The Dynamic Interactions between Situations and Decisions

Jerome R. Busemeyer, Ryan K. Jessup, & Eric Dimperio

Indiana University

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Send Correspondence to:

Jerome R. Busemeyer
Indiana University
1101 E. 10th St.
Bloomington IN 47405
jbusemey@indiana.edu

The majority of judgment and decision making research is based on laboratory experiments using very simple and artificial stimulus conditions. Eliciting preferences between simple gambles of the form 'get $*x* with probability *p*, otherwise $*y*' is the primary basis on which rational principles of decision making are tested (Goldstein & Weber, 1995). The foundation of modern decision theories (see Luce, 2000), are built on findings from these simple gambling paradigms. These laboratory experiments are quite far removed from real-life decisions, nevertheless, many of the findings do generalize to real world applications (Levin, Louviere, Schepanski, 1983). However, new empirical phenomena and unique theoretical issues have surfaced by studying decision making in more natural environments. One of the goals of this chapter is to review these new findings and theoretical issues. A second goal is to examine more closely whether or not theories built from simple laboratory experiments are capable of addressing these new challenges.

1. Situated Decision Making

The term 'situated cognition' may be unfamiliar to many decision researchers, but the ideas are not. Many decision researchers have considered, very seriously, the importance of using realistic environments for the study of decision making. Decision researchers have used terms such as 'social judgment theory' or 'decision analysis' or 'naturalistic decision making', which may be less familiar to cognitive scientists, to describe their explorations into work in the area of situated cognition.

Social judgment theory (see Hammond, Stewart, Brehmer, & Steinmann, 1975) is generally interested in understanding how experts form judgments based on cues provided by the environment. For example, in an experimental study of highway safety policies (Hammond, Hamm, Grassia, & Pearson, 1987), expert highway engineers were asked to predict accident rates for highways described by scenarios (e.g., videos). The scenarios were designed to manipulate 10 cues that were identified as essential by the experts (e.g., highway size, traffic speed, traffic volume, etc.). Each scenario was constructed by sampling a combination of cue values for the 10 cues. To estimate each expert's policy (i.e. the rule mapping cues to predictions), judgments were obtained from each expert using 40 different highway scenarios. Statistical models (e.g., regressing the judgments on the cue values) were then used to estimate the expert's policy. From these analyses one can determine the importance weight of each cue for making a judgment.

Research in social judgment theory is based on Egon Brunswick's (1952) concepts of representative design and ecological validity. A representative design is achieved by sampling judgment situations by a method that preserves ecological validity; ecological validity holds when the sample correlations between cues and the criterion match the corresponding true correlations in the population. For example, highway size, traffic speed, and traffic volume are correlated with each other and correlated with accident rates in the real world, and these correlations should be reflected in sample scenarios presented to the experts. Students of Brunswick reject the use of experimental designs that create artificial and unnatural situations which break these correlations. For example, although the use of uncorrelated cues (e.g., factorial designs) would facilitate the statistical analysis of experts' policies, this artificial design violates the naturally occurring correlations among cues. According to Brunswick (and social judgment researchers, see Dhami, Hertwig, & Hoffrage, 2004 for a recent review), tampering with the naturally occurring environmental relations could destroy the phenomena under investigation. Instead, judgment situations should be sampled in a representative fashion so that the ecological validities of cues are maintained. In the above example of highway safety judgments, a representative sampling of situations was achieved by designing cue combinations that reproduced the true or natural inter-correlations and ecological validities of cues for the population of highways under study.

The discovery of general principles of human judgment is a primary objective of social judgment research. For example, in the highway safety study, researchers may be interested in how the presentation format of the cues (abstract bar graphs vs. concrete videos) generally affects the expert's policies. Experimental methods are still preferred over natural observation or field research for this purpose. However, the experiments are designed so that both the stimuli (situations to be judged) and participants (judges) are sampled in a way that represents the real world population of situations and people.

Decision analysis is concerned with the development of prescriptive methods for improving difficult real-life decisions (Keeney & Raiffa, 1976; Clemens, 1996). A real-life example (see Von Winterfeldt & Edwards, 1986) is a case in which an oil company had to select a site to drill for oil. The basic principle is to divide and conquer – a complex decision is broken down into small manageable parts, judgments are made with respect to each part, and then these small parts are re-combined to form an overall evaluation. Experts consult with decision analysts who help them form a representation of the problem in terms of decision trees (actions and events over time). Then probability estimates are elicited from the experts concerning the uncertain events on the branches of the decision tree. The consequences of the actions along the branches of the trees are decomposed into attributes, and each action is evaluated with respect to each attribute.

For example, on the one hand an oil site may have a large oil reserve, but on the other hand it may be located in an environmentally protected region. Finally, a rational or optimal rule, called the multi-attribute expected utility rule, is used to combine the probabilities and values into a summary measure of utility.

