PAR T V

EMOTION

Integrating Emotions, Motivation, and Arousal in Cognitive Systems

Vladislav D. Veksler & Michael J. Schoelles

If human cognition is embodied cognition, then surely physiological arousal, motivation, and emotions are part of this embodiment. Current theories argue both that cognition affects emotion (Lazarus, 1991; Gratch & Marsella, chapter 16; Hudlicka, chapter 19) and that emotion affects cognition (Busemeyer, Dimperio, & Jessup, chapter 15; Gunzelman, Gluck, Price, Van Dongen, & Dinges, chapter 17; Ritter, Reifers, Klein, & Schoelles, chapter 18). A major issue in understanding cognition is its integration with emotions, and vice versa. Having opened the Pandora's box of affective states, the world of cognitive science will never be quite the same.

Of course, the same logic that lead to 100 years of study of tiny parts of cognitive processes in sterile and unchanging task environments can be used to justify the isolation of the study of cognition from the influence of emotion. However, in the face of mounting evidence that affect is a necessary concomitant of decision making (Damasio, 1995; Mellers, Schwartz, & Ritov, 1999) even the resistance of hard-core experimental psychology seems to be crumbling. The paradigm has shifted; the issue is not how to avoid affect in accounts of cognition but how to account for behavior as emerging from a cognitive–affective control system.

The chapters in this section provide a glimpse of things to come. Emotions are presented as specific mechanisms that are integral and essential to cognition, as opposed to vague concepts that work in opposition to rational thought.

In chapter 15, Busemeyer et al. expand decision field theory (Busemeyer & Townsend, 1993) to account for the interaction of affective states with attention and decision utilities over time. These modifications allow for the direct implementation of affect within an influential theory of decision making.

In laying out another piece of the puzzle, Gratch and Marsella (chapter 16) discuss how appraisal theory of emotion explains the influence of emotion on cognition. They claim that appraisal theory can provide a unifying conceptual framework for control of disparate cognitive functions. They sharpen this argument by showing how appraisal theory influenced the design of the AUSTIN virtual human architecture.

Gunzelmann et al. (chapter 17) take on the specific task of accounting for the effects of fatigue by manipulating execution-threshold and goal-value parameters within an existing cognitive architecture. The resulting model provides a good fit to both fatigued and nonfatigued human performance.

Ritter et al. (chapter 18) propose a hypothetical set of *overlays* to account for the various effects of stress. In step with Gunzelmann et al., Ritter et al.'s overlays include execution-threshold and goal-value parameter manipulation. They also propose a set of other possible parameter, system, and model manipulations that may be the direct effects of emotional states on cognition.

In describing the MAMID architecture, Hudlicka (chapter 19) agrees with the parameter overlay approach of Ritter et al. and Gunzelmann et al. She additionally focuses on the effects of cognition on emotions, implemented as an affect appraiser module in MAMID.

Throughout the following chapters, emotions are treated as Type 1, Type 2, and Type 3 controls. It may be counter to the intuitions of traditional cognitive scientists to imagine that the influence of affective states can be so pervasive in cognition as not to be able to classify emotions as a single control type. On deeper analysis, however, it is surely possible to think of emotions as Type 3 goals, productions, and declarative knowledge, or as a separate Type 2 emotions module. And while implementing drives like arousal or hunger would be simplest to do using a Type 2 module, the neurophysiological elements associated with emotions (e.g., dopamine) are profuse throughout the brain and partake in all cognitive activity, arguing for emotions as part of a Type 1 systems control. At the very least, the basic pleasure/pain (seeking/preventative) behavior would seem to belong in Type 1 systems—at some level of description, this functionality already exists in many cognitive architectures.

Regardless of whether you subscribe to a Type 1, 2, or 3 implementation of emotions, and regardless of whether you subscribe to the dynamic systems approach (Busemeyer et al., chapter 15), the appraisal theory approach (Gratch et al., chapter 16), the ACT-R approach (Gunzelmann et al., chapter 17; Ritter et al., chapter 18), or the MAMID architecture approach (Hudlicka, chapter 19), analysis of the integration of emotions within the cognitive system does much to progress our understanding of the control of human cognition. Indeed, the chapters in this section may well represent the beginnings of the next-generation *mental* architectures—fully embodied and more capable of modeling a wider range of the human experience.

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Integrating Emotional Processes Into Decision-Making Models

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

The role attributed to emotion in behavior has waxed and waned throughout the preceding century. When the recent cognitive revolution hit, theories of mental processes treated the brain as a computer. Models lost sight of the motivations and desires that went into thinking. In this chapter, we review research demonstrating an influential role for motivation and emotion in decision making. Based on these findings, we present a formal model for the selection of goals that integrates emotion and cognition into the decision-making process. This model is a natural extension of decision field theory (Busemeyer & Townsend, 1993), which has been successfully used to explain data in traditional decision-making tasks. This model assumes that emotions, motivations, and cognitions interact to produce a decision, as opposed to being processed independently and parallel. By allowing emotion and cognition to coexist in a single process, we demonstrate a testable model that is consistent with existing findings.

During the heyday of neobehaviorism, motivational processes held sway over general system theories of behavior (Hull, 1943; Skinner, 1953; Spence, 1956). Basic drives and learned incentive motives were postulated to guide behavior. Theorizing about unobservable mental processes was shunned (Tolman, 1958, was an exception). Such a stilted understanding of mental processing eventually led to the downfall of these grand and systematic theories.

The rise of the computer-information-processing metaphor in the 1950s paved the way for a cognitive revolution. Cognitive scientists re-aligned their attention on mental processing mechanisms. Short- and long-term memory storage and retrieval were postulated and serial or parallel processes controlled flow of information. A second major attempt to construct general system theories of behavior was initiated (Anderson, Lebiere, Lovett, & Reder, 1998; Meyer & Kieras, 1997; Newell, 1990). However, motivation and emotion was foreign to computer systems, and it was eschewed by information processing theorists. The "goals" of a production rule system had to be hardwired directly by human hand. The cognitive revolution removed the heart from its systems, leaving an artificial intelligence unable to understand the value of its goals. This restricted view of motivation and emotions may eventually lead to the breakdown of the cognitive revolution.

This chapter presents a formal model for integrating emotion and cognition within the decision process that is used to select goals. Emotion enters this decision process by affecting the weights and values that form the basis of decisions. We begin by reviewing some basic facts and concepts from research on emotion. Then we review recent experimental research that examines the influence of emotion and motivation on decisions. Finally, we present a formal model called decision field theory (Busemeyer, Townsend, & Stout, 2002) where motives and emotions dynamically guide the decision process for selecting goals.

[AQ1] What Are We Trying to Integrate?

Let us begin by defining some basic concepts and summarizing some of their characteristics. *Plans* are action–event sequences designed to achieve specific goals, and *problem solving* is a process used to generate potential plans. *Decision-making* processes are used to select one of the plans generated by problem solving for execution. Decisions are based on *judgments*, which evaluate consequences and estimate likelihoods of events. Evaluations of consequences are based on the satisfaction or dissatisfaction of motives.

