

Cue utilization and strategy application in stable and unstable dynamic environments

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Abstract

The following study examined the profiles of individuals' information sampling behaviour and strategy application in a complex control task in which they were required to reach and maintain a specific outcome (goal) in a task environment which varied according to its stability. We show that the profiles of cue utilization according to whether the control task was extremely unstable or moderately unstable. The strategies employed to control the environment showed sensitivity to the dynamic properties of the environment. Under conditions in which the environment was most unstable people tended to vary all the cues in order to stabilize the outcome, whereas the strategy to vary one cue at a time was adopted under stable task conditions. These findings are discussed with respect to the Monitoring and Control (Osman, 2010a, 2010b) framework and its proposals for cue utilization and strategy application under conditions of uncertainty.

Introduction

We often find ourselves in complex situations in which we are required to take control and develop ways of solving problems in order to generate desirable outcomes. Of interest to research in problem solving and decision making are the types of learning mechanisms that enable us to extract relevant information in order to successfully control outcomes, in particular in dynamic uncertain environments (Cohen, Freeman, & Wolf, 1996; Klein, 1997; Lipshitz, Klein, Orasanu, & Salas, 2001; Lipshitz & Strauss, 1997), such as economic (e.g. stock exchange), industrial (e.g., chemical waste disposal), critical safety (e.g., automated-pilot systems) and biological (e.g., eco-systems). Given the properties of these environments, an action may not reliably produce the same outcome each time, which raises the question: What factors influence how we learn relations between actions and outcomes in an uncertain dynamic environment? The aim of this study is to address this question in detail by examining control-based behaviour using a simulated complex dynamic task environment.

Uncertain dynamic environments

Often when determining the outcome in complex uncertain environments a series of non-independent decisions are made (Brehmer, 1992). A future decision builds on the outcome of a previous decision and so on in order to work towards a goal. For instance, if we decide to take a couple of aspirin when we have a headache, we know that there is a variable delay in taking effect, and that the intensity of headaches changes over time. If after some period the headache persists, we may decide to take more aspirin, but without being sure that it will take effect, and if so, when it will do so. In this case, our decision making requires a series of choices to act towards achieving a specific goal (alleviating the headache), but there is uncertainty attached to our choice of actions (when to take aspirin, and at what dosage), because we cannot be sure we will reliably produce the desired effect. This could be because of: 1) the underlying probabilistic

relationship between decision and outcomes, 2) the dynamic nature of the environment itself - that is, changes in the outcome occur even when no action is taken 3) or both. So, given that in an uncertain environment we are often required to make decisions that are directed towards achieving a particular goal, what is the method by which we learn to do this?

One approach to studying learning behavior in complex dynamic control (CDC) tasks involves the individual interacting with an environment by deciding from various cues (e.g., drug A, B, C) actions that are relevant (e.g., selecting drug A at dosage X) to changing the outcome (e.g., reduce the spread of disease). In CDC tasks, the cue-outcome associations are probabilistic, and the environment is often dynamic which ensures that from trial to trial the effects on the outcome will change.

The effects of instruction during training on control performance

The focus of many studies has been to examine the effects of varying the specificity of the goal under which the individual is instructed to learn about the environment (Burns & Vollmeyer, 2002; Geddes & Stevenson, 1997; Miller, Lehman & Koedinger, 1999; Osman, 2008a, 2008b; Vollmeyer, Burns & Holyoak, 1996). In this way, it is possible to examine the best conditions under which to learn to control an uncertain dynamic environment. The main contrast is between specific goal (SG) conditions, in which people learn to achieve and maintain a particular outcome (e.g., learn to reduce and contain the spread of Disease Y), and non specific goal (NSG) conditions, in which people learn about the environment in an unconstrained way (i.e. learn about the relationship between the different drugs and their effects on the spread of the disease).

The early CDC studies involved SG learning (Berry & Broadbent, 1984, 1987, 1988; Broadbent, 1977; Broadbent & Ashton, 1978; Broadbent, Fitzgerald, & Broadbent, 1986). What they, and others since (Dienes & Fahey, 1995, 1998; Gonzalez, Lerch, &

Lebiere, 2003) have shown, is that SG learning is a successful way of training individuals to select actions (i.e. change the correct cues and to appropriate values) that will reliably control an outcome to a criterion. However, later work contrasting this method with NSG learning, has shown it to be a poor basis for acquiring a deep understanding of the task environment. For instance, under NSG learning there is transfer of control skills to a range of unfamiliar goal criteria, which is not found under SG learning (Burns & Vollmeyer, 2002; Osman, 2008a, Vollmeyer, et al, 1996). In addition, compared to SG instructions, knowledge of the cue-outcome associations is more accurate under NSG training instructions (Burns & Vollmeyer, 2002; Geddes & Stevenson, 1997; Miller, et al., 1999; Osman, 2008a, 2008b; Vollmeyer, et al., 1996)².

The effects of length of training on control performance

Another approach to examining behaviour in CDC tasks outside of varying the goal is to investigate the effects of length of training on control performance. Typically, CDC tasks involve short training sessions (between 12 and 40 trials; Berry & Broadbent, 1988; Burns & Vollmeyer, 2002; Lee, 1995; Sanderson, 1989; Stanley, Mathews, Buss, & Kotler-Cope, 1989). As a result, such short exposure to the CDC task environment means that it is unclear whether poor knowledge of the environment is a result of limited experience with it, or because of the complexity of the actual structure of the actual system people are required to control. To address this, Stanley et al., (1989) examined whether more exposure to the task environment can lead to further improvements in the controllability of the system. They found that, as compared with performance in typical short training schedules, there were increases in control performance, but that this did not in turn lead to additional improvement in knowledge of the system itself. That is, knowledge of the structural properties of the systems, i.e. the causal relations between cues and outcomes, was no better than levels of knowledge after short training procedures. Moreover, later studies suggest that extended practice alone does not, in

turn, reliably lead to improved control performance (Gonzalez, 2005; Kanfer et al., 1994; Kerstholt, 1996; Kerstholt & Raaijmakers, 1997).

