Complex Problem Solving and Dynamic Decision Making: What is the Difference?

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Abstract. Complex Problem Solving (CPS) and Dynamic Decision Making (DDM) are often used as synonymous concepts. In this paper, I will document the similarities between CPS and DDM that emerge from the environments that researchers investigate and from the methodologies they use. However, I will argue that some of the demands and required cognitive processes for general complex problem solving are different from those needed for making decisions in dynamic environments. The distinction between CPS and DDM is of practical and theoretical relevance; it matters for how researchers address the question of people's complex problem solving in dynamic environments, and it also matters to represent cognitive processes precisely in algorithms that can be translated into a computational form. Generating predictive theories of DDM may be very distinct from computational representations of CPS processes.

Herbert Simon used the metaphor of an ant making his way home in a rugged beach landscape to introduce the initial ideas of problem solving (Simon, 1969). The ant makes her way from a starting point to a goal (home or a food source) around a path that is hard to describe: it appears irregular, complex, and not a straight line. Generally, the wavy path emerges because the ant cannot foresee all the obstacles in between the starting point and the goal. Instead, the ant must

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adapt its course based on the difficulties that she might encounter on the way. This metaphor was used to exemplify how humans may address complex problems, and to postulate the study of human reasoning in the information processing theory entitled *Human Problem Solving* (Newell & Simon, 1972). In this theory, a thinking human being is an *adaptive* system, and the behavior is a result of the properties of the human mind and the properties of the environment.

However, it became clear that the kind of problems that a human could address under the general problem solving idea would need to be relatively simple and well defined, in contrast to real-world problems that are ill-defined and cannot easily be translated to mathematical solutions (see Dörner & Funke, 2017, for a historical discussion). The concept of Complex Problem Solving (CPS) advanced the general notion of problem solving with the need to consider "complex" environments. In a historical review of the origins of CPS, Dörner and Funke (2017) document the introduction of the CPS concept to the mid-1970s (Dörner, 1975), and the increased popularity of CPS research after the edited volumes by Sternberg and Frensch (1991) and Frensch and Funke (1995).

The key point of CPS is the *problem complexity*, the type of ill-defined environments that have no clear goal state or well-defined means of moving towards the goal state. In a related and contemporary research tradition, Dynamic Decision Making (DDM) was defined by the characteristics of a complex and dynamic environment in which decisions are made (Brehmer, 1992; Brehmer & Dörner, 1993). DDM involves "conditions which require a series of decisions, where the decisions are not independent, where the state of the world changes, both autonomously and as a consequence of the decision maker's actions, and where the decisions have to be made in real time" (Brehmer, 1992, p. 211). The core aspect of any decision theory is the act of *choice*, the agent's selection among options that might be available concurrently or in a sequence (Payne et al., 1993). An essential element of DDM is the idea of making a *sequence* of decisions (in contrast to making a single choice among simultaneously presented alternatives), based on what was learned from the consequences of decisions made in the past (Edwards, 1962).

This background explains why CPS and DDM are often used as synonymous concepts (e.g., Dörner & Funke, 2017; Dörner & Güss, 2022). They both depend on ill-defined environments of similar characteristics, and they both appear to require a process by which an agent moves towards a goal by making a sequence of decisions, often based on what the agent has learned from past choices. But, are CPS and DDM synonymous? I will argue that while there are similarities between CPS and DDM, they are not synonymous. Differences between CPS and DDM take place in the theoretical developments of algorithmic representations that require significantly more precision and systematic processes. A distinction between these research areas matters for how researchers address the question of people's complex problem solving in dynamic environments and for how research on algorithmic representations will advance.

Two Determinants of Human Behavior

Perhaps the distinction between CPS and DDM can be best illustrated by highlighting the two different but interrelated determinants of human behavior: human mind and the environment. These two elements of human behavior are explained by another famous Simon's metaphor: A pair of scissors in which one blade is the human mind and the other blade is the structure of the environment (Simon, 1991). The idea is that human behavior must be understood by the *joint* effect of the two blades in the scissors. One cannot understand behavior by separately studying the human mind from the environmental structure. In fact, the idea of the scissors metaphor dates back to Simon's earlier work on rational choice and the concept of bounded rationality (Simon, 1956). In the work that led to his Nobel Prize, he introduced the "satisficing" human, who cannot optimize her decisions because the computational demands of the decision environment might be beyond her mental capabilities. Thus, a satisficing human decision maker makes choices that are "good enough" for the demands of the particular environment.