Motives are persistent biological and cultural needs. These consist of basic drives such hunger, thirst, pain, and sex; but secondary needs are built from these primary needs such as safety and affection; and eventually higher-order needs emerge, such as
[AQ2] curiosity and freedom (cf. Maslow, 1962). *Emotions* are temporary states reflecting changes in motivational levels. For example, joy may be temporarily experienced by a sudden gain of power and wealth; anger may be experienced by a sudden loss of power and wealth; fear may be experienced by threatened loss of power and wealth. *Affect* is an evaluation of an emotional state according to a positive (approach) or negative (avoidance) feeling (movement tendency). For example, joy produces positive affect and anger produces negative affect. Emotions have a dynamic time course, and *moods* reflect lingering affect that can moderate later cognitive processing. For example, joy can produce a lingering positive mood, which can make a person feel optimistic about subsequent events; anger can produce a lingering negative mood, which can make a person feel pessimistic about subsequent events (Lewis & Haviland-Jones, 2000). The dynamic nature of motives and emotions present a challenge to traditional static theories of decision making, and decision field theory attempts to address these dynamic characteristics formally.

What Are the Bases for Emotions?

Emotional experiences have broad influences across the neural, physiological, and behavioral systems. Emotional experiences produce changes in neural brain activation, increasing activation in some cases (such as fear), and decreasing activation in other cases (such as sadness). Neural transmitters are released, such as GABA inhibitors, or dopamine reward signals. Emotions produce hormonal responses—either adrenaline (epinephrine), causing anxiety and preparation for fleeing; or noradrenaline (norepinephrine), activating aggression and preparation for a fight. Physiological reactions of the autonomic nervous system consist of changes in pupil size, heart rate, respiratory rate, skin temperature, and skin conductance (from perspiration). The behavioral reactions include changes in facial expression and body posture, as well as programmed reactions and coping responses (fight or flight).

The cognitive system has a crucial function in interpreting, appraising, and facilitating these neural, physiological, and behavioral reactions (Schachter & Singer, 1962; Lazarus, 1991; Weiner, 1986). For example, if someone else caused an event to happen, and the person had substantial control over the event, and the event generated a negative effect, then your cognitive system would categorize this emotional experience as anger toward the person who caused this negative result. However, if you personally caused an event to happen, and you had control over the event, and the event generated a negative effect, then your cognitive system would categorize this emotional experience as guilt for your role in causing this negative result (see Roseman, Antonius, & Jose, 1996). Thus, the cognitive system categorizes the emotional experience on the basis of the affect and contextual information about the event.

Single versus Dual System Views of Emotion

Neurophysiological research on emotions indicates that two neural pathways underlay emotional experiences

(Buck, 1984; Gray, 1994; LeDoux, 1996; Levenson, 1994; Panksepp, 1994; Scherer, 1994; Zajonc, 1980). First there is a subcortical direct route, which is fast, spontaneous, unconscious, physiological, and involuntary reaction. This is mediated through a direct (thalamus → amygdala → motor cortex) limbic circuit. Second, there is an indirect neocortical route, which has a slower-coping response based on a conscious appraisal of the situation. This is mediated through an indirect (thalamus → sensory cortex → prefrontal cortex → amygdala → motor cortex) neocortical circuit. Recently, however, Damasio (1994) has argued for an integration of two systems taking place in the orbital (ventral–medial) prefrontal cortex.

This neurophysiological evidence gives rise to opposing views about how emotions and cognitions interact to influence decision making. Some argue strongly that there are two separate and independent systems for making decisions; while others argue that these two sources are integrated into a single emotional—cognitive decision-making process.

A two-system point of view has been promoted by many theorists (Epstein, 1994; Hammond, 2000; Kahneman & Frederick, 2002; Loewenstein & O'Donoghue, 2005; Metcalfe & Mischel, 1999; Peters & Slovic, 2000; Sloman, 1996; Stanovich & West, 2000). According to this view, the first system is an emotional, intuitive, affective-based system for making decisions. It processes in parallel, is fast, implicit, unconscious, automatic, associative, noncompensatory, highly contextual, and experience based. This system places little demand on working memory. The second system is a rational, analytic, reasoning-based system for making decisions. It is slow, serial, explicit, conscious, controlled, compensatory, comprehensive, and abstractions based. This system places large demands on working memory. The systems operate independently, and only interact by having the second system correct the errors of the first, if needed, and if there is sufficient time and working memory available.

A single integrated system approach has been advocated by a smaller number of theorists (e.g., Damasio, 1994; Gray, 2004; Mellers, Schwarz, Ho, & Ritov, 1997). According to this view, emotions provide dynamic signals that feed into and help guide the cognitive system over time for making decisions. To describe exactly how this temporal integration and interaction occurs is a major challenge for this viewpoint. Decision field theory provides dynamic mechanisms for integrating fast emotional signals with slower cognition information to guide decisions.

Review of Research on Emotions and Decisions

This brief review is organized around a series of questions concerning the relevance of emotions for decision theory. For a more thorough review, see Loewenstein and Lerner (2003).

1. Do we need to change decision theory for emotional consequences?

Early evidence pointing toward a need to include emotion came from studies examining the effects of anticipated regret (Zeelenberg, Beattie, van der Plight, & de Vries, 1996; see also Mellers et al., 1997, for related research). In these experiments, participants were given a series of choices between safe versus risky gambles. On some trials, they were informed that they would receive outcome feedback immediately after the choice, while on other trials they were informed that feedback would not be provided. Standard utility theories predict that the opportunity for outcome feedback should not have any effect on preference; however, the expectation was that regret would be anticipated for not choosing risky options when feedback was presented. In agreement with the latter prediction, preferences tended to reverse and switch toward the riskier gamble when immediate feedback was anticipated.

Another line of evidence petitioning for change came from research on the effects of emotional outcomes on decision weights (Rottenstreich & Hsee, 2001). According to weighted utility theories, the utility of a simple gamble of the form "win x with probability p, otherwise nothing" is determined by the product of the utility of the outcome, x, multiplied by the decision weight associated with the probability p. Both the utility and the decision weight are subjective and depend on an individual's personal beliefs and values. However, a critical assumption is that these two factors are separable, and in particular, the decision weight is a function of p alone and not a function of x. This decision weight function has typically been estimated using monetary gambles, and it is usually found to be an inverse S-shaped function of p (Kahneman & Tversky, 1979). However, Rottenstreich & Hsee (2001) found that the shape of the decision-weight function changed depending on whether the x was a purely monetary outcome versus an outcome with greater affective impact (e.g., avoidance of an electric shock). The decision-weight function was estimated to be flatter in the middle of the probability scale when emotional outcomes were used as compared with monetary outcomes.

Emotions also change the rate of temporal discounting in choices between long-term large rewards over short-term smaller rewards. Gray (1999) found that participants who were shown aversive images (producing a feeling of being threatened) had higher discount rates. Stress focused individuals' attention on immediate returns making them appear more impulsive.

Finally, a third line of evidence comes from research examining the type of decision strategy used to make choices (Luce, Bettman, & Payne, 1997). Compensatory strategies, such as those enlisting a weighted sum of utilities, require making difficult trade-offs and integrating information across all the attributes. Noncompensatory strategies, such as a lexicographic rule, only require rank ordering alternatives on a single attribute and thus avoid difficult trade-offs. Luce, Bettman, & Payne (1997) found that when faced with emotionally difficult decisions, individuals tend to switch from a compensatory to noncompensatory strategies to avoid making difficult negative emotional trade-offs.

2. Can emotions distort or disturb our reasoning processes?

One line of evidence supporting this idea comes from research on emotional carryover effects (Goldberg, Lerner, & Tetlock, 1999; Lerner, Small, & Loewenstein, 2004). For example, in the study by Goldberg et al., participants watched a movie about a disturbing murder. The murderer was brought to trial, and in one condition, the murderer was acquitted on a technicality, but in another condition, the murderer was found guilty. After watching the film, the participants were asked to make penalty judgments for a series of unrelated misdemeanors. Goldberg et al. found that when the murderer was freed on a technicality, anger aroused by watching the murder movie spilled over to produce higher punishments for unrelated crimes, as compared with the condition in which the murderer was convicted.