However, these findings are at odds with evidence that, in real rather than simulated laboratory based CDC tasks, extended practice facilitates accurate reportable knowledge of the CDC task and improves control-based skill (e.g., Lipshitz et al., 2001). In addition, when combined with instructions that direct people to evaluate their behaviours and their knowledge during training, extensive training leads to improved and longer retention of the newly acquired skills (Linou & Kontogiannis, 2004), better resource allocation of executive processes, including attention and working memory (Brehmer & Allard, 1991, as well as encouraging people to set more appropriate goals while operating CDC task (Morin & Latham, 2000)). Clearly, understanding how length of training impacts on our learning, and the longer term effects it can have on our ability to generate desirable outcomes in uncertain dynamic environments is of importance.

What factors influence how we learn relations between cue-outcomes in uncertain dynamic environments?

Returning to the target question of this study, much of the work on control-based behaviours in CDC tasks shows that the most successful methods of learning in a dynamic environment involve presenting people with NSGs which enable people to experience a wide range of states of the system. It may also be the case that the mixed findings concerning the impact of length of training on control performance are due to differences in the goals that people are required to adopt. In summarizing the evidence here, we propose that there are two critical factors that bear relevance on the issue of the success of learning in uncertain dynamic environments: (1) the way in which the outcome is evaluated (i.e. with respect to the goal), and (2) the quality of states of the system experienced (i.e. the range of cue-outcome associations). In addition, we propose a third factor that has not been explored in detail, namely the actual dynamic properties of the environment itself (Osman, 2010b). Therefore, we suggest that in addition to (1) and (2)

the stability of the relationship between cue-outcome associations also influences the success of learning in uncertain dynamic environments.

CDC tasks come in many varieties (for review see, Osman, 2010a), but crucially, they tend to fall into two categories: those that are dynamic, by which we refer to Funke's (1993) definition "An endogenous variable [that] at time t has an effect of its own state at time $t+1$ independent of exogenous influences that might add to the effect", and those that are static; in which the state of the system between t and $t+1$ is only dependent on exogenous influences on the system. Studies using CDC tasks with actual dynamic systems have thus far not systematically examined the effects of varying the statistical properties of the endogenous variables on control performance. In other words, there has been no direct comparison of the effects of instability – in which the fluctuations in the state of the environment that result from the influence of the endogenous variable are high, and stability – in which the fluctuations are low, on control behavior in uncertain dynamic environments. However, comparable work on feedback delays between action and outcome provides some insights into potentially relevant psychological effects of instability of the task environment. Kersholt and Raaijmakers (1997) reviewed a variety of dynamic control systems that incorporated delays between the action taken by the individual and an associated outcome. They claimed that feedback delays are difficult to integrate, and people tend to forget or ignore delays once they have taken an action, which can have serious consequences for later control of the system. Diehl and Serman (1995) also show that people's knowledge of a system can degrade as they encounter repeated delays in feedback to their actions, and attenuate control behaviours.

Thus, as a proxy for instability, the consensus is that feedback delays are difficult to integrate, and that people tend to forget or ignore delays after they have taken an action in a system (Diehl & Serman, 1995; Gibson, 2003; Kersholt & Raaijmakers,

1997). People interpret temporal delays between actions and effects as the result of an unstable system, and so people are unable to understand that their actions can affect it (Diehl & Serman, 1995; Moxnes, 2000). Moreover, cognitive neuroscience and motor control literatures suggests that learning the relation between our actions and outcomes depends on the degree to which there is congruence between the predicted and actual outcome of one's actions (Blakemore, Frith, & Wolpert, 2001; Blakemore, Wolpert, & Frith, 1998), and between predicted and observed outcomes (Osman, Wilkinson, Beigi, Castaneda, & Jahanshahi, 2008).

Present Study

Given that there has been limited attention directed towards examining the effects of the stability of the CDC task environment on control performance, this factor is the focus of the present study. To explore this, the present study examined control performance, cue utilization, and strategy application and development in the same CDC task, under conditions in which stability¹ of the CDC task was varied (Extremely Unstable, Moderately Unstable). This task was used in other research (Osman & Speekenbrink, *submitted*), but there we used less extreme noise levels, as well as relatively short learning episodes (40 trials). To investigate whether more extensive learning is beneficial, we extended the learning episode to 200 trials in the present study.

We base our examination of the effects of stability on Osman's (2010a, 2010b) Monitoring and Control framework (hereafter MC framework). The MC framework proposes that in uncertain dynamic environments, such as those defined by Funke (1993), there are two methods of reducing uncertainty: 1) subjective estimates in predicting outcomes of events (predictability of the environment), and 2) subjective estimates concerning the expectancy that an action can be executed that will achieve a specific outcome (predictability of control). When learning to control outcomes, people judge their performance according to the discrepancy between the achieved and target

outcome. Thus, the quality of states of the system experienced (i.e. the range of cue-outcome associations) have an important bearing on the success of control performance. More opportunity to evaluate the achieved outcome with respect to its relationship to the target outcome (i.e. extensive training situations), should lead to more accurate knowledge of how to utilize the cues with respect to achieving the target outcome. However, under situations in which there are endogenous and well as exogenous influences (i.e. directly through cue manipulation) on the outcome, this increases the difficulty in accurately evaluating the relation between actions and expected outcomes. As endogenous influences on the outcome increase in a system (as in highly unstable conditions), then so too will difficulty in identifying ways of reducing the discrepancy between achieved and target outcome.