Research in decision analysis is primarily concerned with the development and testing of methods for representing decision scenarios, tools for estimating probabilities, and techniques for eliciting value judgments. Decision support systems serve as important external resources for decision makers – statistical analyses and computer simulations are used to help estimate event probabilities; computer analyses are used to provide instant feedback about expected utilities; sophisticated human computer interfaces are used to help elicit judgments, facilitate group discussion, and communicate results.

The most difficult and controversial aspect of this research is assessing the quality of decisions produced by these methods (see Yates, 1990). One cannot simply rely on the outcome of a single decision because of its probabilistic nature. A rational decision process may yield an unfortunate outcome by chance. For example, a carefully selected drilling site may nevertheless turn out to be a disaster because of an unpredictable environmental event (e.g., a hurricane). Many important decisions, such as selecting a drilling site, are made only once, which provide little opportunity to learn from experience. There are no absolute criterion for identifying a ‘correct decision’ because the decisions depend on personal beliefs and subjective values. Assessing decision quality has been a long standing problem in the evaluation of decision analysis tools. Two minimal criteria for evaluating decision quality are consistency and robustness – the decision should not be affected by irrelevant changes in representation or by small adjustments caused by minor judgment errors (Kaplan, 1996).

Naturalistic decision making refers to a research methodology for understanding how actions are selected in dynamic, complex, real-life situations that involve high stakes, a high degree of uncertainty, and high time pressure (Zsambok, & Klein, 1997). For example, in a study of emergency decisions, researchers followed 30 expert firefighting units to 126 emergency scenes and observed and recorded their activities; they also intensively interviewed the command and control decision makers immediately after the incidents (Klein, 1999). The findings from this field research indicated that traditional decision theory provided little help in these types of decisions -- they are much too complex and uncertain, and time is much too short to evaluate all the feasible actions.

Consequently, research on naturalistic decisions has uncovered some new views of decision making (Lipshitz, Klein, Orasanu, & Salas, 2001). First, situation assessment seems to be the most crucial component of the process for these types of decisions. Given a situational assessment, the next most important process is option generation. In many cases, following a situation assessment, the appropriate action is clear and immediate. In these cases, the decision seems fairly obvious, so that there is very little in the way of actual evaluation of alternative actions. This led Klein (1998) to propose what he calls the recognition-primed decision model. According to this model, after completing a situation assessment and developing a mental model of the situation, the decision maker generates or retrieves an action that matches the assessed situation. Then this action is mentally simulated to determine its feasibility and the possibility of failure to achieve the goal. If the initially generated action is evaluated as acceptable (likely to succeed in achieving the goal), then the action is carried out without further deliberation or comparison with competing options. If it is not acceptable, then a second option is generated and evaluated for acceptability, etc. Thus the options are evaluated serially one at a time and never directly compared. This contrasts sharply with traditional decision theory in which all options are carefully compared simultaneously, and the best option in a choice set is selected. In fact, the recognition-primed decision process is more closely related to Herb Simon's (1955) search and satisficing principles. It is also closely related to the 'take the best' heuristic used by Gigerenzer and Todd (see Todd's chapter in this volume).

Given the emphasis on real-life decisions, naturalistic decision making relies heavily on field research and interview methods, and these methods have raised some concerns (LeBoeuf & Shafir, 2001). One is that field research methods lack the control and measurement precision needed to rigorously test for decision biases. For example, much of naturalistic decision research is based on retrospective interviews, and basic research has shown that these retrospective reports (as distinct from online protocols) inaccurately reflect the basis of decisions (Nisbett & Wilson, 1977, Ericsson & Simon, 1984). This is because of possible hindsight biases (Fischoff & Slovic, 1978), and memory recall failures and distortions (Loftus, 2003).

One of the distinct advantages of naturalistic decision making is also one of its greatest disadvantages. On the one hand, an intense focus on a specific yet complex situation generates a detailed description of that one real-life decision. On the other hand, this understanding is limited to that particular situation, and very little generalization to other decision situations is possible. In other words, the approach produces detailed descriptions but fails to produce general principles (Yates, 1990).

Dynamic decision making tasks provide a good compromise between experimental control needed for basic research and simulation of real-life decisions (Edwards, 1962). For example, You (1989) studied a simulated health management task in which subjects controlled their (simulated) patients' health using a (hypothetical) drug treatment. Participants chose a dosage level on each of 14 (simulated) days on the basis of feedback from a patient's previous records (treatments and health states). Each simulated patient was actually programmed to respond according to a delayed second order linear feedback system. The initially novice decision makers were given extensive training with a total of 20 simulated patients so that they develop some expertise for this particular task.

These types of laboratory tasks have some trade-offs that should be recognized. First, these tasks are artificially made to allow for experimental control and theoretical tractability, and they often end up oversimplifying the real-life tasks they simulate. Still, more complex tasks that provide greater realism have been designed without giving up the benefits of the laboratory. (e.g., Brehmer & Allard's, 1991, fire-fighting simulation task, or flight simulators for training pilots). Second, the experimenter is giving up a certain degree of control so that stimulus events are influenced by the behavior of the subject. Thus the design and analysis of such research would be better served if experimenters adapted a more cybernetic paradigm rather than the traditional stimulus-response paradigm. (cf. Brehmer, 1992; Rapoport, 1975).