Shiv and Fedorikhin (1999) examined conflicts between motivation and cognition. Participants were given a choice between a healthy and unhealthy snack under either a high-stimulating condition (real cakes or fruit snacks visibly present) or a low-stimulating condition (symbolic information about cakes and fruits). Also in one condition, they made this decision under a high memory load (they were asked to rehearse items for a later recall test) or under no memory load. Considering the reasons for the choice, participants generally favored the healthy snack. However, when hunger was stimulated under the vivid condition, and the healthy thoughts were suppressed (by the working memory task), then preferences reversed and the unhealthy snack was chosen most frequently.

A similar line of research was conducted by Markman and Brendl (2000). Habitual smokers were offered the opportunity to purchase raffle tickets for one of two lotteries—one with a cash prize and one with a cigarette prize, to be awarded after a couple of weeks delay. Half of the smokers were approached before smoking a postclass cigarette (and hence they had a strong need to smoke a cigarette). The other half were approached just after smoking their postclass cigarette (and hence the strength of the need to smoke a cigarette was diminished). Those who had not yet smoked purchased more raffle tickets to win cigarettes than did those who had already smoked. In contrast, they purchased fewer raffle tickets for the cash prize than did those who already smoked. Thus the need to smoke exaggerated the value of the cigarette lottery relative to the monetary lottery even though the latter could be used to purchase cigarettes.

3. Does reasoning always improve decision making?

Reasoning does not appear to universally improve decisions. Wilson et al. (1993) asked participants to provide their preference for either posters picturing animals in playful poses or posters of abstract, impressionist paintings. One group of participants was forced to provide reasons for their preference whereas the other group was not. Those who were forced to provide reasons for their preference were more likely to prefer the posters of the cute animals, whereas those who were not compelled to provide reasons preferred the impressionist posters. Participants were given the poster of their choice and a few weeks later were asked how satisfied they were with their selection. Those who were forced to provide reasons for their preference were significantly less satisfied with their selection than those who were not. These results suggest that thinking about reasons led to a focus on information about the domain that was not important to people in the long run.

4. Can we predict the effect of emotions on our decisions?

Research indicates we are not very good at predicting the influence of emotions on our choices. Loewenstein & Lerner (2003) review a number of experiments illustrating what they call *hot–cold empathy gaps*. When in a cold state (not hungry), people underpredict how they will feel in a hot state (hungry) (see Read & van Leeuwen, 1998). When in a hot state (sexually aroused), people cannot accurately predict how they will later feel when in a cold state (morning-after effect) and vice versa. This concludes our brief review illustrating some interesting interactions between motives, emotions, and decision making.

Decision Field Theory

Now we summarize a dynamic theory that describes how to incorporate motivational processes into decision making. First, we introduce a dynamic model of decision making called *decision field theory* (DFT). This theory has been previously used to explain choices between uncertain actions (Busemeyer & Townsend, 1993), multiattribute choices (Diederich, 1997), multialternative choices (Roe, Busemeyer, & Townsend, 2001), and the relations between choices and prices (Johnson & Busemeyer, 2005). In this chapter, we build on our previous efforts to extend decision field theory to account for the effects of motivation and emotion on decision making (Busemeyer et al., 2002). DFT advances older static models by providing a dynamic account of the decision process over time. This is important for explaining interactions between emotional and cognitive processes as the product of one integrated system rather than as a two system approach.

Decision Process

It will be helpful to have a concrete decision in mind when presenting the theory. The following example was chosen to highlight the application of the theory to navigational decisions under emergency or crisis conditions producing high time pressure and high emotional stress. A man was on a mission that required riding cross country on his motorcycle. He was cruising around 50 mph down a two-lane state highway when he came up behind a truck full of old car tires. The highway was not in good shape, with many potholes left by snowplows from the previous winter. The truck bumped 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. Although this example concerns navigating a motorcycle, it contains aspects that are shared in other navigational decisions, such as emergencies that occur during a plane flight.

The motorcyclist assessed the situation and noted that there was no shoulder on the road to serve as an escape route and that there was a line of cars following closely behind him. Thus the man was faced with a difficult problem-solving task, upon which he very quickly generated three potential plans of action: (A) drive straight over the tire, (B) swerve to the side, or (C) slam on the breaks. Each action involved planning a complex sequence of perceptual-motor movements. For example, driving straight across the tire required accelerating a little to push across the tire, hitting the tire dead center with sufficient speed to overcome it, a strong grip on the handlebars, and careful balancing of the bike.[1]

Each course of action could result (for simplicity) in one of four possible consequences: (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 the motorcycle, and suffering serious injury; (c_4) flipping the motorcycle over and getting killed.

An abstract representation for this decision problem is shown in Table 15.1, where the rows represent actions, columns represent consequences, and the cells represent the likelihoods that an action produces a consequence. The affective evaluations of the consequences are represented by the values m_j shown in the columns of the table, and the beliefs are represented by decision weights, w_{ij}, shown in the cells of the table. In the motorcyclist's opinion, option A was very risky, with high possibilities for the extreme consequences, c_1 and c_4. Action B was more likely to produce consequence c_2, and action C was more likely to produce consequence c_3.

The basic ideas behind the decision process are illustrated in Figure 15.1. The horizontal axis represents time (in milliseconds), beginning from the onset of the decision (when the tire initially flipped out of the truck) until the action was taken. The vertical axis represents strength of preference for each of the courses of action. Each trajectory represents the evolution of the preference strength for one of the options over time. At each moment in time, the decision maker

TABLE 15.1 Abstract Payoff Matrix for Motorcycle Decision

	Possible Consequences			
Actions	m_1	m_2	m_3	m_4
Act A	w_{A1}	w_{A2}	w_{A3}	w_{A4}
Act B	w_{B1}	w_{B2}	w_{B3}	w_{B4}
Act C	w_{C1}	w_{C2}	w_{C3}	w_{C4}

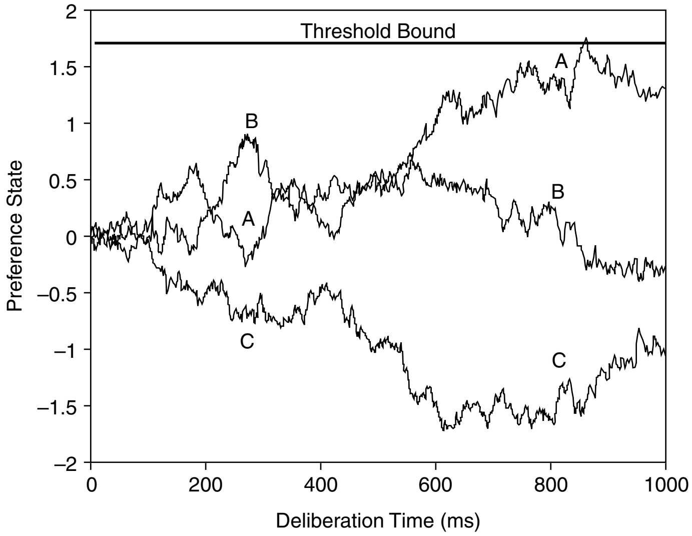

FIGURE 15.1 A simulation of the decision process. Horizontal axis is time, vertical axis is preference strength, and each trajectory represents one course of action. The top bar is the threshold bound. The first option to hit the bound wins the race and is chosen.

