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Psychology of Sport and Exercise 7 (2006) 631–652

Psychology
OF SPORT AND EXERCISE

www.elsevier.com/locate/psychsport

Cognitive modeling of decision making in sports

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Received 2 August 2005; received in revised form 27 March 2006; accepted 27 March 2006

Available online 15 May 2006

Abstract

Objectives: The purpose of this article is to provide an introduction to the theoretical, practical, and methodological advantages of applying cognitive models to sports decisions. The use of sequential sampling models, in particular, is motivated by their correspondence with the dynamic, variable processes that characterize decision-making in sports. This article offers a brief yet detailed description of these process models, and encourages their use in research on decision-making in sports. In addition, Appendix A provides the sufficient detail to formulate, simulate, and compute predictions for one of these models. Although the formulation focuses primarily on deliberation among a set of options, incorporating other critical task components (e.g. option generation, learning) is contemplated.

Conclusions: Empirical evidence is reviewed that supports the use of sequential sampling models over other approaches to decision-making. Finally, future directions for fine tuning these models to the sports domain are discussed.

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Keywords: Sports; Decision-making; Cognitive; Model; Dynamic; Accumulator; Deliberation; Choice; Decision Field Theory

Introduction

The overarching goals of this article are to show how cognitive models can illuminate the processes that underlie overt behavior, and to provide enough detail to enable interested sports

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researchers to utilize (at least) one class of models. To this end, the article proceeds as follows. First, I begin by trying to extract what types of variables characterize sports tasks for which decisions need to be made. Second, I give a brief introduction to the nature of cognitive modeling and what it can contribute. These sections are then paired in providing motivation to determine what types of models might be most successful in the sports domain. Next, the class of sequential sampling models is selected as a candidate modeling framework in which to describe and predict choices in sports tasks. Specifically, one particular model is introduced, including theoretical underpinnings as well as implementation details. Then, model predictions are reviewed and the model is applied to various situations that characterize sports decisions. In conclusion, I relate the cognitive modeling approach outlined here to other approaches, and suggest some interesting directions for future extension of the model in the sports domain.

Decision-making in sports environments

The domain of sports offers an excellent opportunity for the study of decision-making, for a number of reasons. Within the topical scope of sports decision-making, there are a number of different decision *agents* (coaches, players, etc.), *tasks* (play-calling, ball allocation, etc.), and *contexts* (during play, during timeout, etc.). This provides the chance to examine a variety of interesting designs. Yet, each combination of the above factors produces a unique interaction of important elements that affect the way decisions are made. Can we say, then, what features of sports decisions make their study practical? More importantly, can we identify the proper way to study this diverse assortment of decision situations? Although there is no “standard” type of decision in sports, there are some characteristics that seem general enough to abstract from this domain. Let us begin by identifying these features, then relating them to the method used to study decisions.

The key feature of sports decisions is that they are naturalistic, meaning here that they are made by agents with some degree of task familiarity, in the environment with which they naturally encounter the decision (cf. Orasanu & Connolly, 1993). The difference between the study of decision-making in the laboratory and the “real world” is an important distinction that has only recently been appreciated in decision research. Contrast three decision scenarios facing a forward in soccer: selecting the recipient of a pass in a real soccer match; selecting the recipient of a pass in a computer simulation of soccer; and selecting from among a set of gambles. Obviously, if we are interested in how this agent actually makes decisions, then those she normally faces should provide the most valid evidence. In situations where the experimenter attempts to recreate the natural environment, there is the danger of incorrectly specifying the underlying structure (e.g., programming computer players different from the way real players behave). If the experiment uses a different domain altogether, even if the underlying abstract structure is the same, performance often does not transfer to the new domain (e.g., Ceci & Ruiz, 1993; Raab, 2005; see Goldstein & Weber, 1997, for criticisms of the gambling domain as a general “metaphor” of decision-making).

Second, the majority of sports decisions are dynamic. Decisions in sports, as well as in many other domains, unfold over time. The influence of this dynamic aspect is (at least) twofold. There are internal dynamics, meaning there is not so much a single point of decision as there is a course of deliberation. Information is not instantaneously gathered and processed; rather a decision maker must accrue information over time, and subsequent processing of this information takes

additional time. Furthermore, sports situations possess external dynamics, meaning that the situation itself changes over time. At one moment, some information may be available (e.g., goalie position) that is not available in the next moment (e.g., due to obstruction). Other variables, such as available options (e.g., teammates without proximate defenders), may change over time as well.

Third, decisions in sports are often made “online,” or under similar conditions of moderate or high time pressure. This feature is related to, but distinct from, the dynamic nature of sports decisions. While sports are indeed dynamic tasks, the decisions about what to do in these situations can be made either online (during the task), or in a reflective manner. Most decisions made by athletes are made online, while the play is in motion. Alternatively, as an example of a reflective decision, imagine a coach deciding which pitcher to start in an upcoming game, based on all the available information about his pitching staff and the opposing team’s batters.

Finally, an element of variability must be realized when studying sports decisions. It is important, in sports situations, to avoid a deterministic mapping from situation to response. Although the use of “if-then” rules may be a common method for instruction (e.g., McPherson & Kernodle, 2003), one can imagine the peril in performing the same action every time one is found in a given situation. Unpredictability in sports denies an opponent the opportunity to know what offensive play will be called, what defensive formation they will face, or to whom the ball will go in the final seconds of a close contest.

The factors above are by no means complete, and cannot be assumed to describe every sports situation. However, if adopting these characteristics is in error, it is fortunately on the side of handling increased complexity. That is, if one understands behavior in a more complex system, it typically allows straightforward understanding of simpler systems through reduction—such as by focusing on the (static) end state in a dynamic system, or setting the variance in a system to zero. The characterization in this section serves more than just a taxonomy describing sports decisions. An understanding of the situation is crucial for determining how to proceed in research design and theory development. In the following section, the use of cognitive modeling is introduced as an excellent candidate for understanding complex decisions such as those in the sports domain. Then, the field of possible models is narrowed down by considering the characteristics of sports decisions outlined above.

Cognitive modeling

What is cognitive modeling? How does it differ from other research methods? The answers to these questions may not be as straightforward as one would like, but covering a few general distinctions can be instructive. First, consider the difference between a “model” and a “theory” of behavior. In general, a theory describes *what* concepts are related, whereas a model attempts to explicitly capture *how* concepts are related—i.e., a theory may state what comes out of the “black box” depending on what goes in, whereas one develops a model of the black box itself. As such, models are typically more formal, producing precise (and often quantitative) testable predictions and relationships. A theory is an organizational framework for integrating concepts and ideas, and as such is generally more abstract. A theory of behavior may give rise to several specific alternative models that stay true to the theoretical principles. For example, a theory may state that reaction time increases as more information is considered, whereas this may be modeled by any number of intervening processes (underlying mechanisms).