An important question that arises from this research is how to characterize the decision making process for these complex dynamic tasks. One approach (Jagacinski & Miller, 1978; Jagacinski & Hah, 1988) is to estimate the decision maker's control policy by regressing the control decision (e.g., the drug treatment level) on the past decisions and past states of the system (past treatments and health levels). This provides an understanding of the importance of different kinds of information used to make control decisions in dynamic tasks. For example, You (1989) found that subjects' treatment decisions on each trial could be represented by a linear control model in which subjects made use of information about treatments and health states lagging back in time up to two previous (simulated) days.

Although human performers with extensive task training remain sub-optimal in dynamic decision tasks (Sterman, 1994), most of the past studies reveal regular learning effects. Subjective policies may follow different paths but tend to evolve toward the optimal control policy over multiple trial blocks (Jagacinski & Miller, 1978; Jagacinski & Hah, 1988; You, 1989). Therefore, it is the particular learning processes that are more significant for explaining much of the variance in human performance on dynamic decision tasks (cf., Hogarth, 1981). At least three different approaches to learning to control dynamic systems have been developed Anzai (1984) developed a production rule model to describe how humans learn to navigate a simulated ship. An artificial neural network model was developed to describe learning in a sugar production task (Gibson, Fichman, & Plaut, 1997). An exemplar (instance base, or case base) learning approach has been used in several dynamic control applications (Dienes & Fahey, 1995; Gonzalez, Lerch, & Lebiere, 2003; Gilboa, & Schmeidler, 1995).

According to the exemplar learning approach, the decision maker matches the current state of the dynamic task with similar states that occurred in the past, and recalls the outcomes of those past decisions. The action producing the best outcome in the past is then chosen for the current state. This is related to the idea of matching situations with actions in the recognition-primed decision model proposed by naturalistic decision researchers. So it seems that lessons learned from the laboratory using dynamic decision tasks converge on the same answers as those learned from studying naturalistic decision situations.

2. Alternate Approaches to Naturalistic Decisions: Sequential Sampling Processes

Does the decision process really change so dramatically for naturalistic decisions as compared to laboratory decisions? Instead of looking for help from traditional decision theory, perhaps it would be better to look for help from Cognitive Psychology. Researchers from sensation (Smith, 1995), perception (Link & Heath, 1975), memory (Ratcliff, 1978), categorization (Nosofsky & Palmeri, 1997; Ashby 2000) and decision making under uncertainty (Busemeyer & Townsend, 1993) have converged on the common idea that decisions are made by a sequential sampling process: information and evaluations are sequentially sampled and accumulated over time in parallel for each possible course of action, and the process stops as soon as the strength for one action exceeds a threshold bound.

Sequential sampling models of decision making originated in research on signal detection types of decisions. For example, a radar operator may need to decide whether a blip moving on the screen is an enemy or a friendly agent; or a radiologist may need to decide whether an image should be diagnosed as a harmless tumor or a cancerous node. In laboratory studies of signal detection, highly practiced individuals make decisions under uncertainty (e.g., low signal to noise ratio) within short deadlines (e.g., within a second) and real payoffs (e.g., lose $1.00 for each error). Although this situation clearly differs from real-life emergency decisions, the basic theoretical ideas may still be applicable.

The early versions of signal detection theory (Green and Swets, 1966) were static and assumed that a decision was based on a fixed sample of information. These early models were effective for describing how hits (correctly responding signal) and false alarms (incorrectly responding signal) varied as a function of signal strength, prior probabilities, and payoffs. However, these early models failed to account for speed–accuracy trade offs, as they provided no mechanism for predicting choice response time. The subsequent development of sequential sampling models (Vickers, 1979; Luce 1986) provided a dynamic extension of signal detection theory, which not only accounted for hit and false alarm rates, but also choice response time, and the relation between speed and accuracy.

The sequential sampling model of decision making is quite different from the recognition-primed decision model in two important ways. First, several courses of action are evaluated in a *parallel competition* over time for selection, rather than serially. Second, situation assessment *dynamically interacts* with decision making. The assessment process does not run independently until completion; but rather it can terminate early or late during processing depending on the relative strengths of the competing alternatives. Let us analyze a real-life example to see how a sequential sampling model of decision making differs from the recognition-primed decision model.

An experienced motorcyclist is riding cross country on his motorcycle, cruising around 80 km per hour down a two lane state highway when he came 25 meters behind a truck traveling in the same direction, loaded down with old car tires. The highway is in poor condition, filled with pot holes left by snow plows from the previous winter. The truck bumps into of one of these pits, causing a tire to somersault out of the truck and land flat on the road, directly in the motorcyclist's path. Thus the motorcyclist faces an emergency situation, upon which he very quickly generates three potential plans of action: (A) drive straight over the tire, (B) swerve to the side, or (C) slam on the breaks. [1]

Now the standard operating procedure for most motorists in this situation is to slam on the breaks, but the motorcyclist notices that there was a line of cars following closely, and he could get hit from behind. He could also swerve to the side, but he notices that the road had no shoulder, and an abrupt turn could topple the bike. The only remaining option under consideration is to drive straight over the tire, but his chain may get caught, causing the bike to flip over. These and many other thoughts and feelings race through his head during the brief second in which a decision must be made.