anticipates the possible consequences of an action, and attention switches from one action and consequence to another over time. According to this figure, the man begins (in the region of 100–200 ms) considering advantages favoring option A (e.g., he thinks for a moment that he may be able to safely pass over the tire, and slamming on the breaks may cause the car behind to crash into him, and rapidly swerving to the side could cause the motorcycle to flip over). However, some time later (shortly after 200 ms) his attention switches, and he reconsiders advantages of option B (e.g., he now fears choosing option A may cause the tire to get entangled with the chain of the motorcycle and flip the bike over). These comparisons are accumulated or temporally integrated over time to form a preference state for each course of action. For example, just 250 ms into the deliberation process, the preference state for option B dominates; later (at 600 ms), the preference state for A overcomes, and after 800 ms, it crosses a threshold bound and wins the race. It is at this point that option A is chosen as the planned course of action (plan to drive straight over the tire). Note that according to this description, emotions and rational beliefs are integrated rapidly and effectively into a single-preference state across time to guide decisions.

The threshold bound for stopping the deliberation process is a criterion that the decision maker can use to control the speed and accuracy of a decision. If the threshold is set to a very high value, then more information is accumulated, but at the cost of longer decision times. If the threshold bound is set to a very low criterion, then less information is accumulated, but with less time. In this example, under severe time pressure, the threshold bound must be set at a relatively low criterion.

This decision process can be formulated as a connectionist model as illustrated in Figure 15.2.

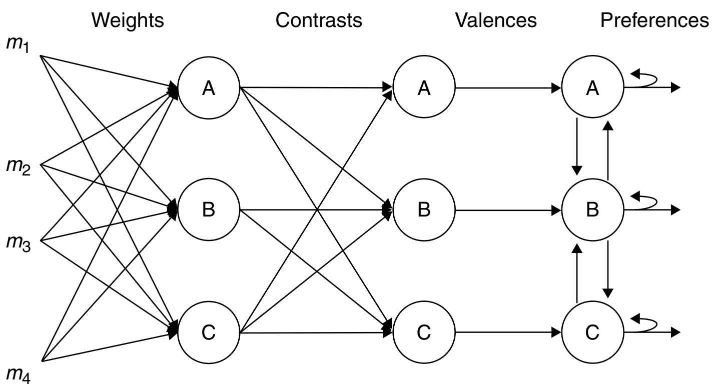

FIGURE 15.2 Diagram illustrating the connectionist interpretation of the decision process. The inputs are the evaluations of consequences, the first layer represents weighted evaluations, the second layer represent valences for each option, and the third layer represents the preference state for each option.

Affective evaluations of the various possible consequences represent the inputs into the decision system. (These are represented by the *m*s shown on the far left.) The input evaluations are filtered by an attention process, which maps the evaluations of consequences into a momentary evaluation for each course of action (represented by the second layer of nodes). Then the momentary evaluations are transformed into valences, one for each course of action, represented by the third layer of nodes. The valence of an action represents the momentary advantage or disadvantage of that action compared to the other actions. Finally, the valences are input to a recursive system at the final layer, which generates the preference states at each moment in time. These preference states are the final outputs, which produce the trajectories shown in Figure 15.1.

More formally, the amount of attention allocated to the *j*th consequence of the *i*th action at time *t* is denoted, $W_{ij}(t)$. This attention weight is assumed to fluctuate from moment to moment, according to a stationary stochastic process. The mean of this process generates the decision weight, $E[W_{ij}(t)] = w_{ij}$. For example, if attention switches in an all or none manner, then $W_{ij}(t) = 1$ or 0, and $w_{ij} = E[W_{ij}(t)]$ is the probability that attention will be focused on a consequence of an action at any moment. Thus, the decision weight is the average amount of time spent thinking about a consequence. It is assumed to be affected by the likelihood of the consequence, but according to this interpretation, other factors that attract attention may also affect these decision weights.

The momentary evaluation of the *i*th action is an attention-weighted average: $U_i(t) = \sum W_{ij}(t) \cdot m_j$, where *j* is an index associated with one of the possible consequences of an action, $W_{ij}(t)$ represents the amount of attention allocated to a particular consequence at any moment, and m_j is the affective evaluation of a consequence. Note that $U_i(t)$ is a random variable [because $W_{ij}(t)$ is a random variable], but its mean is a weighted average $E[U_i(t)] = \sum w_{ij} \cdot m_j = u_i$, which corresponds to a weighted utility commonly used by decision theorists (cf. Luce, 2000).

The valence of an action is defined as the difference $v_i(t) = U_i(t) - U(t)$, where $U(t)$ is the average evaluation over all actions.[2] The valence represents the momentary advantage/disadvantage for option *i* at time *t* compared with the average of all actions at that moment. The sum across valences always equals zero.

The valences for an action are integrated over time to form a preference state for each action, denoted P_i for option *i*. This preference state can range from positive (approach) to zero (neutral) to negative (avoidance). Each preference state starts with an initial value, $P_i(0)$, which may be biased by past experience (in Figure 15.1, they start out unbiased). The preference state evolves during the deliberation according to the following linear dynamic stochastic difference equation (where *h* is a small time step):

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

The coefficients s_{ij} allow feedback from previous preference states to influence the new state. The self-feedback coefficient, s_{ii} for $i = j$, controls the memory for past valences. The lateral inhibitory links, $s_{ij} = s_{ji}$ for $i \neq j$, produce a competitive system in which strong preferences grow and weak preferences are suppressed. Lateral inhibition is commonly used in artificial neural networks and connectionist models of decision making to form a competitive system in which one option gradually emerges as a winner dominating over the other options (cf. Grossberg, 1988; Rumelhart & McClelland, 1986). The lateral inhibitory coefficients are important for explaining context effects on choice (see Roe et al., 2001).

In summary, a decision is reached by the following deliberation process: As attention switches across consequences over time, different affective values are probabilistically considered, and these values are compared across actions to produce valences, and finally these valences are integrated into preference states for each action. This process continues until the preference for one action exceeds a threshold criterion, at which point the winner is chosen. Note that a single system is postulated to temporally integrate rational beliefs about potential consequences with affective reactions to these consequences over time.[3]

To illustrate the dynamic behavior of the model, consider a decision whether to take a gamble. Suppose action A has an equal chance of winning \$250 or losing \$100, and action B is just status quo (not gambling, not winning, or lose anything). In this simple case, we set the evaluations to the following values: ($m_1 = 250/250 = 1$, $m_2 = 0$, $m_3 = -.100/250 = -.4$). For Action A, we assume a .50 probability of attending to m_1 and .50 probability of attending to m_3; that is, $w_{A1} = E[W_{A1}(t)] = .50$, and $w_{A3} = E[W_{A3}(t)] = .50$. For action B, only one outcome is possible, zero, so that $w_{B2} = E[W_{B2}(t)] = 1$. The time step was set to $h = .01$, self-feedback was set to $s_{ii} = 1 - (.07) \cdot h$, the lateral inhibition was set to $s_{AB} = s_{BA} = 0$, and the initial state was set to $P_A(t) = -1$ (initially biased in favor of not playing).

