# Controlling Uncertainty: A Review of Human Behavior in Complex Dynamic Environments

Magda Osman[1,2]

[1]University of Surrey

[2]University College London

[1]Department of Psychology, University of Surrey, Guildford, Surrey, GU2 7XH, UK

[2]Cognitive, Perceptual and Brain Sciences, Division of Psychology and Language Sciences, University College London, Gower Street, London, WC1E 6BT, UK

Correspondence to: m.osman@surrey.ac.uk

Abstract

Complex dynamic control tasks (CDC tasks) are a type of problem-solving environment used for examining many cognitive activities (e.g., attention, control, decision making, hypothesis testing, implicit learning, memory, monitoring, planning, and problem solving). Because of their popularity, there have been many findings from diverse domains of research (Economics, Engineering, Ergonomics, Human Computer Interaction (HCI), Management, Psychology), which remain largely disconnected from each other. The objective of this article is to review theoretical developments and empirical work on CDC tasks, and to introduce a novel framework (Monitoring and Control framework) as a tool for integrating theory and findings. The main thesis of the Monitoring and Control framework is that CDC tasks are characteristically uncertain environments, and subjective judgments of uncertainty guide the way in which monitoring and control behaviors attempt to reduce it. The article concludes by discussing new insights into continuing debates and future directions for research on CDC tasks.

Key words: Monitoring, Control, Uncertainty, Dynamic, Complex tasks, Causality, Agency

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Problem solving is regarded by many (Anderson & Lebiere, 1998; Laird, Newell, & Rosenbloom, 1987; Newell & Simon, 1972; Sweller, 2003) as the most important cognitive activity in everyday and professional contexts, especially problem solving of the kind needed to control complex dynamic environments. As the complexity of the systems that we interact with in our daily lives grows (e.g., phones, computers, automated driving systems) so too does the importance of research on how we learn to control dynamic environments. Before detailing the issues surrounding the various research domains that investigate control behaviors, the illustrations below provide a general flavor of the kind of real world and laboratory tasks in which control behaviors have been studied.

Illustration 1: Ecosystem Control System. In a laboratory-based task, people are presented with a simulated environment of an African landscape with different flora and fauna. The goal is to manage the environment in order to improve the living conditions of the native population. This involves controlling the system over several weeks by managing many interconnected variables that have a complex feedback process, both negative and positive, and with time delays.

Illustration 2: Automated Pilot System. Trained pilots are required to take part in flight scenarios (including take-off and landing) in a flight simulator, in which they control the system while responding to a variety problems, including delays between their commands and their actual execution in the system, failings in the system, and miscued problems from the control panel.

Illustration 3: Solid Incineration Plant. A municipal solid waste incineration plant is a large-scale industrial system that requires the interaction of skilled process and control engineers. The main objectives of operators a control system of this kind are (1) to keep the furnace temperature at its set point; (2) to avoid bad combustion caused by a lack of waste; (3) to avoid the flame going out because of overfeeding; and (4) to maintain stable steam production.

Illustration 4: Investment Game. In a simulated task environment, trainee economists assume the role of traders. On each trading day, traders receive information on market fluctuations, news reports, and rumored information. They can buy as many shares as their cash holdings allow, sell up to the number of shares they currently possess, or refrain from trading that day with the aim of maximizing end of period profits.

Illustration 5: Sugar Factory Plant Control Task. In a laboratory task, people are told to adopt the role of a worker in the plant, and their job is to control the rate of production of sugar, by deciding exactly what work force to use at a given time. The system operates based on the following rule: ($P = (2 * W – P1_{t-1}) +R$) in which the relevant variables are the work force (W), current sugar output (P), previous sugar output (P1), and a random variable (R).

Illustration 6: Water Purification System. In a laboratory-based task, people are told that there are three substances (Salt, Carbon, Lime) which are used to change the water quality of a processing plant designed to purify the water supply. There are also three indicators of water quality: Chlorine Concentration, Temperature, Oxygenation. By manipulating the levels of the three substances, people are expected to control the water quality to specific criteria.

What do the above examples have in common?

The first is one of the earliest control tasks devised (Dörner, 1975). It is classed as a dynamic system because the problem solvers interact with variables that change in real time, both as a consequence of the problem solvers' actions, and autonomously. To achieve a particular outcome, people are required to make multiple decisions that have to accommodate multiple elements of the system, each of which can change in real time, and with different forms of feedback (i.e. random, positive, negative, delayed). The next three examples (Brandouy, 2001; Carrasco, Llauró, & Poch, 2008; Sarter, Mumar, & Wickerns, 2007), like the first, involve controlling variables as they change in real time. However, these tasks examine how experts interact with genuine or simulated control systems. In contrast, the last two examples (Berry & Broadbent, 1984; Burns & Vollmeyer, 2002) are static systems, and only the interventions of the problem solver will affect a change in the system from one trial to the next. Complexity comes from the structure of the systems, which may include a combination of non-linear, linear, and noisy relations between inputs and outputs.

In general terms, control tasks involve complex sequential decision making. The decisions are interrelated[1], and the cumulative effects are designed for the purpose of achieving a desired goal (Brehmer, 1992). The environment in which decisions are made can change autonomously, and as a direct consequence of the decision maker's actions; and often, decisions are made in real time (Brehmer, 1992). The examples above have been variously described as complex problem solving tasks (e.g., Burns & Vollmeyer, 2002; Miller, Lehman, & Koedinger, 1999), computer-simulated scenarios (e.g., Brehmer & Dörner, 1993), dynamic decision making tasks (e.g., Berry & Broadbent, 1984), micro-worlds (e.g., Dörner, 1975; Kluge, 2008a), naturalistic decision making tasks (e.g., Lipshitz et al., 2001), process control tasks (e.g., Sun et al., 2007), simulated task environment/microworlds (e.g., Gray, 2002), and system control tasks (e.g., Kaber & Endsley, 2004). For the sake of simplicity, the present article will refer to them all as Complex Dynamic Control tasks (hereafter CDC tasks).

## A paradigm in search of a framework

CDC tasks have their roots in problem-solving research (Broadbent, 1977; Dörner, 1975; Toda, 1962), and were originally devised to examine how people learn to make appropriate decisions that control highly complex simulated environments. The aim was ambitious. Given that the tasks were micro-simulations of real-world scenarios in which numerous variables could interact in thousands of possible ways, they would offer the opportunity to understand how people learn to respond (i) to ill-structured problems (ii) in uncertain dynamic environments, (iii) with shifting, ill-defined, or competing goals, (iv) feedback loops, (v) time pressures, (vi) high stakes, (vii) multiple players, and (viii) under the presence of organizational goals and norms (Funke, 2001).

It seems that the complexity of the paradigm itself is in turn an indication of the complexity and range of the psychological phenomena involved. Since their conception, CDC tasks have spawned much interest, and provided fertile ground for the study of Implicit learning (Berry & Broadbent, 1984; Dienes & Fahey, 1998), Skill learning (Sun et al., 2005; Sun et al., 2007; Vicente & Wang, 1998), Observational learning (Osman, 2008a, 2008b, 2008c), Dynamic decision-making (Busemeyer, 2002; Lipshitz et al., 2001), Group behavior (e.g., Broadbent & Ashton, 1978), Motivation (e.g., Bandura & Locke, 2003; Locke & Latham, 1990, 2002), Motor control (e.g., Osman et al., 2008; Witt et al., 2006), Memory (Broadbent, 1977; Gonzalez, Lerch, & Lebiere, 2003), Planning (Dörner, 1989), and Attention (Burns & Vollmeyer, 2002; Gonzalez et al., 2003; Lerch & Harter, 2001).

Despite the many reviews of Complex problem solving (Dörner, 1989; Funke, 2001; Gonzalez, Vanyukov, & Martin, 2005; Gray, 2002; Hsiao & Richardson, 1999; Quesada, Kintsch, & Gomez, 2005), Implicit learning (Dienes & Berry, 1997; Sun et al., 2007), Dynamic learning (Gibson, 2007; Sterman, 2002), Dynamic decision making (e.g., Busemeyer, 2002; Kerstholt & Raaijmakers, 1997; Lipshitz, Klein, Orasanu, & Salas, 2001), and Goal-setting (Locke, 1991, 2000; Locke & Latham, 2002) that have drawn on work using CDC tasks, they have had limited success in bridging the many disparate fields of research.

For example, Busemeyer's (2002) review discusses the various computational models (e.g., Anzai, 1984; Dienes & Fahey, 1995; Gibson, Fichman, & Plaut, 1997; Sutton & Barto, 1998) used to describe the findings from Berry and Broadbent's (1984) sugar factory task, and other laboratory-based CDC tasks. However, the models are based on a small sub-set of the wide range of research on CDC tasks. Likewise, Lipshitz et al.'s (2001) discussion of different theoretical accounts of CDC tasks (e.g., Cohen, Freeman, & Wolf's (1996) Recognition/Metacognition model; Klein's (1998) Recognition-primed model of naturalistic decision making; Lipshitz & Strauss's (1997) RAWFS [Reduction, Assumption-based reasoning, Weighing pros and cons, Forestalling and Suppression] heuristic model), although extensive, focuses on how people behave in CDC tasks after they have developed expertise.

The above reviews examine the theories and evidence within the range of CDC tasks that they were developed to explain, but their focus is too narrow to provide a broad understanding of how the different domains of research on CDC tasks relate to each other. Moreover, while the many theoretical accounts of CDC task behavior may claim that they are generalizable across domains, attempts to do so have thus far been limited. This is problematic, because a continuing lack of unity is likely to produce a great deal of redundancy in research. For instance, many different research domains overlap with respect to critical issues concerning the psychological and task properties that define CDC tasks, contrasts between experts and novices, the success of using measures of cognitive ability to predict performance in CDC tasks, and “scaling up” issues concerning whether cognitive modeling of complex behaviors in the lab can be scaled up to complex environments such as aviation and driving (Kirlik, 2007).

Crucially, the lack of unity in the study of CDC tasks is compounded by a continuing debate as to whether there are in fact underlying associations between the different research domains (Economics, Engineering, Ergonomics, HCI, Management, Psychology) that have used CDC tasks (Buchner & Funke, 1993; Campbell, 1988; Funke, 2001; Gatfield, 1999; Kerstholt & Raaijmakers, 1997; Quesada et al., 2005). In particular, given the difficulty in defining the dynamical and relational properties of CDC tasks, and how complexity is treated (i.e., should research focus on psychological complexity, or task complexity, or the interaction between the two? (Campbell, 1988)), the lack of cohesion amongst the different research domains remains. Clearly then, there is, at the very least, a need to consider how the different research approaches to CDC tasks may relate, in order to achieve a general understanding of psychological behavior in complex dynamic control environments.

