

Running head: TAKE THE FIRST

Take The First: Option generation and resulting choices

Joseph G. Johnson<sup>1,2</sup> and Markus Raab<sup>1</sup>

<sup>1</sup>Max Planck Institute for Human Development, Center for Adaptive Behavior and Cognition,  
Berlin, Germany

<sup>2</sup>Indiana University, Bloomington, Indiana, USA

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### Abstract

Experimental decision-making research often uses a task in which participants are presented with alternatives from which they must choose. Although tasks of this type may be useful in determining measures (e.g., preference) related to explicitly stated alternatives, they neglect an important aspect of many real-world decision-making environments—namely, the option-generation process. The goal of the present research is to extend previous literature that fills this void by presenting a model that attempts to describe the link between the use of different strategies and the subsequent option-generation process, as well as the resulting choice characteristics. Specifically, we examine the relationship between strategy use, number and order of generated options, choice quality, and dynamic inconsistency. “Take The First” is presented as a heuristic that operates in ill-defined tasks, based on our model assumptions. An experiment involving a realistic (sports) situation was conducted on suitable participants (athletes) to test the predictions of the model. Initial results support the model’s key predictions: strategies producing fewer generated options result in better and more consistent decisions.

Key words: option generation, decision making, heuristic, strategy, “less-is-more” effect, inconsistency, memory representation

### Take The First: Option generation and resulting choices

How do people choose what to choose from? That is, how do people generate possible solutions to a task when they are not restricted to selecting from among a set of alternatives given to them? Unfortunately, this question has received relatively little attention in the judgment and decision-making literature, compared with the study of people's choices among given alternatives. Although there exist research streams such as the work of Gettys and colleagues (e.g., Engelmann & Gettys, 1985; Gettys, Mehle, & Fisher, 1986; Gettys, Pliske, Manning, & Casey, 1987) and Klein and colleagues (e.g., Klein & Wolf, 1998; Klein, Wolf, Militello, & Zsombok, 1995), the topic of option generation seems to be underrepresented, when considering its vital importance. Descriptively, examining the option-generation process can help us to better understand human decision behavior and develop more precise models than can be achieved solely through, e.g., process-tracing techniques of choices among given gambles. Practically, we can use this information to assist decision makers in some settings (e.g., business) to be more aware of their "predecisional" behavior, and perhaps we can develop prescriptive tools to help them in systematic analysis. Although contemporary decision-making models make assumptions about how people search through a set of given options—such as by using "normative" optimization methods (e.g., Luce, 2000) or "fast and frugal" heuristics (e.g., Gigerenzer, Todd, & The ABC Research Group, 1999)—the question remains of where these options come from, if they are not readily available. For example, Bayesian models require that the hypotheses be precisely formulated, and thus they could not be applied to option generation. Although some research makes the distinction between external search for information in the environment and internal search for information in memory (e.g., Hastie & Pennington, 1995), it is often assumed that the options are there, and one must simply discover a way to get to them. For example, subjective utility theories describe how the attributes for various options are weighted and integrated, without mentioning from where the options under consideration come.

In contrast, the current research will examine the option-generation process—how alternatives are generated “from scratch,” when they are not “out there” in the environment. To do so, the current research differs from the majority of decision-making studies in the use of a divergent-thinking task. That is, we employ a procedure that presents an ill-defined problem to which participants must develop possible solutions and select among them, rather than presenting information such that participants need only to integrate it and choose. Our theoretical model does draw on the topics mentioned above, such as memory retrieval and decision strategies (fast and frugal heuristics), as well as the existing research on generation. A brief review of the previous literature, therefore, will first be presented and related to our approach. This is followed by an introduction to the relevant concepts (memory and search). Then, we will integrate these into “Take The First,” an option-generation and choice heuristic for use in divergent-thinking situations. This will lead to predictions regarding the resultant choice behavior, and the presentation of an experiment to test these predictions. In conclusion, we will assess the validity of the model, relate our model predictions and findings to previous work, and propose directions for future research.

#### Review of literature on option generation

A great deal of relevant work has been done by Gettys and colleagues, who examined the processes that precede active choices, such as the generation of possible actions, the potential outcomes of these actions, and the assessments of each outcome’s plausibility. They propose many concepts that will be incorporated in our model, in both the generation of acts (Gettys, et al., 1987) and hypotheses (Gettys, et al., 1986). Gettys, et al. (1986) assume that hypotheses are generated by searching memory using retrieval cues, and the hypotheses that are retrieved (generated) are those that most closely match the available data. In act generation, Gettys, et al. (1987) also make the assumption that there exists in memory some available “menu” of options. While we incorporate similar use of memory retrieval as a driving force in the generation process,