Under these assumptions, we ran a simulation 5,000 times (see Appendix A) to generate the choice probabilities and the mean deliberation times, for a wide range of threshold parameters (θ ranged from 1 to 5 in steps of .25).[4] Figure 15.3 plots the relation between choice probability and mean decision time for option A, the gamble, as a function of the threshold parameter. Both decision time and choice probability increase monotonically with the threshold magnitude, starting below 50% choice of the gamble (because of the initial bias) and gradually rising above 50% choice for the gamble (because it has a positive expected value). Busemeyer (1985), Diederich (2003), and
[AQ3] Diederich and Busemeyer (in press) presents empirical evidence supporting these types of dynamic predictions for choices between gambles.

Affective Evaluation of Consequences

Now we turn to a more detailed analysis of the evaluations, m_j, and how they are affected by emotions. In general, consequences are described and evaluated according to various objectives or attributes that a person is trying to maximize (or, as in this case, minimize). In the motorcycle example, the evaluation of consequences depends on minimizing two attributes: personal injury and motorcycle damage. Note that the motorcyclist may be willing to sacrifice some personal injury to avoid motorcycle damage. The success of the mission (the cross-country trip) depends on an operational motorcycle, and a few cuts and bruises will heal and can be tolerated.

The effect of an attribute on an evaluation of a consequence depends on two factors: (1) the quality or amount of satisfaction that a consequence can deliver with respect to an attribute and (2) the importance or need for the attribute. For example, suppose a consequence scores high with respect to minimizing personal injury but low with regard to minimizing motorcycle damage. The final evaluation depends on the importance of the motorcycle relative to personal injury. If the mission is very important, and the motorcycle is crucial for completing the mission, then this is evaluated as an unattractive consequence; however, if the mission and the motorcycle are not considered very important, then this is an attractive consequence. Thus attribute importance moderates the effect of attribute quality.

More formally, decision theorists (cf. Keeney & Raiffa, 1976) generally postulate that each consequence can be characterized by a number of attributes, and each attribute has an importance weight, here denoted n_k for the kth attribute. Additionally, each consequence has a quality (amount of satisfaction) that can be gained on an attribute, here denoted as q_{jk} for the value of the jth consequence with respect to the kth attribute. These two factors are combined according to a multiplicative rule, $n_k \cdot q_{jk}$ to produce the net effect

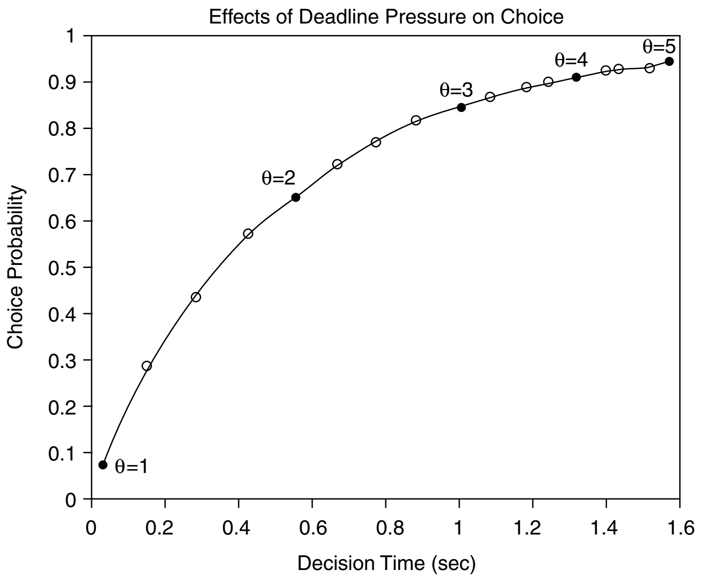

FIGURE 15.3 Multiple simulations demonstrate that the choice probability and the average decision time increase monotonically as the threshold θ is increased.

of an attribute on the evaluation of a consequence. Furthermore, if the attributes are independent, then the effects of each attribute add to form a weighted value of a consequence: $m_j = \sum n_k \cdot q_{jk}$.

So far, this is simply a static representation of an evaluation, which is commonly used by decision theorists. Decision field theory (Busemeyer et al., 2002) departs from this static representation by postulating that importance weights depend on personal needs, which are assumed to vary dynamically across time: $n_k(t)$. DFT also diverges by considering the quality a consequence has on an attribute as the degree of satisfaction a consequence is expected to provide with respect to the attribute: q_{jk}. Consequently, we assume that evaluations are changing across time according to $m_j(t) = \sum n_k(t) \cdot q_{jk}$, and momentary evaluations now involve stochastic attention weights as well as dynamic evaluations: $U_i(t) = \sum W_{ij}(t) \cdot m_j(t)$. The rest of decision field theory (e.g., Equation 1) accommodates this new dynamical feature in a natural way, as it continues to operate in the same manner as previously described for making decisions. This is one of the advantages of using a dynamic model for decision making.

Personal needs, $n_k(t)$, are postulated to change across time. A control feedback loop forms the basis for adjusting these needs over time (Busemeyer et al., 2002; see also Carver & Sheier 1990; Toates, 1980). We assume that an individual has an ideal point on each attribute, denoted as g_k (for goal state) as well as a current level of achievement or status quo for an attribute, denoted $a_k(t)$. The discrepancy between these two values, $[g_k - a_k(t)]$, provides a feedback signal for adjusting the need for that attribute, $n_k(t)$. For example, if g_k is the ideal level of hunger, and $a_k(t)$ is the current level of hunger (operationalized as hours without food), then the difference between these two determines the adjustment for the need to eat. Positive discrepancies produce an increase in need, and negative discrepancies produce are decrease in need. Accordingly, the need for an attribute varies across time according to the following difference equation:

$$n_k(t+h) = L_k \cdot n_k(t) + [g_k - a_k(t+h)], \qquad (2)$$

where L_k is a constant that determines the rate of feedback control of needs over time, which may depend on the type of attribute. For example, the consumatory effect of eating when hungry may be slower than the consumatory effect of drinking when thirsty. These differential feedback rates provide a formal means to account for the fast direct versus slow indirect neural pathways for emotion in the brain.

Figure 15.4 provides a depiction of the integrated cognitive–motivational network, illustrating how cognitions and emotions interact over time. Returning to the motorcyclist's decision, we can trace the decision process along the network. We assume that there is an ideal goal state for maintaining the operation of the motorcycle (and completing the mission) g_m as well as a goal for personal safety g_p. Let us focus on changes in the needs for personal safety $n_p(t)$ during the deliberation process. The sudden appearance of the tire in the middle of the road produces an abrupt drop in the

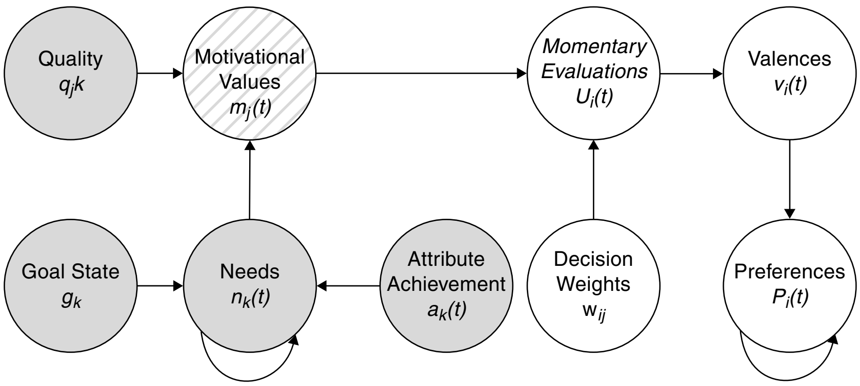

FIGURE 15.4 Cognitive–motivational network. The highlighted regions indicate the parts of the decision process related to emotions. The difference between the *goal state* and the actual *attribute achievement* is used to update the *need* for a given attribute. This need is in turn combined with expected satisfaction (*quality*) to provide a motivational value for all considered consequences.