Cognitive modeling, in particular, has enjoyed a recent surge of popularity. The “cognitive revolution” during the last half of the last century has permeated much of psychology, promoting cognitive mechanisms to describe behavior. In particular, there has been an increase in attention to the information processing that underlies human behaviors, in contrast to the behaviorist viewpoint of the first half of the century. That is, rather than simply viewing behavior as conditioned responses, or matching of situations to actions, the cognitive processing that drives these responses is taken into consideration.

The increased interest in cognitive modeling is due in large part to the success these models have enjoyed across domains outside of mainstream cognitive psychology (i.e., beyond memory, language, categorization, etc.). This advance is not yet apparent to the same degree in examining decision-making and other behaviors in sports. The cognitive approach has gained some ground in sports, such as the influence of cognitive psychology on the study of sport-specific expertise and cue use (see also Tenenbaum & Bar-Eli, 1993). However, for making tactical decisions, the use of “if-then” rules still appears to be the dominant framework that guides training (e.g., McPherson & Kernodle, 2003).

The current article makes the case that cognitive models can also be successfully applied to the sports domain. However, it is important to select the right type of model, especially when initially examining their efficacy. Otherwise, selection of a model that is ill-suited to sports decision-making could be rejected based on its incompatibility. This, in turn, might set an unwarranted negative precedent for an entire class of models. Therefore, one should examine which model type is most appropriate for sports decisions.

Choosing the right tool for the job

Various quantitative methods exist for comparing formal cognitive models. The goal of these methods is to select a preferred model based on relevant criteria such as explanatory power, parsimony, etc. (see Zucchini, 2000, for an introduction; and the remainder of Myung, Forster, and Brownse, 2000, for detailed procedures). However, it is equally important to consider the qualitative aspects of candidate explanations *before* attempting to apply them. That is, there should be an adequate degree of *model correspondence*, or fit between the phenomenon and the model used to explain it. As motivation psychologist Abraham Maslow put it, “if the only tool you have is a hammer, you tend to see every problem as a nail.” If one indeed wants to strike a nail, a hammer is appropriate; but for chiseling a masterpiece sculpture, one needs control for finer detail. With this in mind, it is possible to deduce the best type of models for sports decisions as characterized in the previous section.

Incorporating relevant variables. Sports domains, as naturalistic environments, contain many important variables which may not be easily abstracted to some models. There are often subtle nuances that affect decisions and interactions between variables in natural environments. It is imperative for any model to include the relevant variables in order to be successful in describing, explaining, and predicting decisions in naturalistic environments. This is not to say that a model must be bogged down with parameters and variables to the point that it is rendered intractable, redundant, and therefore useless. Rather, key components of both the agent *and the environment* should be considered, instead of relying on unjustified simplifications.

Dynamic vs. static modeling. Put simply, dynamic decisions require dynamic models. Because relevant variables change over the course of a decision, it is impossible to treat these as static entities in models. For example, a particular teammate may be defended at the beginning of a play, freed by tactical maneuvers (e.g., setting screens), and eventually covered again when the defense responds (e.g., by rotating defenders). A static model cannot capture this important sequence of events, and must treat the teammate discretely as either defended (thus missing a possible opportunity) or undefended (thus allowing pursuit of an erroneous course of action). Only a dynamic model can incorporate the time course of events that is crucial in sports situations (see Williams, Davids, & Williams, 1999, for a related argument). Also, incorporating dynamics in modeling often entails modeling of the decision process, not just the outcome, discussed next.

Process vs. outcome modeling. Placing a caterpillar in a box, only to find a butterfly when the box is opened some weeks later, may be quite puzzling if one does not observe the process of the transformation. Similarly, for online decisions in sports, not only the outcome is important, but the means by which one obtains this outcome. Although studying decision outcomes may help in cataloging which situations produce each outcome, only by considering the process can we gain an understanding of how decisions are actually *made*. Therefore, for decision-making in sports, it seems essential that process models be employed (Alain & Sarrazin, 1990). This is also pertinent to instruction and coaching in sports; it takes very little to convey which outcome should occur in a given sports situation, but it is only through training of the process that this outcome is brought about.

Probabilistic vs. deterministic modeling. There may not be a single instance of truly deterministic human behavior, aside from reflexive or “hard-wired” mechanisms. Certainly in sports and other natural decision-making environments, variability is the norm rather than the exception. To model this variable behavior requires probabilistic models. Oddly, the vast majority of popular decision-making models are deterministic (cf. Fishburn, 1988). That is, for a given set of inputs or choice options, these models predict the same output will always occur. This output is generally a set of expected utilities—holistic values for each option—with the assumption that the option with the highest expected utility is always selected. Granted, it is simple to generate choice probabilities and thus predictions of behavioral variability from deterministic output values, such as by calculating ratios of an option’s value to the sum of all options’ values (Luce, 1959). However, this is a different theoretical pursuit than appreciating the variance in human behavior generally, and sports decisions in particular, through direct modeling thereof.

In sum, the sports domain supports the use of dynamic, probabilistic process modeling. Static, deterministic, outcome models—although the dominant type in general decision research—are flawed in their ability to account for key aspects of human behavior, especially in sports. It is important to have correspondence between the type of behavior under investigation and the tool (model) that is applied. Admittedly, the modeling preferences established in the preceding paragraphs, just like the situational characteristics they are meant to mirror, may not apply across the entire spectrum of sports decisions. The baseball coach’s choice of a starting pitcher may be adequately modeled by, e.g., the deterministic weighting and integration of static cues. The majority of sports decisions, however, will benefit from a dynamic, probabilistic, process-oriented approach, such as the class of models introduced in the following section.

Sequential sampling models of decision-making

Sequential sampling models, also known as accumulator or “horse race” models (Townsend & Ashby, 1983), have a long and successful history in the study of judgment and decision-making (Aschenbrenner, Albert, & Schmalhofer, 1984; Wallsten & Barton, 1982), as well as other domains including perception (Link & Heath, 1975), memory (Ratcliff, 1978), and more. These models are constructed from simple assumptions about the fundamental mechanisms of information processing, but can result in complex behaviors in line with empirical results. In this sense, they provide an elegant yet powerful method for modeling phenomena.

Sequential sampling models of decision begin with the psychological assumption of selective, limited attention. This is a basic property of the human perceptual system, and has been implicated as a source of “bounded rationality” in decision-making (Simon, 1955). At each moment during a task, attention shifts to a particular dimension of task information. This prompts affective evaluation of each option, or *valence*, based on the currently attended information. As attention shifts among dimensions, valences accumulate to produce an overall level of activation, or *preference*, for each option. This continues until the preference for one option exceeds some *threshold* level of activation—this option is then the “winner” of the “race,” and is chosen. Interestingly, this process has received empirical support on the level of individual neurons, suggesting that such an accumulation-to-threshold model may represent the way the brain determines responses to differentially rewarding stimuli (e.g., Gold & Shadlen, 2001).