we do not assume summations of cue-activated hypotheses but rather spreading activation from one single initially-activated node. In addition to their treatment of memory, we agree with their belief that it may not always be better to generate as large a set of options as possible, although we use a serial position explanation rather than a cost/benefit rationale. In their empirical work, a hierarchical tree structure is used to assess performance of participants in terms of the number and quality of generated acts (Engelmann & Gettys, 1985; Gettys, et al., 1987). In contrast, we use what they term an “authoritative expert approach,” where experts make judgments of the quality of acts. However, the concept of a hierarchical tree of possible generations is in line with our assumptions of memory organization. More recently, Klein and colleagues have studied option generation processes, within a research program that focuses on expert performance (naturalistic decision making; see Lipshitz, Klein, Orasanu, and Salas, 2001, and the associated commentaries). Klein, et al. (1995) studied the performance of chess players in generating potential moves in a game situation, with findings supporting their predictions that the first option generated was not random. This work, then, is in line with our concern for serial position of generated options, and uses expert ratings for assessment as we do. Furthermore, the concept of “leverage points,” as introduced in Klein and Wolf (1998), parallels the initiation of the option generation process in our approach. Klein and Wolf (1998) also distinguish between views of option generation as construction and retrieval, and our model incorporates both, to some degree. In sum, the previous literature on option generation has many common concepts that contribute to the development of our model and methods, while some aspects remain unique to previous studies (e.g., treatment of experience) or ours (e.g., process mechanisms).

Research on creativity in idea generation should also be mentioned here, although there do exist key differences between these studies and the option generation task with which we are concerned. First, one major branch of the creativity literature tends to focus on performance of groups, as opposed to individuals, under labels such as “groupthink” and “brainstorming” (see Esser, 1998, for a review). Although the present study (and those cited above) focuses on

individual option generation performance, one could consider expanding these to group settings. A second, more fundamental distinction is that creativity research has tended to focus largely on the quantity of ideas generated (e.g., León, 1999; Valacich, Wheeler, Mennecke, & Wachter, 1995), and the uniqueness of these ideas (Paulus & Yang, 2000), with little regard for evaluating the resulting decision quality (see Kramer, Kuo, & Dailey, 1997, for a criticism and exception). Lastly, the creativity literature has a largely prescriptive goal, such as deriving techniques for improved creative generation (Smith, 1998). This does not exclude, however, the potential application of our model prescriptively—in fact, our model could be classified alongside the 172 techniques in Smith’s (1998) formulary, by considering the component processes (e.g., “association”).

A final realm of research that affords attention to generation processes is work in artificial intelligence (AI). In fact, Gettys, et al. (1987) and Klein and Wolf (1998) also draw such connections. “Classical AI” research (e.g., Newell & Simon, 1972) has examined search through a “problem space,” but in this sense the search is more explicitly-guided by algorithms than we propose. While Newell and Simon (1972) consider constraints and operators, which determine how the search algorithm progresses, we propose the use of a focusing strategy, that determines the manner of spreading activation. Although there are similarities in these approaches, AI search through a problem space requires the existence of a known “end state” which must be obtained from a “current state.” This does not describe exactly the option generation process as we envision it—as Klein and Wolf (1998, p. 159) stated, “the programs are for locating options, not for generating them.” Furthermore, the use of ill-defined problems in our task (see below) does not allow for the specification of a definite “end state.” Such differences across research areas warrant the following section, which attempts to clarify the fundamental concepts as treated here before introducing our model.

## Organization and Search Principles

Search, as conceptualized in AI search, could be regarded as synonymous with the option-generation process, although we feel there is a necessary distinction between the two. Whereas option generation is defined herein as the production of alternatives from which to choose, search is defined as the process of sequential consideration of these options. This distinction corresponds to hypothesis retrieval and plausibility assessment, respectively, that are treated as separate subprocesses by Gettys, et al. (1986). As mentioned above, tasks that present all of the alternatives to the decision maker do not involve option generation, although they do necessitate some method of considering the alternatives in turn (search). Keller and Ho (1988, p. 718) suggest that “different option-generation procedures can be seen as different strategies for traversing the cognitive network to search for and/or create new options.” We would prefer to exclude the notion of active search as resulting from the same procedures that create new options, although certain principles of the search process must be understood to provide context for option generation. Whereas in our approach the options are contained within the memory network, it is from the environment that any options are originally encountered, and immediate environmental characteristics influence the operation of the model for any given task. Furthermore, especially in novel tasks, possible options may not be contained in memory at all, but are indeed generated from perceptions of the present environment. While an exploration of novel tasks that depend on a Brunswikian coupling of the agent and the environment is interesting, here we focus on familiar tasks that can take advantage of memory structure.