From this, the following prediction was examined in the present study: Conditions in which there is high instability in the environment should increase the difficulty in evaluating the achieved outcome with respect to its relation to the target outcome, as indexed by poorer control performance compared with conditions in which there is lower instability.

Methods

Participants: Eighteen graduate and undergraduate students from University of Surrey volunteered to participate in the experiment for reimbursement of £6. The assignment of participants to the two groups was randomized. There were two conditions (Extreme Noise (n=9), Moderate Noise (n=9)). Participants were tested individually.

Design and Materials: The study was a mixed design that included one between subject variable comparing the effects of a noisy environment on control performance (Extreme Noise, Moderate Noise). The same environment was presented to both groups. The design of the environment involved four continuous variables, three of which were

Cue Utilization & Strategy Application

cues and one outcome. The cues varied in their relation to the outcome in the following ways: one was positively associated, the other negatively associated, and a third was unrelated to the outcome (null).

Structure of System: $y(t) = y(t-1) + b_1 x_1(t) + b_2 x_2(t) + e_t$

Positive cue = x_1 , Effect of positive cue = $b_1 = 0.65$, Negative cue = x_2 , Effect of negative cue = $b_2 = -0.65$, Random noise = e_t , (the random noise component, with a mean of 0, is normally distributed with a standard deviation of 32 (Extreme Noise) and 16 (Moderate noise), Outcome value = $y(t)$, Previous outcome value = $y(t-1)$. The visual layout of the screen, cover story, and the main instructions were identical for all four groups. Participants were presented with a summarized report of an article appearing in a medical journal.

It has recently been reported in The Lancet (##/##/##) "Patients under stress" (pp23-29) Special issue, that the Neurotransmitter (N) is released when patients are experiencing intense stress-related symptoms that slow down recovery. In addition, the research reported that three different naturally occurring hormones A, B, C also affect the release of the same neurotransmitter N. The basis of the research that you will be taking part in is to look at the relationship between the three different hormones A, B, C and their affects on the neurotransmitter N.

Participants were informed that as part of a medical research team they would be conducting tests in which they would inject a patient with either one, or any combination of the three hormones, with the aim of maintaining a specific safe level of neurotransmitter release. The system was operated by varying the cue values (hormones A, B and C) that would effect the level of neurotransmitter release. The screen included the three labeled cues, and the outcome which was presented in two ways, as a value

Cue Utilization & Strategy Application

presented in the top right of the screen, and also in a small progress screen in which a short trial history (5 trials long) of outcome values was presented. The progress screen included a bar which highlighted the target value to which the outcome needed to be maintained. Thus, for each training trial participants received feedback concerning their current level of the neurotransmitter (i.e. achieved outcome) and the target value.

Procedure: The task included a total of 200 trials in the extensive training condition. Participants were presented with a computer display with three cues (hormones A, B, C) and the outcome (neurotransmitter). Each trial consisted of participants interacting with the system by changing cue values using a sliders corresponding to each cue with a scale that ranged from 0-100. On the start trial, the cue values were set to '0' and the outcome value was 178. Participants were instructed to maintain the outcome within a safe range (± 10) of the target value, which was set at 62 throughout. After making their decisions, participants clicked a button labeled 'Submit' which made the cues inactive, and revealed on the progress screen the effects of their decisions on the outcome. The effects on the outcome value were cumulative from one trial to the next, and so while the cue values were returned to '0' on the next trial, the outcome value was retained from the previous trial. The cumulative effects on the outcome value were presented as a trial history on screen which contained the outcome values of the last five trials. When participants were ready to start the next trial, they clicked a button labeled 'Continue', after which the cues became active and were reset to '0'. After they completed the learning phase, participants then proceeded to the test phase.

Scoring: The training trials of the four different groups were scored according to three different criteria (control performance, control optimality, cue utilization, and strategy development). *Control performance* was based on error scores calculated as the absolute difference between the achieved and desired outcome value on each trial for

Cue Utilization & Strategy Application

each participant. *Control optimality* was based on the how much participants' cue manipulations deviated from the optimal cue settings. In the control task used here, for a given (previous) outcome value and goal, the optimal cue settings define a line in a two-dimensional plane. E.g., if the deviation between the previous outcome and goal is 50, then the optimal cue settings are all values for the positive cue x_1 and negative cue x_2 such that $50 = 0.65 x_1 - 0.65 x_2$, for instance a value of $x_1 = 77$ and $x_2 = 0$, or $x_1 = 78$ and $x_2 = 1$, $x_1 = 87$ and $x_2 = 10$, etc. Control optimality scores are computed as the (shortest) distance between a participant's actual settings for these two cues and the line defining the optimal cue settings. For the environment used here, this distance is computed as in the following equation:

$$D(t) = | x_1(t) - x_2(t + [y(t-1) - g]/0.65) | / \sqrt{2}$$

in which $g = 62$ denotes the target outcome value. On those trials in which the difference between previous outcome and target was larger than 65, or smaller than -65, in which case it was not possible to reach the target outcome in a single trial, the value $y(t-1) - g$ was replaced by either 65 or -65 to compute the distance. Note that as the null cue has no effect on the outcome, it is not taken into account in the control optimality scores. Cue Utilization was scored in two ways: Cue manipulation and Parameter setting. For each participant, *Cue manipulation* was based on calculating the proportion of occasions across all training trials that each of the three cues was manipulated. Second, *Parameter setting* was calculated based on the mean cue value that participants chose across all training trials for each of the three cues. The *strategies* that were identified during training were based on calculating for participant the proportion of trials across blocks of training in which no cue was changed (No-intervention strategy), one cue was changed (Vary one thing at a time (VOTAT) strategy), two cues were changed (Vary two things at a time (VTAT) strategy), and all three cues were changed (Vary all (VA) strategy).