## Goal of the Article

The main objective then, is to adopt a unifying approach throughout this review by considering the underlying associations between the theoretical developments and the evidence from the different domains of research on CDC tasks. First, the review presents the theoretical foundations of research on psychological behavior in CDC tasks. To this end, five main classes of theoretical accounts are presented (Exemplar/Instance-learning, Hypothesis-testing, Self-regulation, Expert Adaptive Decision Making, and Computational). Given the wealth of theories, the aim here is to introduce the key claims that they make, in order to identify their family resemblances more easily. It then becomes possible to discuss the various approaches to understanding CDC task behavior in a way that cuts meaningfully across research boundaries. In so doing, this section concludes that the different accounts are unified by the psychological processes that help to reduce uncertainty.

This lays the foundations for detailing the Monitoring and Control framework (hereafter MC framework). Monitoring involves processing the task environment (i.e., Task-monitoring) and tracking actions and decisions in the pursuit of goals (i.e., Self-Monitoring). Control involves the generation and application of relevant actions to reach goals. This section presents the two main tenets of the framework: 1) Uncertainty has a mediating role in Monitoring (Task-monitoring, Self-monitoring) and control behaviors and 2) that there is a reciprocal relationship between Monitoring (Task-monitoring, Self-monitoring) and control behaviors. While the different theories that have been reviewed may share common underlying themes, they have established their own research focus, and the empirical findings in the different domains remain disparate. Thus the function of the MC framework is to provide some basic principles from which research findings across the different research domains can be integrated. From this, the evidence from the different research domains is reviewed, summarized, and integrated with respect to the framework.

The concluding section presents new insights and future directions for research on CDC tasks. First, the final discussion considers how the MC framework provides ways of tackling the following questions: Can we define complexity in CDC task? Are there differences between experts and novices? Is there a relationship between cognitive ability and CDC task performance? What are the effects of practice on CDC task performance? Are their dissociable mechanisms for declarative and procedural knowledge? Are there differences between Prediction and Control? Second, in their work on control behavior in highly skilled engineering environments, Kirlik, Miller, and Jagacinski (1993, p. 933) emphasize that 'without detailed consideration of the task environment human behavior is simply too unconstrained to be effectively modeled.' If we assume that one of the main goals of research on CDC tasks is to model human behavior in complex dynamic environments (Rothrock & Kirlik, 2003), then developing models of the underlying causal relations in the environment, and relating these to how we learn causal relations, and how agency[2] influences this, would be a significant step toward achieving this objective.

## Theories of CDC task behavior

The following section begins by introducing the various theoretical accounts of CDC tasks, in order to discuss their key claims and arguments. There are five classes of theoretical accounts of CDC tasks, each focusing on particular aspects of behavior found in CDC tasks: Exemplar/Instance-learning, Hypothesis-testing, Self-regulation, Expert Adaptive Decision making, and Computational.

### Exemplar/Instance-learning accounts

One of the earliest theories of CDC tasks arose from pivotal work by Broadbent (Berry & Broadbent, 1984, 1987, 1988; Broadbent, Fitzgerald, & Broadbent, 1986) and others (Marescaux, Luc, & Karnas, 1989; Stanley et al., 1989): the Instance-based theory (alternatively referred to as Exemplar theory). The theory proposes that in the early stages of goal-directed learning every encounter with the system generates an instance which comprises the perceptual features of the system and the decisions-actions taken (i.e. the specific input values that were varied on that occasion, and the output value that was generated). Only instances that lead to successful outcomes are stored in memory, in a type of "look-up table" (Broadbent et al, 1986); this determines what response is made by matching the perceptual properties of the current situation to stored instances. Because learning relies on generating responses from memory, there is a distinct lack of analytical thinking about the rules that govern the behavior of the CDC task. Thus, instance based learning leads to successful control of a CDC task, but at the expense of gaining knowledge of the underlying structural properties of it, and with limited transferability of knowledge, because it is bound to tasks that are structurally and perceptually similar to the original training task (Berry & Broadbent, 1987; Buchner, Funke, & Berry, 1995; Lee, 1995; Stanley et al., 1989).

Formal models of Instance-based theory of control learning (Dienes & Fahey, 1995, 1998) like other Instance-based models of learning and memory (e.g., Logan, 1988; Medin & Schaffer, 1978; Nosofsky, Kruschke, & McKinley, 1992) propose that instance-based processes involve a similarity match between environmental cues with previous stored instances. The most similar of which will be activated in memory without reference to any explicit rule that would govern their activation. In contrast, rule-based processes involve directly inferring the relationship between inputs and outputs and forming abstract propositional representations of the structural properties of the task during learning (Dienes & Fahey, 1995). The distinction between instance and rule based knowledge maps onto that of procedural knowledge and declarative knowledge, and are commonly regarded as sub-served by different underlying brain regions[3]. Procedural knowledge includes knowledge of how to perform skills and operations via goal-directed incidental learning, while declarative knowledge includes knowledge of episodes and facts which is propositional in form (Anderson, 1982; Squire, 1986).

Though Gilboa and Schmeidler's (1995) Case-based decision theory describes naturalistic repeated decision making in uncertain environments, theirs is essentially an instance-based theory, and has wide applications in CDC tasks in naturalist decision making environments (see 'Expert

Adaptive Decision-making'). They propose that when faced with a new problem, decisions are made based on the outcome of behaviors in similar previously encountered problems. Given the sample of instances or 'cases,' which consists of details of the prior problem, actions taken, and outcomes generated, the crucial processing step is the comparison of these cases to a new problem scenario. The cases are weighted according to their similarity to the new problem, and as with the Instance-based theories of learning and memory, the most weighted will be triggered in memory, from which a decision will be made.

Gonzalez et al.'s (2003) recent advancement of the instance theory—the IBLT model (Instance-based learning theory)—describes instances as having three properties: the environmental cues in which they arise, the decisions taken at the time that generate the action, and the utility of the outcome of that decision. Their instance theory draws on the work of Gilboa and Schmeidler (1995), by suggesting that instances are essentially decisions made under uncertainty. They retain the basic assumptions of instance-based theory, but in addition propose an analytical component to initial knowledge acquisition which early Instance-based theories do not include. Under situations of high uncertainty, the learner evaluates the best action to take by relying on heuristics (referred to here as contextual factors that guide attentional focus) to determine which cues it is relevant to act upon in the task. As uncertainty decreases, the learner then evaluates the utility of an action by combining the utility from similar instances generated in the past. Therefore, people begin by assessing the relevancy of task information from which to base their decisions, but after extensive interaction with the task they replace this with instance-based learning.

Summary: Early Instance-based theories and models describe instance-based and rule-based knowledge as independent of each other because they are encoded, stored, and utilized entirely differently. Some theoretical developments have retained this idea, for example the case-based decision theory (Gilboa & Schmeidler, 1995) in which the course of action taken is determined by the similarity between a stored instance and a new problem, not by inferences from judgments of the similarity between the two. However, recent developments of the instance theory (Gonzalez et al., 2003) include an initial abstraction process that suggests that inferences are used to evaluate action-outcomes as well as formulating rules about the environment. Moreover, this also signals a shift in theory toward emphasizing the importance of explicit processes, in particular executive functions, such as monitoring, while learning to control a CDC task.

Hypothesis-Testing accounts

Many laboratory-based studies of CDC tasks have examined the effects of different methods of learning on control behavior (Burns & Vollmeyer, 2002; Vollmeyer, Burns, & Holyoak, 1996). Sweller's (Paas, Renkl, & Sweller, 2003; Sweller, 1988; van Merriënboer and Sweller, 2005) Cognitive Load Theory is a cognitive architecture that has been applied to many complex problem solving environments. It outlines the conditions in which expertise is developed, and in particular the way in which goals influence the success of problem solving skills (Sweller, 1988). When goal-directed, the solver is concerned with achieving a particular outcome (i.e. a Specific Goal (SG)) typically through means-end analysis (a method of incrementally reducing the distance between the current and desired end state). Because means-end analysis increases working memory load, only task information that directly bears on the immediate demands of the goal is learnt. This prevents any development of a deep understanding of the underlying properties of the task because there is limited opportunity to evaluate the information that is gained at any one time. For this to occur the problem solver needs to pursue a Non-Specific Goal (NSG). NSGs are constraint-free because knowledge acquisition is based on an exploratory hypothesis testing method which aims to find the best solution to the problem. Without the memory demands imposed by a SG, problem solving under NSG conditions in turn leads to domain general knowledge. The specific methods (e.g., instructions, goals) that Cognitive load theory describes for improving learning and problem solving skill in complex environments have been successfully applied to CDC tasks such as air traffic control (Camp, Paas, Rikers, & van Merriënboer, 2001; Salden, Paas, & van Merriënboer, 2004) and interactive games (Miller, Lehman, & Koedinger, 1999).

Burns and Vollmeyer (2002) offer an alternative to Sweller's (1988) Cognitive load theory of the goal-specificity effect. Their Dual-space hypothesis is a development of Klahr and Dunbar's (1988) and Simon and Lea's (1974) theory of problem solving and scientific thinking (Klahr & Simon, 1999). Rather than relating the effects of goal specificity to different demands of cognitive load, Burns and Vollmeyer (2002) described the goal-specificity effect in terms of the problem solver's focus of attention in the task. Burns and Vollemeyer claimed that a CDC task can be deconstructed into spaces: the rule space, which determines the relevant relationship between inputs and outputs, and the instance space, which includes examples of the rule being applied. Under SG instructions, the instance space is relevant because it is integral to the goal: that is, the solver's attention is focused primarily on achieving a particular instantiation of the rule, not on discovering the rule itself. Because NSGs lead to unconstrained attention is distributed across both instance and rule space. Moreover, searching through the rule space encourages hypothesis testing, which leads to a richer understanding of the underlying structure of the problem (e.g., Burns & Vollmeyer, 2002; Geddes & Stevenson, 1997; Vollmeyer, Burns, & Holyoak, 1996).

Summary: At heart, these theories focus on the relationship between the specificity of the goals pursued and how this can affect the development of expertise. Generally, knowledge acquired under SG instructions is pertinent only to CDC tasks that follow the same goal structure, whereas knowledge gained under NSG instructions is transferable beyond the original learning context. For this reason, Burns and Vollmeyer (2002) have suggested that the types of behaviors associated with instance based learning (see previous section) are consistent with those found under SG learning. Sweller's (1988) Cognitive Load theory claims that the greater expenditure of cognitive effort incurred under SG instructions helps guide the problem solver to the problem goal, but prevents the uptake of knowledge of the underlying structure of the problem. Dual-space accounts claim that the reason for this is because SG instructions focus attention away from the rule space. However, both theories are in agreement that hypothesis testing promotes rule formation, and leads to superior structural knowledge about the system, because the learner is able to examine and evaluate their understanding of the task. This then suggests that rule- and instance-based knowledge combined is more effective in skill acquisition in CDC tasks than instance-based knowledge alone.