To clarify the similarities and highlight the differences between CPS and DDM, it is relevant to go back to the two blades of Simon's scissors. I will argue that the similarities between CPS and DDM emerge from the environments that researchers of CPS and DDM investigate and from the methodologies they use. But I will also argue that their distinction relies on the demands and required mental processes which need to be made precise and systematically described to generate predictive theories of CPS and DDM.

Complex Cognition and Complex Environments

In the study of CPS, there has been confusion about where the complexity emerges from, whether it emerges from the cognition or from the environment. Complex cognition has been understood as involving high-level cognitive processes such as problem solving and decision making, as well as their interaction with basic cognitive processes including perception, learning, motivation and emotion (Schmid et al., 2011). But in many problem solving situations, as in the ant metaphor, the agent (i.e., the ant) is quite simple. Simon suggested that the apparent complexity of the agent's behavior over time is largely a reflection of the complexity of the environment, not of the ant's cognition (Simon, 1969). In fact, an organism might be simple if it has a single goal, it has a fixed aspiration level that does not change, and a definite path to achieve the goal. In contrast, complex organisms might have the capability of searching and responding to multiple goals, and satisfying the needs that reach a threshold that may change dynamically (Simon, 1957). In other words, the complexity of the cognition depends on the complexity of the environment demands.

While much effort in psychological research has been dedicated to generate integrated theories of cognition (Newell, 1994), less effort in psychology has been dedicated to create an integrated theory or a taxonomy of environments. Newell and many followers argued for the need to create a unified theory of cognition. For example, the Adaptive Control of Thought-Rational (ACT-R, Anderson & Lebiere, 1998) evolved into an integrated set of mental modules that produce a wide range of behavior including perceptual-motor modules, declarative and procedural learning. These efforts have been essential for the development of common understanding of the mental processes involved in CPS and DDM. However, similar efforts are required for developing integrated theories of environments.

Use of Microworlds to Represent Environmental Complexity

CPS and DDM research share similarities in the investigation of complex environments and their effects on human behavior as they are studied using graphical interactive simulations, called *microworlds*. In psychological research, CPS and DDM are perhaps the areas that have contributed most insights regarding an integrated view of complex environments. Complex environments, particularly in CPS research, have often been characterized by the number of elements represented: the number of variables, the number of interconnectivities among those variables, and the way these variables and connections change over time (Schmid et al., 2011). Complex environments would correspond to a large number of variables, many interconnectivities, and complex dynamics (Dörner & Funke, 2017). For example, early CPS work involved scenarios with a large number of variables (e.g., more than 2000 variables in "Lohhausen") in simulated microworlds. Lohhausen involved a group of activities in a small town where participants played the role of a mayor that controlled the well-being of the population (Dörner, 1980; Funke, 1988).

These highly complex scenarios are represented computationally in microworlds (Brehmer & Dörner, 1993; Gonzalez et al., 2005; Omodei & Wearing, 1995; Turkle, 1984). Microworlds represent the essential characteristics of real-world decision making and problem solving environments. However, microworlds range in the characteristics of complexity that are included. For example, *structural complexity* refers to the number of elements in the environments; number of variables, exogenous changes, and opaqueness, while *dynamic complexity* refers to the interrelationships of all these elements over-time (Gonzalez et al., 2005).

Microworlds used to study DDM have been characterized in a continuum of structural and dynamic complexity (Gonzalez et al., 2017). Dynamic environments may involve various degrees of change, as alternatives may vary independently from external events or endogenously because of the decisions made previously (Edwards, 1962). Thus, DDM environments vary from structurally complex (i.e., they consist of a large number of alternatives, high time constraints, and high uncertainty) to structurally simple (i.e., they have few alternatives, no time constraints, and little uncertainty), and structurally simple tasks can have high or low dynamic complexity. Dynamic complexity emerges from the relationship between choices and their effects over time, from the sequential nature of these interdependencies, and from the various lags between actions and their effects on the environment (Gonzalez, 2017; Sterman, 1989).

Both, CPS and DDM researchers have investigated complex cognition using complex environments represented in microworlds. From this research, we have learned about extreme demands that complex environments place on human cognition and the role of experience to improve performance in such tasks (Brehmer, 1980; Diehl & Sterman, 1995; Sterman, 1994). We know that humans are generally poor at handling systems with long feedback delays (Brehmer, 1992; Sterman, 1989), and they have difficulty learning in situations involving environmental constraints, such as workload and time pressure (Gonzalez, 2004, 2005; Kerstholt & Raaijmakers, 1997).