TABLE 15.2 Decision Weights for Motorcycle Example

Consequence / *Action*	c_1 *No damage; no injury*	c_2 *Damage motorcycle; minimal injury*	c_3 *Damage motorcycle; serious injury*	c_4 *Get killed*
Action A (Drive straight)	.55	0	0	.45
Action B (Swerve)	0	.90	.10	0
Action C (Slam brakes)	0	.10	.90	0

current level of personal safety, that is a drop in the variable $a_p(t)$ (emotionally felt as fear). This generates a gap or an error signal, $[g_p - a_p(t)]$, which causes a rapid growth in the need for personal safety, $n_p(t)$. The quality (amount of satisfaction) that a consequence produces for personal safety, q_{jp}, will then be combined with the need for personal safety, $n_p(t)$, to generate a dynamic value $m_j(t)$ of each consequence. These dynamic values are combined with the shifting attention weights, $W_{ij}(t)$, to form momentary evaluations, $U_i(t)$. The momentary evaluation of an action is compared with other actions to produce a valence for each action, $v_i(t)$. Finally, the valences feed into the preference states $P_i(t)$ to determine the selected course of action.

Computation Example Applied to Emergency Decisions

To illustrate an important dynamic property generated by Equation 2, let us return to the motorcyclist's dilemma. Tables 15.2 and 15.3 show the decision weights and the quality values used in this example. According to Table 15.2, action A (driving straight across the tire) is risky—it is likely to produce either of the two extreme consequences, a c_1 (safe maneuver) or c_4 (getting killed); action B (swerving) is likely to produce an intermediate but safer consequence c_2 (laying down the motorcycle); and action C (slamming the brakes) is likely to produce consequence c_3 (hitting a vehicle). The qualities, q_{ik} (achievement scores), on the personal safety and motorcycle maintenance attributes, are shown in Table 15.3 (higher scores are more desirable). According to Table 15.3, c_1 scores best on both attributes, c_2 score well on the first attribute but very poorly on the second, c_3 score moderately bad on both, and c_4 scores the worst on both. Additionally, the predictions for the mean preferences were computed from Equations 1 and 2 using the following dynamic parameters: we set the gaps equal to $[g_p - a_p(t)], = .80$ and $[g_m - a_m(t)], = .40$, indicating a larger gap for personal safety; $L_P = .90$ and $L_M = .70$, indicating a larger feedback control parameter for the personal safety attribute; and finally we set $s_{ii} = .9$ (self-feedback for $i = j$) and $s_{ij} = -.05$ (lateral inhibition for $i \neq j$) in Equation 1 to control the dynamics of the preference states. (The time step was set to $h = 1$ for simplicity.)

TABLE 15.3 Quality Values for Motorcycle Example

Attribute / *Consequence*	*Personal Safety*	*Motorcycle Maintenance*
c_1 (Safe maneuver)	1	1
c_2 (Lay down motorcycle)	.70	0
c_3 (Crash into vehicle)	.20	.40
c_4 (Flip motorcycle)	0	0

Note: In DFT, quality is the degree of satisfaction a consequence is expected to provide with respect to the attribute.

The predictions are shown in Figure 15.5. As can be seen in the top panel of this figure, the need for personal safety grows more slowly and to a much higher asymptote as compared with the need for motorcycle maintenance. This shift in needs produces a reversal in preference over time between actions A and B. As can be seen in the bottom panel, the risky action, A, initially is preferred, but later the safer action B dominates. In other words, as deliberation progresses, the person's preference switches from the risky to the safer action. This shows how the model can explain what is called the chickening out effect (Van Boven, Loewenstein, & Dunning, 2005). In conclusion, DFT allows for preference reversals over time, which cannot occur with a static utility theory.[5]

Applications to Previous Research

Let us briefly outline a DFT account of some of the past findings reviewed earlier. Consider first the emotional carryover effect reported by Goldberg et al. (1999). In this case, anger aroused in the first part of an experiment carried over to affect punishment decisions in second phase. According to DFT, the anger aroused in the first stage decays exponentially over time as described by Equation 2. This persistence of anger would enhance the need and thus the importance for the retribution attribute of later punishment decisions. The earlier studies did not examine how this effect changes over time, but one testable prediction from the present theory is that the effect should decay exponentially as a function of the time interval between the initial arousal of anger and the subsequent test on irrelevant penalty judgments.

Next consider the experiment by Shiv and Fedorikhim (1999) who examined conflicts between reasons and emotions. According to DFT, hunger stimulation produces an increase in the need to satisfy hunger, increasing the importance of the food taste attribute, and consequently increasing the preference for the unhealthy snack; at the same time, the memory load would decrease the attention weight to the attributes related to health maintenance. A test of this

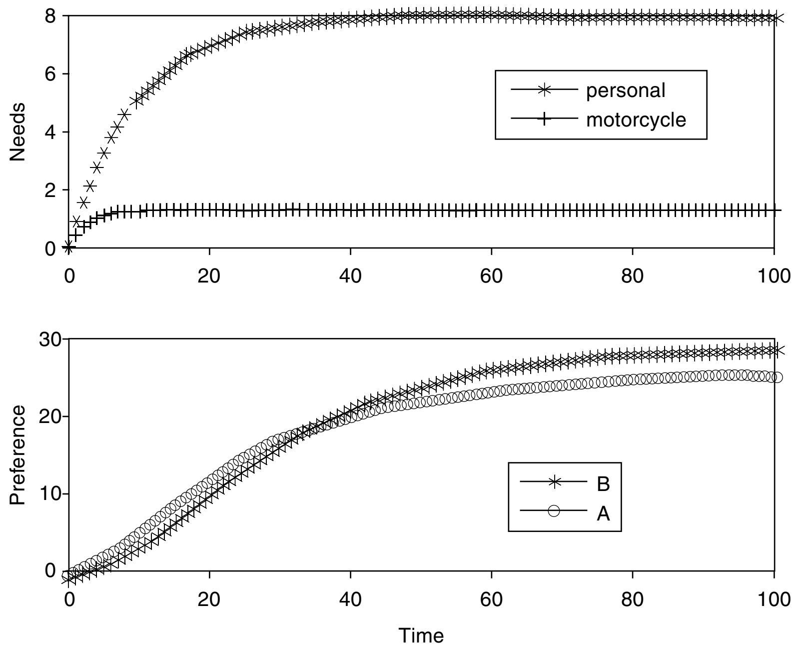

FIGURE 15.5 Results of simulations run under conditions $\lambda_P = .80$ and $\lambda_M = .40$; indicating a larger gap for personal safety; $L_P = .90$ and $L_M = .70$ indicating a larger feedback control parameter for the personal safety attribute; and $s_{ii} = .90$ and $s_{ij} = -.05$ for $i \neq j$. The need for personal safety gradually grows toward an asymptote. This change in need directly causes an increase in preference for the less risky Action B.

theory could be performed by factorially manipulating the taste quality of the unhealthy snack and the degree of hunger. We predict that these two factors should interact according to a multiplicative rule.

In the study by Markman and Brendl (2000), unsatiated smokers were more interested in winning cigarettes than those who had just finished smoking. In the framework of DFT, smoking decreases the need for future smoking and decreases the importance of obtaining more cigarettes. The motivation for winning cigarettes over money is lowered. We predict that the size of the cigarette prize will interact according to a multiplicative rule with the time since smoking a cigarette.