To understand the detailed operation of these models, and facilitate their use, it will be helpful to consider a particular model in detail. To ground the model introduction in a concrete sports example, consider a playmaker faced with an allocation decision (e.g., a point guard in basketball running a play). The playmaker has a variety of cues, or dimensions of task information, to consider when making this decision (e.g., defender distances, teammate shooting percentages, etc.). The decision itself is choice of a teammate to receive a pass (and possibly how to pass, but we refrain from this complication for the illustrative example); the objective is obviously to score a goal. Next, decision field theory (DFT; Busemeyer & Townsend, 1993; Roe, Busemeyer, & Townsend, 2001) is introduced as a specific sequential sampling model of this playmaker’s deliberation process (see Fig. 1). The mathematical equations used to formally represent this model have been omitted to facilitate discussion, but can be found in Appendix A.

Deliberation

DFT makes specific assumptions about each of the basic processes described above. First, DFT allows for a non-neutral *initial preference*, meaning there may be preference for a particular option before any task-relevant information is considered. The playmaker may exhibit some favoritism for a particular teammate, regardless of the specific situation. Second, DFT assumes that the information sampling is based on the *relative importance* of the various task dimensions. However, the process is also stochastic, such that the exact order in which information is considered is probabilistically determined. For example, if teammates’ shooting percentage is the most important aspect for the playmaker, this information will be most likely—although not necessarily—considered at a particular moment.

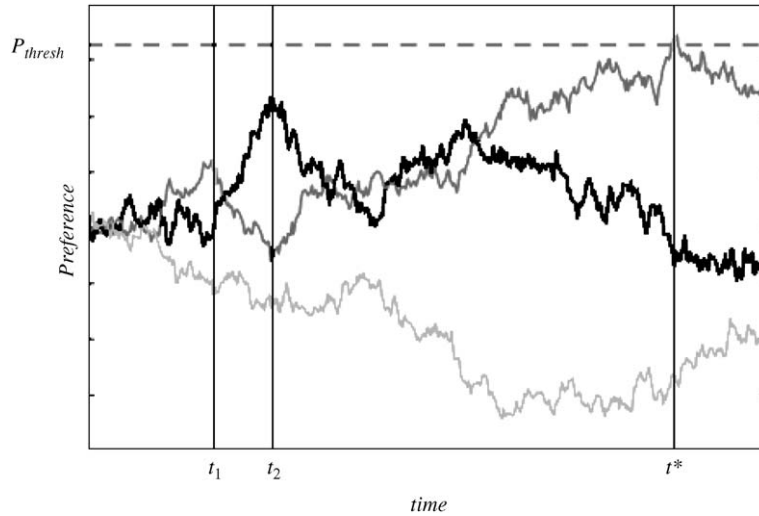


Fig. 1. Simulated sequential sampling process for deliberation among three options. Preference for passing to teammate A (dark line), B (gray line), and C (light line) accumulates over time based on shifts in momentary attention. For example, during the interval $t < t_1$, attention is generally on cues that favor teammate B; but the attended information mostly favors teammate A while $t_1 \leq t < t_2$. The dashed line, P_{thresh} , indicates the preference required in order to pass to any teammate; this results in choice of teammate B at time t^* .

Psychologically, DFT assumes that the attended information brings to mind affective reactions to each option, largely based on previous experiences (if available). If the playmaker considers defender distances, and one teammate is closely guarded, this may produce a negative reaction towards passing to this teammate based on recalled instances of turnovers. Furthermore, these reactions are assumed to be scaled relative to the reactions across the entire set of options (a *contrast* operator). In other words, if there are strong positive reactions to one option, and weak positive reactions to another, then the latter option would be considered relatively unfavorable. For example, if one teammate has a good shooting percentage, but another teammate has an even better percentage, then the valence assigned to the former would actually be unfavorable, due to comparison with the latter teammate.

The valences that are produced for each option, at each moment in time, are integrated over time to derive a preference state for each option. DFT makes two important assumptions about this process. The first assumption involves the dynamics of integration for each preference state. Specifically, DFT includes the psychological notion of *decay*, such that more recent valences “count more” than earlier (in the task) valences in contributing to the overall preference state. If the playmaker only considers, e.g., teammate ball-handling ability at the onset of the play, then subsequent attention to other information results in relative neglect of teammates’ ball-handling skills. The second critical assumption is that of *competition* among options, such that the evolution of preference for a given option is affected by preference for other options. In other words, as preference grows for a particular option, this also results in inhibition of the other options under consideration. As the playmaker increasingly favors passing to a particular teammate, this simultaneously suppresses the urge or tendency to pass to the others. The

evolution of preference states proceeds according to the above assumptions, but at some point an option must be selected—after all, the playmaker must pass to allow a shot before the shot clock expires. DFT introduces a threshold, or level at which an option is considered “good enough,” to determine choice. As preferences for passing to each teammate accumulate, the playmaker eventually must decide that the preference for a teammate is enough to deserve the ball.

DFT provides a specific model of the deliberation process, but this procedure does not occur in isolation. Contrary to the assumptions and tasks in a great deal of laboratory decision experiments, making a decision entails more than the solitary deliberation about a set of options. For example, from where do these options come? How do previous related decisions influence the current task? Next, these two questions are given brief treatment in the context of sequential sampling models.

Additional cognitive processes

The generation of possible courses of action is absent from the majority of decision research, which primarily focuses instead on the choice among alternatives (see [Gettys, Pliske, Manning, & Casey, 1987](#); [Johnson & Raab, 2003](#); [Klein, Wolf, Militello, & Zsombok, 1995](#); for notable exceptions). However, option generation is another behavior that is important in sports tasks, such as the generation of possible moves in board games ([Klein et al., 1995](#)), or possible ball allocation decisions in ball games ([Johnson & Raab, 2003](#)). In a sequential sampling model, there are at least two distinct ways that option generation could be incorporated. First, option generation may be a discrete stage that precedes the deliberation process. This would allow for any conceivable generation method to be specified, such as associative generation in a semantic network ([Anderson & Lebiere, 1998](#); [Collins & Loftus, 1975](#)), in defining the set of options that are input to the deliberation process.

