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The use of microworlds to study dynamic decision making

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Abstract

Dynamic decision-making (DDM) research grew out of a perceived need for understanding how people control dynamic, complex, real-world systems. DDM has describable characteristics and, with some unavoidable sacrifice of realism, is suitable for study in a laboratory setting through the use of complex computer simulations commonly called 'microworlds'. This paper presents a taxonomic definition of DDM, an updated review of existing microworlds and their characteristics, and a set of cognitive demands imposed by DDM tasks. Although the study of DDM has garnered little attention to date, we believe that both technological advancement and the relationships between DDM and naturalistic decision making, complex problem solving, and general systems theory have made DDM a viable process by which to study how people make decisions in dynamic, real-world environments.

Keywords: Dynamic decision making; Microworlds; Synthetic task environments; Cognitive demands

1. Introduction

Dynamic decision making (DDM) involves a sequence of interdependent decisions made in an environment that changes as a function of the decision sequence, independently of the decision sequence, or in both ways (Edwards, 1962). Because the environment is dynamic, decisions must be made in real time (Brehmer, 1992).

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Examples of routine DDM tasks include choosing which routes to take while driving a car, developing and selecting the best strategy while playing basketball, and investing in the stock market while prices are changing. More specialized examples include military command and control during battle, air traffic control, chemical processing control, and supply chain management. It was these more specialized tasks that spurred the development of DDM as an area of research (Brehmer, 1992; Edwards, 1962).

The issues addressed by DDM researchers are closely related to (and often indistinguishable from) the issues addressed by researchers focusing on complex problem solving (Frensch & Funke, 1995), systems thinking (Booth-Sweeney & Sterman, 2000; Senge, 1990), and naturalistic decision making (Lipshitz, Klein, Orasanu, & Salas, 2001). Although these areas of research are all concerned with the investigation of how people understand and control dynamic, complex situations, the fields diverge – sometimes greatly – in terms of the investigators' research methods.

Computer simulations play an integral role in DDM research. DDM researchers refer to these simulations by various names, including 'microworlds', 'synthetic task environments', 'high fidelity simulations', 'interactive learning environments', 'virtual environments', and 'scaled worlds', just to name a few. We use the term 'microworlds' here because it appears to be the earliest term used to describe the complex simulations utilized in controlled experiments designed to study decision making (Turkle, 1984).

The use of microworlds, which represent a compromise between experimental control and realism, enables researchers to conduct experimental research within the dynamic, complex decision-making situations that characterize DDM and complex problem solving (Funke, 1995). The assumption is that although microworlds are relatively simple, they embody the essential characteristics of real-world DDM environments. By compromising the mundane realism often emphasized by naturalistic decision-making researchers, microworlds provide the experimental control needed to develop explanations of decision-making processes rather than task-specific descriptions of decision making, and thereby can lead to results that are generalizable across a variety of DDM tasks.

We address three general topics in this chapter. First, we provide an updated description of the abstract characteristics of DDM environments, in hopes that this description will serve as a common ground for reviewing complex DDM tasks and ultimately will motivate more systematic study of the characteristics of real-world situations. Second, we discuss some microworlds and summarize their DDM characteristics, thus revealing how these microworlds can facilitate the study of dynamic, complex situations. Finally, we describe the cognitive demands associated with various features of DDM environments – demands that presumably are similar to those imposed by real-world dynamic tasks.

2. Taxonomic definition of DDM

A primary goal of DDM research is to systematically study the characteristics of dynamic systems, including dynamics, complexity, opaqueness, and dynamic complexity (Brehmer, 1992; Diehl & Sterman, 1995; Sterman, 1989), and the relationship of these characteristics to cognitive decision processes. We discuss these system characteristics, which are closely related and in some cases represent overlapping constructs, in more detail below.

2.1. Dynamics

In dynamic systems, the system's state at time t depends on the state of the system at the previous time $t - 1$ (Rouse, 1981). The state of the system is influenced both endogenously (by the decision maker's decisions) and exogenously (by factors beyond the decision maker's control) (Edwards, 1962).