### Self-regulatory accounts

While some (Vancouver & Putka, 2000) have proposed that the internal dynamic process involved in attaining and maintaining goals in CDC tasks maps neatly on to control theories developed in cybernetics (Wiener, 1948), others (Bandura & Locke, 2003; Locke, 1991) question whether it is appropriate to draw an analogy between self-regulatory mechanical, biological, and electrical systems (e.g., thermostat, cells, circuits) and humans' self-regulatory control system. However, despite these differences, self-regulatory theories (Bandura and Locke's Social Cognitive Theory, 2003; Locke and Latham's Goal setting theory, 2002; Vancouver and Putka's Control theory, 2000) agree on a number of basic processes (e.g., goal setting, self-efficacy, motivation, evaluation) associated with learning to operate and control CDC tasks.

The general claim of these accounts is that, at the heart of human cognition, are evaluative judgments of the success of self-generated actions, commonly referred to as perceived self-efficacy

(Bandura, 1977), and these help regulate motivational, affective, and decisional processes (e.g., Earley, Connolly, & Ekegren, 1989; Spering, Wagener, & Funke, 2005). Therefore, people's expectancies of their ability to exercise control over their environment determines the goals they assign themselves and the set of actions designed to meet them (Olson, Roese, & Zanna, 1996). A goal is referred to as a standard by which an individual evaluates the feedback received from their chosen action as a 'good' or 'poor' reflection of their performance (Locke & Latham, 1990). Goal directed behaviors are guided by attending to qualitative (i.e. perceived self efficacy) and quantitative (e.g., time, effort) 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, evaluative judgments of self generated actions track goal-relevant information, modulate motivation, and maintain or terminate actions.

Bandura's (Bandura, 1991; Bandura & Locke, 2003) Social Cognitive theory proposes that evaluation of the relationship between behavior and goals occurs in two different ways. Goals can be met through a feedback mechanism, common examples of which include error detection and correction, in which the individual reduces the discrepancy between the actual outcome and the desired outcome (Bandura, 1991; Bandura & Locke, 2003; Karoly, 1993; Lehmann & Ericsson, 1997; Rossano, 2003). Working in concert is a type of feedforward mechanism which involves incrementally setting difficult challenges that broaden one's knowledge and experience of a skill (e.g., Bandura & Wood, 1989; Bouffard-Bouchard, 1990; Wood & Bandura, 1989).

In contrast to Bandura's Social Cognitive theory is Control theory (Miller, Galanter, & Pribram, 1960; Powers, 1978; Vancouver & Putka, 2000). As with the main proposals of cybernetics, negative feedback drives behavior, and so regulation of behaviors is achieved by tracking the discrepancy between a desired goal and the actual outcome of behavior via a negative feedback loop. Through this method, progress is made by modifying behavior to reduce that distance, thereby incrementally progressing toward the goal, but this also depends on the allocation of effort commensurate with one's perceived ability: the greater the ability, the fewer cognitive resources allocated (Vancouver & Kendall, 2006). Vancouver, More, and Yoder's (2008) most recent development of the Control theory captures the dynamic psychological process of control by proposing that there is a single nonmonotonic relationship between self-efficacy and motivation. Self-efficacy determines the amount of time and/or effort required to achieve a goal. The success in achieving a goal will change during interactions with a task, and if in some cases becomes increasingly more difficult to achieve, then this will switch from an online evaluation to a global assessment of the level of progress toward reaching and maintaining the goal. If the estimated probability of reaching a goal drops below a self assigned threshold, and the amount of estimated effort exceeds a certain judged threshold, this will determine whether or not continued effort will be spent in organizing behaviors designed to reach the goal.

Summary: The general consensus amongst Self-regulatory theories is that because controlling a CDC task is a goal-directed pursuit, and because such environments are uncertain, people must track and evaluate their behaviors in relation to the goals they pursue. Usually, identifying the right kind of goals to begin exploration of the task leads to the discovery of relevant strategies, and of the structural properties of the task, for which controlling the task is crucial. Regulatory processes enter into the early stages of acquisition, because monitoring serves as a self-correcting process; but they are also relevant when expertise has developed, because they are a means of building on and extending the reach of more complex goals.

## Expert Adaptive Decision-making

Inherent in theories in the class of adaptive decision-making is the notion of uncertainty and how it affects what people decide to do, and how people differ according to their subjective experiences of uncertainty: i.e., the type of uncertainty experienced by a novice is different from that of an expert (Lipshitz & Strauss, 1997). The theories describe the interactions between individual and complex tasks in terms of a naturalistic dynamic decision-making process. For example, Vicente's (Chery, Vicente, & Farrell, 1999; Jamieson, Miller, Ho, & Vicente, 2007; Vicente & Wang, 1998) work examines human-computer interaction in industrial scale control systems (nuclear power plant, petrochemical production, radio communication, thermo-hydraulic processor).

In the initial stages of controlling a CDC task, many models that take an ecological perspective in describing expertise propose that pattern matching is involved. Cohen, Freeman, and Wolf's (1996) Recognition/Metacognition (R/M) model proposes that, when people interact with CDC tasks, the events (states) that are generated by the system cue related schemas (e.g., knowledge, goals, action-plans) via a recognitional pattern matching. This process bears a close resemblance to that described by instance-based theories.. In Lipshitz and Strauss's (1997) RAWFS model, people begin generating actions, evaluating them, and mentally simulating the outcomes, but are also cued to recall relevant previously stored plans of behavior through pattern matching. People cycle through a process of implementing actions, monitoring the success of their understanding of the task, and modifying them to maintain the desired goal. In Klein's (1993, 1997) Recognition-Primed Decision (RPD) model, the expert decision-maker begins by identifying critical cues, to attain a match between the current situation and previously experienced plans of action. During early interactions with a CDC task attention is focused on evaluating the conditions of the task itself, and by establishing early on what the task demands are then a course of action can be implemented with little need for evaluating behaviors. This tends to be a very robust finding, and is supported by research suggesting that, in long-term memory, expert knowledge is pattern-indexed in relation to domain-specific tasks, including those of fire fighters (Klein & Wolf, 1995), medical doctors (Einhorn, 1974), naval mine sweeping (Randel, Pugh, & Reed, 1996), and nursing (Crandall & Calderwood, 1989).

As interactions with the task progress, the RM model proposes that monitoring and evaluative processes are recruited to help decision makers refine those past actions that may be repeatedly cued to better suit the demands of the task. This is achieved through *critiquing*, which involves identifying sources of uncertainty in the task, and *correcting*, which is designed to reduce uncertainty by searching through memory for relevant knowledge or using cues from the task. Similarly, in the RAWFS model, the decision maker judges their uncertainty in achieving a desired outcome, and if progress is judged to be slow in reducing it, this prompts them to devise plausible alterative actions. If, at any stage, no good action can be identified, or the decision maker cannot differentiate between several sensible options, they resort to suppression. This is a tactical and practical decision that enables the decision maker to continue operating within the system, while ignoring undesirable information, and to develop strong rationales for the course of action that is eventually decided upon. Similarly, the RPD model proposes that extensive interaction with a CDC task prompts diagnostic decision making, and the way in which it is carried out distinguishes expert from novice decision makers. Experts are adept at realizing when they do not have sufficient information to assess the uncertainty generated in a CDC task. The diagnosis is conducted using techniques such as *feature matching* – comparing current situations to previously experienced ones, and *story building* - mentally simulating actions and their consequences. Experts are also adept at recognizing anomalies between current and past situations where as novices are inexperienced in the task domain and so are less to detect them.

Kirlik, Miller, and Jagacinski's (1993) HEI (Human Environment Interaction) model is unlike R/M, RAWFS and RPD in that it focuses on describing the properties of the CDC task domain along side the skilled operator's behavior. In fact, the HEI model avoids separating the interactions between human and environment into stages, because the interaction is cyclic and dynamic, with the operator acting in a constant supervisory control capacity to respond to the frequently changing task demands of the environment. The environment is described according to 'affordances,' which refer to the relationships between the causal structure of the environment and an operator's cognitive capabilities (e.g., work load, experience, working memory capacity, optimality of decision making). Successfully extracting relevant information from the environment enables the operator to shift from resource-intensive inferential processes (problem solving, decision making, planning) to a 'perceptual mode.' Reaching this mode indicates expert decision making, because the same kinds of inferential processes are automatically invoked there, because the diagnostic information for choosing an action has been encoded.

Summary: Expertise is a shift from inefficient processing of the problem space to fluently reducing the uncertainty of the task. As with early knowledge acquisition in Instance/Exemplar-based theories, Adaptive decision making theories describe pattern matching as an essential mechanism, which is able to automatically retrieve relevant action plans from memory. Cohen et al.'s (1996) (R/M) and Lipshitz and Strauss's (1997) RAWFS model discusses the way decision makers utilize their skills to reduce uncertainty. Klein's (1993, 1997) (RPD) model describes how people use their experience to make rapid decisions under conditions of time pressure and uncertainty that preclude the use of analytical strategies. Moreover, the RPD model and much of Vicente's work also considers the impact of pressured high stake CDC tasks on decision making. While Kirlik, Miller, and Jagacinski's (1993) HEI model, and developments of it by Kirlik (Kirlik, 2007; Kirlik & Strauss, 2006) and Jagacinski (Jagacinski & Flach, 2003), specifically concerns the relationship between the structural properties of the task domain and expert dynamic decision making.

Computational Accounts

Connectionist models have provided the most popular formal description of learning mechanisms in CDC tasks, and have also been implemented in general cognitive architectures such as CLARION (Connectionist Learning with Adaptive Rule Induction Online) and ACT-R (Adaptive Control of Thought-Rational).

Neural Networks: Gibson's (Gibson, 2007; Gibson, Fichman, & Plaut, 1997) neural network model assumes that people adapt the knowledge they acquire during learning, based on their mental model of the environment: that is, they develop hypotheses about the input-output relations from which they decide which actions to take. The model makes two basic assumptions about knowledge acquisition in control tasks: 1) People acquire knowledge about how their actions affect the outcomes in the system, and 2) this knowledge is based on which actions are chosen to achieve specific desired outcomes. To achieve this, the model captures learning as two submodels: forward models and action models. The action submodel takes as input the current state of the environment and the specific goal to achieve, and generates as output an action that achieves that goal. The action then leads to an outcome that can be compared with the goal which guides the forward model. This model takes as input the current state of the environment and an action, and generates as output a predicted outcome. The predicted outcome is compared with the actual outcome to derive an error signal. Back propagation is then used to adjust the connection weights between action and predicted outcome, to improve the ability to predict the effects of actions on the environment. Gibson's (2007) later model builds on this by incorporating a process that described how people decide on which action to take online while tackling the changing demands of the environment. To achieve this, the model assumes that people begin by generating possible options and assessing their relative likelihood of success. The cumulative support for each decision option is calculated by summing over the absence and presence of all possible pieces of evidence, weighted by past associations with success. Thus learning is accomplished by continually adjusting the weights based on the decision outcome, which is updated as changes in the CDC task occur.