Second, and perhaps more in the spirit of the current article, option generation could be formalized as dynamic additions to the deliberation process. In other words, the option generation process would dynamically alter the options in the choice set during deliberation. For example, rather than having a preconceived set of options in mind, perhaps a playmaker dynamically generates these options as she scans the field during a play. This could in turn affect the patterns of attention, such as by explicitly seeking information to confirm a new option that comes to mind ([Montgomery, 1989](#)). Furthermore, this may change other characteristics of deliberation, such as by shifting attention across alternatives rather than across information dimensions (i.e., alternative-wise vs. attribute-wise search). The complex interaction between dynamic option generation and concurrent deliberation is an interesting possibility for future research in sports decision-making—and one that the current model can uniquely handle.

Another important element that impacts deliberation is learning; or more precisely, the incorporation of feedback from prior experience. Again, there are a number of ways this could be formally modeled. These different possibilities are not mutually exclusive, either, so the influence of prior experience may be multifaceted. First, prior experience may determine the initial preference for each particular option. In a novel situation there may be no initial preference, but in a familiar task there are almost certainly predispositions towards options that are known to be successful. Thus, each successful choice would improve the initial preference for the chosen option in subsequent situations. In sports, this explanation can account for sequential effects in referee

decisions (Plessner, 2005; Plessner & Betsch, 2001). Second, there may be other model parameters that change as a function of experience (see Appendix A for parameter details). For example, explicit training in a sport may determine the order in which dimensions should be considered (Raab & Johnson, 2006), or provide more precise knowledge about the functional similarity between options.

Learning can also be formally modeled in its own right (i.e., as a separate process) using sequential sampling models. Johnson and Busemeyer (2005a) recently introduced a second “layer” to DFT that models rule or strategy learning and the development of routine behavior. These authors noted that deliberation is likely to entail application of particular rules or strategies, in addition to (or instead of) incremental preference updating. That is, attention may also be allocated to discrete rules, rather than to dimensions of information. The formulation of such rules by Johnson and Busemeyer (2005a) is abstract enough that virtually any protocol that assigns preference (or deterministic choice) to options could be included in their definition. For example, “if-then” rules would dictate a specific course of action (option choice); i.e., specify immediate updating of preference for the associated option to a level exceeding the threshold. Successful rules are reinforced and are more likely to guide future behavior, which could eventually result in more “automatic” processing (see Johnson & Busemeyer, 2005a, for details). Essentially, choice and evaluation drive a learning mechanism, which then feeds information back into the deliberation process on subsequent trials.

Predictions and applications of sequential sampling models

Sequential sampling models can provide a comprehensive, psychologically plausible model of decision-making. Yet, it remains to be seen whether these models are successful in accounting for observed behavior. In this section, the novel predictions of the model are discussed, including their empirical assessment and the explanatory power gained. Then, DFT is evaluated in terms of its ability to explain general phenomena and specific empirical data related to sports tasks. Finally, it is shown how the model can be “fine tuned” by considering individual difference variables.

Novel predictions

Sequential sampling models generate a number of quantitative predictions that are beyond the scope of other approaches to decision-making. First, their dynamic quality allows for predictions about the deliberation time for a particular decision. Specifically, mathematical theorems exist for predicting entire response time distributions from these models (e.g., Busemeyer & Townsend, 1992; Shiffrin & Thompson, 1988). This is important theoretically when the time required to make a decision is important, as is often the case in sports. It is important practically in that the response time is an additional dependent variable which can be used to evaluate the model.

DFT, in particular, is a probabilistic sampling model; therefore, it predicts entire choice distributions across a set of options, rather than deterministic choice of a single option. Indeed, this quality was tied to the corresponding variability that is indicative of the sports domain, to motivate the use of the model in the first place. Given a set of choice options, DFT predicts the

probability of choosing each option. Thus, the model can predict choice variability as a result of deliberation, rather than as simply a byproduct of “error” or “randomness.” Practically, choice probabilities can be compared to choice frequencies in both within- and between-subjects designs.

The sampling assumption in DFT is driven by attention to different dimensions, allowing this property of cognitive functioning to be explicitly modeled. The importance of such an allowance has not gone unnoticed in sports (cf. Nougier, Stein, & Bonnel, 1991, for relevant discussion). There is also considerable empirical evidence in sports of distinctive use of information dimensions, such as differences between experts and novices (e.g., Abernethy, 1991; Araújo, Davids, & Serpa, 2005; Goulet, Bard, & Fleury, 1989; among others). Experts and novices in sports may also differ when it comes to the relative importance of various dimensions (e.g., McPherson, 1993). Such findings can be instantiated in sequential sampling models by directly specifying the attention shifts or constraining the attention probabilities.

By specifying a deliberation process, rather than just an outcome, it is possible to conduct further tests of sampling models as well. There are a number of process predictions that are implied by DFT and other sampling models. For example, the use of a constant threshold places constraints on feasible information search and preference updating patterns. Also, the comparative (contrast) evaluation mechanism is open to independent verification, as is the form of feedback (decay and competition) assumed to operate in DFT. Clever process-tracing designs and experiments examining component processes of these models can support or refute these assumptions in the sports (or any other) domain.

Accounting for empirical results

DFT and other sequential sampling models of decision-making have been applied primarily to “standard” laboratory decision tasks outside of the sports domain. Nevertheless, it is possible to draw tentative conclusions about their success by examining their ability to explain robust phenomena that seem to be task-independent, as well as phenomena that have been shown to exist in the sports domain. Rather than an exhaustive review, only two general types are covered here: context effects and dynamic effects.

Context effects refer to situations where seemingly innocuous context factors influence choice. These are particularly important in sports due to the rich context in which sports decisions are embedded. Three common context effects in multiattribute, multialternative choice situations are similarity effects (Tversky, 1972), attraction effects (Huber, Payne, & Puto, 1982), and compromise effects (Simonson, 1989). A similarity effect is when two similar options “steal” preference from each other, often resulting in ultimate choice of a third, dissimilar option. If two teammates possess similar qualities, indecision about the better of these two may result in selection of a third teammate with noticeably different qualities. However, if two teammates are similar, but one dominates the other (i.e., is slightly better on all attributes), this accentuates the superiority of the dominant teammate. This “attraction effect” results in boosting, rather than hindering, the choice probability of the similar (dominant) teammate relative to a third, dissimilar teammate. Finally, given three teammates, perhaps they are “spread out” over the attribute space such that one excels on some attributes but falls short on others, the second complements the first (excels/fails on the converse attributes), and the third is mediocre on all attributes. In this case, choice probabilities are typically highest for the third “compromise” option.