The basic ideas behind the sequential sampling model for this example can be understood by considering Figure 1 below. The horizontal axis of the figure represents time, and the vertical axis represents the strength of preference. Each trajectory shows the preference strength for an action across time. The zero time point marks the onset of the decision process (that is, the onset of the emergency situation). The top flat line represents the threshold bound (located at .70 in the figure), i.e., the strength of preference that an action needs to exceed in order to make a decision. Notice that Action C (slam on breaks) begins with a positive bias because this is the standard operating procedure for this type of emergency; Actions A and B start at lower initial values because they are more unconventional.

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[1] This incident happened to the first author who decided to drive straight over the tire and survived to tell this story.

As the deliberation process unfolds, evaluations start pouring into the decision maker’s mind. In this example, evaluations favoring Action A (drive straight over) steadily overcome action C (slam on breaks), and action B (swerve) is driven systematically downward in preference. Before 250 ms, action C dominates the race; Actions A and C strongly compete at 350 ms; but after 600 ms, Action A overcomes Action C. However, the threshold is set to low criterion, allowing it to be reached for the first time by Action C at 250 ms, and so Action C is executed at this moment (for this example).

<Insert Figure 1 about here>

Notice that this description of the decision process is quite different from that given by the recognition-primed decision model. According to the latter, the rider would spend most of his time making a situation assessment, and would not even consider actions until the situation assessment process was complete. In contrast, the sequential sampling model allows situation assessment to feed online into action evaluation. It can stop early if there is a sufficiently strong preference to warrant action, or it can continue longer if necessary to more clearly discriminate the competing options.

According to the recognition-primed model, once the situation was assessed, a single action that matches the situation is activated. The action that best matches this particular situation would be to slam on the breaks, which is the standard operating procedure for this kind of situation for most drivers. Only if the evaluation of the first action failed to exceed a threshold would another action be considered. Thus actions are evaluated in a serial manner, and very likely only the first action is considered at all. This contrasts sharply with the sequential sampling model in which all three actions are retrieved simultaneously, and all three dynamically compete over time in a race for threshold bound to be selected.

The threshold bound has a crucial function in the sequential sampling process. It determines the strength of preference required before making a decision. If this is set to a very low value, then very little strength is needed to make the decision. For example, if the threshold was set to 1.0 instead of .70, then Action A would be selected a little after 750 ms. Setting the threshold to a high value requires more information to be processed and longer average decision times. Thus the threshold is used to control speed – accuracy trade-offs. Short deadlines would require low thresholds to make quick decisions, but high stakes would push the threshold up higher to avoid making fast errors. Impulsive decision makers tend to use a low threshold and act with little thought, while careful decision makers tend to use a higher threshold and spend more time in thought before acting. In short, the threshold is a parameter used to control the average amount of time to spend on making a decision.

A threshold parameter is also used in the recognition-primed model, but it serves a different purpose. Rather than controlling the length of time spent on situation assessment, it determines the likelihood of choosing the first action that matches the situation. If the threshold is very high, then the first action is likely to be passed up even if it is the best. If the threshold is very low, then the first action is likely to be chosen even if it is actually the worst. Thus, increasing the threshold does increase decision time, but it does not necessarily increase accuracy in the recognition-primed decision model.

Despite the differences mentioned above between the two models, they can mimic each other under certain circumstances. Suppose one used the sequential sampling process to make decisions. If there is a strong bias for the standard operating procedure for a given situation, and if the threshold bound is set very low under extreme time pressure, then the sequential sampling model behaves very much like the recognition-primed decision model. For in this case, it is very likely that the sequential sampling model will select the initially favored action for a particular situation.

There is a simple empirical test that can be performed to distinguish these two models. The sequential sampling model predicts that the average amount of time required to make a decision depends not only on the action that is chosen, but also on the nature of the action that was not chosen. If the discriminability is high, that is, the incoming information strongly and consistently favors one action over another, then a decision will tend to be made very quickly; but if the discriminability is low, that is, the incoming information inconsistently or weakly favors one action over another, then a decision will tend to be made more slowly. In short, average decision time is inversely related to discriminability between the competing actions. In contrast, the recognition prime model assumes that actions are evaluated serially, and the time required to evaluate a given action only depends on the comparison of this action with a threshold, and it does not depend on the strength of other possible competing actions. In laboratory experiments using signal detection type of tasks, the evidence clearly indicates that decision time is inversely related to discriminability between competing options (see Luce, 1986; Vickers, 1979). However, this finding may be restricted to choices between a small number of competing options, and it may not be true for situations that provide a very large number of choices (e.g., choosing a move in chess, see Klein, 1989).