As a final example, consider the study by Rottenstreich and Hsee (2001) who found that emotions cause changes in the probability weighting function. This finding cannot be readily explained in terms of the effects of emotions on needs for attributes. In this case, we may be required to formulate a new mechanism that allows emotions to moderate the amount of attention various consequences receive (i.e., a model for changing the decision weights, w_{ij}, depending on the quality of the emotion produced by an outcome). This has yet to be done within the DFT framework.

Concluding Comments

Emotions and motives are dynamic reactions to environmental challenges. A threat, for example, rapidly generates a fear reaction, promoting actions to seek safety to quell the rising fear. Consequently, dynamic models are required to track their effects on decisions over time. Decision field theory differs prominently from other standard decision theories by providing a dynamic description of decision processes. This characteristic of the theory provides a natural way to incorporate the dynamic effects of emotions and motivations. The goal of this chapter was to present a formal model for integrating cognition and emotion into a single decision process.

At the beginning of this chapter, we presented two opposing views about the way emotions could influence decision making. According to a two system view, there is a Type 1 (emotion-based system) and a Type 2 (reason-based system), and the Type 1 system is corrected by the Type 2 system. Alternatively, according to a single-system view, motives, and emotions control cognition by adjusting the importance weights on the basis of needs, which vary dynamically over time. This integrated view of emotion and cognition was actually proposed long ago by one of the founders of the cognitive revolution, Herb Simon (1967). Decision field theory provides a formal mechanism for implementing the single system view.

It is worthwhile to step back and try to assess the advantages and disadvantages of each approach. One of the important reasons for advocating a two-system approach is the fact there are at least two separate neural pathways for emotions, the direct versus the indirect path. However, the two-system approach has not been clearly articulated as a detailed neural model and so this remains a fairly rough correspondence at best. Furthermore, it not difficult to incorporate fast and slower emotional signals into a dynamic integrated model of cognition, and so this is not strictly speaking evidence for a two systems approach. In particular, the dynamic model for need (represented by Equation 2) provides differential feedback rates to accommodate fast direct versus slow indirect neural pathways for emotion.

One of the main advantages of the integrated approach presented here is that we have a formal or computational model that is able to derive precise predictions for cognitive and emotional interactions. The separate systems approach fails on this criterion. Although the System 2 part of the theory is precisely worked out (this is just the standard utility theory), there is a lack of formal modeling for the Type 1 (the emotional) component of this approach. Thus one cannot predict a priori whether a decision will be based on the Type 1 versus the Type 2 system, nor is it clear what decision the Type 1 system will make.

Finally, we have tried to emphasize two important points in this chapter: (a) inclusion of motivation and emotional processes are critical and are necessary for the development of a complete computational model of cognition; and (b) it is feasible to formulate computational models that integrate emotion and cognition by having what are commonly thought of as two processes combined in the decision making process. Decision field theory provides one example of how this can be accomplished.

Appendix A

```
% Simulate DFT predictions for two alternative choice
% Simulation Parameters
```

```
N = 1000; % no of reps
% model parameters
h = .01; hh = sqrt(h); % time step
theta = 5; % threshold bound
W = [.5 ; .5]; % Attention weights for two outcome gamble
b = .07; c = 0; % Feedback matrix
S2 = [b c ; c b];
C2 = [1 −1; −1 1]; % Contrast matrix
M2 = [250 −100; 0 0]/250; % Value Matrix
P0 = [−1; 1]; % initial preference state
% Model
P2 = []; T2 = [];
U2 = M2*W;
V2 = U2-mean(U2);
for n = 1:N % Replication loop
B = 0; t = 0; P = P0;
while (B < theta) % Choice Trial
w = W(1) > rand; w = [w ; (1−w)];
U2 = M2*W;
E2 = U2*(w−W) ;
P = P + (S2*h)*P + V2*h + hh*E2;
[B,Ind] = max(P); t = t+h;
end
P2 = [P2 ; Ind]; T2 = [T2; t];
end
P2 = [sum(P2 = 1) ; sum(P2 = 2)]/N; % Choice Probability
T2 = mean(T2); % Mean Choice Time
```

Appendix B

This appendix presents a detailed derivation from the equations presented earlier. To simplify the analysis, we will examine a special case in which the time step is set to $h = 1$ (this only fixes the time unit and does not change the qualitative conclusions). Furthermore, we commonly assume that the self-feedback coefficients are all equal ($s_{ii} = s$). Usually, we assume that the lateral inhibition coefficient connecting a pair of actions depends on the similarity between the two actions. However, if all the actions are equally dissimilar, which we will assume in this case, then all of the lateral inhibitory coefficients are equal ($s_{ij} = -c$ for $i \neq j$). Finally, we commonly assume the initial preference states sum to zero, $\sum_j P_i(0) = 0$, from which it follows that $\sum_j P_i(t) = 0$ for every t. Under these assumptions, Equation 1 reduces to

$$\begin{aligned} P_i(t+1) &= s \cdot P_i(t) - c \cdot \textstyle\sum_{i \neq j} P_j(t) + v_i(t+1) \\ &= s \cdot P_i(t) - c \cdot [-P_i(t)] + v_i(t+1) \\ &= (s+c) \cdot P_i(t) + v_i(t+1) \\ &= \alpha \cdot P_i(t) + v_i(t+1), \end{aligned} \tag{3}$$

where $\alpha = (s + c)$. The expected value of Equation 3 is equal to

$$\begin{aligned} E[P_i(t+1)] &= E[\alpha \cdot P_i(t) + v_i(t+1)] \\ &= \alpha \cdot E[P_i(t)] + E[v_i(t+1)]. \end{aligned} \tag{4}$$

Assuming that $0 < \alpha < 1$, then the solution to Equation 4 is

$$\begin{aligned} E[P_i(t+1)] = \alpha^{t+1} \cdot P_i(0) + \textstyle\sum_{\tau = 0,t} \alpha^{\tau} \\ \cdot E[v_i(t - \tau + 1)]. \end{aligned} \tag{5}$$

Next consider the expectation of the valence, which is given by

$$\begin{aligned} E[v_i(t)] &= E[U_i(t) - U_{.}(t)] = E[U_i(t)] - E[U_{.}(t)] \\ &= u_i(t) - u_{.}(t), \end{aligned}$$

where $u_i(t) = E[U_i(t)]$ and $u_{.}(t) = \sum u_j(t)/N$ for N alternatives. Substituting this into the solution Equation 5 yields

$$\begin{aligned} E[P_i(t+1)] = \alpha^{t+1} \cdot P_i(0) &+ \textstyle\sum_{\tau = 0,t} \alpha^{\tau} \cdot [u_i(t - \tau + 1) \\ &- u_{.}(t - \tau + 1)] = \alpha^{t+1} \cdot P_i(0) \\ &+ \textstyle\sum_{\tau = 0,t} \alpha^{\tau} \cdot u_i(t - \tau + 1) \\ &- \textstyle\sum_{\tau = 0,t} \alpha^{\tau} \cdot u_{.}(t - \tau + 1). \end{aligned} \tag{6}$$

Choice probabilities are determined by the mean difference between any two preference states. Consider the difference between two actions, i versus i^*. The second sum in Equation 6 cancels out when we compute differences:

$$\begin{aligned} E[P_i(t+1)] - E[P_{i^*}(t+1)] = \alpha^{t+1} \cdot [P_i(0) - P_{i^*}(0)] \\ + \textstyle\sum_{\tau = 0,t} \alpha^{\tau} \cdot [u_i(t - \tau + 1) \\ - u_{i^*}(t - \tau + 1)]. \end{aligned} \tag{7}$$