DFT can account for these three effects without changing any model parameters, methods, or mechanisms (see Roe et al., 2001, for a detailed discussion). The similarity effect is produced primarily by attention-switching in the model. Attention to attributes favoring the similar options results in moderate valence for each, but attention to attributes favoring the dissimilar option produces positive valence only for that single option, which is thus greater in magnitude. The attraction effect is produced by the competitive feedback between options. Competitive feedback suggests not only that strong options suppress weaker options, but also reciprocally that weak options bolster stronger ones. Because the influence of feedback increases with similarity (see Appendix A; and Roe et al., 2001), a dominated option bolsters the similar option more than the dissimilar option. Finally, the two mechanisms used to explain these effects interact to produce the compromise effect. Attention to either attribute favors one extreme option and hurts the other extreme option, but produces a slight advantage for the compromise option. Thus, attention to either attribute slightly favors the compromise option, which inhibits *both* of the other options (and reciprocally bolsters the compromise option) due to similarity.

Phenomena related to the dynamic course of decision-making are also evident in both the sports and decision research literatures. First, consider the effects of time pressure. Under time pressure, an option may be selected that was not favored under conditions without time pressure (e.g., Edland & Svenson, 1993; Raab, 2001). A coach may elect to pursue a particular strategy or call a specific play during a timeout, but when the same decision must be made online during the course of action a different play may be selected. A related phenomena is the “speed-accuracy tradeoff” that has been observed in sports domains (Schmidt & Lee, 2005), among others. This refers to the inverse relationship between the two variables—as the speed increases with which a decision is made, the accuracy of the decision decreases. A quick, impulsive decision by a quarterback can easily lead to an interception, whereas a more careful (although time-consuming) assessment of the defense may prevent the turnover and possibly result in a pass completion.

Sequential sampling models easily predict the effects of time pressure and the speed-accuracy tradeoff (see Diederich, 2003; Raab, 2001). For sports in particular, Raab (2001) has shown the ability of DFT to explain the effects of time pressure in basketball. Two key factors contribute to the time-dependent predictions of these models. First, increasing time pressure reduces the total amount of information sampled, implicating the interaction between time available and the nature of attention-switching. For example, if dimensions are considered in a particular order, such as by salience or importance, then increasing time pressure decreases the likelihood of sampling some (e.g., less salient) dimensions. This attenuates the choice probabilities of options that excel on these dimensions, relative to more complete information processing (see also Lee & Cummins, 2001). Finally, the decision threshold may mediate the relationship between time pressure and choice. If a decision maker is in a situation with known time pressure, then an adaptive response would be to reduce the amount of information necessary to make a decision. This would be modeled by lowering the threshold, which results in decisions that are quicker but more variable (i.e., with more moderate choice probabilities). In other words, speed-accuracy tradeoffs can easily be modeled using the decision threshold.

Sequential sampling models can account for context effects and time-dependent phenomena that are ubiquitous to many domains, including sports decisions. Their success results from concentrating on the underlying processes that give rise to decision behavior. These models can also account for other robust effects. Busemeyer and Townsend (1993) explain the ability of DFT

to account for serial position effects, approach-avoidance distinctions, violations of transitivity and dominance, and more. Johnson and Busemeyer (2005b) apply a sequential sampling model to explain preference reversals across different response methods, and Johnson and Busemeyer (2006) model attention-switching as sequential sampling to derive the weight allocated to each information dimension.

Individual differences

Sequential sampling models are representations of the individual deliberation process, and should be interpreted as such. There is a danger in using aggregate data to make inferences about individual tendencies (e.g., Maddox, 1999). Therefore, it is also important to examine whether these models can explain individual difference variables.

Raab and Johnson (2004) used DFT to compare different underlying mechanisms giving rise to an individual's action orientation, a well-known individual trait utilized in sports research (Roth & Strang, 1994). Greater action (vs. state) orientation is described by concentration on specific goals, is highly correlated to risk taking, and behaviorally produces greater capitalization on scoring opportunities and quicker decisions (Raab & Johnson, 2004; Roth & Strang, 1994). Raab and Johnson (2004) examined the explanatory power of four different methods of modeling increased action orientation in DFT: lower decision thresholds, suggesting less inhibition and a greater tendency to act (score); greater approach tendencies modeled via the decay parameter; greater attention to dimensions associated with action (scoring); and greater initial preference for action (scoring). Experimental data and action-orientation inventory scores from basketball playmakers revealed that action orientation was best formalized using the initial preference parameter, which provided an excellent fit to the choice and response time data.

An individual difference variable that has received perhaps the most attention in sports decision-making is expertise (Chamberlain & Coelho, 1993). Although the results are somewhat equivocal, there seems to be a general tendency for experts in sports to make decisions that are both faster and better than those of novices (e.g., Paull & Glencross, 1997). Analyses similar to those of Raab and Johnson (2004) can determine the underlying cognitive mechanisms that may best characterize the differences between novices and experts. Perhaps experts have different initial preferences based on their experience, which could indeed facilitate quicker and more accurate responses. Other hypothesized expertise-based differences, such as in knowledge representation and information use (Chamberlain & Coelho, 1993; Chase & Simon, 1973), can also be explicitly modeled by detailing the dimensions of information and the transitions among them. Finally, perhaps expertise “frees” mental resources that may effectively increase working memory capacity or attention, which could thus be modeled by an increase in number of dimensions attended in a given period of time, or in decreased decay of previously attended information.

Other individual differences can be incorporated through appropriate sequential sampling parameter interpretations. Johnson (2003) has related parameters in DFT to various individual traits that have been included in decision research, such as self-monitoring, impulsivity, accountability, attention span, persistence, and sensitivity to omissions (missing information). Individual differences unique to the sports domain could also be included, such as differences in coaching or motivational style, which have been shown to impact decision-making (Frederick &

Morrison, 1999). The impact of individual learning history and experience has also received some attention within the sequential sampling framework (Johnson & Busemeyer, 2005a), as has individual use of different strategies (Lee & Cummins, 2001). This latter topic, as well as other extensions of sequential sampling models, is discussed in the following section.

Connections, extensions, and conclusions

In this final section, the sequential sampling models are compared to other contemporary approaches to decision-making research. Also, some speculative discussion is devoted to extensions of the models and further tailoring of the models to sports decision-making.

Relation to other approaches

There are other general approaches to decision-making that are closely related to the cognitive (sequential sampling) models introduced in this article. By far the most popular framework for the study of decision-making is the expected utility framework. This approach assumes that choices are driven by the goal of maximizing the expected subjective value of a course of action. Cognitive process modeling is actually quite different from this approach—but this is an asset rather than a drawback. Decades of research have refuted expected utility theories as descriptive models of human behavior. Although sequential sampling models can mimic expected utility models with the proper assumptions (see Busemeyer & Townsend, 1993), these reductions eliminate the dynamic and probabilistic predictions that describe sports decisions.