This brings us to ask -- under what conditions might one expect the sequential sampling process versus a recognition-primed decision process to be used in naturalistic decisions? In the motorcyclist example, only a very small number of competing actions are immediately available, and there is a great deal of conflict among the competing actions. This is very likely to be a situation where a sequential sampling type of deliberation process is needed to separate out one option from a few strong competitors. However, consider for example searching through a very large set of possibilities, such as an escape route in an emergency with many possible exits. Here a serial search through options until one exceeds a threshold is a more likely description of the process. There is a growing literature examining stopping rules that individuals use to serially search through large option sets (e.g. see Beardon, 1997, for a review see Diederich, 2003).

3. Decision Field Theory

Figure 1 provides only a descriptive illustration of how a sequential sampling decision process works. To get a clearer idea, we will provide a more formal specification of a theory, called decision field theory[2], which was specifically designed for decision making under uncertainty with time stress (Busemeyer & Townsend, 1993; Roe, Busemeyer, & Townsend, 2001). However, we should mention that there are also other competing theories that provide alternate dynamic accounts of the decision making process (see, e.g., Holyoak & Simon, 1999; Usher & McClelland, 2004).

Consider the motorcyclist's decision once again, and for simplicity, suppose that there are four possible outcomes that could result from each action: (c_1) a safe maneuver without damage or injury; (c_2) laying the motorcycle down and damaging the motorcycle, but escaping with minor cuts and bruises; (c_3) crashing into another vehicle, damaging

[2] The name decision field theory reflects the influence of Kurt Lewin's (1936) Field theory of conflict.

the motorcycle and suffering serious injury, (c_4) flipping the motorcycle over and getting killed. In the motorcyclist's opinion, driving straight over the tire (action A) is very risky, with high possibilities for the extreme consequences, c_1 and c_4. Swerving (action B) is more likely to produce consequence c_2, and slamming on the brakes (action C) is more likely to produce consequence c_3. The affective evaluation of the j^{-th} consequence is symbolized as m_j, which is a real number that represents the decision maker's personal feelings about each consequence, such that higher m_j's are evaluated as better consequences (clearly $m_1 > m_2 > m_3 > m_4$ in this example).

Figure 2 provides a connectionist interpretation of decision field theory for this example. The affective evaluations shown on the far left are the inputs to this network. At any moment in time, the decision maker anticipates the consequences of each action, which produces a momentary evaluation, $U_i(t)$, for action i, shown as the first layer of nodes in Figure 2. This momentary evaluation is an attention weighted average of the affective evaluation of each consequence: $U_i(t) = \sum W_{ij}(t)\cdot m_j$. The attention weight, $W_{ij}(t)$ for consequence j produced by action i at time t, is assumed to fluctuate according to a stationary stochastic process. This reflects the idea that attention is shifting from moment to moment, causing changes in the anticipated consequences of each action across time. For example, at one moment in time the decision maker may believe he can successfully drive straight over the tire, but at the next moment he may change his mind and fear that the tire will get entangled with the motorcycle chain.

The momentary evaluation of each action is compared with other actions to form a valence for each action at each moment, $v_i(t) = U_i(t) - U_.(t)$, where $U_.(t)$ equals the average across all the momentary actions. The valence represents the momentary advantage or disadvantage of each action, and this is shown as the second layer of nodes in Figure 2. If the decision maker is being attracted to one action by a positive valence, then he or she must be repelled from other actions by negative valences, so that the total valence balances out to zero. All the actions cannot become attractive simultaneously.

Finally, the valences are the inputs to a dynamic system that integrates the valences over time to generate the output preferences states. The output preference state for action *i* at time *t* is symbolized as $P_i(t)$, which is represented by the last layer of nodes in Figure 2 (and plotted as the trajectories in Figure 1). The dynamic system is described by the following linear stochastic difference equation:

$$P_i(t+h) = \sum s_{ij} \cdot P_j(t) + v_i(t+h) \qquad (1)$$

where h is a small time step in the deliberation process. The positive self feedback coefficient, $s_{ii} = s > 0$, controls the memory for past input valences for a preference state. The negative lateral feedback coefficients, $s_{ij} = s_{ji} < 0$ for $i \neq j$ produce competition among actions so that the strong inhibit the weak. The magnitudes of the lateral inhibitory coefficients are assumed to be an increasing function of the similarity between choice options. These lateral inhibitory coefficients are important for explaining context effects on preference, which are described later.

The initial state of preference, $P_i(0)$, represents the effect of past experience on the current decision. In the above example shown in Figure 1, the option representing the standard operating procedure for a decision may start with a positive bias. The initial state can also reflect the status quo or default option. It is generally assumed that the initial preference states sum to zero, so that positive initial biases must be offset by negative initial biases.