Weber, Goldstein, and Barlas (1995) present a discussion of the importance of incorporating memory processes in judgment and decision-making research, and we concur. Many popular models suggest that recall from memory is performed by search through an associative network (e.g., Anderson & Lebiere, 1998; McClelland & Rumelhart, 1985; Murdock, 1982; Raaijmakers & Shiffrin, 1981). Similarly, we employ the notion of spreading activation within memory (e.g., Collins & Loftus, 1975). This concept refers to the proposition that information can be represented by different nodes, and that the many connections between these

nodes link information items of similar form, content, and so forth. Within this framework, when a node is activated (such as by priming, or by focusing attention), connected nodes are also activated to some degree, depending on the strengths of the connections between them and the originally activated node. These connections can be enhanced by simultaneous activation, such as when they appear concurrently in a given context, and increasing such occurrences would build strong associations that could be activated quite regularly (e.g., through expertise; see Chase and Ericsson, 1982), determining the resultant organization of associative memory. Keller and Ho (1988) used this type of representation to derive their option-generation procedures, and we follow suit in developing our model. However, the difference lies in the processes assumed to result from this associative characteristic of memory. Whereas Keller and Ho (1988) consider option generation to be closely linked to both the search for and evaluation of options, we dissociate these processes. Also, whereas Keller and Ho (1988) discuss option generation in the context of how to structure decision problems and improve decision making, we are more concerned with identifying what generation strategies can perform well, and which people naturally use in real situations.

Finally, a brief discussion of the operation of fast and frugal heuristics (Gigerenzer, Todd, & The ABC Research Group, 1999) will help explain the motivation and development of our model. Most fast and frugal heuristics are based on three basic elements—a search rule, a stopping rule, and a decision rule, such as Take The Best (TTB; Gigerenzer & Goldstein, 1996). Applied to preferential choice tasks, this lexicographic strategy uses a search rule of decreasing (highest to lowest) importance, or quality, of attributes; a stopping rule determined once an attribute is reached that sufficiently discriminates; and a decision rule of selecting the alternative with the highest value on this final attribute. Our model applies these rules to option generation via an associative network framework.

Another heuristic that has been proposed directly relates to our approach as well. Connolly (1999) has proposed “highly active decision strategies,” that also stress the lack of need

for extensive deliberation. Essentially, he asserts that action itself—or, more precisely, taking quick action after little or no thought—can be considered a heuristic. This is plausible in contexts where decision making can be considered in a dynamic sense, rather than an isolated decision. Connolly uses the term “decision cycles” to refer to these contexts, where a situation is faced repeatedly and a “nibbling” or “trial and error” strategy, coupled with the feedback from taking such action, is appropriate. Applying these concepts to option generation, it would seem that in the proper contexts one might employ the first generated option without further deliberation or generation, and this initially-generated option may in fact be quite appropriate. An important requirement for successful application is repeated exposure to situations with feedback. The sports domain seems like a natural candidate for employing this heuristic for precisely these reasons. In most sports, within a single contest, there are many repetitions of scoring opportunities (e.g., possession of the basketball), quick decision acts (attempting a three-point basket), and feedback (whether a goal was scored). The same is true for handball, the experimental task we use, and the athletes who were participants in our task are familiar with this domain. Thus, the Connolly (1999) approach further motivates our “Take The First” heuristic presented shortly.

Gigerenzer and Todd (1999, p. 31) state “that some higher order processes, such as the creative process...are probably beyond the grasp of simple heuristics,” but we would disagree. We believe the framework of fast and frugal heuristics has the ability to bring creative decisions out of the realm of intuition and into the domain of systematic thought (Goldenberg, Lehmann, & Mazursky, in press; Weber, Moder, & Solie, 1990). One step in this direction came from Langley, Simon, Bradshaw, and Zytkow (1987), who showed with a computer program called BACON that very simple search heuristics can account for some degree of the creative process in drawing inferences from data. In many examples from the cognitive science literature, the emphasis is on narrowing down the number of solutions, whereas the emphasis of the creativity literature is to show how to generate many solution paths under a divergent-thinking label. As

Hayes (1989) stated, it may be interesting to look for the connection between how solutions or options are generated and the heuristic search used to narrow down and select from these generated options. We next present our attempt at achieving this goal.

#### Take The First: An option-generation heuristic

It is imperative that we use some framework for making predictions as to how people generate options—what are the possible processes responsible, and how can these be formulated in terms of definable strategies? The model we propose and the resulting heuristic, “Take The First,” utilizes the principles of associative memory networks in conjunction with the rules of fast and frugal heuristics, discussed above:

Take The First: In familiar yet ill-defined tasks, choose one of the initial options generated once a goal (and strategy) has been defined, rather than exhaustively generating all possible options and subsequently processing them deliberately.

In general, our model assumes that simple strategies coupled with the current environment determine which options are generated by an associative memory network, and the initial resulting options will thus be good ones. The fast and frugal heuristic approach defines the “entry point,” or initially-activated memory node, and the criteria for determining the similarity rules that guide the spreading activation, whereas the associative network provides the structure that determines which options are generated. Thus, similar to the work of Klein and Wolf (1998), we propose the “application of experience to detect fruitful starting points in the construction of novel courses of action,” (p. 158)—the initially-activated node in our model. From here, we adopt the principle of sequential (serial) search through an associative network based on the options’ likely ability to meet some goal, in line with Anderson and Schooler (1991). Finally, the reader should not consider the “associative network” to be memory per se, but instead it may be clearer conceptually to think of it as the “possible solution space.” This set of possible options is not necessarily contained entirely internally (in memory), although this may indeed be the case,

for example, when an expert is faced with an instance of an often-repeated task. Alternatively, for novel tasks, the possible solution space could be constructed “on-the-spot” as a result of immediate perceptual input. Our treatment here, and the experiment reported below, will focus on the previous case, where experienced agents are facing a familiar environment.