The so-called “adaptive decision maker” framework is an alternative cognitive modeling approach to that detailed in this paper. This approach formalizes a variety of different decision strategies as production rule systems (Payne, Bettman, & Johnson, 1993). A key assumption of this approach is that decision makers, rather than attempting to maximize expected utility, attempt to strike a balance between accuracy and effort in a decision task (see Proteau & Dorion, 1992, for a similar concept in sports). For example, a decision maker may select the lowest-effort strategy that provides a sufficient level of performance. This approach can easily coexist with the sequential sampling approach. Because parameter assumptions can result in different strategies within the sequential sampling models (see below), this is another method for formalizing the same basic idea. For example, the decision threshold in sampling models can control the effort-accuracy tradeoff, and plays a role in mimicking other strategies.

A similar framework to the “adaptive decision maker” hypothesis is the work of Gigerenzer, Todd, and The ABC Research Group (1999). These researchers posit a “toolbox” or collection of simple yet powerful heuristics that are adapted to function well in specific environments. These researchers also recognize the importance of studying decision processes, rather than just outcomes. Their heuristics are typically described by an information search rule, a stopping rule for terminating search, and a decision rule applied to the information obtained. Again, the sequential sampling models can provide a formal mathematical framework for the theoretical postulates of simple heuristics (Lee & Cummins, 2001).

Sequential sampling models can also be integrated into the naturalistic decision-making program (NDM; Klein, Orasanu, Calderwood, & Zsombok, 1993). This program is to be

commended for its attention to the decisions of experienced individuals in real domains—such as in sports tasks (Martell & Vickers, 2004). NDM research is also very much concerned with the processes used to make decisions, rather than just the outcomes. However, this program has been criticized for its lack of specificity, formalization, and generalizability; even the pioneers of NDM suggest that formal models are not indicative of this approach (see Lipshitz, Klein, Orasanu, & Salas, 2001; and the associated replies). Sequential sampling models are a method of contributing formality to this approach, while retaining the desirable theoretical focus of NDM.

Extensions and future directions

There are a number of other possible extensions to sequential sampling models, in addition to incorporating the theoretical stances of the research programs identified above. Some of these have been alluded to throughout other sections of this article, such as incorporating option generation or learning mechanisms. Here, some additional avenues for potentially rewarding future work are briefly mentioned.

The motivation for the current analysis was the correspondence between sequential sampling models and dynamic, probabilistic, online decisions in sports. However, not all decisions in sports are of this variety. Recall the decision of the baseball coach, who is not under dramatic time constraints to select a starting pitcher, and who has a catalog of static cues on which to base a choice. An additional advantage of sequential sampling models is the ability to incorporate these simpler assumptions in the same framework. For example, removing the decision threshold results in exhaustive processing of task information, or specifying a deterministic progression of attention eliminates choice variability, and so on.

Rather than simplifying the assumptions in sequential sampling models, applications to sports decisions may require finer specification of the model's components. For example, perhaps the threshold is not constant, as assumed here, but decreases over the course of deliberation. That is, the longer deliberation takes, the less evidence is necessary to make a decision. This assumption could avoid predictions of functional paralysis (e.g., a shot clock violation) should no option emerge as clearly superior. It is also necessary in some situations to include the possibility of an indifference response (see Busemeyer & Townsend, 1992; Johnson & Busemeyer, 2005b). Other assumptions may alter the nature of processing, such as using time-variant attention shifting, or including dependencies of attention on the immediately prior attended dimension.

The ability to produce a variety of potential models, as illustrated in the preceding two paragraphs, can afford the sports psychologist a common framework to compare possible models. This can help in understanding circumstances where specific (different) strategies may be used. In sports, the use of various heuristic strategies has been documented among athletes (Johnson & Raab, 2003), judges (Plessner, 1999) and referees (Nevill, Balmer, & Williams, 2002). Furthermore, Poplu, Baratgin, Mavromatis, and Ripoll (2003) have shown how the nature of processing when making sports decisions is variable, and specifically, task-dependent. It is therefore beneficial to adopt a flexible framework such as sequential sampling that can formalize a wide range of theoretical possibilities.

When viewed as a modeling framework, rather than as a specific model, the sequential sampling approach can offer great precision as well as flexibility. Whereas this article speaks

to the advantages of importing models from cognitive psychology into sports, ultimately it will be beneficial to use research from sports to reciprocally inform the models. In this sense, modeling behavior in sports will best be pursued as a cyclic endeavor that embodies the scientific process. That is, we as theorists should formulate models of sports behavior, test these models empirically, and use experimental results to refine the model and make additional predictions.

Model refinement specific to sports tasks will certainly include features not mentioned in this survey article. A key future extension of sequential sampling models in sports will require appreciation of interactive dynamics. In sports situations, the athlete is embedded in the choice situation, where momentary fluctuations abound in both the context and the decision maker. Even though the current models make room for environmental dynamics, as well as personal dynamics (e.g. shifting attention), these are not independent systems. Thus, application of these models to many decisions in sports will first need to formalize the dependencies between athlete and environment. To this end, it would be worthwhile to explore the possible contributions of dynamic control theory and cognitive engineering to the current approach.

Finally, although the advantage of cognitive modeling is to reveal what happens in the athlete's head, a decision does not occur in the mind alone. In sports, rackets, bats, clubs, and sticks are swung; balls are hit, thrown, kicked, rolled, and dribbled. Thus, the motor component of decision-making is crucial to understanding the totality of sports decisions (see [Rosenbaum, 2005](#)). Further influences upon the observed decision may then come from the motor system, which is prone to unique sources of error—the playmaker may overshoot the pass to one teammate, resulting in possession by another (unchosen) teammate. In fact, the motor component may even “close the loop” by providing perceptual (in addition to kinesthetic) feedback that subsequently affects cognitive processing ([Raab & Green 2005](#)). This is perhaps the most exciting and relevant application of cognitive models to athletes' decision-making.

Conclusion

The purpose of this article is to provide an introduction to the benefits of cognitive models applied to sports decision-making. While the focus of the current paper is on decision-making, the use of cognitive models in sports offers advantages for other aspects of behavior as well, such as perception and memory. Sequential sampling models in particular have been applied to these domains, and it would be interesting to see if sequential sampling principles could explain a wealth of cognitive activity in sports, such as memory organization or knowledge representation of sports experts (e.g., [Chase & Simon, 1973](#); [Zoudji and Thon, 2003](#)).

Above all, the goal here was to provide enough background on these models to encourage their use in research on decision making in sports. In addition, Appendix A provides sufficient detail to formulate, simulate, and compute predictions for one specific class of models. The use of sequential sampling models was motivated by their correspondence with the dynamic, stochastic processes that characterize decision making in sports. Hopefully, the introduction given here, in conjunction with the extensions for future work, will provoke research in sports built on the foundations laid in cognitive psychology.