Similarly, Sun's (Sun, Merrill, & Peterson, 2001; Sun et al., 2005; Sun et al., 2007) CLARION (Connectionist Learning with Adaptive Rule Induction ONline) model has, like Gibson's model, been applied to CDC task behavior in Berry and Broadbent's sugar factory task. The motivation for the model comes from work on both the early stages and advanced levels of skill development. The main claim is that, early on, knowledge development moves from implicit to explicit knowledge: that is, trial and error learning progresses toward hypothesis testing, and, as the success of the action outcomes increases, these instances become regulated by explicit representational structures. With extensive experience of the CDC task, behavior moves from a process of explicit hypothesis testing to the automatic implementation of practiced instances (procedural knowledge referred to as ACS: action-centered subsystem) in combination with representations of the underlying structure and rules governing the task (declarative knowledge referred to as NACS: non-action-centered subsystem). Sun's (Sun et al., 2005; Sun et al., 2007) two recent additions to the CLARION framework are a motivational subsystem (the MS), and a meta-cognitive subsystem (the MCS). The former self-regulates behaviors from the ACS and NACS, whereas the latter functions to monitor and evaluate, by refining and improving the quality of the rules and instances generated by the ACS and NACS.

Probabilistic decision making: Decision Field theory (Busemeyer & Townsend, 1993; Busemeyer, Jessup, Johnson, & Townsend, 2006) formally described dynamic decision making under uncertainty, and has recently been applied to CDC tasks in which the individual chooses between allowing the system to operate automatically, and intervening directly (Goa & Lee, 2006). Dynamic decision making takes on two different meanings in this model: one refers to decision making behavior over time, and the other refers to the multiple interrelated decisions that are made in response to the changing task environment. In general, the model considers how we decide between multiple decisions that are likely to vary in their respective outcomes at different points in time. Thus, the decision maker attaches a particular outcome to each risky option that they must choose between, where a change in choice behavior occurs will depend on the valance of the decision options. Goa and Lee (2006) treat the affect of outcomes as a reflection of the individual's trust in the ability of the control system to execute them. They connect this to perceived self-efficacy (Bandura, 1977) by proposing that the expectation of an outcome, and the fulfillment of it, influences judgments in successfully generating and controlling a desired outcome.

ACT-R is a cognitive architecture that describes goal-directed behavior (Anderson & Lebiere, 1998; Ehret, Gray, & Kirschenbaum, 2000). The components of the cognitive system (i.e., goal, declarative memory, perceptual, and motor modules) contain information that production rules (conditional statements 'if…then') use to carry out a cognitive operation (e.g., problem solving, decision making). There are separate stores of information for declarative knowledge, and for procedural knowledge – represented as production rules that control cognition. Collections of production rules (like action-plans) are formed to carry out a specific task and retrieved via a pattern-recognition system that matches the task demands to previously stored productions. ACT-R has been successfully applied to model behavior in realistic CDC task domains that include navigation of a submarine by submarine-trained officers (Ehret et al., 2000), operating radar control systems (Gray, Schoelles, & Myers, 2002), and air traffic control (Taagten & Lee, 2003).

Summary: Thus far, most models discussed here describe learning and decision making of non-experts in laboratory CDC tasks that are static environments (e.g., Berry & Broadbent's sugar factory task). This is largely because developing formal descriptions of realistic control systems is problematic given that the properties that need to be described (e.g., random fluctuations, probabilistic relationships between cause and effect, non-linearity) are not well understood

(Lipshitz and Strauss, 1997). This is why formal models face an ongoing problem in closing the gap between the aim of modeling (i.e. formally describing the environment and what contributes to it being uncertain, complex and dynamic along with the skilled behaviors developed to manage and control it) and what they are equipped to model (Kirlik (2007).

Family Resemblances

The first integrative step is to consider how the accounts are connected according to their proposals of the psychological processes involved in CDC tasks, and view the tasks themselves.

*Common proposals of psychological behaviors*: For almost all theoretical accounts, the acquisition of instance based knowledge is pivotal to the development of skill learning, particularly when there is a clearly defined goal. This is because a set of decisions and actions can be established early on which map the task demands to previously experienced decisions and actions. While, the accounts are divided as to the stage at which rule-based knowledge is acquired (e.g., initial (e.g., Hypothesis testing accounts) vs. extensive CDC task experience (Exemplar/Instance-learning accounts)), they do make similar claims concerning its involvement in monitoring behaviors. Monitoring involves tracking discrepancies between events based on expectancies which are formed from judging the outcome of goal-directed actions (self-monitoring) or from judging the outcome of learnt input-output relations (task monitoring). Most accounts posit that rule-based knowledge is needed to predict outcomes, and enable flexibility in cases where the task demands require sudden changes in behavior.

Instance and rule-based knowledge has been described as dissociated (e.g., Exemplar/Instance-learning) as well as integrated (e.g., Hypothesis testing accounts, Expert Adaptive Decision making). Despite these differences, there is general agreement across the accounts that expertise depends on the mediation between exploration in order to refine control behaviors, and reinforcement of instance based knowledge through repeated practice. This is because uncertainty is managed by 1) extracting and evaluating relevant task information, on which to base their actions, while also 2) implementing actions without the need to evaluate them. Pursing both ensures that decisions and actions are sufficiently flexible in order to respond to the shifting demands of the situation which requires monitoring behaviors.

*Common proposals of task uncertainty*: The common view of CDC tasks is that they are psychologically demanding because they are uncertain environments, and the source of uncertainty seems to either located at the task level, i.e. Environmental (e.g., random fluctuations, probabilistic relationships between cause and effect, non-linearity) or psychological level (e.g., inaccurately representing the structure of the task, poorly estimating the probabilistic relationship between Inputs and Outputs) (for review see Lipshitz and Strauss, 1997). Given that formal descriptions of the task environment are lacking in most accounts reviewed here, the psychological processes identified are specific to reducing psychological-based sources of uncertainty. The processes involved in reducing uncertainty can be organized as follows: Task-monitoring — tracking the events occurring in the task (e.g., decision-making, hypothesis testing); Self-monitoring — tracking the events occurring as a result of goal-directed behaviors (e.g., goal setting, self-efficacy); Control behaviors-generating goal-directed actions (e.g., pattern matching previous action-outcomes to current goal states).

## Novel aspects of the MC-Framework

The next integrative step is to introduce the MC framework, which describes how Task-monitoring, Self-monitoring, and Control behaviors are involved in CDC tasks. The MC framework differs from previous accounts of CDC tasks in two substantive ways. First, many studies on CDC task accounts have discussed the relationship between uncertainty and control

(Dörner, 1975; Kerstholt, 1996; Klein, 1997; Lipshitz & Strauss, 1997; Sterman, 1989; Toda, 1962), particularly Expert Adaptive Decision-making accounts. Moreover, some (e.g., Bandura & Locke, 2003; Kirlik, 2007) have highlighted that judgments of uncertainty are pivotal to understanding how the environment is perceived and what behaviors are marshaled to control it. However, thus far the relationship between psychological uncertainty and how it guides behavior in CDC tasks has remained unspecified. The innovation of the MC framework is to propose that all CDC tasks generate psychological uncertainty which can be indexed according to: 1) people's subjective confidence in predicting outcomes of events in a CDC task (predictability of the environment), and 2) their expectancy that an action can be executed that will achieve a specific outcome (predictability of control). Uncertainty influences control behaviors in the same way regardless of expertise in the task because complete knowledge of the environment cannot be achieved, and processing costs are high (e.g., loading on working memory, processing time of task information), which can raise uncertainty (for real world examples, see Degani, 2004; Hoffman, Shadbolt, Burton, M, & Klein, 1995; Sheridan, 2002).

Second, what has been overlooked in previous accounts of CDC task behavior is that monitoring and control behaviors change over time, and the source of change is most often, though not exclusively, the result of perceived judgments of uncertainty[4]. The MC framework proposes that as representations of uncertainty change so too will the behaviors involved in trying to reduce it. Indeed, recent neuropsychological, (e.g., Daw, Niv & Dayan, 2005; Huettel, Song, & McCarthy, 2005; Yu & Dayan, 2005), behavioral (e.g., Kording & Wolpert, 2006), and computational (e.g., Chater, Tenenbaum, & Yuille, 2006) work uses Bayesian learning algorithms to describe how estimations of the uncertainty of outcomes of actions influences the decisions people make and how prediction accuracy can change as a consequence of the dynamic properties of the environment. Thus, adapting to any uncertain environment requires that control behaviors (i.e. goal-directed decision and actions) are flexible, and successful adaption depends on the accuracy of estimations of uncertainty.

What are Monitoring and Control behaviors?

Thus far, what has been established is that CDC tasks are uncertain environment that may be changing, either as a consequence of our actions, or autonomously, or both, and that goal-directed behaviors are recruited to reduce uncertainty. This can be in terms of determining the outcome through direct interactions with the environment (control), developing an understanding of the environment (task-monitoring), and tracking the relationship between actions and outcomes (self-monitoring). Because monitoring and control behaviors have been referred to in many different ways, the aim here is to clarify what they mean with respect to the MC framework.

Control behaviors: Control behaviors are goal-directed, that is, they involve the generation and application of actions designed to generate a particular future event (e.g., Lerch & Harter, 2001; Locke & Latham, 2002; Rossano, 2003; VanLehn, 1996; Vollmeyer et al., 1996). Actions are generated either by mapping previous experiences of a control task to the current situation, or developing them online. In the latter case people quickly develop expectations of the likely outcomes of self-generated events from relatively little experience of the conditional relationship between the two (Bandura 1989). Also, close temporal proximity between self-initiated actions and outcomes in the world helps to bind these events, and to form causal representations (Lagnado & Sloman, 2004). Therefore, as purposive actions, control behaviors contribute to our sense of agency (Bandura, 2001; Pacherie, 2008)[5]. Control behaviors reduce uncertainty because determining the outcome through direct intervention generates feedback about the outcomes produced in the task environment which can be used to update the individual's understanding of the task.

Task-monitoring: To manage a complex dynamic environment successfully people need to understanding the task itself which requires task-monitoring. This involves processes that draw from memory prior knowledge that informs assumptions about the task (Cohen et al., 1996; Klein, 1993), or developing hypotheses online from the available information in the task. Processes that draw from memory may be either cognitively expensive (e.g., decision making, hypothesis testing, hypothetical thinking) or inexpensive (e.g., pattern matching). Hypothesis testing enables the development of structural knowledge of the task, by regularly updating and integrating feedback from the predictions of outcomes (e.g., Burns & Vollmeyer, 2002), while hypothetical thinking enables the simulation of various outcomes if prior relevant knowledge to test hypotheses is not available (Klein, 1993; Papadelis, Kourtidou-Papadeli, Bamidis, & Albani, 2007). Task monitoring behaviors reduce uncertainty by generating testable predictions about the behavior of the environment, the feedback of which can be used to update the individual's knowledge of the environment.