The continuous changes within a dynamic system give rise to loops through which a variable can influence itself or other variables over time. These 'feedback loops' underlie all growth, fluctuation, and decay in dynamic systems. Feedback loops that are self-reinforcing or self-amplifying are called 'positive feedback loops', while those that are self-correcting or self-dampening are referred to as 'negative feedback loops'. A savings account is a simple example of a positive feedback loop. As interest accrues, principal grows, and the higher principal leads to the accrual of even more interest. Eating is a simple example of a negative feedback loop. As people eat more, they feel less hungry and, ultimately, they decide to stop eating.

Concomitant with these feedback loops motivated both by a decision maker's actions and by the interactions among the system variables, autonomous evolution occurs in dynamic systems. For example, although investors decide how much money to leave in their personal savings account, the accrual of interest and any fluctuations in interest rates occur independently of these investing decisions and are beyond the investors' control.

2.2. Complexity

Complexity, a second shared characteristic of DDM systems, is a multifaceted construct that defies simple definition. In general, dynamic systems comprise parts that interact or interconnect in an intricate manner, making it difficult to understand or predict system behavior. Several factors contribute to system complexity: (1) the number of components in the system, (2) the number of relationships among the components (i.e., the degree of coupling), and (3) the types of relationships among the components. None of these factors in isolation directly corresponds with the demands imposed on dynamic decision makers performing a task. One cannot say with any certainty, for example, that a system with 10 parts is twice as difficult to control as one with 5 parts (Funke, 1988).

When DDM researchers attempt to define the complexity of a task, they do so with respect to a particular decision maker (Brehmer & Allard, 1991). A task that appears complex to a novice may well seem simple to an expert. Individuals with different cognitive abilities also may perform differently when making decisions in a dynamic system (Gonzalez, in press). Therefore, decision makers' knowledge and their possession of the cognitive abilities needed to control the system also influence the complexity of DDM systems.

Because complexity is a relative term, it is unclear how to best assess the complexity of a particular system. Brehmer and Allard (1991) evaluate complexity by considering the parts of the system and the structure of the relationships among them in functional terms. They claim that the psychologically relevant parts include the number of goals, action possibilities, side-effects, and processes that a decision maker must control. Calculating system complexity by using Brehmer and Allard's functional perspective, however, can be difficult because the number of functional (i.e., relevant) parts varies over time as the decision maker interacts with the system.

Decision makers may be able to achieve the goals of some DDM systems by considering only a subset of system variables. In such cases, system complexity may be substantially reduced because the decision maker's attention can be restricted to a subsystem that is relatively independent of the rest of the system. However, as the interrelatedness among system components increases, the components may become so intricately connected that relatively independent subsystems cease to exist. In such tightly coupled systems, complexity remains relatively constant because each dynamic decision requires consideration of most or all system variables.

The relationships among system components also can produce unintended consequences of a user's decisions. As the number of relationships among system components increases, it becomes more likely that deliberate changes made to one system variable will propagate unintended changes to variables in other parts of the system. The occurrence of such 'side effects' increases the likelihood that the decision maker will confront goal conflicts and be forced to make trade-offs.

The relationships among system variables can take various forms. Component relationships may be linear or (more frequently) nonlinear and quantitative or qualitative. Furthermore, system components may influence themselves via various pathways, giving rise to positive or negative feedback loops. These feedback loops make empirical findings presumably related to complexity suspect because the dynamics may influence the system complexity (Kerstholt & Raaijmakers, 1997).

2.3. Opaqueness

In DDM research, opaqueness refers to the 'invisibility' of some aspects of the system (Brehmer, 1992). Like complexity, defining opaqueness requires consideration of a decision maker's knowledge about a system. Although information about a system's state may be available (i.e., observable), it is accessible only if the decision maker knows where to find it. Furthermore, the usefulness of the available information depends upon what the decision maker knows about its relationship to current goals.

For example, computer software programs often provide context-sensitive speed menus. These menus are of absolutely no use to end-users who never think to right-click their mouse (or are unaware of the right-click option on the mouse). The speed menus are available but not accessible to these end-users because they do not know how the menus relate to their goals. Some side effects of decisions in complex systems may not even be known by system designers or experienced operators. As these users interact with the system, they might discover these unknown side effects gradually or accidentally – possibly with catastrophic consequences.