However, recently a concrete taxonomy of human errors in CPS has revealed some of the distinctions between CPS and DDM. The errors reported along the CPS steps reflect the influence of factors beyond cognitive inability to handle complex tasks: motivation and emotions (Dörner & Güss, 2022). A taxonomy of human errors in CPS was developed using classic microworlds including: CHOCO FINE, a simulation of a chocolate production company; MORO, a simulation of a tribe with semi-nomads; and WINFIRE, a simulation of firefighting units engaging in protecting cities from wildfires (Dörner & Güss, 2022). The three microworlds differ in their characteristics of exogenous changes, number of variables, opaqueness, and over-time interrelationships. The observations of individuals working on these three microworlds led to the characterization of 24 errors generally grouped in categories defined by the steps required for CPS (Dörner & Güss, 2022): (1) problem identification, (2) goal definition, (3) information gathering, (4) elaboration and prediction, (5) planning, decision making and action, and (6) evaluation of outcome and self-reflection. The influence of motivational, emotional, and cognitive processes, and how they interact together has been formalized in a theory of CPS, called PSI, named as an abbreviation for the word psychology (Dörner & Güss, 2022; 2013). It is precisely in the details of this PSI theory defined for CPS, that the differences emerge from the theories of DDM.

Theories and Predictive Models

The most well-known theory of DDM is Instance-Based Learning Theory (IBLT) (Gonzalez et al., 2003). IBLT emerged from a set of behavioral phenomena discovered in experiments using microworlds, and from the efforts to implement computational algorithms that would replicate the decision process involved in the microworlds, using a cognitive architecture (Gonzalez et al., 2003; Gonzalez, 2013, 2022). ACT-R (Anderson & Lebiere, 1998) is a cognitive architecture that intends to represent mathematically and computationally, the various aspects of human mind, including perception and action, learning, memory, and other processes. To demonstrate IBLT, ACT-R was used initially as the implementation platform of a concrete predictive model of the decisions that humans took in a complex microworld, called the Water Purification Plant (WPP) (Gonzalez et al., 2003). WPP is an example of a microworld that encompasses all the characteristics of DDM: multiple sequential decisions need to be made under uncertainty, in an environment that changes exogenously, and as a result of the decisions made, and in which there is high workload and time constraints (Brehmer, 1992). As such, WPP is a task that is structurally and dynamically complex and needs to be resolved from experience and extended practice by noticing patterns of exogenous events (Gonzalez, 2004, 2005; Gonzalez et al., 2003).

The theoretical process and mechanisms proposed in IBLT have been used in the computational implementation of a large number of models. It is important to highlight that IBLT is not only a picture with a description of the processes involved in DDM, but IBLT presents a concrete algorithm and the associated mathematical mechanisms that are used to implement the algorithm in computational form. IBLT's algorithm has been published in multiple places, but I recommend Gonzalez et al. (2003), Gonzalez and Dutt (2011), Gonzalez (2013), and to more recent presentations of the theory, Nguyen, Phan, and Gonzalez (2023) for the details.

The IBL decision process involves the following steps: (1) recognition and retrieval of past experiences (i.e., instances) according to their similarity to an ongoing decision situation, (2) generation of the expected utility of various decision alternatives by using past experiences, (3) choice of the option that best generalizes past experiences to new decisions, and (4) feedback processes that update past experiences based on the observation of decision outcomes.

In IBLT, an "instance" is a memory unit that results from the potential alternatives evaluated. These memory representations consist of three elements, which are constructed over time: a situation (a set of attributes that give a context to the decision), a decision (the action taken corresponding to an alternative in a state), and a utility (expected utility or experienced outcome of the action taken in a state). Each instance in memory has an *activation* value, which represents how readily available that information is in memory, and it is determined by similarity to past situations, recency, frequency, and noise (Anderson & Lebiere, 2008). Activation of an instance is used to determine the probability of retrieval of an instance from memory (i.e., *cognitive probability*) which is a function of its activation relative to the activation of all instances in memory. The expected utility of a choice option is calculated based on *blending* past outcomes. This blending mechanism for choice has its origins in a more general blending formulation (Lebiere, 1999), but in discrete choice models, blending is defined as the sum of all past experienced outcomes weighted by their probability of retrieval (e.g., Gonzalez & Dutt, 2011; Lejarraga et al., 2012). This formulation of blending represents the general idea of an *expected value* in decision making, where instead of using the factual probability, blending uses a cognitive probability, a function of the activation equation in ACT-R. At each time step, the IBL algorithm recognizes a situation in the environment (based on similarity), calculates the expected utility of the option being evaluated, determines when to stop evaluating additional alternatives, and at that point decides to make a choice by selecting the option that has the highest blended value. Feedback, which might be immediate or delayed, updates all instances in memory that lead to a particular outcome in the task. This process goes on over time.