The first step in applying our model is to define specifically the strategies that are to be used in a particular task. For example, suppose a company manager must generate alternative methods to meet new government pollution guidelines. The manager may adopt a waste disposal strategy, or she may choose to consider waste reduction options. These task-specific strategies will necessarily vary greatly depending on the individual’s goals, constraints, and other characteristics of the particular domain. For the sake of maintaining generality in our initial presentation of the model, we will not yet define the (hypothesized) strategies involved in the present experimental task (see Methods). Once the initial option has been identified, in accord with the applicable strategy, spreading activation determines the other options that may appear in the generation set. The rules that govern the similarity measure (which nodes are activated) as well as the likelihood or weight measure (how strongly these nodes are activated) are also specified by the strategy. Assume the manager chooses to consider a waste disposal strategy in our pollution-reduction example, to reduce the burden of internal handling. The initial option would then be some particular disposal method to meet this goal, such as exporting waste to a third party. Then, the similarity measure of other options in the associative network would be in terms of “how disposal-like and burden-reducing the new option is,” and the weight would be where each (proposed) new option stands on this scale. Spreading activation to other options, and consequently the order with which they are considered by the manager, would proceed accordingly from the initial option. So, the next option she generates may be to buy land from a third party for a new landfill, and after that it could be to illegally dump the waste off-site, then to recycle the waste internally, and so on. This process is sequential in that the options are generated one at a time (i.e., “one thing leads to another”), rather than in parallel such that all

similar options are simultaneously generated.<sup>1</sup> Furthermore, note how the options generated by the manager decrease in their similarity to the initial option as more options are generated—the second option is more like the initial option than the third, which is more like the initial option than the fourth, and so on. This illustrates our assumption that a generated option is used as the probe for determining the immediately following option. Note also how it is akin to fast and frugal heuristics, in that no complex “expectation” equations are performed, and there are no attempts to “optimize” the generated options. For example, there is no attempt to define important characteristics of possible options, weigh them, and then generate on the basis of how the features of an option would maximize some integration of these weighted characteristics—such as by neglecting to generate illegal options because the penalties are too high. Finally, to the extent that the initial option is subjectively the “best” or “most preferred” alternative that could be generated with respect to some measure (e.g., disposal-like), we would expect each successive generation to be less important than the previous one, in a manner that parallels the TTB-P procedure. Thus, the “Take The First” label for our heuristic, which conveys that the first generated option in these “relatively routine” situations will likely be one of the best. These points will be expanded below, along with other predictions of how differences in option generation affect choice behavior. Before proceeding to the next section of the paper, however, it will be useful first to specify exactly the proposed strategies with which we are presently concerned. However, this specific formulation should not be mistaken with an implied restriction of the applicability of the model.

We propose a distinction between spatial and functional strategy use in sports situations such as the one in the experimental task below. Across sports, one of the most common decisions is what a player decides to do with the ball and how he does it. For example, in soccer, basketball, and handball, the options may be to move somewhere with the ball, pass it to a teammate, or shoot it at the goal; in tennis and golf, the options concern where to place the ball, and how (e.g., with or without backspin). When a sports player has to decide quickly what to do in a given

situation, such as how to allocate the ball, the possible options can be classified based on their spatial result (to the left wing player, to the right sideline, etc.) or on their functional result (pass, shoot, lob, spike, etc.). Furthermore, coaches instruct players in condition-action rules (if-then rules, see Raab, 2002), which are either functional (“if situation A, then shoot”) or spatial (“if situation A, then open the play to the left”). Thus, we propose that this classification is also appropriate for defining the strategies at use in sports situations—as either spatially-focused or functionally-focused. In handball, for instance, description of these spatial (Mariot & Delerce, 2000) and functional (Gerard, 1978) if-then rules are well-known in textbooks and are used to describe the tactical behaviors of attackers (Zantop, 1986). We now proceed to describe predictions from our model for how these different strategies may result in not only differentiation of the number, order, and type of options generated, but how this in turn can lead to variation in the characteristics of the ultimate choice behavior.