Appendix A

Decision field theory (DFT) has been formulated both as a system of dynamic equations and as an artificial neural network (e.g., Busemeyer & Johnson, 2004). The formulation given here provides a conceptual system for simulation (Roe et al., 2001). An alternative method, not detailed here, allows for precise computation of predictions for choice probabilities and response times using numerical methods (see Diederich & Busemeyer, 2003).

The affective assessment of relevant information in a decision task can be represented in a canonical form using an $N \times M$ matrix, called \mathbf{A} , for M dimensions of information that describe N choice options; the affective evaluation of option n when considering dimension m is represented by $a_{m,n}$. At each discrete moment in time, t , a particular dimension receives attention. This is modeled by an $M \times 1$ attention weight vector, $\mathbf{W}(t)$. If attention at time $t = t'$ is on dimension k , then $w_k(t') = 1$, and $w_j(t') = 0$, for all $j \neq k$; effectively isolating a column of the information matrix \mathbf{A} . That is, the product $\mathbf{A} \cdot \mathbf{W}(t')$ results in an $N \times 1$ vector containing the affective values of the N options on dimension k . Previous applications of DFT have assumed stochastic attention-switching based on importance weights. That is, the probability that attention is on dimension k at time t is determined by the relative importance, q_k , of the dimension, where $0 \leq q_k \leq 1$ for all q_k , and $\sum q_k = 1$:

$$Pr[w_k(t) = 1] = q_k, \quad (\text{A.1})$$

An $N \times N$ contrast operator, \mathbf{C} , computes the relative evaluation of each option, depending on the evaluations of other options (see text for theoretical discussion). Formally, the element $c_{i,j}$ describes the influence of option i on option j . In DFT, it is commonly assumed that the evaluation of an option i is scaled by the average of the remaining $N-1$ options (Roe et al., 2001):

$$\mathbf{C} = \begin{bmatrix} 1 & -\frac{1}{N-1} & \dots & -\frac{1}{N-1} & -\frac{1}{N-1} \\ -\frac{1}{N-1} & 1 & \dots & -\frac{1}{N-1} & -\frac{1}{N-1} \\ \dots & \dots & \dots & \dots & \dots \\ -\frac{1}{N-1} & -\frac{1}{N-1} & \dots & 1 & -\frac{1}{N-1} \\ -\frac{1}{N-1} & -\frac{1}{N-1} & \dots & -\frac{1}{N-1} & 1 \end{bmatrix}. \quad (\text{A.2})$$

Then, the valence for each option n at time t , labeled $v_n(t)$, can be expressed in an $N \times 1$ vector, $\mathbf{V}(t)$:

$$\mathbf{V}(t) = \mathbf{C} \cdot \mathbf{A} \cdot \mathbf{W}(t). \quad (\text{A.3})$$

Finally, the momentary preference for each option i , labeled $p_i(t)$ and contained in a vector $\mathbf{P}(t)$, is simply a weighted summation of the previous preference state and the current valence input:

$$\mathbf{P}(t) = \mathbf{S} \cdot \mathbf{P}(t-1) + \mathbf{V}(t). \quad (\text{A.4})$$

The form of the matrix \mathbf{S} is crucial for incorporating key assumptions of DFT. The diagonal elements $s_{i,i} > 0$ control the growth or decay over time of the preference for option i . Defining all $s_{i,i}$ on the interval $[0, 1)$ suggests decay of the preference state, or decreasing influence of valences over time (recency effects); $s_{i,i} = 1$ suggests perfect system memory for the previous state; and $s_{i,i} > 1$ suggests growth of the previous state, or increasing influence of valences over time (primacy

effects). The off-diagonal elements $s_{i,j}$ represent the influence of option i on option j . In DFT, this influence is assumed to follow two principles (see text for theoretical discussion). First, options are assumed to be competitive: $s_{i,j} < 0$ for all $i \neq j$. Second, the influence of option i on option j is assumed to be an increasing function of psychological similarity, $f()$, between the options: $abs[s_{i,j}] = f(i,j)$. Roe et al. (2001) discuss this in detail using psychological distances.

The last step in formalizing DFT is to specify a beginning and end for the dynamic accumulation process described above. The distribution of initial preference across options is contained in an $N \times 1$ vector, $\mathbf{P}(0) = \mathbf{P}_0$. The process terminates when preference for an alternative surpasses the inhibitory threshold, θ . That is, $p_i(t^*) > \theta$, for any option i , suggests choice of option i at time t^* .

The above system of equations can be used to simulate the DFT deliberation process by numerical assignment to option values (\mathbf{A} , \mathbf{S}), setting free parameters (\mathbf{P}_0 , θ), and specifying the importance of each dimension (q_k , for $k = 1, \dots, M$). Then, the attention at time $t = 1$ is determined by Eq. (A.1), producing $\mathbf{V}(1)$ through Eq. (A.3), which in conjunction with \mathbf{P}_0 produces $\mathbf{P}(1)$ via Eq. (A.4). The attentional algorithm then determines $\mathbf{W}(2)$, updating $\mathbf{V}(2)$ and $\mathbf{P}(2)$, and this process continues until $P_i(t^*) > \theta$, for any option i .

This formulation of DFT makes transparent the psychological processing implications of the model, and has been successfully applied to the sports domain by Raab and Johnson (2004). However, because of the stochastic attention mechanism, using the above form requires extensive Monte Carlo simulation to produce stable predictions. Alternatively, existing mathematical theorems can be used to derive precise quantitative predictions (i.e., choice probability distributions across options, response time distributions) for many sequential sampling models, including DFT (cf. Busemeyer & Townsended, 1992). Details of easy-to-implement matrix methods for deriving these predictions can be found in Diederich and Busemeyer (2003).

An example application

A simple example is given here, to show interested researchers how to implement sequential sampling models for decision-making research in sports (see also Raab & Johnson, 2004). Consider the playmaker faced with an allocation decision, as introduced in the DFT introduction in the text.

First, one must specify the relevant information dimensions in a task or experiment. Assume for simplicity that these dimensions are (a) the distance of each teammate to the nearest defender; (b) the shooting percentage of each teammate; and (c) the ball-handling ability, such as ratio of assists to turnovers, for each teammate. If the playmaker can (even implicitly) assign a subjective value to each teammate on each dimension, this creates the attribute matrix \mathbf{A} for use in DFT (Table A1). In practice, these cell values are typically divided by the column maximum, to place all dimensions on a common scale with the interval $[0, 1]$.

Next, the attention weights (q_a , q_b , q_c) need to be defined, such as by experimental instruction, verbal report from the playmaker, analysis of looking times, or other methods. These determine the probability of each of three possible attention weight vectors, $\mathbf{W}(t)' = \{[1\ 0\ 0], [0\ 1\ 0], [0\ 0\ 1]\}$, at each moment. The form of \mathbf{C} is given by Eq. (A.2), and for three options it is a 3×3 matrix.