Results

The learning phase was divided in four blocks (block = 50), control error scores were averaged across each block for each participant. The following analyses were based on the mean error scores by block presented in Figure 1.

Insert Figure 1 about here

Control performance: The following analysis compared control performance by noise level. A 4x2 ANOVA was conducted on control performance scores using Block (Learning Block 1, 2, 3, 4) as within subject factor, and Noise (Extreme Noise, Moderate Noise) as the between subject factors. As indicated in Figure 1, Controllers improved in their ability to control the outcome to criterion as they became more familiar with the task. This was confirmed by a main effect of Block, $F(3,48) = 4.368, p = .008$, partial $\eta^2 = .214$. There was a main effect of Noise on error scores $F(2,16) = 30.218, p = .0004$, partial $\eta^2 = .654$. Overall control performance was poorer in the extreme noise condition compared with the moderate noise condition.

There was also a significant Noise x Block interaction, $F(3,48) = 5.796, p = .001$, partial $\eta^2 = .266$. Univariate analyses conducted comparing error scores separately for each block revealed that there were significant differences between both groups each of the four training blocks ($p < .005$).

Control optimality: A 4x2 ANOVA was conducted on control optimality scores Block (learning block 1, 2, 3, 4) as within subject factor, and Noise (Extreme noise, Moderate noise) as a between subject factor. As indicated in Figure 2, participants improved in their ability to select the optimal cue settings as they became more familiar with the task. This was confirmed by a main effect of Block, $F(3,48) = 10.090, p < .0001$, partial $\eta^2 = .387$. There was a main effect of Noise on error scores $F(1,16) = 16.398, p =$

Cue Utilization & Strategy Application

.0009, partial $\eta^2 = .506$. Overall, participants in the Extreme noise condition chose less optimal cue values than participants in the moderate noise condition.

Insert Figure 2 about here

Cue Manipulation: An analysis was conducted to compare pattern of behavior concerning the three different types of cues (positive, negative, null) based on the proportion of manipulations made collapsed across blocks. A 3x2 ANOVA was conducted on mean proportion of changes with Cue (positive, negative, null) as within subject factor, and Noise (Extreme noise, Moderate noise) as a between subject factor. Figure 3 shows that there appear to be differences between the groups based on the extent to which they intervened on the cues. The analysis revealed that there was no significant main effect of Cue, $F(2,32) = 0.224, p = .801$, partial $\eta^2 = .001$, suggesting that the occasions on which the three different cues were intervened upon was equally distributed. However, there was a significant main effect of Noise, $F(1, 16) = 20.115, p = .0003$, partial $\eta^2 = .557$, indicating that participants in the moderate noise group utilized the three cues less frequently than the extreme noise group.

Insert Figure 3 about here

Parameter Setting: Turning now to the actual values that participants had selected, the next analysis examines the pattern in the cue values for each of the three different cues. Figure 4 shows that the values for the three cues appears to be overall lower in the groups with moderate noise in the task environment as compared with the extreme noise group.

Insert Figure 4 about here

A 3x2 ANOVA was conducted on mean values selected for the three cues with Cue (positive, negative, null) as within subject factor, and Noise (Extreme noise, Moderate noise) as the between subject factor. Confirming the trend indicated in Figure 3, the

Cue Utilization & Strategy Application

analysis revealed a significant main effect of Noise, $F(1, 16) = 18.997, p = .0001$, partial $\eta^2 = .543$. No other effects were significant.

Strategy: The following analysis first considers whether there were differences in the types of strategies that were adopted by the different groups as shown in Figure 5, the next analysis focuses in detail, on the profile of strategy development across blocks of training trials presented in Figure 6. To begin, a 4x2 ANOVA was conducted on the proportion of trials in which cues were varied using Strategy (No Intervention, VOTAT, VTTAT, VA) as a within subject factor, and Noise (Extreme noise, Moderate noise) and as the between subject factor. The analysis revealed a main effect of Strategy, $F(3, 48) = 8.991, p = .0001$, partial $\eta^2 = .360$, suggesting that there were differences in the types of strategies favoured overall, as indicated in Figure 5. There was also a main effect of Noise, $F(1,16) = 23.852, p = .0001$, partial $\eta^2 = .599$, and a significant Strategy x Noise interaction $F(3, 48) = 14.890, p = .0005$, partial $\eta^2 = .482$.

Insert Figure 5 about here

To locate the source of the Strategy x Noise interaction, univariate analyses revealed that compared with the moderate noise, the extreme noise group adopted the VA strategy (vary all three cues) was more frequently, $F(1, 16) = 23.852, p = .0001$, partial $\eta^2 = .599$, and VOTAT strategy (Vary one cue at a time) was less often applied, $F(1, 16) = 19.336, p = .0005$, partial $\eta^2 = .547$. No other analyses were significant.

Strategy development. The final set of analyses concern the way in which strategies change across the course of training. Here we focus on stable strategy application separately for each of the four conditions across the four blocks of training, as presented in Figure 6.

Insert Figure 6 about here

For the Extreme noise group, 4x4 ANOVA conducted on strategies for each of the four blocks revealed that there was a main effect of Strategy, $F(3,32) = 42.403, p =$

Cue Utilization & Strategy Application

.0001, partial $\eta^2 = .799$, however no main effect of Block suggesting that the pattern of strategy application across blocks remained the same. Post hoc tests revealed that the VA strategy was applied more often than any of the other strategies ($p < .0005$). No other analyses were significant suggesting that most participants' preference was for the VA strategy and of the occasions in which other strategies were adopted, the frequency with which this they were applied during training was equal.