#### Effects of Option Generation on Decision Making

Hypothesis 1 (H1). There will be differences in the number of options generated, depending on the strategy employed. Our definition of the strategies necessarily implies that different types of options will be generated, depending on the strategy used. However, it seems likely that there will also be different numbers of options generated depending on the strategy. For example, if there are more spatially-connected nodes in a sports player’s memory (due to experience, training, perceptual bias, etc.) than functionally-connected nodes, the use of a spatial strategy could result in generation of more options. In contrast, it could be that if a large number of options are associated with a strategy, then none of the options will receive enough activation to be selected (see work concerning the “fan effect” on performance, e.g., Anderson, Lebiere, & Lovett, 1998). These competing forces on option generation, in addition to the lack of knowledge concerning which strategy has more connections in the current task, consequently do not allow for more precise predictions of which strategy may produce more options. Furthermore,

alternative strategies could be utilized in the present task, and broad application of the model to other situations would require knowing the applicable strategies to make precise predictions in each domain. Nevertheless, it should be that some strategy is incorporated into each task, even if it is merely a specification of the ultimate task goal (e.g., score vs. defend in sports). Similarly, while one strategy may incorporate descriptively the same elements as another, the distinction is which dimension serves as the basis of organization. For example, while a spatial and functional strategy may both produce the option “lob pass to the left,” the former would be produced by thinking “I need to go left, how do I get it there,” whereas the second would be the result of thinking “I want to pass, to where should it be.” It is not essential to our model that all tasks can be easily decomposed into orthogonal strategies. Here, we are not concerned with how the strategy evolves, but rather the differential number of option generations it produces.

Hypothesis 2 (H2). Due to the (near) monotonic decrease in option quality with serial position, an inverse relationship will exist between the number of generated options and the quality of both the generated options and the final choice. This prediction is actually twofold. First, it suggests that the serial position of the generated option will be inversely related to the relative quality of the option—the earlier an option is generated, the better it will be. We believe that options are not generated randomly (see Klein, et al., 1995) but are implicitly selected on the basis of their quality. That is, the strength of the connections in the associative network will be stronger among “better” options, and thus they will be activated first. Second, we believe the increase in number of options generated will also have a detrimental effect on the quality of the finally chosen option. In particular, our argumentation follows a variation of the “less-is-more” effect that has been used to support the benefits of other fast and frugal heuristics (Goldstein & Gigerenzer, 2002). This effect was originally used to describe situations in which one who recognizes fewer of the options in an inference task may produce better judgments than one who recognizes more; we predict a parallel effect in option generation. That is, because we expect

earlier-generated options to be better than later-generated ones, stopping the option-generation process sooner should result in better decisions, on average.<sup>2</sup>

Hypothesis 3 (H3). Increasing the number of generated options will result in an increase in inconsistency between the first option generated and the option finally selected. As the number of generated options increases, so too will the likelihood that the final option chosen is different from the first option generated. This phenomenon of a switch (or preference reversal) between one's initially-planned choice and final choice in a single task is referred to as dynamic inconsistency and has been shown in tasks involving decision trees (e.g., Busemeyer, Weg, Barkan, Li, & Ma, 2000). The prediction of increasing dynamic inconsistency with increases in number of nodes is positively supported by findings of previous experimental tasks (Johnson & Busemeyer, 2001). In line with this result, we predict similar results here and propose a specific explanation—that as the number of generated options increases, one is more likely to doubt one's initial choice. For example, if one can think of only two alternatives to an initial plan of action, then there may be less doubt concerning the initial plan. Alternatively, if one can think of ten different courses of action, then perhaps this acts as a signal that the initial plan is not so original, and the alternatives may merit further consideration.

When all of the possible alternatives are explicitly presented to participants, as in “traditional” preferential choice tasks, they merely have to figure out a strategy for determining what their subjective “best” choice is. There is no opportunity for option generation and, thus, no opportunity to study what the underlying processes are. Perhaps the most relevant study (of those mentioned earlier) in the formulation of the current work was that of Klein et al. (1995). They derived their predictions about option generation in a chess study focusing on the experience of the decision maker and the decision context, aspects to which we have not afforded great attention. However, it follows that experience could provide what we referred to earlier as the “entry point,” or initially-activated node, in a manner similar to how experience identifies “leverage points” (Klein & Wolf, 1998)—although we do not make specific hypotheses regarding

the possible moderating effect of experience. Klein et al. (1995) also found that option generation was not random among their participants, but they rely on experience as opposed to specific strategies for describing the generation process mechanisms. In contrast, we develop and test specific strategies in relation to differences in the generated options (e.g., number and quality) and characteristics (e.g., consistency) of choices.

The aims of the following experiment were to investigate whether different strategies lead to different quality and quantity of options generated, and how this may in turn affect final choices and/or dynamic inconsistency. Specifically, we were testing the three hypotheses (H1, H2, H3). We will also report post-hoc analyses of an experiential variable conducted solely for direct comparison with the Klein et al. (1995) study.

## Methods

### Participants

Eighty-five German and Brazilian male handball players of medium skill level between the ages of 13 and 18 ( $\underline{M} = 15.6$ ,  $\underline{SD} = 1.54$ ) participated. Local clubs close to the departments' locations in Heidelberg and Belo Horizonte were asked to send us some of their teams. In total, six teams took part in the experiment. The distribution of experience in club practice varied between 6 months and 11 years ( $\underline{M} = 4.8$ ,  $\underline{SD} = 3.9$ ), and the distribution of training time per week varied between 1 and 12 hours ( $\underline{M} = 4.2$ ,  $\underline{SD} = 2.1$ ). We used intermediate expertise in handball with a large range of experience to produce variable responses and different numbers of generated options.