Self-Monitoring: To manage an uncertain environment effectively involves self monitoring behaviors that track and evaluate the effectiveness of plans of action that have been implemented to reach a desired goal. Failing to accurately track the relationship between self-generated actions and decisions and outcomes in the environment can have severe consequences in the real world (e.g., disasters in aviation [1996 Charkhi Dadri mid-air collision], nuclear power systems [i.e., Chernobyl disaster], and rail [China Railway train disaster T195], as well as more frequently in the context of automated driving systems (Degani, 2004). Self-monitoring offers an adaptive advantage, because regularly assessing the effectiveness of actions can prompt quick adjustments in behavior in order to respond to the changing demands of the environment[7]. Many (e.g., Goldsmith & Koriat, 2003; Smith, Shields, & Washburn, 2003) have argued that conditions of uncertainty require a supervisory mechanism like monitoring because scrutinizing self-generated actions and their effects reduces human and animals' (Kornell, Son, & Terrace, 2007)[6] experiences of uncertainty.

Main tenets of the MC-Framework

Central to the MC framework is psychological uncertainty which is based on two types of judgments (predictability of the environment & predictability of control) and its influences on monitoring and control behaviors. It is important to distinguish between the kinds of effect that psychological uncertainty may have based on high and low experiences of uncertainty.

Experiences of high uncertainty indicate that the environment is unpredictable and unstable. This may lead to behaviors designed to explore the task, which will prompt a change in the goal-directed actions produced with the aim of controlling the environment and better understanding how it operates (e.g., Korbus, Proctor, & Holste, 2001). But, a sustained experience of high uncertainty may also lead to the abandonment of accurate hypotheses, which will also affect goal directed actions, and turn a seemingly controllable system into an impossible one (Osman, 2008a, 2008b). Experiences of low uncertainty indicate that the environment is predictable and stable (Latham & Locke, 2002), and can successfully lead to identifying good strategies to adjust goal directed behaviors as and when the environment fluctuates (e.g., Coury, Boulette, & Smith, 1989; Seijts & Latham, 2001; Wood & Bandura, 1989). However, this type of experience may also encourage the persistence of inappropriate strategies, because well-rehearsed behaviors are easily implemented, and there is less scrutiny of the events in the environment, and so if undetected can quickly increase uncertainty and reduce control (Dörner, 1989). From this, the first tenet proposed is

1. Psychological uncertainty mediates monitoring (task-monitoring, self-monitoring) behaviors each of which in turn affect control behaviors. High uncertainty will lead to

continuous monitoring of the task and goal directed actions, and low uncertainty will lead to periodic monitoring of the task and goal directed actions

Across the many interactions an individual has with a CDC task, their experience of uncertainty will fluctuate. This is why changes in performance have been reported, although they might be expected to stabilize after lengthy exposures to a CDC task (Sterman, 1989; Yeo & Neal, 2006). The MC-framework describes the relationship between Monitoring (self-monitoring, task-monitoring) and control as reciprocal. Monitoring (self-monitoring, task-monitoring) and control alternate in a cascaded pattern (Koriat, 1998; Koriat, Ma'ayan, & Nussinson, 2006), with the outcomes generated from goal-directed actions (i.e. control behaviors) serving as the input for adjusting knowledge of the relationship between inputs and outputs (Task-monitoring), and adjusting evaluations of the success of self-generated actions (Self-monitoring) . From this, the second tenet proposed is

2. There is a reciprocal relationship between monitoring and control behaviors. The relationship between both types of monitoring behavior and control behavior involves feedforward from monitoring to control, to generate appropriate control behaviors, and feedback to update knowledge of the task, and knowledge of the status between desired and achieved outcomes.

The following discussion relates the key findings reported from studies on CDC tasks to the MC framework, by specifying how they can be grouped according to the two main tenets, as presented in Table 1. The full list of studies is presented in Table 1 are concerned with psychological phenomena found under conditions of either high or low uncertainty[8]. The framework proposes that, by examining changes in psychological uncertainty, it is also possible to describe the effects that these will have on monitoring and control behaviours, and on the reciprocal relationship between monitoring (task-monitoring, self-monitoring) and control behaviors. Therefore, the explication of the tenets of the framework, and how they apply to CDC task phenomena, is organized according to what happens under high and low experiences of psychological uncertainty[9].

Insert Table 1. about here

Task-Monitoring behaviors:

The general classes of behaviors that are associated with task monitoring across the different research domains under high and low experiences of uncertainty are as follows: the reliance on biases, the applicability of previously learnt behaviors through pattern matching, the accuracy of task knowledge, and the development of strategies.

*High uncertainty*: Einhorn and Hogarth (1981) claimed that biases reflect the response tendencies that are typically functional in dynamic environments. Biases are assumptions that people make about the behaviour of the task, and are designed to reduce uncertainty by generating hypotheses to test, or for predicting outcomes that are likely to occur (Brehmer, 1992; Coury, et al, 1989; DiFonzo & Boridia, 1997; Shanteau & Stewart, 1992). They economize the search through task information that may be relevant based on prior expectancies (Degani, 2004). Both experts and novices are susceptible to biases, particularly under highly pressurized conditions in which immediate actions need to be generated in response to the demands of the environment (e.g., Kreuger, 1989; Lichacz, 2005), or because there simply is not enough information to decide on, or to predict, the outcome in the environment (Degani, 2004; Klein, 1997; Orasanu & Connolly, 1993; Sauer et al., 2008). The most common biases involve assumptions such as one-to-one mapping of inputs to outputs (Schoppek, 2002), or that the action-outcome links are salient (i.e., their simplicity, plausibility, cause, and effect conform to expectations) (Berry & Broadbent, 1988; Chmiel & Wall, 1994). The input-output links are also assumed to be positive (Diehl & Sterman, 1995; Sterman, 1989), linear (Brehmer, 1992; Strohschneider & Guss, 1999), and unidirectional

(Dörner, 1989). People are also biased towards inferring that changes occur only as a result of their actions (Kersholt & Raaijmakers, 1997), and expectancies of effects of their actions are assumed to be immediate, and long temporal delays between actions and effects tend to be forgotten or ignored (Bredereke & Lankenau, 2005; Brehmer, 1992; Degani, 2004; Diehl & Sterman, 1995; Kersholt & Raaijmakers, 1997).

These biases, while offering a basis on which to test hypotheses and develop plans of actions that can advance the individual towards a goal, interfere with forming accurate representations of the environment, and prolonged reliance on biases leads to poor task knowledge, and poor control. As with biases, pattern-matching is a speedy means of isolating any features of the task that may relate to previous experiences of similar situations (Berry & Broadbent, 1984, 1987, 1988; Degani, et al, 2006; DeShon & Alexander, 1996; Hunter, et al, 2000; Schmitt & Klein, 1996), and these can be used as a basis for developing appropriate strategies (e.g., Kobus, Proctor, & Holste, 2001). However, evoking previously developed plans of actions through pattern matching may also lead to ineffective strategy application, and if such plans are inappropriate for the current CDC task then inaccurate knowledge of the task develops (Brandouy, 2001; Brézillon, et al, 1998; Dienes & Fahey, 1995; Geddes & Stevenson, 1997; Diehl & Sterman, 1995; Monxes (2000). This is further compounded under conditions of high uncertainty, because unsuccessful strategies can be difficult to identify, and people are also reluctant to change them after they have invested some effort in developing them (Bisantz, et al,2000; Brehmer, & Dörner, 1993; Gonzales, et al, 2003; Kleinmuntz, 1985, Langley & Morecroft, 2004). Moreover, it is easier to maintain consistency in hypothesis testing behavior in a changing environment than it is to continually shift decisions, particularly with time dependencies, and when there are time restrictions on taking actions (Langley & Morecroft, 2004).

*Low uncertainty*: Because the process of detecting action-outcome associations is more accurate because the environment is easier to predict under low uncertainty, there is less reliance on biases (Dorner, et al, 1983; Schoppek, 2002; Sterman, 1989, 2002; Strohschneider & Guss (1999). However, pattern matching is still relied upon but for the reasons that there is a close match between the prior experience and task behavior and so previously stored knowledge can be applied quickly to the task (Degani et al, 2006; Klein & Hoffman, 1993; Mosier, et al, 2007; Pomerol & Brezillion, 1999, 2001; Strauss & Kirlik, 2006). In addition, task knowledge more accurately reflects the actual environment, because predicted outcomes from hypothesis testing are easier to detect (Anzai, 1984; Buchner, et al, 1995; Christoffersen, et al, 1998; Chmiel & Wall, 1994, Monxes, 2000; Fredrickson & Mitchell, 1984, Rasmussen, 1985). However, in highly familiar settings in which expertise is relied upon, misperceiving delays in outcomes, or the severity of the consequences of failing to accurately control the outcome is more likely (Gonzales, et al, 2003; Kleinmuntz, 1985; Strohschneider & Guss, 1999; Langley & Morecroft, 2004; Thomas & Russo, 2007).

Self-Monitoring behaviors

Self-monitoring refers to a host of behaviors that have a supervisory role in regulating many cognitive functions (e.g., conflict monitoring, conflict detection, overriding pre-potent behaviors, self-evaluation) in complex problem solving domains. Moreover, in the social cognition domain, self-monitoring includes judgments of self-efficacy, which is distinct from self-monitoring in the MC framework. The focus here is on discussing behaviors that track self-generated actions. From this, studies that have examined behavior of this kind under high and low experiences of uncertainty are known as detection and recall of action-outcomes.

*High uncertainty*: People's ability to successfully isolate action-outcome associations in the task environment is commonly reported to be poor (Broadbent, & Ashton, 1978; Gonzales, et al, 2003; Jensen & Brehmer, 2003; Kluge, 2008b; Kobus, et al, 2001; Sarter, et al, 2007; Sauer et al, 2008); this is because the task environment appears unstable, and unpredictable. Consequently, accuracy in recalling action-outcome associations is also degraded, because of the high demands placed on working memory at the time in which the individual experiences uncertainty (e.g., Metzger & Parasuraman, 2006). More specifically, accuracy in recalling action-outcome associations is specific to events in which successful outcomes were achieved. This is because people ignore those actions that lead to unpredicted or negative outcomes (Bucher, Funke, & Berry, 1995; Stanley et al., 1989; Vicente & Wang, 1998).