The pattern of strategy application during training for the Moderate noise group also indicated that strategy application did not change significantly across blocks, but there were differences in the extent to the four different strategies were applied, $F(3,32) = 22.239, p = .0006$, partial $\eta^2 = .569$. No other tests were significant. With the exception of VA and VTAT, and VA and no intervention strategy comparisons, all other comparisons revealed significant differences in application across training trials ($p < .05$).

General Discussion

The present study investigated the effects on control performance and cue utilization when varying the stability of the relationship between cue-outcome associations; this was achieved by manipulating the endogenous properties of the CDC system. Overall, the evidence from this study supports the prediction made from the Monitoring and Control framework (Osman, 2010a, 2010b).

Conditions in which there is high instability in the environment should increase the difficulty in evaluating the achieved outcome with respect to its relationship to the target outcome, as indexed by poorer control performance compared to Conditions in which there is lower instability. In support of this, the Extreme noise group showed poorer control performance as compared to the Moderate noise group. While both groups clearly improved over blocks of training, the differences in control performance were sustained, suggesting that the extreme level of instability of

Cue Utilization & Strategy Application

the system increased difficulty in reducing the discrepancy between achieved and target outcome.

Cue utilization increased as a result of increases in the instability of the system, suggesting that participants tended to interact with the system more often because the outcome would fluctuate more often and more dramatically as a result of the internal properties of the system. Moreover, in support of this, the pattern of behaviour for parameter setting of the three cues suggested that the values chosen for all three cues was consistently greater for both extreme noise group compared with the moderate noise group. However participants set the values of all three cues to equivalent levels despite the presence of a null cue, which was ineffective but nevertheless, when utilized it was set to values equivalent to the positive and negative cues.

Clearly, the fluctuations in the outcome value encouraged participants in the extreme noise group to select more extreme cue values in an attempt to reduce the discrepancy between achieved outcome and target outcome from trial to trial. In terms of optimality of cue utilization, while both conditions showed improvement as the task progressed, participants in the Moderate noise condition clearly outperformed those in the Extreme noise condition. Finally, the pattern of strategy application of the Extreme noise group appeared to differ markedly from the Moderate noise group in its application which tended to apply the VA strategy most often and the VOTAT least often.

Overall, the types of strategies applied during training were influenced by the stability of the system, with the VA and VOTAT strategies more sensitive to stability than the VTTAT and no-intervention strategies. This is reflected in the change in frequency with which VA and VOTAT strategies were applied between the four groups. However, previous findings also suggest that VA and VOTAT are the most popular strategies used in CDC tasks (Putz-Osterloh, 1993; Tschirgi, 1980; Vollmeyer, Burns, & Holyoak, 1996). Therefore it may be the case that, despite the four available strategies

Cue Utilization & Strategy Application

options that could be used in the system present to participants, there is an overriding preference for either manipulating all of them at once, or only one on each occasion. Clearly when the outcome value appears to fluctuate in range, as with the extreme noise groups, the perceived effective strategy was to manipulate all three cues.

When examining the profiles of strategy application over blocks of trials, the distribution of strategies remained unchanged throughout training, suggesting that once participants had decided which types of strategies to use, the frequency with which they were applied was consistent throughout. This is at odds with Vollmeyer, Burns & Holyoak's (1996) CDC task, in which they reported differences in the frequency with which VA and VOTAT were applied across training trials. They found that when training was not constrained by an SG, participants increased their application of the VOTAT strategy towards the latter stages of training, whereas when training involved an SG, VOTAT decreased across blocks. The differences in findings between studies could be considered in light of the fact that in the present study the four blocks of trials were not physically separated, whereas in Vollmeyer et al's (1996) study after each block participants were presented with additional tests of knowledge. It may have been the case that by separating the blocks, as well as measuring knowledge of the structure of the system, these factors encouraged participants to evaluate their understanding of cue-outcome associations and the methods by which they were learning about them, which in turn led to a change in strategy application between blocks of trials. Because in the present study training trials were presented without any breaks in between, and no tests of knowledge of the system were presented between blocks, there was little reason to change the types of strategies that were applied. Though, it remains an empirical question whether tests of knowledge interleaved during training act as a status check of the success of strategies and so this encourages a shift in strategy application, or whether

Cue Utilization & Strategy Application

simply separating training trials into blocks can also lead to changes in strategy application.

Conclusion

The evidence from the present study suggests that varying the instability of a control system has marked effects on the way in which individuals utilize cues while interacting with the system, as well as the strategies they apply in order to control outcomes. Through a detailed examination of cue utilization and strategy application we developed a profile of learning behaviors, which suggest that with respect to moderate noise conditions, those in the extreme noise condition showed more evidence of sub optimal behaviour, however, there as evidence of optimal cue utilization with more exposure to the system. Clearly, people are capable of learning to control outcomes in which cue-outcome associations are obscured by the dynamic properties of a control task environment which is extremely unstable.

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References

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.

Brehmer, B., & Allard, R. (1991). Dynamic decision making: The effects of task complexity and feedback delay. In J. Rasmussen, B. Brehmer, & J. Leplat (Eds.), *Distributed decision making: Cognitive models for cooperative work* (pp. 319–334). Brisbane, Queensland, Australia: Wiley.

Broadbent, D. E., (1977). Levels, hierarchies and the locus of control. *Quarterly Journal of Experimental Psychology*, *32*, 109–118.

Broadbent, D., & Ashton, B. (1978). Human control of a simulated economic system. *Ergonomics*, *78*, 1035-1043.

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.

Burns, B. D., & Vollmeyer, R. (2002). Goal specificity effects on hypothesis testing in problem solving. *Quarterly Journal of Experimental Psychology*, *55*, 241-261.

Catrambone, R. (1998). The subgoal learning model: Creating better examples so that students can solve novel problems. *Journal of Experimental Psychology: General*, *127*, 355–376.