### Apparatus and Materials

#### Description of Handball and the Selected Situations

The material for the participants' option generation was taken from indoor handball. Handball is a ball game of two teams that compete against each other. Each team consists of six

field players and one goalkeeper. The winner is the team that makes more goals in 60 minutes (two halves of 30 minutes). The playing field is 20 meters in width and 40 meters in length and it is divided into two halves (Figure 1). Each team owns one of the two goals and there is an area in front of the goal, up to 6 meters away, called the 'circle,' wherein only the goalkeeper is allowed to stay. Except for the goalkeeper, all players are only allowed to throw the ball with their hands. A player owning the ball can hold it for three seconds or go for three steps, then he must either tip the ball to the ground, throw the ball to another player, or shoot at the goal. The goal is three meters in width and two meters in height and is located in the middle of the circle at the end of the playing field. No field player is allowed to advance all the way to the goal, but they are allowed to jump into the circle, if they are leaving immediately after the jump.

INSERT FIGURE 1 ABOUT HERE

The situations were taken from a videotape of a high-level handball team during practice. The team was asked to perform as if it was in competition. Two coaches selected on a five-point Likert scale from the videotape those scenes that (a) were most similar to competition and (b) allowed for a number of possible solutions, when stopped at a specific point in time. The coaches were well-calibrated both in their judgments of competition-similarity (a) ( $r = .38$ ,  $p < .01$ , with a mean rating of 3.17,  $SD = .76$ , and a mean difference of 0.2) and allowance for possible solutions (b) ( $r = .55$ ,  $p < .01$ , with a mean rating of 3.31,  $SD = 1.08$ , and a mean difference of 0.3). The correlation between coaches of the total judgment of whether or not a specific scene should be incorporated into a video test was  $r = .60$ ,  $p < .01$ , and the mean difference was 0.3. To generate a variety of situations, the team depicted in the scenes varied its attack and defense systems among six alternatives. The six alternatives represent six different trigger actions of attack players (Figure 1). These situations can be labeled as ill-defined problems because no information is provided on the goal state, the operators, or the choice alternatives (Kahney, 1993).

### Divergent test

We developed a divergent test, which can be classified in the family of Guilford tests (Berger & Guilford, 1969; Christensen, Guilford, Merrifield, & Wilson, 1960; Christensen, Merrifield, & Guilford, 1958; Torrance, 1974). Creativity was fostered by reducing time-pressure or other constraints (Amelang & Bartussek, 1996; Facaoaru, 1985). The divergent test was a video test with 31 scenes of a handball team that is currently attacking. Every scene was approximately 10 seconds long, after which it was stopped and held in a freeze frame of 45 seconds. The presentation time of the video situation, as well as the time of the freeze frame, was tested in pilot studies to ensure enough time to experience the flow of the situation and to avoid putting too much time pressure on the participants (cf. Klein et al., 1995, p. 64, for a similar procedure in chess). The video scenes were presented on a large video projection board. Participants stood in front of the screen and were provided with a portable recorder and a microphone. So, for every initial verbal statement participants made, we could measure decision time and record all the subsequent answers, in order to separate functional and spatial generation strategies for analysis.

### Procedure

Participants received written instructions for the test and watched two video scenes for practice with the test condition. They were instructed to imagine they were the player with the ball when the scene was frozen, and to do three consecutive tasks: first, to name as quickly as possible the first decision that intuitively came to mind; second, to name as many additional options they could conceive, including to whom they would pass or if they would shoot at the goal (what decision), and also to define how they would pass the ball to the player or shoot the ball at the goal (how decision); third, at the end of the freeze frame, after naming all possible decisions they could think of, they were asked to decide which one was the best for this specific

situation. Although from our participants' perspective, then, the initial, quickly-generated choice was a "fast, intuitive choice," and the final choice was their (subjective) "best choice," hereafter we will refer to them as the "first" and "final" choice, respectively, to coincide with our model representation. The test administrator used a protocol to check whether the first option the participant named was the first input in the interface for measuring the reaction time, to avoid anomalous inputs (e.g., clearing the throat). The test concluded with a questionnaire asking participants to verbalize where their attention had been drawn, and how they had made their first and final choices. In addition, there was a check of motivation and instruction, and the experiment ended with a debriefing session.

A second phase of the experiment was a tournament in which the six teams played against each other (in two groups of three teams). These contests were videotaped for later evaluation by four qualified professional-league handball coaches (hereafter, judges). The judges assigned a score to each player based on his performance in the tournament. This measure was used as an expertise variable in addition to, but more realistic than, self-reports of experience and training time.

## Results

The results will be presented as follows. First, data transformations, operational variable definitions, and assessments of control will be reviewed. Next, global measures of generated options, choice quality, and inconsistencies are reported, followed by the strategy-specific analyses. Finally, a number of additional analyses are presented for relation to other work and to confirm the control of potential confounds.