Are dynamic models of decision making, such as decision field theory, radically different from the traditional expected utility model? To answer this question, it is informative to analyze the simple binary choice case in which the decision maker must choose between actions A versus B (let us set $h = 1$ for simplification). In this simple case, Equation 1 implies

$$[P_A(t+1) - P_B(t+1)] = \alpha \cdot [P_A(t) - P_B(t)] + [U_A(t+1) - U_B(t+1)] \quad (2)$$

where $\alpha = (s_{11} - s_{21})$ and $0 < \alpha < 1$. The solution to this difference equation is

$$[P_A(t) - P_B(t)] = \alpha^{t+1} \cdot [P_A(0) - P_B(0)] + \sum_{\tau=1}^{t} \alpha^{t-\tau} [U_A(\tau) - U_B(\tau)] \quad (3)$$

The stochastic element $U_i(t)$ can be broken down into two parts: its expectation plus its stochastic residual. The expectation of $U_i(t)$ is given by

$$u_i = E[U_i(t)] = E[\sum W_{ij}(t) \cdot m_j] = \sum \mathrm{E}[W_{ij}(t)] \cdot m_j = \sum w_{ij} \cdot m_j \ , \quad (4)$$

where $w_{ij} = E[W_{ij}(t)]$ is the mean attention weight or decision weight as it is called in traditional decision theory. The last expression on the right hand side of Equation 2 is the same formula that defines the weighted utility of an action according to modern decision theories (see, e.g., Tversky & Kahneman, 1992). Therefore we can define the residual as $\varepsilon_i(t) = [U_i(t) - u_i]$. Inserting $U_i(t) = [u_i + \varepsilon_i(t)]$ into Equation 3 produces

$$[P_A(t) - P_B(t)] = \alpha^{t+1} \cdot [P_A(0) - P_B(0)] + \sum_{\tau=1}^{t} \alpha^{t-\tau} (u_A - u_B) + \sum_{\tau=1}^{t} \alpha^{t-\tau} [\varepsilon_A(\tau) - \varepsilon_B(\tau)] \, ,$$

which can be simplified as follows

$$[P_A(t) - P_B(t)] = \alpha^{t+1} \cdot bias + \left(\frac{1 - \alpha^{t+1}}{1 - \alpha} \right) \cdot (u_A - u_B) + error(t) \, . \quad (5)$$

The bottom line, according to Equation 5, is that the difference in preference states evolves from an initial bias toward the difference in expected utilities over time (plus sampling error). Thus there is a direct connection between the difference in expected utility and the difference in preference states of decision field theory. Both models share a common set of parameters: the decision weights, w_{ij}, representing the belief that an action will produce a consequence; and the values, m_j , of the consequences. Decision field theory also includes three new parameters: the initial bias $[P_A(0) – P_B(0)]$, the growth rate parameter α , and the variance of the residual error. The variance of the residual is important for explaining the probabilistic nature of choice behavior (Busemeyer & Townsend, 1993), the growth rate parameter is important for explaining changes in strength of preference strength as a function of deliberation time (see Busemeyer, 1985), and the initial bias is important for producing reversals (for examples of bias under time pressure, see Diederich, 2003).

In summary, we examined a claim that naturalistic decisions required a completely new type of decision theory. Next, we argued that sequential sampling theory, which assumes a dynamic interaction between situation assessment and decision processes, provides a viable explanation for many naturalistic decisions. Finally, we showed that sequential sampling models, such as decision field theory, can be viewed as dynamic extensions of the traditional decision theories. Therefore, sequential sampling models provide a theoretical bridge between traditional decision theories and naturalistic decisions.

4. Situated Cognition in the Laboratory: Context Dependent Preferences

Effects of choice context on preference are not limited to naturalist situations. On the contrary, basic research with simple choice problems provides compelling evidence that our preferences are constructed in a highly context-dependent manner (Payne

Bettman, 1992). Consider the following experiment by Tversky and Kahneman (1991) which was designed to test a rational principle of choice called independence from irrelevant alternatives. According to this principle, if option X is favored over Y in the choice context that includes option R_x, then X should also be preferred over Y in the choice context that includes option R_y.

The basic ideas of the experiment are illustrated in Figure 3, where each letter shown in the figure represents a choice option described by two attributes; for example, consumer products that vary in price and quality. In this case, option X is low on price and quality, whereas option Y is high on price and quality. When presented with a straight binary choice between options X and Y, the options are (approximately) equally favored. The main theoretical question concerns the addition of a third option to the set, which is used to manipulate the choice context.

The critical context manipulation in this experiment was the introduction of a third option, called the reference option, represented by either option R_x or option R_y. Under one condition, participants were asked to imagine that they currently owned the commodity R_x, and they were then given a choice of keeping R_x or trading it for either commodity X or commodity Y. From the reference point of R_x, option X has a small advantage on price and no disadvantage on quality, whereas Y has large advantages on quality and large disadvantages on price. Under these conditions, R_x was rarely chosen, and X was favored over Y. Under another condition, participants were asked to imagine that they owned option R_y, and they were then given a choice of keeping R_y or trading it for either X or Y. From the reference point of R_y, Y has a small advantage and no disadvantages, whereas X now has both large advantages and disadvantages. Under this condition, R_y was rarely chosen again, but now Y was favored over X.