Cue Utilization & Strategy Application

Cervone, D., Jiwani, N., & Wood, R. (1991). Goal setting on the differential influence of self-regulatory processes on complex decision-making performance. *Journal of Personality and Social Psychology*, *61*, 257-266.

Chesney, A., & Locke, E. (1991). An examination of the relationship among goal difficulty, business strategies, and performance on a complex management simulation task. *Academy of Management Journal*, *34*, 400-424.

Cohen, M. S., Freeman, J. T., & Wolf, S. (1996). Meta-cognition in time stressed decision making: recognizing, critiquing and correcting. *Human Factors*, *38*, 206-219.

Diehl, E., & Serman, J. D. (1995). Effects of feedback complexity on dynamic decision making. *Organizational Behavior and Human Decision Processes*, *62*, 198-215.

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.

Earley, P. C., Connolly, T., & Ekegren, G. (1989). Goals, strategy development and task performance: Some limits on the efficacy of goal setting. *Journal of Applied Psychology*, *74*, 24-33.

Early, P. C., Northcraft, G. B., Lee, C., & Lituchy, T. R. (1990). Impact of process and outcome feedback on the relation of goal setting to task performance. *Academy of Management Journal*, *33*, 87-105.

Funke, J. (1993). Microworlds based on linear equation systems: A new approach to complex problem solving and experimental results. In G. Strube & K.-F. Wender (Eds.), *The cognitive psychology of knowledge* (pp. 313-330). Amsterdam: Elsevier.

Geddes, B. W., & Stevenson, R. J. (1997). Explicit learning of a dynamic system with a non-salient pattern. *Quarterly Journal of Experimental Psychology: Human Experimental Psychology*, *50(A)*, 742-765.

Gonzales, C. (2005). Decision support for real-time, dynamic decision making tasks. *Organizational Behavior and Human Decision Processes*, *96*, 142–154.

Gonzales, C., Lerch, J. F., & Lebiere, C. (2003). Instance-based learning in dynamic decision making. *Cognitive Science*, *27*, 591-635.

Kanfer, R., Ackerman, P. L., Murtha, T. C., Dugdale, B., & Nelson, L. (1994). Goals setting, conditions of practice, and task performance: A resource allocation perspective. *Journal of Applied Psychology*, *79*, 826–835.

Kerstholt, J. H. (1996). The effect of information cost on strategy selection in dynamic tasks. *Acta Psychologica*, *94*, 273–290.

Kerstholt, J. H., & Raaijmakers, J. G. W. (1997). Decision making in dynamic task environments. In R. Ranyard, R. W. Crozier, & O. Svenson (Eds.), *Decision making: Cognitive models and explanations* (pp.205–217). New York, NY: Rutledge.

Lee, Y. (1995). Effects of learning contexts on implicit and explicit learning. *Memory & Cognition*, *23*, 723–734.

Linou, N., & Kontogiannis, T. (2004). The effect of training systemic information on the retention of fault-finding skills in manufacturing industries. *Human Factors and Ergonomics in Manufacturing*, *14*, 197– 217.

Lipshitz, R., Klein, G., Orasanu, J., & Salas, E. (2001). Taking stock of naturalistic decision making. *Journal of Behavioral Decision Making*, *14*, 332–351.

Miller, C. S., Lehman, J. F., & Koedinger, K. R. (1999). Goals and learning in microworlds. *Cognitive Science*, *23*, 305-336.

Morin, L., & Latham, G. P. (2000). Effect of mental practice and goal setting as a transfer of training intervention on supervisors' self-efficacy and communication skills: An exploratory study. *Applied Psychology: An International Review*, *49*, 566–578.

Osman, M. (2008a). Evidence for positive transfer and negative transfer/Anti-learning of problem solving skills. *Journal of Experimental Psychology: General*, *137*, 97-115.

Osman, M. (2008b). Observation can be as effective as action in problem solving. *Cognitive Science*, *32*, 162-183.

Osman, M. (2010a). Controlling Uncertainty: A Review of Human Behavior in Complex Dynamic Environments. *Psychological Bulletin*, *136*, 65-86.

Osman, M. (2010b). *Controlling Uncertainty: Learning and Decision Making in complex worlds*. Blackwell Publishers

Osman, M., & Speekenbrink, M. (under review). Learning to predict vs. learning to control a dynamic environment. *Journal of Experimental Psychology: Learning, Memory & Cognition*.

Putz-Osterloh, W. (1993). Strategies for knowledge acquisition and transfer of knowledge in dynamic tasks. In G. Strube & K.F. Wender (Eds), *The cognitivepsychology of knowledge*. Amsterdam: Elsevier.

Tschirgi, J.E. (1980). Sensible reasoning: A hypothesis about hypotheses. *Child Development*, *51*, 1-10.

Sanderson, P. M. (1989). Verbalizable knowledge and skilled task performance: Association, dissociation, and mental models. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *15*, 729–747.

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 control task. *Quarterly Journal of Experimental Psychology: Human Experimental Psychology*, *41(A)*, 553–577.

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.