### Data Transformations, Definitions, and Control Assessments

Data transformations were performed on the generated options as follows. Participants produced (free response) a total of 107 options. This high number of options results from the

variety of passes, and moves before the pass, that could be defined. For example, the pass to the player at the goal area line (see Figure 1) could be done by a straight pass, loop throw, off the ground, or into the goal area (Kemper trick). Furthermore, each of these could be performed with or without a movement before (left or right), and with or without a “fake” (shot fake or pass fake). Finally, most of these various possibilities could also be used to describe the other options, namely, passes to other players or shots to the goal. Thus, the 107 different participant-produced solutions were reclassified into nine categories (Table 1) based on the functional result (move or double pass, shoot, or pass) as well as the spatial result of the passes (left, right, center). These reclassified data were the basis of further option analyses (below) and allowed for more direct tests of the spatial and functional strategies.

INSERT TABLE 1 ABOUT HERE

Next, measures of decision quality were computed for use in the subsequent analyses. The same four judges participated in rating the solutions of the handball players. Each judge was asked to rate the list of 107 options for each of the 31 video situations—a total of 3317 ratings per judge. For each video situation they received the list without knowing how many participants named each alternative, or at what serial position of the option generation. First, they had to mark on the list every solution they thought was an “appropriate choice” in the displayed situation by marking it as 1 = appropriate, 2 = moderately appropriate, 3 = very appropriate, 4 = best possible solution, or leaving it blank (0 = inappropriate). The significant correlations between the judges averaged over all 31 situations was  $r = .56$ ,  $p < .01$ , indicating that the situations resulted in creative solutions that all judges found appropriate. A “majority rules” procedure was used, meaning that if at least three of the four judges rated an option as appropriate, it was classified as such. In the event that a majority did not exist for a particular option on a particular trial, the judges discussed the item in question until resolution. Thus, for each option in each video scene,

an expert-based quality score could be calculated by averaging across trials and judges ( $\underline{M} = 2.57$ ,  $\underline{SD} = 0.76$ ). The pattern of agreement and disagreement between judges was considered by analyzing the standard deviations among judges' ratings, averaged over the 31 scenes. We found a standard deviation of .49 for best choices and a standard deviation of .56 overall—in other words, the difference in judges' ratings was around half a point, on average.<sup>3</sup>

In addition, the divergent test was checked for performance of the participants. First, a split-half test (first- and second-half of trials) of the judge-based quality of the final choices by the participants resulted in a significant correlation ( $\underline{r} = .75$ ,  $\underline{p} < .05$ ), showing only modest learning over the course of the test. Second, participants' motivation and understanding of the instructions were examined on a Likert scale (0, "poor" to 4, "excellent"), since participants were of varying age. Results suggest the motivation to participate ( $\underline{M} = 3.30$ ,  $\underline{SD} = .20$ ), and understanding of instructions ( $\underline{M} = 3.21$ ,  $\underline{SD} = .11$ ) were sufficient, to say the least. Finally, a review of the process-tracing questionnaires suggested that participants were not explicitly using particular strategies to produce their first choice, generated options, or final choice, indicated by many (over 30% of participants) "reactive" responses such as doing "what came to mind first," or responding "by intuition." We conclude from these findings that the rationale of the decision could not be verbalized. However, some responses give more general hints about their motivation (e.g., play to a free teammate, in a hole of the defense, or to a player with the best goal chances).

### Global Analyses

First, the following aggregate-level measures were computed based on the transformations described above (see Table 1). Frequencies of each of the nine response categories were determined across participants and trials. Averaging determines the mean number of times each participant selected each response category per trial, or average generations. Also, weighted frequencies were calculated by multiplying the total frequencies by the proportion of 107 possible options that were assigned to the particular response category,

subtracted from one. For example, the total frequency of category 1, shoot at the goal, was 1112. However, of the 107 generated options, 25 were classified as belonging to response category 1. Therefore, the weighted frequency of category 1 responses was  $1112 * (1 - (25 / 107))$ , or 852.19 instances pooled across participants and trials. Next, summing the average generations across response categories produces the average number of total responses per participant per trial ( $\underline{M} = 4.23$ ,  $\underline{SD} = .95$ ). Finally, by excluding the “first” and “final” responses, we determined the mean number of generated options per participant per trial (2.30). Similarly, the mean number of generations per trial was computed for each participant individually. The correlation between this individual measure (mean number of generated options) and choice quality (expert-based quality) was not significant for the first choice,  $\underline{r} = .10$ ,  $\underline{p} > .10$ , but was for the final choice,  $\underline{r} = -.38$ ,  $\underline{p} < .01$ . Although this strongly suggests that an increase in the amount of generated options decreased the quality of the final choice (H2), it does not describe the (option quality) dynamics over the course of the option-generation process itself. The next analysis was conducted to achieve this goal and evaluate the performance of the “Take The First” heuristic in option generation.