2.4. Dynamic complexity

When controlling a dynamic system, decision makers access information about the system's state by monitoring feedback loops. Usually, decision makers make dynamic decisions by using information obtained from multiple feedback loops that collectively constitute the system's 'feedback structure'. Sterman's (1989) concept of dynamic complexity combines elements of dynamics and complexity to emphasize the effect of feedback structures on a decision maker's ability to control a dynamic system.

Diehl and Sterman (1995) claim that three elements of a system's feedback structure are particularly relevant to DDM. We discuss two of these (side effects and nonlinearity) above. The third element is feedback delays. Any process or action takes a certain amount of time to complete, resulting in delays between when a decision is made and the time at which information about the effect of the decision input on the system's state is available. For instance, delays could occur in a system in which a commander issues an order to subordinates who then wait before acting on the command. Alternatively, there may be lag between the time at which a system outputs a response and the time at which the decision maker receives that output. For example, a store manager may observe an increase in inventory (i.e., feedback regarding the effect of an order on a supplier's output) only after a delay due to the time required to ship the ordered goods from the supplier to the manager's store.

The characteristics described above help to clarify the conditions that a task must meet to be designated as a DDM task. This standardized definition of DDM tasks also has facilitated the development of microworlds that allow researchers to systematically control or vary the different aspects of complex, dynamic situations. We next describe some existing microworlds and evaluate them in terms of the characteristics discussed above.

3. Microworlds for DDM research

Naturalistic decision-making researchers view decision making in the real world as dynamic, time-constrained, ill-structured, and ill-defined (Lipshitz et al., 2001). These researchers traditionally have used field methods (e.g., observation, interviews, and verbal protocols) to collect realistic decision-making data in complex, natural settings. Field research methods present significant advantages and disadvantages over experimentally controlled methods (Kluwe, 1995). Among the most relevant advantages is the richness of realism incorporated within results. Among the most notable disadvantages is the unavailability of experimental controls to support causal claims. Although this type of tradeoff is not new or limited to naturalistic decision-making research, it still impedes progress in decision-making research

(Brehmer & Dörner, 1993; Ehret, Wayne, & Kirschenbaum, 2000; Omodei & Wearing, 1995).

Microworlds have been hailed as tools that bridge the gap between laboratory and field research (Brehmer & Dörner, 1993). Microworlds are designed to allow researchers to control the essential characteristics of DDM tasks such as those described above. Furthermore, researchers who use microworlds know the decision-making system to a degree that is unattainable by practitioners who study real-world decision-making systems.

Admittedly, microworlds do require researchers to give up some of the control they would have were they conducting more standard laboratory experiments – i.e., although microworld experimenters may manipulate general system characteristics, the participants determine the trajectory taken through the DDM environment. On a positive note, however, microworlds are relatively simple in comparison to real-world systems and, unlike real-world systems, microworlds tend to present decision-making problems solvable by individuals rather than teams (Brehmer & Dörner, 1993).

During the past 20 years, researchers have developed several microworlds in an effort to study DDM. Table 1 summarizes the 10 microworlds that we have surveyed according to the characteristics described above. Although there is a large variety of simulated task environments, we have selected only those that have been used to study DDM (Gray, 2002). Other simulated task environments are used to study attention, to help train individuals and teams among other things, but not specifically designed to study decision making.

The microworlds presented in Table 1 all incorporate temporal dependencies among system states (i.e., dynamics), nonlinear relationships among system variables, and opaqueness. With the exception of the Sugar Production Factory microworld (Berry & Broadbent, 1984), they also all involve side effects and goal conflicts or trade-offs. Side effects and goal conflicts do not occur in the Sugar Production Factory microworld because it is a single input, single output control system. In addition, performance in all the microworlds except for the Sugar Production Factory requires goal elaboration and information search.

Eight of the 10 microworlds feature feedback delays and require decision makers to consider multiple time horizons or deadlines. Seven of the 10 incorporate irreducible uncertainty in the form of exogenous inputs or disturbances from the environment beyond the system boundaries. Six of the 10 microworlds evolve autonomously, while three provide a team environment.