Cue Utilization & Strategy Application

Figure 1. Mean SE (+/-) Control Performance by Group

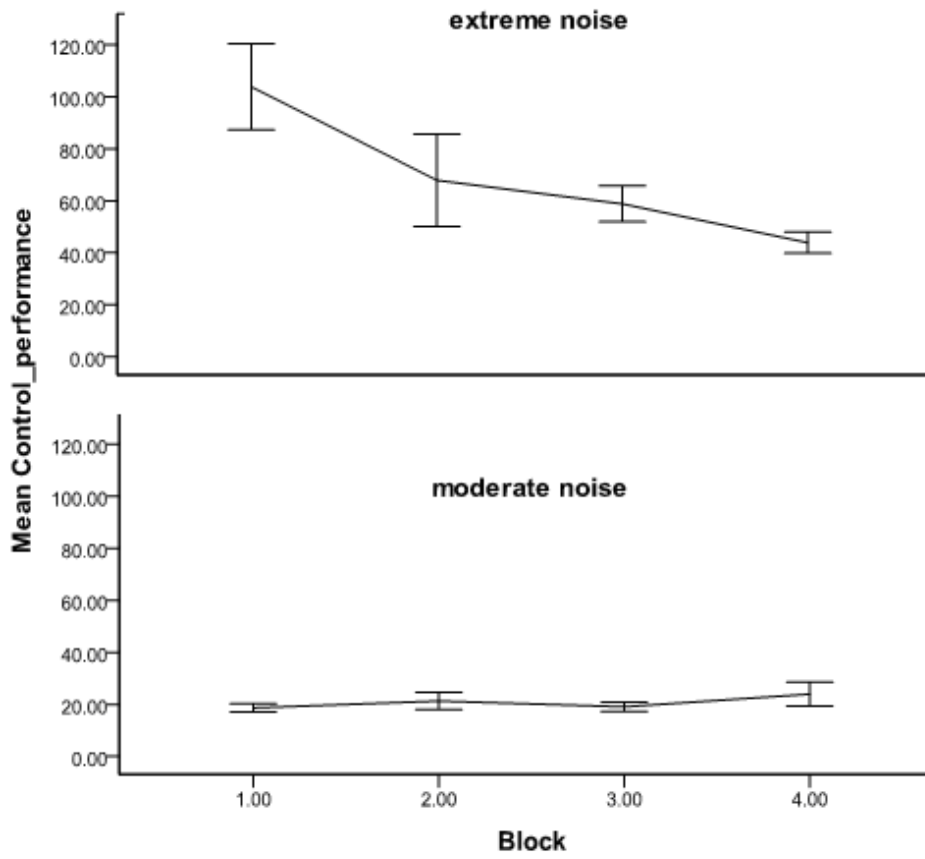


Figure 2. Control Optimization by group

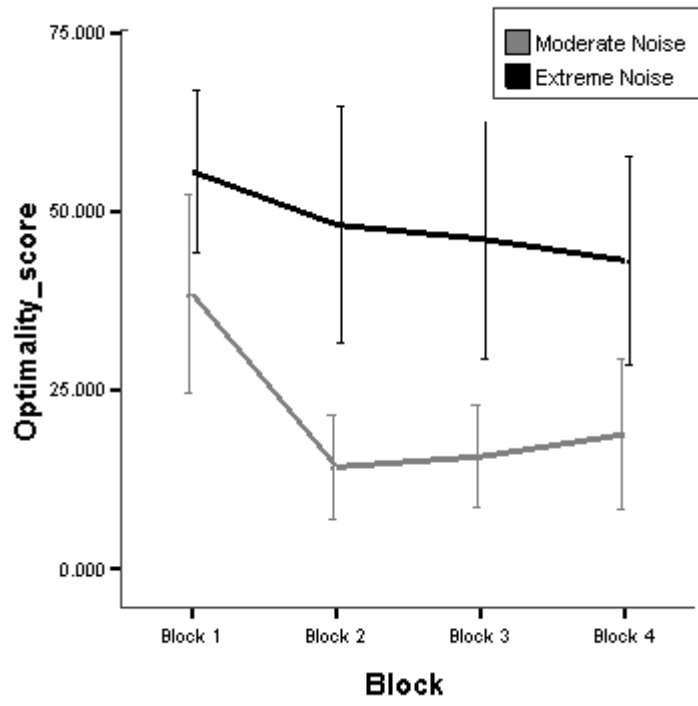


Figure 3. Mean SE (+/-) Proportion of occasions that Cues were manipulated by Group