In summary, even though the reference options, R_x and R_y, were rarely ever chosen, nevertheless, they changed the choice context, causing the preference order for X and Y to reverse across the two contexts. This preference reversal violates the rational principle of choice called independence from irrelevant alternatives. This is just one example violation of this principle, but there are many others (see Tversky & Simonson, 1993; Roe et al., 2001).

What causes these context effects on preferences? Tversky and Kahneman (1991) interpreted this particular result in terms of a loss aversion effect: Option X was favored when Y entailed large losses relative to the reference point R_x, but the opposite occurred when X entailed large losses relative to the reference point R_y. But this explanation leaves one to wonder about the mechanism that causes loss aversion.

Decision field theory provides a dynamic mechanism for explaining the reference point effect as well as many other context dependent preference effects (see Roe et al., 2001; Busemeyer & Johnson, 2004). According to decision field theory, these context effects are generated by the recurrent network shown as the third layer in Figure 2. We will skip the mathematical derivations here, and simply present the conceptual ideas.

According to decision field theory, these effects are contrast effects like edge enhancement effects that occur in the retina (alternately, these effects can be conceptualized in the context of the lateral inhibition occurring within the striatum, part of the basal ganglia, during the process of action selection; see Frank, 2005; Wickens, 1997). The inferior reference option makes the closely related attractive option shine.

First consider the choice set that includes options X, Y, and R_x. Recall that according to decision field theory, the lateral inhibitory links in the network depend on the similarity between options. Note that the reference point R_x is very similar to X, and so the lateral inhibitory link between these two is strong; whereas R_x is very dissimilar to Y, and so the lateral inhibitory link between these two is weak. Also note that R_x always experiences a disadvantage with respect to option X. This arrangement of options then produces the following dynamics: as processing time passes, option R_x is slowly driven down toward a negative preference state; this negative preference feeds back through a negative lateral inhibitory link to produce an enhancement or bolstering of option X. In other words, the relatively poor reference option, R_x, makes its close neighbor, option X, shine brighter. The distant option Y does not experience this enhancement because the lateral inhibitory link is too weak. Therefore the preference state for X gradually dominates Y. When the choice context is changed to include X, Y, and R_y, the same reasoning holds, but now option Y is bolstered by being close to a relatively poor reference R_y.

The above explanation for context dependent preferences depends on a dynamic inhibitory mechanism that takes time to build up. Thus, decision field theory predicts that these context effects should get stronger as deliberation time gets longer. In contrast, if these effects were caused by the use of simple heuristics to save time and effort, then the opposite is predicted – context effects should get larger with shorter deliberation times that force individuals to fall back on simple heuristic rules to save time. In fact, past research has found that the context effects get larger with longer deliberation times, consistent with the predictions of a dynamic model and contrary to a heuristic choice model (see Simonson, 1989; Dhar, Knowlis, & Sherman, 2000).

5. Concluding Comments

The majority of decision research is based on simple laboratory experiments, and modern decision theories have been built on the basis of these findings. Recently, various groups of researchers have questioned the usefulness of these theories when applied to real-life situations. Three related programs of research have examined judgment or decision making through from what could be called a situated cognition perspective. Social judgment theory focuses on expert judgments using environmentally-provided cue – criterion relations. Decision analysis endeavors to provide people with optimized decision tools for real life decisions in order to improve the quality of these decisions. Naturalistic decision making represents a paradigm in which descriptive models of dynamic, complex, high uncertainty, high stakes, and real-life decision situations are sought. Furthermore, they argue that in these complex, real-life situations, there is not enough time or computational resources to systematically evaluate all the options. Consequently, naturalistic decision researchers claim that new theories and methods of research are needed.

In this chapter, we have attempted to address these concerns, specifically those of naturalistic decision researchers, through the use of dynamic, as opposed to static, tools. Rather than rejecting traditional decision theory and research when we enter naturalistic situations, we have tried to argue that a dynamic perspective (see Port & Van Gelder, 1995, Van Gelder, 1998) provides a foundation for building bridges between traditional decision theories and naturalistic decisions. Sequential sampling models were developed from Cognitive Psychology to understand real-time cognitive processes observed in simple laboratory experiments. According to these models, decision makers make an online assessment of the situation which interacts with the evaluation of competing options over time; likewise, information accumulates in real-time and decision times are influenced by a threshold for accrued information. We have argued that dynamic theories of decision making have the power to explain the basic findings from laboratory experiments, such as context dependent preferences, as well as new phenomena that arise in the study of naturalistic decisions.

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Figures

Figure 1. Example of the decision process for the motorcyclist's decision. Horizontal axis is time, and vertical axis is preference, and each trajectory represents an action. The top flat line is the threshold bound.

Figure 2. Connectionist interpretation of decision field theory for the motorcyclist's example.

Figure 3. Illustration of stimuli used to produce reference point effects. The horizontal axis represents price, the vertical axis represent quality, and each point represents a consumer product.