This sample of microworlds indicates that DDM researchers generally agree that temporal dependencies among system states, nonlinear relationships among system variables, and a lack of user access to complete information about the system state and system structure are defining features of DDM environments. Furthermore, most researchers seem to agree that side effects, goal conflicts, feedback delays, and uncertainty (at least in the form of exogenous disturbances) also constitute characteristic features of DDM environments. Characteristic cognitive demands imposed by the microworlds appear to include goal elaboration, information search, and consideration of multiple time horizons. Few microworlds provide a version intended to evaluate teamwork.

Table 1
Comparison of microworlds

Source for more details	Microworld	Dynamics	Complexity	Opaqueness	Dynamic Complexity
Funke (1988)	Lohhausen	Low: Task environment changes only when user makes a decision	High: More than 2000 interrelated variables can be manipulated	Moderate: The variables' relationships are hidden from the user	High: The system variables are interrelated due to positive and negative feedback loops. There are feedback delays present, as some variables exhibit exponential growth
Gibson, Fichman, and Piaut (1997) and Stanley, Mathews, Buss, and Kotler-Cope (1989)	Sugar Production Factory	Low: Environment changes after the user makes a decision, but the simulation does not occur in real time	Low: Only the input variable can be manipulated, and only the production variable can be observed	Moderate: The user is not aware of the equation that relates the production variable and the input variable, but with practice can make a well-educated guess	Moderate: The current production value influences the next production value according to an equation that is not visible to the user: $P_{t+1} = 2W_{t+1} - P_t + \varepsilon$
Brehmer (1992)	Dessy, New-fire, D^3Fire	High: User makes decisions in real time and the environment changes both autonomously and in response to the user's decisions	Moderate: User can manipulate several appliances and must manage resources wisely	Low: The user does not know how or where the fire will spread	Moderate: Although certain feedback delays exist between when the user decides to send an appliance (or when the units report to the user) and the state of the system at the moment, most decisions are not irrevocable and have short-term effects
Omodei and Wearing (1995)	Fire Chief	High: User makes decisions in real time and the environment changes both autonomously and in response to the user's decisions	High: Simulation allows development of scenarios in which multiple variables (appliances, resources) can be manipulated (have multiple functions); the relationships among variables result in greater amounts of dependencies	Moderate: The relationships between the fire spread, wind direction, and wind strength may not be immediately obvious to the user. Nor is it obvious how the type of landscape influences the spread of the fire	Moderate: Feedback delays exist between the state of the system and the time during which the user makes a decision, and it is possible to change the scenario to incorporate a higher degree of dynamic complexity

(*continued on next page*)

Table 1 (*continued*)

Source for more details	Microworld	Dynamics	Complexity	Opaqueness	Dynamic Complexity
Sterman (1989)	Beer Game	Low: The simulation state changes only when a user makes decisions, and the user has plenty of time to deliberate	Low: Production variable is manipulated. Backlog, inventory, and current demand are the three observable variables	High: Most participants in the simulation are not aware of the consumers' demand	High: From the team's perspective it is necessary to keep in mind the ripple effect of the demand's perception throughout the chain. The feedback of the consumers' demand is delayed, particularly in the factory position, which is last in the production chain. From the individual's perspective there is a delay between the time at which one places an order to fill inventory and the time when that new inventory arrives. The constant arrival of new customer orders makes it difficult to stabilize one's inventory numbers
Christoffersen, Hunter, and Vicente (1998)	Duress II	High: The environment changes both autonomously and in response to a user's decisions, and the user makes decisions in real time	Moderate: User can manipulate eight valves, the temperature of heaters, and two pumps. Each manipulation changes the user's short-term goals	Moderate: Different states of the system may lead to its failure, thereby forcing the user to explore different methods. However, with background knowledge and additional information on the interface, the relationships between some variables become obvious	Low: Some feedback delays are present. By increasing the temperature of the heaters and turning off the pump, the volume of water in the reservoir may become very low and result in system failure. The effects of most decisions, however, are short term, because it is possible to correct the state of the simulation quickly