Recall that $u_i(t) = E[U_i(t)] = E[\sum W_{ij}(t) \cdot m_j(t)]$
$= \sum w_{ij} \cdot m_j(t)$, so that

$$\begin{aligned} u_i(t) - u_{i^*}(t) &= \textstyle\sum w_{ij} \cdot m_j(t) - \sum w_{i^*j} \cdot m_j(t) \\ &= \textstyle\sum (w_{ij} - w_{i^*j}) \cdot m_j(t), \end{aligned}$$

and inserting this into Equation 7 produces

$$E[P_i(t+1)] - E[P_{i*}(t+1)] \\ = \alpha^{t+1} \cdot [P_i(0) - P_{i*}(0)] \\ + \Sigma_{\tau=0,t}\, \alpha^{\tau} \cdot \left[\Sigma_j (w_{ij} - w_{i*j}) \cdot m_j(t-\tau+1)\right]. \tag{8}$$

At this point, note that if $m_j(t)$ was fixed across time at $m_j = \Sigma n_k \cdot q_{jk}$ (i.e., a static weighted value), then Equation 8 reduces to

$$E[P_i(t+1)] - E[P_{i^*}(t+1)] \\ = \alpha^{t+1} \cdot [P_i(0) - P_{i^*}(0)] + (\Sigma_{\tau=0,t}\, \alpha^{\tau}) \cdot (\Sigma_j (w_{ij} - w_{i^*j}) \cdot m_j) \\ = \alpha^{t+1} \cdot [P_i(0) - P_{i^*}(0)] + \left(\frac{1-\alpha^{t+1}}{1-\alpha}\right) \\ \cdot (\Sigma_j (w_{ij} - w_{i^*j}) \cdot mj) \\ = \alpha^{t+1} \cdot [P_i(0) - P_{i^*}(0)] + \left(\frac{1-\alpha^{t+1}}{1-\alpha}\right) \cdot (u_i - u_{i^*}). \tag{9}$$

It is informative to compare Equation 9 with a static weighted utility model, where the latter assumes that the preference between actions i and i^* is determined solely by the static difference in weighted utilities $(u_i - u_{i^*}) = \sum_j (w_{ij} - w_{i^*j}) \cdot m_j$. Both theories share a common set of parameters: the decision weights w_{ij} and the values m_j; but DFT adds two new parameters, the initial state $P_i(0)$ and growth-decay rate α. If the initial preference state is zero (neutral), then the first term in Equation 9 drops out, and the mean difference in preference states for DFT is always consistent with the mean difference in weighted utilities. However, if the initial preferences are ordered opposite of the weighted utilities, then preferences will reverse over time (as illustrated in Figure 15.3). To simplify the remaining analyses, we will assume that the initial preference state is zero.

Now let us examine the crucial issue: how are the affective evaluations influenced by the emotional process across time? In this case, the evaluations change dynamically across time according to the needs, $m_j(t) = \sum_k n_k(t) \cdot q_{jk}$, and inserting this into Equation 8 yields the new result [assuming for simplicity hereafter that $P_i(t) = 0$]:

$$E[P_i(t+1)] - E[P_{i^*}(t+1)] = \sum_{\tau=0,t} \alpha^{\tau} \\ \cdot \sum_j (w_{ij} - w_{i^*j}) \cdot (\sum_k n_k(t-\tau+1) \cdot q_{jk}). \tag{10}$$

As can be seen from Equation 10, the dynamics depend on the solution of $n_k(t)$, which is derived from Equation 2. However, the solution for Equation 2 depends on assumptions about changes in the current status on an attribute $a_k(t)$ at each moment in time, which in turn, depends on past decisions and on the exogenous environmental disturbances that must be specified.

Suppose that before the onset of the decision, the current state matches the goal state so that the need adjustment is zero for each attribute, $[g_k - a_k(t)] = 0$ for $t < 0$, and the need system is at equilibrium. Then suddenly, because of exogenous events, the current status on an attribute $a_k(t)$ drops far below the ideal point g_i at time $t = 0$ (decision onset), so that there is a gap between the current state and the ideal state, symbolized as $\Delta_k = [g_k - a_k(t)] > 0$ for $t > 0$. In this case, we need to solve the simple difference equation

$$n_k(t+1) = L_k \cdot n_k(t) + \Delta_k$$

and assuming $0 < L_k < 1$, then the solution is given by

$$n_k(t) = \Sigma_{\tau=0,t-1}\, L_k^{\tau} \cdot \Delta_k = \Delta_k \cdot (\Sigma_{\tau=0,t-1}\, L_k^{\tau}) = \left(\frac{1-L_k^t}{1-L_k}\right) \cdot \Delta_k \tag{11}$$

Substituting this solution into the expression for $u_i(t)$ yields

$$u_i(t) = \Sigma_j\, w_{ij} \cdot m_j(t) = \Sigma_j\, w_{ij} \cdot (\Sigma_k\, n_k(t) \cdot q_{jk}) \\ = \Sigma_j\, w_{ij} \cdot \left(\Sigma_k \left(\frac{1-L_k^t}{1-L_k}\right) \cdot \Delta_k \cdot q_{jk}\right).$$

Finally, inserting the solution given by Equation 11 into Equation 10 produces the final solution:

$$E[P_i(t+1)] - E[P_{i*}(t+1)] \\ = \Sigma_{\tau=0,t}\, \alpha^{\tau} \cdot \Sigma_j (w_{ij} - w_{i^*j}) \cdot \left(\Sigma_k \left(\frac{1-L_k^{t-\tau+1}}{1-L_k}\right) \cdot \Delta_k \cdot q_{jk}\right). \tag{12}$$

It is instructive to compare Equation 12 with the static weighted utility theory, according to which $(u_i - u_{i^*}) = \sum_j (w_{ij} - w_{i^*j}) \cdot (\sum_k n_k \cdot q_{jk})$ completely determines preference. Both theories share a common set of parameters: n_k, q_{jk}, w_{ij}, but DFT adds the following two additional parameters, α and L_k. The critical qualitative property that distinguishes DFT from the static utility model is that DFT allows preferences to reverse across deliberation time, which is impossible with the static theory.

Notes

1. This example is based on a personal experience of the first author, who decided to go straight across the tire, and managed to survive to tell this story.

2. In the past, we defined $U_{.}$ as the average of all options other than option i. Here we define it as the average of all options. However, the definition used here produces a valence that is proportional to the previous version: the previously defined valence equals $[N/(N-1)]$ times the currently defined valence, where N is the number of options in the choice set.

3. Formally, this is a Markov process, and matrix formulas have been mathematically derived for computing the choice probabilities and distribution of choice response times (see Busemeyer & Diederich, 2002; Busemeyer & Townsend, 1992; Diederich & Busemeyer, 2003). Alternatively, computer simulation can be used to generate predictions from the model. Normally, we use the matrix computations because they are more precise and faster, but to show how easy it is to simulate this model, we used the simulation program shown in the Appendix A for the analyses presented next.

4. These closely matched the calculations from the Markov chain equations; however, the latter are more accurate and didn't produce the little dip that appears at the end of Figure 15.3. The Markov chain method was also a couple of orders of magnitude faster to compute.

5. Appendix B provides a more formal derivation of this property of the theory.

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