IBLT and the power of the predictions of IBL models compared to human decisions have been demonstrated in a large diversity of tasks that vary in structural and dynamic complexity. The demonstrations include structurally and dynamically simple tasks, such as binary choice (Gonzalez & Dutt, 2011; Lejarraga et al., 2012); structurally simple but dynamically complex tasks such as control of carbon dioxide in the atmosphere (Gonzalez & Dutt, 2011) and supply chain inventory management; structurally complex and dynamically simple tasks such as search and rescue and navigation in non-stochastic situations (Nguyen et al., 2023); and structurally and dynamically complex tasks, such as dynamic resource allocation of resources (Gonzalez et al., 2003) and cyber defense (Cranford et al., 2020; Aggarwal et al., 2022).

Theories of Complex Problem Solving

For CPS, a main theory is PSI (Dörner & Güss, 2013, 2022). In contrast to IBLT, PSI aims at integrating not only the cognitive processes but motivational and emotional processes as well. Because of addressing the complex challenge of integrating motivation, cognition, and emotion into a single theory, PSI is extremely complex, and it can be difficult to validate (Dörner & Güss, 2013). The validation approach of PSI has been to determine whether the theory predicts potential reactions of humans to specific conditions. Researchers have attempted to conduct experimental research to compare the behavior predicted by PSI with the actual behavior of humans. For example, researchers analyzed the strategies of 30 participants and compared their behavior with 30 different PSI agents to explore a simulated island and how they solved the problem of survival on the island. The authors compared information on "when planning occurred and to what extent, the number of locations on the island visited by participants at the beginning and at the end of the simulation, what emotions were shown, when those emotions changed and how often" (according to Dörner & Güss, 2013, p. 312, these results are reported in Dörner et al., 2002, and in Detje, 1999, but both of these references are written in German, not translated to English). Other efforts to validate PSI involve using the steps in the theory to explain cases of complex historical events (e.g., Dörner & Güss, 2011). Using historical documents, the authors analyzed decision making errors and potential causes for those errors using PSI.

Dörner and Güss (2013) suggest that PSI theory may be compared to other theories, for example, to ACT-R. However, for such a comparison to take place, the process and mechanisms proposed in PSI will need to be converted into algorithmic and mathematical form. To make an algorithm computational, the set of steps proposed in a theory should have a level of precision and systematic calculation so that they could be carried out automatically (Chabert, 1999). Unfortunately, PSI appears to be imprecise, thus making the generation of computational algorithms impossible. Furthermore, to achieve the level of computational algorithms, the mathematical formulations of the PSI steps would need to be developed and validated against human behavior.

Conclusions

This manuscript aims at clarifying the similarities and differences between CPS and DDM. In many publications CPS and DDM are used as synonymous concepts. However, I argue that they are not synonymous and should not be used interchangeably.

In this paper, I clarify that there are important similarities between CPS and DDM. The similarities emerge from the common interest and definitions of the study of complex environments. Both CPS and DDM engage in the investigation of ill-defined environments that demand a series of interdependent decisions, made in real-time, while the state of the world changes, both autonomously and because of the decision maker's actions (Dörner & Funke, 2017; Gonzalez et al., 2017). Furthermore, both CPS and DDM use microworlds, which are computational interactive representations of complex tasks, to investigate human behavior in experimental studies (Brehmer, 1992; Gonzalez et al., 2005).

However, CPS and DDM differ in the demands and required cognitive processes, and in the theoretical representations of these processes. When the goal is to advance theory and to develop precise predictive computational models of behavior, the specific processes and mechanisms used in these advancements are very distinct for CPS and DDM. PSI, the relevant theory for CPS is a large-encompassing endeavor, aiming at including cognitive, motivational, and emotional processes and their interactions (Dörner & Güss, 2013, 2022). In contrast, IBLT, the relevant theory for DDM, is a cognitive theory that has little or no relevance for motivational and emotional processes (Gonzalez et al., 2003; Gonzalez, 2013). Furthermore, regarding the development of predictive behavioral models, IBLT provides clear and precise algorithmic and mathematical formulations that are needed to implement computational representations and make predictions in a large variety of tasks (e.g., Gonzalez et al., 2003; Nguyen, et al., 2023). Significant work will be required to turn PSI into an algorithmic and mathematical theory.

Author Note. Joachim Funke's work represents key intersections between Complex Problem Solving (CPS) and Dynamic Decision Making (DDM) research. I am honored to be part of this commemorative publication to celebrate Jofu's contributions, and to enhance our understanding of the similarities and distinctions between CPS and DDM. I thank all the organizations that sponsor my research and all the current and past members of the Dynamic Decision Making Laboratory (DDMLab) at Carnegie Mellon University.

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