Strohschneider and Guss (1999)	Moro	Moderate: Task environment changes autonomously and when user makes a decision, but the user does not make decisions in real time	High: More than 45 interrelated variables can be manipulated	High: Variables such as ground water level and their relationships with other variables are not immediately known	High: Feedback delays are present. For example, an increase in population attributable to improved health conditions leads to an increase in consumption of cattle. If the numbers of cattle are insufficient to sustain the population, famine will result
Gonzalez, Lerch, and Lebiere (2003)	Water Production Plant	High: The simulation evolves autonomously and in response to a user's actions. Pumping, water transfer and water loss rates; time needed to clean pumps; and deadlines create complex temporal relationships	High: Forty-four pumps must be controlled in a system of 23 tanks connected with pipes that transfer water at various rates. Pumps must be used to meet 11 deadlines	High: The total amount of water to deliver by each deadline is unknown, as is the time required to pump water from a particular tank. Subtle variations in water transfer and loss rates tend to go undetected. Users must learn to account for pump-cleaning time	High: A resource limitation dictating only five active pumps at any given time creates complex interdependencies between scheduling of pumps and meeting deadlines. Resource limitations require the user to consider multiple deadlines simultaneously, because pump selection and activation has short- and long-term effects. Pump deactivation results in a "cleaning" delay during which the user cannot activate a new pump. Feedback regarding the effectiveness of a pumping schedule is delayed until expiration of each deadline

We were surprised to find that DDM researchers appear to be split in regards to the importance they place upon autonomous evolution. Because autonomous evolution is integral to dynamic environments, this finding raises questions as to the ability to generalize DDM research based on such microworlds. Perhaps the use of such discrete, decision-driven environments is simply a matter of convenience for data collection, similar in spirit to Gray (2002) ('s) description of a simulation's tractability. However, these microworlds fail to incorporate the timing demands widely viewed as central to DDM. Thus, the fundamental question is one of subtractive logic: Can researchers assume that decision-driven environments require a subset of the cognitive processes engaged by a truly dynamic environment that evolves autonomously? Or, are the cognitive processes elicited by these two types of environments qualitatively different?

Little is known about the cognitive demands associated with DDM and the cognitive abilities required for decision makers to succeed in dynamic environments. The following section outlines a set of abilities that decision makers might need to possess to be successful in dynamic environments and, presumably, in the real world.

4. Cognitive demands of DDM

Dynamic decision-making environments engage a variety of closely related processes (e.g., monitoring, recognition, causal learning, search, planning, judgment, and choice). The ability to coordinate these interrelated processes while acting under system-driven time constraints is essential to an individual's DDM performance. The identification of a set of cognitive demands associated with the aforementioned features of dynamic tasks would help researchers to explain and predict human behavior and performance during DDM.

We have used a cognitive theory called 'Instance-Based Learning Theory' (IBLT) to identify possible cognitive demands imposed by DDM (Gonzalez et al., 2003). IBLT describes a decision process that we believe encompasses the cognitive mechanisms common to all DDM situations, and IBLT thus extends the classical view of decision making based on judgment and choice to a view of decision making based on recognition, judgment, choice, and feedback. According to IBLT, individuals acquire and store 'instances' that contain information about a particular decision-making situation, and then use these instances to make decisions during subsequent interaction with a dynamic environment. The decision maker upgrades the utility of these instances in response to the system's feedback and uses these upgraded instances to make better decisions upon encountering similar situations in the future.

Many of the key activities involved in DDM occur early in the decision-making process. That is, DDM performance is highly determined by variables such as a decision maker's ability to recognize that a decision must be made and to use information seeking strategies to alter decision processes in an effort to meet the time-constraints imposed by the system. Gonzalez and Quesada (in press) examined individuals' recognition process by measuring the similarity of decisions made by participants completing a DDM task (Gonzalez & Quesada, in press). Their findings indicate that decisions became increasingly similar with task practice. As participants acquired more experience in a task, their ability to discriminate and understand the multiple variables that affected task performance improved.