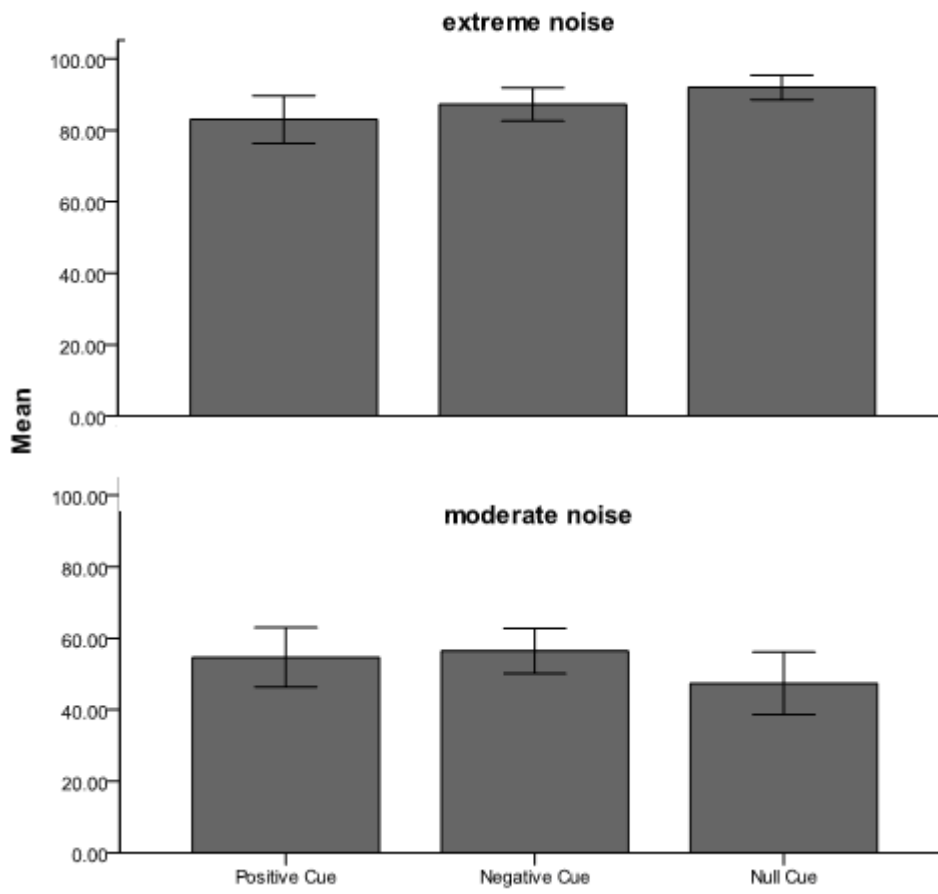


Figure 4. Mean SE (+/-) Values Set by Cue and Group

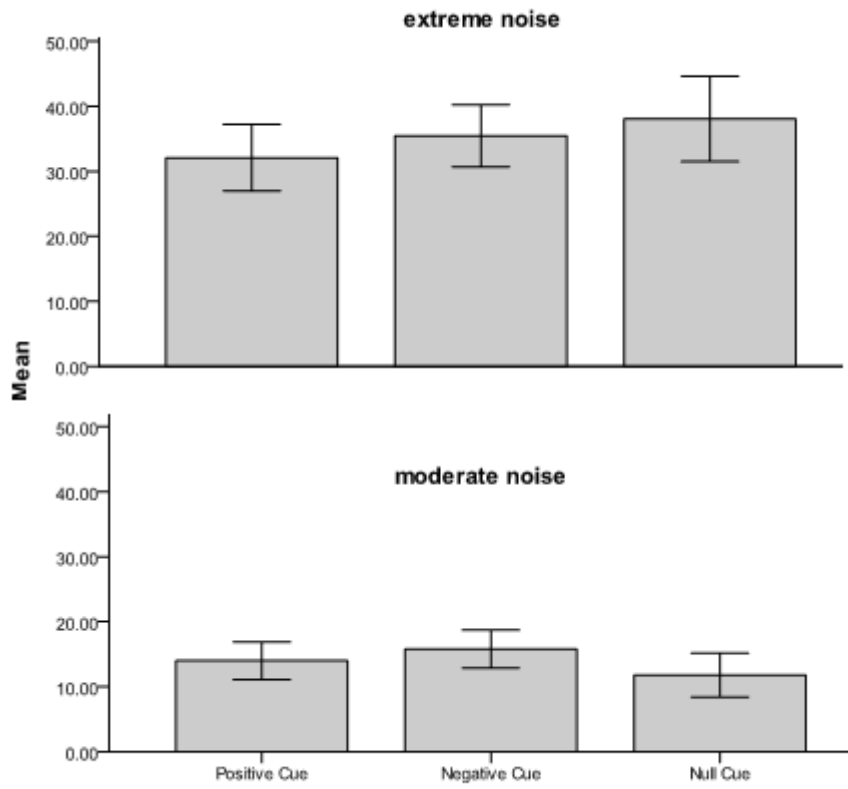


Figure 5: Mean SE (+/-) Proportion of the Four Strategies Employed During Training by Group

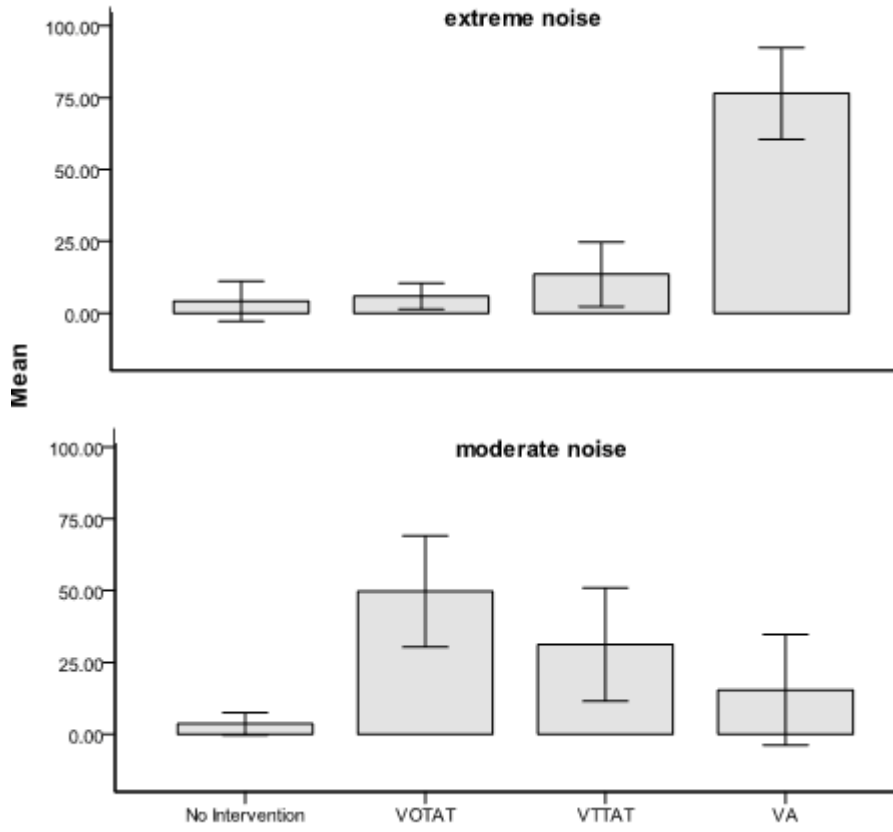


Figure 6: Mean SE (+/-) Proportion of the Four Strategies applied by group