*Low uncertainty*: Studies in which high accuracy of detection and recall of action-outcome associations is demonstrated (Lipshitz & Barak, 1995; Kluge, 2008b; Kobus et al, 2001; Sauer, et al, 2008; Vicente, et al 2001) suggest that the effects of actions and decisions are easier to isolate because the behaviors themselves are either well practiced, or salient to the individual (e.g., Buchner, Funke, & Berry, 1995).

Relationship between Monitoring (task-monitoring, self-monitoring) and control

There is strong support for a reciprocal relationship between monitoring (task-monitoring, self-monitoring) and control behaviors in complex decision making environments in studies of Economics (DiFonzo, et al, 1998; Earley, et al, 1990), Engineering (Kirlik et al., 1993; Jagacinski & Flach, 2003), Ergonomics (Farrington-Darby & Wilson, 2006; Kaber & Endsley, 2004), HCI (Brézillon, et al, 1998), Management (Aitkins, Wood, & Rutgers, 2002), Problem solving (e.g., Osman, 2008b), and Social cognition (Cervone, Jiwani, & Wood, 1991; Chesney & Locke, 1991; Kanfer et al., 1994).

*High uncertainty*: Concurrent monitoring (task-monitoring, self-monitoring) of control behaviors is commonly reported under experiences of high uncertainty (Cohen, et al, 1996; Dörner, 1989; Goa & Lee, 2006; Jamieson, et al, 2007; Sarter, et al, 2007). In general, difficulty in organizing plans of action designed to reduce the discrepancy between one's current and desired goals leads continual monitoring of behaviors (e.g., Bredereke & Lankenau, 2005; Degani, 2004; Degani, Shafto, & Kirlik, 2006; Sarter, Mumaw, & Wickens, 2007; Thomas & Russo, 2007). Many real-world examples involve this type of resource-intensive online monitoring that requires continual feedback from control behaviors, particularly in critical safety situations (e.g., air traffic control, automated piloting). In such cases, the user is highly skilled but, without accurate monitoring (task-monitoring, self-monitoring), there may appear to be a lack of continuity between the perceived state of the control system and the actual state of the system (e.g., Degani, 2004; Degani, Shafto, & Kirlik, 2006; Sarter, Mumaw, & Wickens, 2007).

Often, resource allocation is not well calibrated to the task (e.g., Camp, et al, 2001; Diehl & Sterman, 1995; Gonzales, 2005; Joslyn & Hunt, 1998; Yeo & Neal, 2006), because the individual is unable to gauge accurately the distance between the current status of the CDC task and the intended target (e.g., Diehl & Sterman, 1995; Jones & Mitchell, 1994). Consequently, there is often no relationship between performance and effort (Gonzalez, 2005; Vicente & Wang, 1998). Poor resource allocation is also evident in the way in which attention is directed toward actions and their outcomes in the task (Lipshitz & Strauss, 1997). While there is greater vigilance—or sustained attention to the task—people are unable to prioritize the relevant feedback from their actions, and so there is more attentional shifting (Patrick & James, 2004). For example, Metzger and Parasuraman (2006) examined expert air traffic controllers in a simulated task, in which they varied the air traffic (high traffic load, low traffic load). Under highly uncertain conditions, the controllers found it harder to detect and assess the outcome of the decisions they made in the task.

In laboratory-based control tasks of the sugar factory kind, contradictory feedback from the actions taken is harder to resolve when the environment to be controlled appears unpredictable (Kersholt & Raaijmakers, 1997). Moreover, such conditions can disrupt the way in which feedback from action outcomes is re-interpreted (Atkins, et al, 2002; Bredereke, & Lankenau, 2005; Brehmer & Allard, 1991; Osman, 2008b; Goa & Lee, 2006; Mosier, et al, 2007; Sterman, 1989), and used to generate different plans of action, and so inaccurate assessments distort the distance between achieved and target goals, leading to poor control performance (Osman, 2008a).

*Low uncertainty*: The alternation between monitoring (task-monitoring, self-monitoring) and control behaviors is less frequent when the individual judges the environment to be sufficiently familiar to draw on highly practiced plans of actions (Cohen, et al, 1996; Kaber & Endsley, 2004; Goa & Lee, 2006; Hunter, et al, 2000; Kirlik, 2006; Kleinmuntz, 1985; Sarter, et al, 2007; Vicente, et al, 2001; Yeo & Neal, 2006), or is deemed predictable enough to plan actions and decisions online (e.g., Hogarth & Makridakis, 1981; Kersholt, 1996). Typically, people feels confident of judging accurately the outcome of their actions, and so this lowers the demand on cognitive resources (Camp, et al, 2001; Jones & Mitchell, 1994; Kluge, 2008a, 2008b; Mosier, et al, 2007; Orasanu & Connolly, 1993; Vincente, 2002; Yeo & Neal, 2006), because a highly familiar series of planned actions or decisions, which do not do require continual tracking of action-outcome, are implemented (e.g., Metzger & Parasuraman, 2006). For the same reason, other behaviors that have been commonly reported under these conditions include reduced attention to feedback from the actions and decisions taken (Kaber & Endsley, 2004; Kleinmuntz, 1985; Kirlik & Strauss, 2006; Lerch & Harter, 2001; Moxnes, 2000; Mosier, et al, 2007). However, when goals need to be changed, in response to changes in the task, responses can be adjusted to the demands of the task, and advance the individual towards their target goals more efficiently, without regular monitoring.

## Stimulating Debate

The concluding section of this article presents new insights and future directions for research on CDC tasks. Having drawn together the theoretical and empirical findings, the MC framework is used here as a way to address critical questions concerning the study of CDC tasks: How do we define complexity? What are the differences between experts and novices? What is the relationship between cognitive ability and CDC task performance? What are the effects of practice on CDC task performance? Are there distinct functional mechanisms that support declarative and procedural knowledge? What are the differences between Prediction and Control?

The aim of the concluding section of this article is also to discuss future research directions, and in doing so to draw attention to the potential of the CDC task paradigm for examining the role of causal learning and agency in complex dynamic environments.

## New Insights into Old Issues

*Can we define complexity in CDC task?* There have been considerable efforts to identify complexity in complex problem solving contexts (Buchner & Funke, 1993; Campbell, 1988; Funke, 2001; Gatfield, 1999, Jonassen & Hung, 2008; Kerstholt & Raaijmakers, 1997; Quesada et al., 2005). As yet, however, there has been no agreement on how it should be defined. In the main, from the variety of definitions of complexity that exist, complexity is determined by the objective task characteristics (e.g., transparency, time variance (dynamic, static), the number of information cues, cue intercorrelations, cue reliabilities, cue validities (i.e., task predictability, function forms (i.e., linear, curvilinear, stochastic, deterministic etc.)), and feedback (delayed or immediate)). For instance, even when individuals have become highly skilled, certain objective task characteristics of a CDC task may produce highly erratic and damaging outcomes (e.g., Degani, 2004; Hunter, Hart, & Forstye, 2000; Thomas & Russo, 2007). However, problems have arisen because defining complexity in this way has not always been a successful predictor of performance on CDC tasks (e.g., Campbell, 1988; Quesada et al., 2005). However, direct comparison of CDC tasks on multiple dimensions of task complexity has yet to be investigated, and until work of this nature is conducted, this issue will remain. Regardless, complexity may also be the result of psychological factors, for instance, Campbell (1988) claims that that factors such as self-doubt, anxiety, and fear can make a CDC task appear complex, while Bandura (1989, 2001) basis this in terms of self-efficacy, and Sterman (1989, 1994) suggested misperceptions of task properties make a task appear complex.

The implications here are that, objective task characteristics may not be sufficient to capture what makes a CDC task complex, and that, in part, it may be that complexity is in the eye of the beholder (Degani & Heymann, 2002; Kleinmuntz, 1985). So, a pragmatic way of approaching the issue of complexity is to examine what the underlying factors are that reliably lead to deterioration as well as improvements in performance in these tasks. From the vast work on CDC tasks reviewed here, the one most reliable factor appears to be psychological uncertainty. More generally, beyond CDC tasks, belief updating models that use Bayesian algorithms formally describe how subjective uncertainty influences they way people make decisions in probabilistic and dynamic environments similar to those in CDC tasks. Until formal descriptions of the CDC task environment can be developed, the best solution to defining complexity is in terms of psychological uncertainty, which the MC framework has operationalized, and for which there are existing formal descriptions of (e.g., Chater, et al, 2006; Tenenbaum, Griffiths, & Kemp, 2006).

*Are there differences between experts and novices?* What makes an expert? How do they differ from novices? These questions have been the source of much debate (Bandura & Locke, 2003; Ericsson & Lehman, 1996; Karoly, 1993; Lerch & Harter, 2001; Rossano, 2003; Sweller, 1998; VanLehn, 1996). Sweller (1998) proposed that at a representational level, one way to distinguish novices from experts is that what a novice sees as separate experiences of a task, an expert can put together as a single recognizable configuration (Schema). At a processing level, examples of experts' superior processing prowess compared with novices in CDC tasks, include well-developed metacognitive abilities (Cohen et al., 1997), situational awareness (also referred to as pattern matching) (Kirlik & Strauss, 2006; Klein & Hoffman, 1993), accuracy of memory recall of action outcomes tied to specific goals (Vincente & Wang, 1998), and the ability to forward reason (i.e., simulation of prospective outcomes) (Patel & Groen, 1991). However, having reviewed these studies in the context of laboratory and real world examples of CDC task behavior, there are commonalities between early formation of skill as well as extensive training in CDC tasks. The MC framework proposes that, under conditions judged highly uncertain, experts can fall into the same traps as novices, and return to default-based assumptions or make errors in judgment, and their control performance degrades much in the same way as novices.

*Is there a relationship between cognitive ability and CDC task performance?* The relationship between cognitive ability and control performance has a long history in research on complex problem solving. However, the evidence that IQ can predict performance in CDC tasks is unclear: some have observed associations (e.g., Gonzalez, 2005; Joslyn & Hunt, 1998; Rigas, Carling, & Brehmer, 2002) between the two, and others have reported dissociations (e.g., Gebauer & Mackintosh, 2007; Kanfer & Ackerman, 1989; Rigas & Brehmer, 1999). For Instance-based theorists (e.g., Berry & Broadbent, 1987, 1988; Dienes & Berry, 1997), the lack of association between IQ and control performance also supports the position that, for early skill acquisition, people rely on implicit processes that are not tracked by IQ measures (Gebauer & Mackintosh, 2007).

This has become a puzzling issue, particularly because control tasks appear to be good measure of executive functions that should be indexed by general measures of cognitive ability (for discussion see Funke, 2001). One reason why there is mixed evidence concerning this is that control performance may be more accurately indexed by perceived estimates of uncertainty rather than of cognitive ability (Kluge, 2008a). If so, as proposed in the MC framework, the mixed findings concerning associations between IQ and control performance may be alternatively explained according to people's subjective experiences of uncertainty, and this third factor may help to account for when associations between ability and performance are found or absent.