Researchers have hypothesized that the recognition or detection phase of DDM is followed by an information seeking phase during which decision makers attempt to identify the specific control action required for improved task performance (Simon, 1972). If the task's goals lack specificity or the decision maker lacks sufficient prior task knowledge, a goal elaboration phase may follow the detection phase. In essence, DDM tasks require decision makers to control one time-dependent process by completing another time-dependent process (Brehmer, 1992). If the system evolves more quickly than the decision process used to control it, the decision maker might be forced to use outdated or "stale" information to make dynamic decisions. As argued by Ariely and Zakay (2001), system-driven demands for decision input require dynamic decision makers to actively consider the duration of their decision processes, the best time at which to make a decision, and how the decision environment changes as a function of time.

Research has shown that time constraints have a negative effect on individuals' ability to make decisions effectively (Maule & Edland, 1997; Svenson & Maule, 1993). Most of this research, however, has emphasized traditional, static decision-making tasks and has investigated almost exclusively the effects of time pressure on one-time decisions rather than on a series of decisions (Kerstholt & Raaijmakers, 1997). Gonzalez (in press) determined that in DDM, time constraints have serious detrimental effects on performance and that extended practice does not enable decision makers to overcome these effects. Her study also demonstrated that, in addition to time constraints, individuals' cognitive abilities directly influence the strategies they used to make decisions. For example, individuals under more stringent time constraints were inclined to use simpler heuristics for DDM while individuals under less stringent time constraints gradually gave up their use of simple heuristics, presumably taking advantage of context-acquired knowledge. Similarly, participants with lower cognitive abilities depended more on simple heuristics for task performance than did individuals with higher cognitive abilities.

In drawing a similar conclusion, Kleinmuntz (1985) distinguished between judgment- and action-oriented strategies. Judgment-oriented strategies involve an information seeking phase, whereas action-oriented strategies do not. More specifically, individuals using action-oriented strategies avoid information seeking by issuing control actions on the basis of general, high-level feedback from the system. Thus, while individuals using judgment-oriented strategies seek to reduce uncertainty by gathering more specific information, persons using action-oriented strategies seek to reduce uncertainty by observing general system responses to incremental adjustments.

Feedback loops, the specificity and frequency of the feedback, and the feedback delays pose additional influential demands in dynamic systems. In at least some cases, dynamic decisions appear to require mental representations that explicitly encode the expected utility of decisions and the actual or real utility of decisions upon receipt of the output feedback (Gonzalez et al., 2003). Decision instances – and their utility – resemble causal networks or interdependent chains rather than isolated, one-way causal chains (Funke, 1988).

In summary, DDM demands more from decision makers than do other types of choice situations. Research in DDM has demonstrated that people fail to learn a dynamic task due to their misperception of the feedback provided by the environment and a lack of control over the effects of their decisions (Diehl & Sterman, 1995; Sterman, 1989). Other research indicates that cognitive abilities and time constraints influence DDM performance (Gonzalez, in press). Specifically, decision making in complex situations does not involve only judgment and choice. IBLT also implicates the cognitive processes of recognition and feedback in DDM (Gonzalez et al., 2003). Systematic empirical research is needed to foster a better understanding of the effects of these cognitive demands during DDM.

5. Conclusions

Dynamic decision-making tasks have describable and testable characteristics, including dynamics, complexity, opaqueness, and dynamic complexity, all of which influence decision making and place demands on human cognition. Systematic research of these characteristics, the associated cognitive demands, and cognitive support is essential to making progress in the study of decision making in the dynamic environments typically found in the real world.

The real world, however, is complex and difficult (if not impossible) to control. Researchers use microworlds to study DDM in a laboratory setting and believe that these simulations contain many of the same abstract cognitive characteristics as real-world tasks. Our review of microworlds discussed in the literature suggests high variability in microworld characteristics. Although most microworlds are complex and opaque, they vary considerably in terms of dynamics and dynamic complexity. To bolster our knowledge of dynamic tasks, microworlds must provide the characteristics of DDM environments and facilitate researchers' control over those environments. The lack of research investigating the cognitive demands and possible cognitive support of dynamic tasks hinders progress toward an improved understanding of decision making in the real world.

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