Figure 1

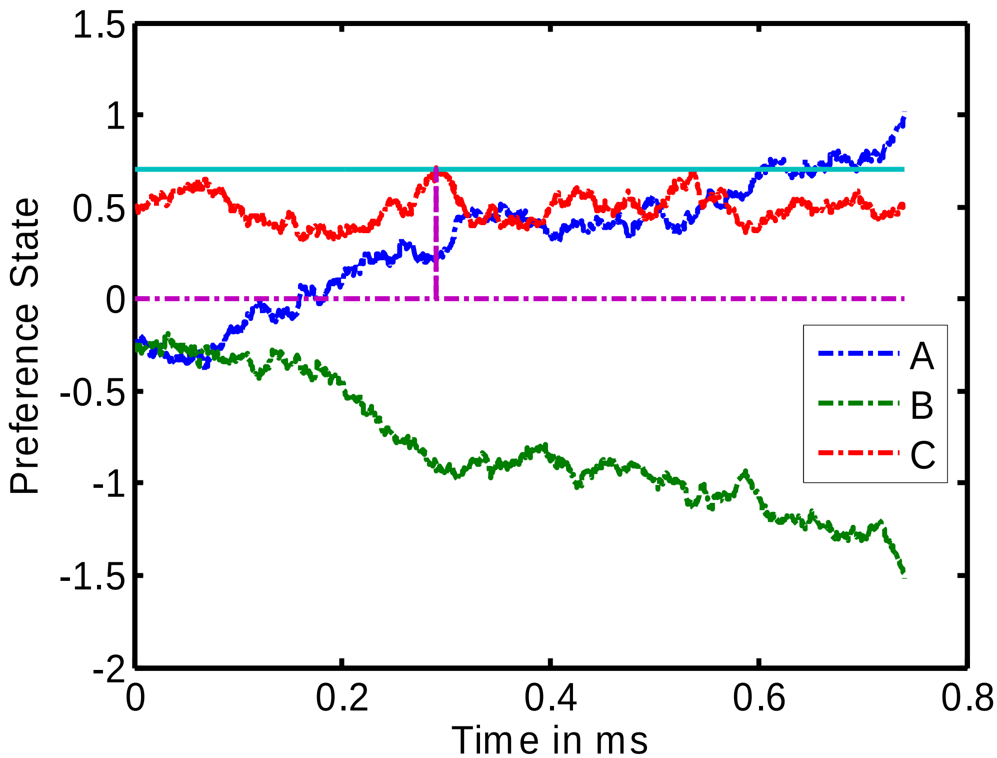

Figure 1

Figure 2

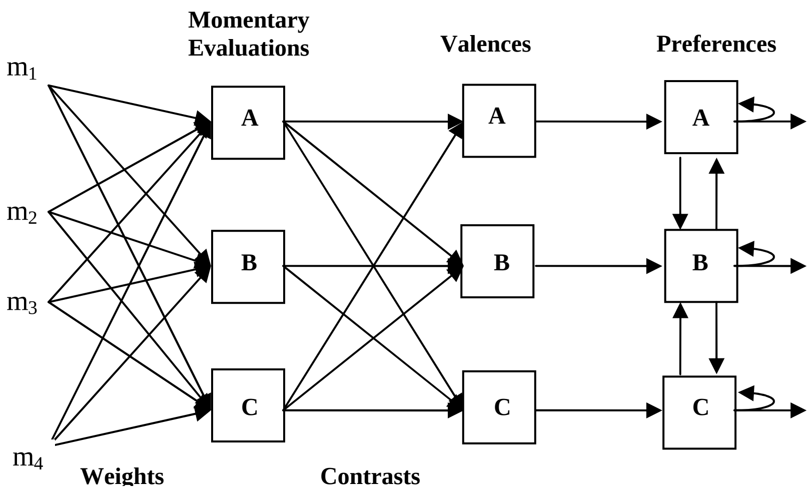

Figure 2

Figure 3

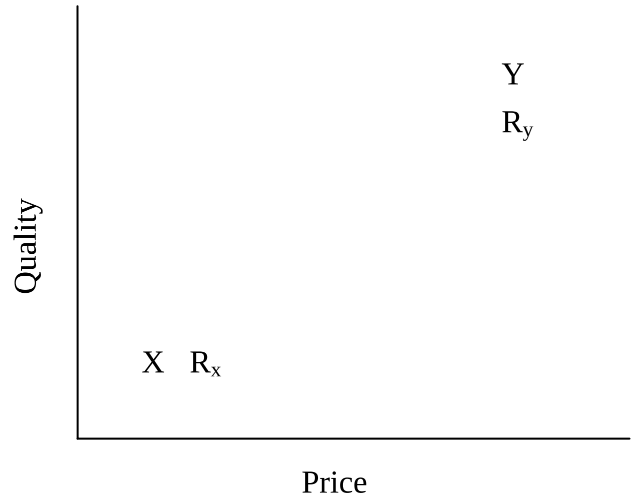

Figure 3