*What are the effects of practice on CDC task performance?* It is perhaps strange that, given the general processing difficulty commonly attributed to operating CDC tasks, the training procedure in laboratory versions of CDC tasks tends to be rather short (between 12 and 40 trials) (Berry & Broadbent, 1988; Burns & Vollmeyer, 2002; Lee, 1995; Sanderson, 1989; Stanley et al., 1989). Consequently, such limited training in CDC tasks also maintains people's experiences of uncertainty. However, strong evidence suggests that extended practice alone does not, in turn, reliably lead to improved performance (Gonzalez, 2004; Kanfer et al., 1994; Kerstholt, 1996; Kerstholt & Raaikmakers, 1997). However, in real world CDC task domains there is evidence that extended practice facilitates accurate reportable knowledge and improves skill (e.g., Lipshitz et al., 2001). In addition, if the extended training also includes instructions that encourage meta-cognitive thinking, then this improves task knowledge (Beradi-Coletta et al., 1995; Gatfield, 1999), longer retention of the newly acquired skills (Linou & Kontogiannis, 2004), appropriate goal setting (Morin & Latham, 2000), and better resource allocation (Brehmer & Allard, 1991).

Again, the mixed findings concerning the relationship between practice and improved skill can be viewed in the context of the MC Framework. Regardless of practice, if experiences of uncertainty are maintained, then no improvements in control behaviors will be observed. Therefore, it is important to identify experiences of uncertainty in conjunction with training methods in order to understand their effects on performance.

*Are their dissociable mechanisms for declarative and procedural knowledge?* Since Berry and Broadbent's (1984) seminal study, there have been nearly 300 citations of their work. It has been pivotal in maintaining the prevailing view that instance based learning underpins early skill acquisition in CDC tasks, and that knowledge is procedural-based. The main proposal is that instance based learning produces procedural knowledge, and that the way in which this knowledge is acquired is inaccessible to consciousness, and dissociated from declarative knowledge of the CDC task. This view remains popular amongst researchers studying skill acquisition in laboratory based (e.g., Eitam, Hassan, & Schul, 2008), as well as real world CDC tasks (e.g., Gardner, Chmiel, & Wall, 1996).

Common to studies that have shown dissociations between procedural and declarative knowledge in CDC tasks is the prevention of monitoring behaviors designed to evaluate action-outcomes and input-output associations. Many classic studies that claim dissociations (Berry, 1991; Berry & Broadbent, 1984, 1987, 1988; Lee, 1995; Stanley et al., 1989) instruct people to avoid hypothesis-testing during learning, or do not provide sufficient information for them to track their history of decisions and action-outcomes during learning - which has also been known to prevent hypothesis testing (Burns & Vollmeyer, 2002; Sanderson, 1989). Furthermore, in all studies demonstrating dissociation, tests probing task knowledge and recognition test of self generated behaviors are always presented at the end of the learning period. This is a methodological rather than a psychological factor because presenting knowledge tests after, rather than during the actual time at which it is acquired, indexes less accurate memory of the events that occurred in the task (Chmiel & Wall, 1994; Shanks & St John, 1994). When regular tests of knowledge are presented during learning, association rather than dissociation between procedural and declarative knowledge is found (Burns & Vollmeyer, 2002; Dandurand et al., 2004; Gonzalez, 2005; Osman, 2007, 2008a, 2008b). Similarly, a close correspondence between declarative and procedural knowledge has been founding using process tracing techniques. This refers to using verbal protocols in conjunction with other measures of self and task knowledge during different stages of experts control performance (e.g., blast furnace operators, nuclear reactor technicians, submarine operators, super tanker engine controllers - for review see Patrick and James, 2004).

As has been suggested, dissociation between procedural and declarative knowledge relies on the prevention of concurrent monitoring behaviors during learning, and presenting knowledge tests at the end of learning. The MC Framework proposes that monitoring and control behaviors have a reciprocal relationship, and therefore there are no dissociable learning mechanisms that support procedural and declarative knowledge, because both types of knowledge are generated from monitoring and control processes.

*Are there differences between Prediction and Control?* Alongside research on control behavior in dynamic environments, there has been a long tradition of research founded on Brunswik's Lens Model, which examines predictive behavior in uncertain decision making environments (for review see Karelaia & Hogarth, 2008). In essence, Brunswick's model describes how we utilize "seen" information from the environment in order to make inferences about the "unseen," and compares this with the actual structure of the environment. One paradigm designed to exploit this comparison has been multiple cue probability learning (MCPL) tasks. Through a series of trials, an individual learns the probabilistic relationship between multiple cues (e.g., symptoms) and outcomes (e.g., diseases), by predicting the outcome of each trial based on the particular pattern of cues. Feedback on predictions comes in the form of either outcome feedback (e.g., the particular disease for that trial), or cognitive feedback (e.g., information about the relationship between symptoms and a disease).

In general terms, MCPL and CDC tasks can be viewed as sharing fundamental characteristics: From limited available information, an individual learns either to predict, or to control, a probabilistic and often dynamic environment. Some have drawn attention to this similarity (e.g., Bisantz et al., 2000; DeShon & Alexander, 1996) and have applied the lens model to describe judgment strategies in CDC tasks (e.g., simulated dynamic Anti-air warfare) (Bisantz et al., 2000; Degani, Shafto, & Kirlik, 2006; Rothrock & Kirlik, 2003). In the social cognition domain, the connections made between CDC tasks and MCPL tasks are based on goal-setting behaviors. In complex MCPL/CDC tasks, in which specific goals are set, the strategies that are developed are often too simple, and inappropriate to meet the demands of the goal (e.g., Burns & Vollmeyer, 2002; Cervone et al., 1991; Earley et al., 1990). However, following general goals (e.g., 'do your best', 'explore the task') enhances predictive/control behavior, and a less constrained approach increases the likelihood of attending to relevant task cues that increase the accuracy of task knowledge (Locke & Latham, 1990). This has led some theorists to suggest that the way in which people judge self-efficacy is central to understanding how they learn about MCPL tasks (e.g., Bandura & Locke, 2003; Locke & Latham, 1990, 2002). As has been proposed in the MC framework, the second tenet outlines the relationship between monitoring and control in terms of feedback from the success of outcomes from self-generated actions, as well as feedforward estimations of the success of future actions. Therefore, prediction contributes to judgments of the uncertainty of the environment as well as developing methods to reduce it.

## Agency and Causality

*Reciprocal relationship between Agency and Causality:* The interpretation of the relationship between causality and agency offered by the MC framework is that it is reciprocal, in that people treat the task environment as an uncertain one, and that, if there are factors contributing to dissonance between the predicted and actual outcomes, this will further reduce people's sense of agency which is a reflection of their ability to control the outcome in the CDC task and uncertainty, and disrupt their causal understanding (e.g., their representations of the input-output associations in the CDC task). For example, in studies of CDC tasks, judgments of self-efficacy have used as an index of agency, and been shown to have powerful effects on causal knowledge (Jensen & Brehmer, 2003; Osman, 2008a). Osman (2008a) revealed that high judgments of self-efficacy in turn led to the successful identification of causal structures in the CDC task, and to better control performance, which in turn lead to further increases in self-efficacy. However, low judgments of self-efficacy disrupted the way in which self-generated actions and their outcomes were perceived. Control performance suffered, and causal knowledge of the system was impaired, and further reduced the subsequent judgments of self-efficacy. Findings of this kind (e.g., Bandura & Wood, 1989; Bouffard-Bouchard, 1990; Osman, 2008a; Woods & Bandura, 1989) highlight the reciprocal relationship between agency and causality (Bandura, 2001; Pacherie, 2008). Correspondingly, findings on the temporal factors affecting control performance in CDC tasks indicates the same type of relationship between agency and causal knowledge based on action and their effects. The consensus is that long delays in experiencing effects from actions generated in the task are difficult to integrate, and so people reduce their expectancies of the effects because they have not been immediately experienced (Diehl & Sterman, 1995; Gibson, 2003; Kersholt & Raaijmakers, 1997). Consequently when the delayed effects are actually experienced, people interpret them as resulting from an unpredictable system, and so they reduce their expectancies of controlling it which undermines their sense of agency (Diehl & Sterman, 1995; Moxnes, 2000).

Insights into the relationship between agency and causality can also be found in work on perception-action associations in simple motor behaviors (Hommel, 1998). To initiate actions, there needs to be some anticipation of the effects they will produce, much like formulating a hypothesis about the outcome of an action in a CDC task. In turn, attending to the corresponding causal dependency is crucial: if it goes unnoticed, this will result in the failure to perceive an outcome-action (Elsner & Hommel, 2001; Flach et al., 2005) as well as action-outcome associations, and a decrease in any anticipatory behavior (Elsner & Hommel, 2004). Only in the case in which we have attended to a regular causal relationship between an intended action and an outcome can we form a representation that enables a sense of agency to develop (Hommel, 2003).

In addition, the cognitive neuroscience and motor control literatures suggest that our sense of agency depends strongly 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 the predicted and observed outcomes (Osman, Wilkinson, Beigi, Castaneda, & Jahanshahi, 2008). Although David, Newen, and Vogeley (2008) highlight the limits of perception-action research in understanding the relationship between agency and causality, they share the same view as Bandura (2001), in proposing that the reciprocal relationship between causality and agency needs to be understood in terms of environmental, cognitive, and biological events.

A real world example in which causal knowledge and our sense of agency have consequences in controlling a CDC system is cars. If the vehicle breaks down, the driver must diagnose the cause of the failure (casual knowledge) (Klostermann & Thüring, 2007), and judge their capacity to control it (sense of agency) (Degani, 2004). However, these issues do not only arise during vehicle break down, but also as a result of the continued development of automated functions (e.g., Electric Power Assisted Steering (EPAS), Semi-Automatic Parking (SAP), Adaptive Cruise Control (ACC), Lane Departure Warning (LDW)). Here, the problem is that these systems are implemented based on specific information received from the state of the car and the environment. If the information is not sufficient, or does not satisfy certain condition, then the system will automatically hand back control to the driver. In most situations, drivers are unaware of this with the result that they may believe that the system is always operating under full automated control (Leen & Hefferman, 2002). Some awareness of the causal structures that describe how the system operates is of critical importance to ensure driver safety, because this contributes to their agency in determining accurately when they actually have control of the vehicle.