Table A1
Attribute matrix for hypothetical playmaker decision among three teammates

	(a)	(b)	(c)
Importance weight:	Defender distance 0.3	Shooting percent 0.5	Ball handling 0.2
Teammate A	0.8	52.5	2.3
Teammate B	1.0	42.0	3.8
Teammate C	0.6	47.3	2.7

Notes: Defender distances are in meters; ball handling is the ratio of assists to turnovers; thus, all dimensions are positively scaled. The row “Importance weight” shows the probability of attending to each dimension at any given moment.

By appropriate substitution in Eq. (A.3), then with a probability of $q_a = 0.3$ the momentary valence $\mathbf{V}(t)$ at any given moment is

$$\begin{bmatrix} 1 & -\frac{1}{N-1} & -\frac{1}{N-1} \\ -\frac{1}{N-1} & 1 & -\frac{1}{N-1} \\ -\frac{1}{N-1} & -\frac{1}{N-1} & 1 \end{bmatrix} \cdot \begin{bmatrix} 0.8 & 1.0 & 0.6 \\ 1.0 & 0.8 & 1.0 \\ 0.6 & 0.9 & 0.7 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.00 \\ 0.30 \\ -0.30 \end{bmatrix}. \quad (\text{A.5})$$

With a probability of $q_b = 0.5$ the momentary valence is

$$\begin{bmatrix} 1 & -\frac{1}{N-1} & -\frac{1}{N-1} \\ -\frac{1}{N-1} & 1 & -\frac{1}{N-1} \\ -\frac{1}{N-1} & -\frac{1}{N-1} & 1 \end{bmatrix} \cdot \begin{bmatrix} 0.8 & 1.0 & 0.6 \\ 1.0 & 0.8 & 1.0 \\ 0.6 & 0.9 & 0.7 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.15 \\ -0.15 \\ 0.00 \end{bmatrix}. \quad (\text{A.6})$$

With a probability of $q_c = 0.2$ the momentary valence is

$$\begin{bmatrix} 1 & -\frac{1}{N-1} & -\frac{1}{N-1} \\ -\frac{1}{N-1} & 1 & -\frac{1}{N-1} \\ -\frac{1}{N-1} & -\frac{1}{N-1} & 1 \end{bmatrix} \cdot \begin{bmatrix} 0.8 & 1.0 & 0.6 \\ 1.0 & 0.8 & 1.0 \\ 0.6 & 0.9 & 0.7 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} -0.25 \\ 0.35 \\ -0.10 \end{bmatrix}. \quad (\text{A.7})$$

At each moment, one of the above three valences is produced based on the probabilistic shifts in attention (momentary realization of a random variable). The corresponding valence is then added to the (weighted) previous preference state, from time $(t-1)$, to determine the new preference state at time t via Eq. (A.4). So, depending on the momentary focus of attention to attributes that differentially favor each teammate, one of three changes takes place at each moment. Either preference increases for teammate B at the expense of teammate C (Eq. (A.5)); or preference increases for teammate A at the expense of teammate B (Eq. (A.6)); or preference increases for teammate B at the expense of both teammates A and C (Eq. (A.7)).

The rate of increase or decrease in preference for each option—i.e., the weight given to the previous preference state—is controlled by the feedback matrix, \mathbf{S} . The diagonal elements of \mathbf{S} represent the rate of decay; suppose that there is excellent system memory so that $s_{1,1} = s_{2,2} = s_{3,3} = 0.995$. The off-diagonal elements of \mathbf{S} are typically inversely related to the

psychological distance between options (Roe et al., 2001). For example, if there are two very similar teammates, then they may “steal preference” from each other because if attributes favor one of them, then they also favor the other. If we assume for this example that the competitive feedback elements are equal to one-tenth of the Euclidian distance between options (when options are represented as points in a multidimensional space), we obtain:

$$S = \begin{bmatrix} 0.995 & -0.049 & -0.025 \\ -0.049 & 0.995 & -0.051 \\ -0.025 & -0.051 & 0.995 \end{bmatrix}. \tag{A.8}$$

To complete the model of preference evolution for this example, it is necessary to specify the initial preference, if any, for passing to each teammate. Perhaps the playmaker has a certain rapport with one of the teammates, and therefore has some bias towards passing to this teammate regardless of situational information. Suppose there is weak initial preference for teammate A, and moderate initial preference for teammate C. Then the initial preference vector might be modeled using $P_0 = [0.05 \ 0.00 \ 0.10]^T$. If attention at the first moment focuses on shooting percentage (Eq. (A.6)), then we obtain:

$$P(1) = \begin{bmatrix} 0.995 & -0.049 & -0.025 \\ -0.049 & 0.995 & -0.051 \\ -0.025 & -0.051 & 0.995 \end{bmatrix} \cdot \begin{bmatrix} 0.05 \\ 0.00 \\ 0.10 \end{bmatrix} + \begin{bmatrix} 0.15 \\ -0.15 \\ 0.00 \end{bmatrix} = \begin{bmatrix} 0.197 \\ -0.157 \\ 0.098 \end{bmatrix}. \tag{A.9}$$

If attention at the next moment focuses on ball handling (Eq. (A.7)), then:

$$P(2) = \begin{bmatrix} 0.995 & -0.049 & -0.025 \\ -0.049 & 0.995 & -0.051 \\ -0.025 & -0.051 & 0.995 \end{bmatrix} \cdot \begin{bmatrix} 0.197 \\ -0.157 \\ 0.098 \end{bmatrix} + \begin{bmatrix} -0.25 \\ 0.35 \\ -0.10 \end{bmatrix} = \begin{bmatrix} -0.049 \\ 0.179 \\ -0.001 \end{bmatrix}. \tag{A.10}$$

Preference waxes and wanes for each teammate accordingly as attention continues to focus on different dimensions over the course of deliberation. Finally, once the preference for passing to one of the teammates exceeds the threshold, the corresponding option is chosen (i.e., the model predicts a pass to the corresponding teammate). Note that, due to the probabilistic nature of attention-switching, Monte Carlo simulation methods are required to use the approach outlined here.

A researcher desiring to use sequential sampling models need only make the appropriate model assumptions and assign the necessary values, based on experimental design and/or empirical data. For example, decision thresholds may be determined by personality measures or by task instructions emphasizing the use of a certain degree of information. Importance weights and subjective values may be elicited from participants or imposed on them. Stimulus similarities can be manipulated and measured in a variety of ways, as can initial preferences for options. Alternatively, if only some model parameters are clearly specified, then optimization methods can be used to determine values for the remaining parameters that best-fit empirical data. For implementation purposes, various software packages such as MATLAB can easily perform the necessary computations.

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