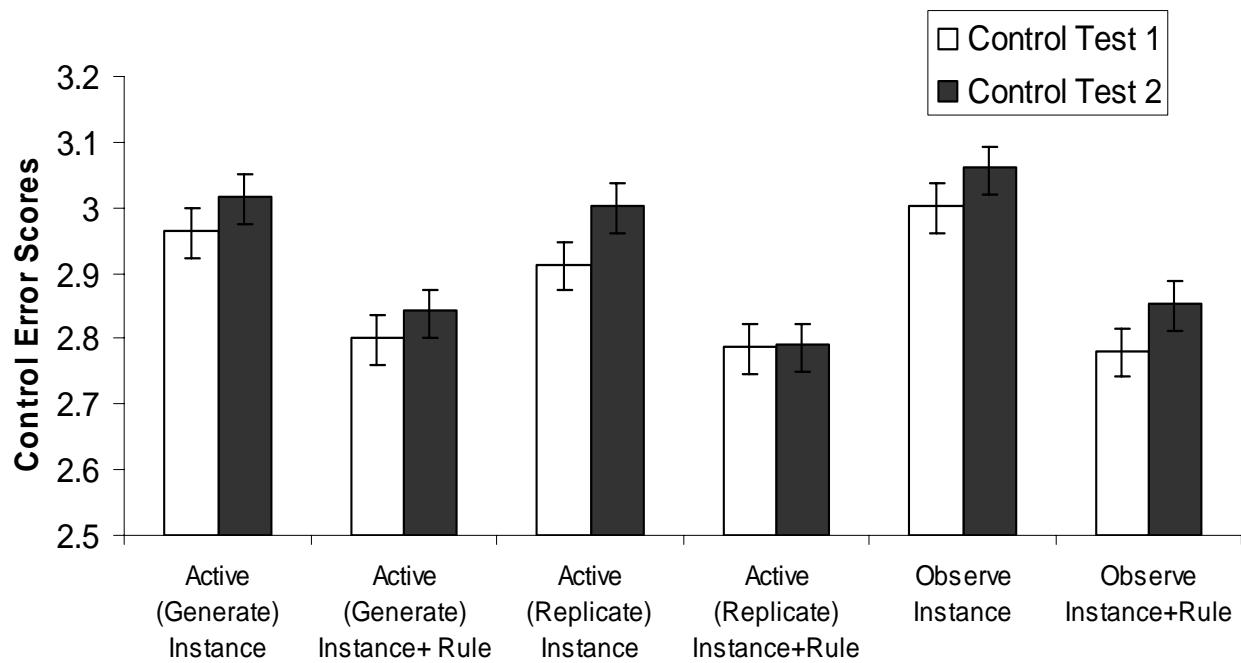


Figure 3. Mean Structure test scores (\pm SE) averaged across the learning phase and again for the Control test phase for each condition. Successful performance is indicated by *higher* structure scores.

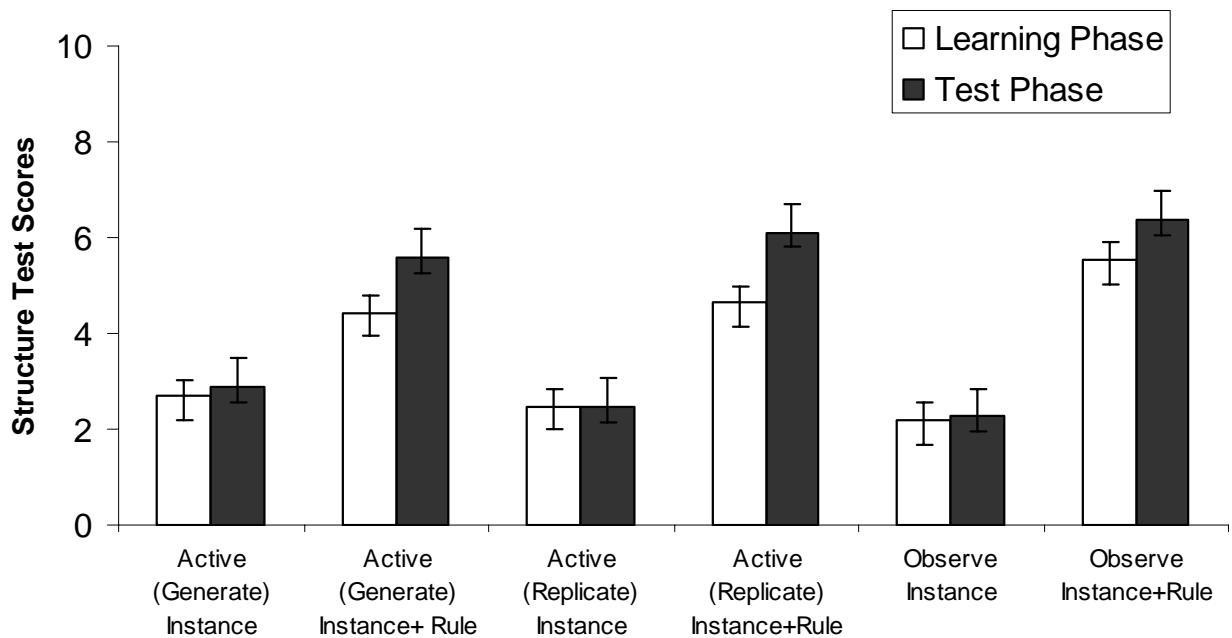


Table 1. Frequency of responses to questions concerning the identification of the trial history experienced during the learning phase, and the basis for making that response by condition.

Condition	Basis for Identification			
	No. of Correct Identifications	Feeling of Familiarity	Recognize specific instances	Guess
Active (Generate) Instance	5	5	5	6
Active (Generate) Instance + Rule	9	6	8	2
Active (Replicate) Instance	4	5	4	7
Active (Replicate) Instance + Rule	10	3	8	5
Observe Instance	4	6	3	7
Observe Instance + Rule	9	5	9	2