*Future Directions*: Our experiences of uncertainty, and their effects on our causal knowledge, have also been explored by a number of theorists (e.g., Jungermann & Thüring, 1993; Kersholt, 1996; Krynski & Tenenbaum, 2007; Pearl, 2000; Tenenbaum et al., 2006). Much of this work considers how we make causal judgments using a Bayesian belief-updating process. There is considerable evidence supporting the claim that people often make causal judgments that approximate this form of reasoning (e.g., Krynski & Tenenbaum, 2007; Steyvers et al., 2003), but it has yet to be used to describe how people formulate causal models in complex dynamic environments. There is scope to do this, given that causal modeling has been used to formally describe CDC systems in artificial intelligence (e.g., Horvitz, Breese, & Henrion, 1988), engineering (Carrusco, Llauró, & Poch, 2006), and molecular biology (e.g., McAdams & Shapiro, 1995). Clearly, it still remains to be explored how people develop and adapt their causal models online while interacting with a dynamic environment, and how that impacts on our sense of agency (and vice versa), and the point to take away here is that CDC tasks actually provide a ideal paradigm with which to study this. Moreover, if the common underlying goal of research in CDC tasks is to describe formally human behavior in complex dynamic environments (Rothrock & Kirlik, 2003), then the synthesis of causal structure learning research and CDC tasks research would be a significant step towards achieving this.

## Conclusions

This article introduces and integrates research from many domains (i.e., Economics, Engineering, Ergonomics, Human Computer Interaction (HCI), Management, Psychology) that has examined behavior in complex dynamic environments. In essence, work on CDC tasks can be characterized as addressing the following question: How do we learn, and control online, an environment that is changing, either as a consequence of our actions, autonomously, or both? Viewed in this way, CDC tasks are uncertain environments, and addressing this question involves understanding the psychological mechanisms that help to reduce uncertainty. The MC Framework is presented as a method of integrating the different domains of research under a single framework. It describes three main classes of behaviors involved in reducing uncertainty in CDC tasks: Task-monitoring, Self-monitoring, and control behaviors. Task-monitoring behaviors are directed towards processing task information, Self-monitoring tracks and evaluates one's behaviors in the task, and Control behaviors are actions and decisions that are guided by goals. The way in which we learn to control the changing demands of the CDC environment is described in terms of the mediating role that uncertainty has in monitoring behaviors, and the interactive relationship that monitoring and control behaviors share.

Footnotes

1. This poses a problem for many decision theories that assume that successive decisions are independent of each other (see Brown & Steyvers, 2005).
2. David, Newen, and Vogeley (2008) insist that the sense of agency is not a unitary phenomenon, and that it comprises an implicit level of "feeling of agency," which is a low-level, pre-reflective, sensorimotor processes; and an explicit level of "judgment of agency which is high-order, reflective or belief-like process (i.e., the awareness or attribution of who has caused an action)." For the purposes of the review, "sense of agency" is taken to refer to the latter.
3. The basal ganglia is thought to be implicated in most motor functioning and supports procedural knowledge, and the medial temporal regions associated with episodic and semantic memories supports declarative knowledge. Much of the evidence of dissociations between procedural and declarative knowledge has come from patient studies. Amnesic patients with damage to medial parts of the temporal lobe (with specific focus on the hippocampus and amygdala) show deficits in declarative memory, but intact procedural memory of newly acquired skills (Squire, 1986). To compliment this, studies of Parkinsons patients with damage to the basal ganglia show impaired procedural learning, but intact declarative knowledge (Knowlton, Mangels & Squire, 1996).
4. As discussed earlier, based on Lipshitz and Strauss's (1997) distinctions between objective task properties and psychological behaviors that contribute to experiences of uncertainty, the focus of the MC Framework is on the psychological sources of uncertainty, and their effect on subsequent monitoring and control behaviors.

5. Causality and Agency are revisited in the concluding discussion section of this review.
6. This is a particularly contentious point, implying that animals have the capacity for metacognition (For a discussion of this issue see Smith et al. (2003)).
7. However, it seems that humans' ability to accurately monitor their behaviors is somewhat paradoxical, given that subject and object are one and the same (Comte's paradox).
8. The list of studies included in Table 1 is designed to provide a comprehensive list of studies across the different domains of research on CDC tasks. However, because the terminology across the studies varies with respect to the treatment of uncertainty, the general descriptions of the task environment have been used as a guide to categorizing them according to high or low uncertainty.
9. The studies presented in the table include those that recorded subjective judgments of uncertainty (e.g., confidence ratings, estimations of the action-outcome links, judgments of self-efficacy), as well as those that discussed uncertainty in association with the conditions of the task.

Table 1.

| | Pattern of behavior under High subjective experiences of uncertainty | **Representative Evidence** | **Research Discipline** | Pattern of behavior under Low subjective experiences of uncertainty | **Representative Evidence** | **Research Discipline** |
|---|---|---|---|---|---|---|
| Task Monitoring | High reliance on biases | Brehmer (1992)<br>Coury, Boulette, & Smith (1989)<br>DiFonzo & Boridia (1997)<br>Shanteau & Stewart (1992) | Psychology<br>HCI<br>Economics<br>Psychology | Limited-reliance on biases | Dorner, Kreuzig, Reither, & Staudel (1983)<br>Schoppek (2002)<br>Sterman (1989, 2002)<br>Strohschneider & Guss (1999) | Psychology<br><br>Psychology<br>Psychology<br>Psychology |
| | Patten-matching | Berry & Broadbent (1984, 1987, 1988)<br>Degani, Shafto & Kirlik (2006)<br>DeShon & Alex&er (1996)<br>Hunter, Hart, & Forsythe (2000)<br>Schmitt & Klein (1996) | Psychology<br><br>Engineering<br>Psychology<br>Management<br>Management | Patten-matching | Degani, Shafto & Kirlik (2006)<br>Klein & Hoffman (1993)<br>Mosier, Sethi, McCauley, & Khoo (2007)<br>Pomerol & Brezillion (1999, 2001)<br>Strauss & Kirlik (2006) | Engineering<br>HCI<br>HCI<br><br>Management<br>Engineering |
| | High persistence of unsuccessful strategies | Bisantz, Kirlik,Gay, Phipps, Walker, & Fisk (2000)<br>Brehmer, & Dörner, (1993)<br>Gonzales, Lerch, & Lebiere (2003)<br>Kleinmuntz (1985)<br>Langley & Morecroft (2004)<br>Strohschneider & Guss (1999) | Engineering<br><br>Psychology<br>Psychology<br>Psychology<br>Management<br>Psychology | Limited persistence of unsuccessful strategies | Gonzales, Lerch, & Lebiere (2003)<br>Kleinmuntz (1985)<br>Strohschneider & Guss (1999)<br>Langley & Morecroft (2004)<br>(1999)<br>Thomas & Russo (2007) | Psychology<br>Psychology<br>Psychology<br>Management<br><br>Engineering |
| | Poor strategy development | Brandouy (2001)<br>Brézillon, Pomerol, & Saker, (1998) | Economics<br>HCI<br>Psychology | Good strategy development | Anzai (1984)<br>Buchner, Funke, & Berry (1995)<br>Christoffersen, Hunter, & | HCI<br>Psychology |

| | | | | | | |
|---|---|---|---|---|---|---|
| | / rule-based knowledge | Dienes & Fahey (1995)<br>Geddes & Stevenson (1997)<br>Diehl & Sterman (1995)<br>Monxes (2000) | Psychology<br>Psychology<br>Engineering | / rule-based knowledge | Vicente, (1998).<br>Chmiel & Wall (1994)<br>Monxes (2000)<br>Fredrickson & Mitchell (1984)<br>Rasmussen, (1985) | HCI<br>Engineering<br>Engineering<br>Management<br>HCI |
| Self-Monitoring | Poor knowledge of action-outcomes | Broadbent, & Ashton (1978)<br>Gonzales, Lerch, & Lebiere, (2003)<br>Jensen & Brehmer (2003)<br>Kluge (2008b)<br>Kobus, Proctor, & Holste (2001)<br>Sarter, Mumaw, & Wickens, (2007)<br>Sauer, Burkolter, Kluge, Ritzmann, & Schüler (2008) | Economics<br>Psychology<br>Psychology<br>HCI<br>Engineering<br>HCI<br>HCI | Good knowledge of action-outcomes | Lipshitz & Barak, (1995)<br>Kluge (2008b)<br>Kobus, Proctor, & Holste (2001)<br>Sauer, Burkolter, Kluge, Ritzmann, & Schüler (2008)<br>Vicente, Roth, & Mumaw (2001) | HCI<br>HCI<br>Engineering<br>HCI<br>Engineering |
| Monitoring (Self, Task) & Control Interaction | Concurrent monitoring of control behaviors | Cohen, Freeman & Wolf (1996)<br>Dörner (1989)<br>Goa & Lee (2006)<br>Jamieson, Miller, Ho, & Vicente, (2007)<br>Sarter, Mumaw, & Wickens, (2007) | HCI<br>Psychology<br>Engineering<br>Engineering<br>HCI | Intermittent monitoring & control behaviors | Cohen, Freeman, & Wolf (1996)<br>Kaber & Endsley (2004)<br>Goa & Lee (2006)<br>Hunter, Hart & Forstye (2000)<br>Kirlik (2000)<br>Kleinmuntz (1985)<br>Sarter, Mumar & Wickerns (2007)<br>Vicente, Roth, & Mumaw (2001)<br>Yeo & Neal (2006) | Managment<br>HCI<br>Engineering<br>Management<br>HCI<br>Psychology<br>Engineering<br>HCI<br>Psychology |
| | Poor resource allocation | Camp, Paas, Rikers, & Van Merriënboer (2001)<br>Diehl & Sterman (1995)<br>Gonzales (2005)<br>Joslyn & Hunt (1998)<br>Yeo & Neal (2006) | HCI<br>Psychology<br>Psychology<br>Psychology<br>Psychology | Good resource allocation | Camp, Paas, Rikers, & Van Merriënboer (2001)<br>Jones & Mitchell (1994)<br>Kluge (2008a, 2008b)<br>Mosier, Sethi, McCauley, & Khoo (2007) | HCI<br>HCI<br>HCI<br>HCI |

| | | | | | |
|---|---|---|---|---|---|
| | | | | Orasanu & Connolly (1993) | HCI |
| | | | | Vincente (2002) | HCI |
| | | | | Yeo & Neal (2006) | Psychology |
| Mis-perception of feedback | Atkins, Wood, & Rutgers (2002) | Psychology | Poor attention to feedback | Kaber & Endsley (2004) | HCI |
| | Bredereke, & Lankenau, (2005) | Engineering | | Kleinmuntz (1985) | Psychology |
| | Brehmer & Allard. (1991) | Psychology | | Kirlik & Strauss (2006) | HCI |
| | Osman (2008b) | Psychology | | Lerch & Harter (2001) | HCI |
| | Goa & Lee (2006) | Engineering | | Moxnes (2000) | Engineering |
| | Mosier, Sethi, McCauley, & Khoo (2007) | HCI | | Mosier, Sethi, McCauley, & Khoo (2007) | HCI |
| | Sterman (1989) | Psychology | | | |

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