Seeking to substantiate that generating fewer options may actually be better than generating more options (H2), we examined the quality of the generated options by serial position. For each participant, we counted the number of trials in which the generated option in each serial position (1 to 5) was rated as “appropriate” by the experts (Figure 2). The trend of decreasing option quality with each successive option generated is quite clear and is supported by a repeated-measures ANOVA:  $\underline{F}(4, 84) = 107.96$ ,  $\underline{p} < .01$ . This trend was extremely well fit by a linear model with (slope)  $\underline{B} = -3.57$ , explaining over 98% of the variance. Also, the 95% confidence intervals around each of these means do not overlap with those of adjacent options, showing differences between each successive pair of means as opposed to all of the variance stemming from one pair with a large difference. Apparently, less is indeed more—the sooner an option was generated (serial position), the higher likelihood that it was appropriate. Thus,

stopping the option-generation process sooner would result in better decisions, on average. In fact, had participants not generated any options but instead relied solely on their first choice (“Take the First”), they would have, on average, chosen options with higher quality—a result of the decline in the average frequency of appropriate choices from the participants’ first choices (16.21) to their final choices (15.65). This finding also implies inconsistency—otherwise the quality of the first and final choices would be equal. However, the 95% confidence intervals overlap for these choices, and thus this difference is not statistically reliable. Thus, this quality discrepancy between the first and final choices provides only weak support for the proposition that generating options may result in an increase in inconsistency. A more direct examination of this possible inconsistency (H3) between the initial and final choice is provided next.

INSERT FIGURE 2 ABOUT HERE

Participants seemed to be rather inconsistent in their first and final choices. The inconsistency rate was determined by first calculating the number of first choices that were not the same as the final choices, then dividing by the number of trials. This figure was .39, averaged across participants, showing that participants often chose as their final choice an option that was different from their first choice as proposed. Specifically, as stated in H3, the more options that were generated seemed to increase the dynamic consistency. A linear regression equation predicting inconsistencies from mean number of generations supports this hypothesis,  $F(1, 83) = 16.74$ ,  $p < .01$ , adjusted  $R^2 = .16$ . Although the task is different, this finding is in accord with those of Johnson and Busemeyer (2001), who found not only a dynamic inconsistency rate (.41) very close to ours but also that an increase in distance (in a decision tree) from the initial to final choice increased inconsistency. Here, increasing the number of generated options is similar to increasing the number of nodes in a decision tree. Furthermore, the number of generated options could correspond to a measure of psychological distance, such as in our associative memory

network, so that increasing the number of intervening options takes one further from the starting point of the process. Finally, a comparison of decision quality shows that the mean number of times participants switched from a good first choice to a poor final choice (3.20,  $SD = 1.94$ ) was greater than the mean number of times participants switched from a poor first choice to a good final choice (2.78,  $SD = 1.91$ ). Although this difference is only marginally significant ( $t(84) = 1.41$ ,  $p = .08$ , one-tailed), it suggests further that had participants “gone with their guts,” and chosen their first option as their final one instead of switching to another option, they could have improved the quality of their final decisions.

#### Analysis of Strategy Use

Considering the aggregate results reported above and the arguments put forth in the Introduction, further analyses were conducted to determine if specific strategies were used by different individuals. More importantly, we are concerned with whether these strategies were the originating factor in producing the options generated, the degree of inconsistency, and/or the quality of the final choice.

The procedure for assessing the strategy used by each participant was as follows. Based on the categorized data, a program was written in C++ to look for sequences of similar generations that would support the use of a particular strategy (see Table 2). For example, if a participant named an option categorized as “4, pass to rear left” followed by an option categorized as “3, pass to front left,” or another “4, pass to rear left” this sequence would support the left-oriented subset of the spatial strategy. The computer program checked every consecutive pair of generations, beginning with the first option and ending with the last option generated (maximum of five); that is, the final option was not included since it was not newly generated but rather a choice among the previously stated options. Thus, for each participant and within each trial, each of five pairs in the set {First, 1; 1, 2; 2, 3; 3, 4; 4, 5} was checked to see if the corresponding options were members of the same strategy subset (e.g., spatial-left). The number

of consecutive pairs supporting a particular strategy subset (see Table 2) was then tallied for each trial of each participant. Then, these tallies were summed across all subsets (e.g., spatial-left, spatial-center, and spatial-right) of a particular strategy (e.g., spatial) to determine the total number of sequences supporting that strategy over the course of the experiment (31 trials). An overall strategy score was computed for each participant by subtracting the number of sequences classified as spatial from the number classified as functional. Thus, increasingly positive strategy scores indicate increased use of a functional strategy, whereas more negative scores represent increasing use of a spatial strategy.

INSERT TABLE 2 ABOUT HERE

The distribution of these scores is characterized by a mean of 12.91 and standard deviation of 11.97, with scores ranging from 46 to -18 and skewness of .27. The relationship between mean number of generations and strategy is supported by a linear regression,  $F(1, 83) = 22.57, p < .01$ , adjusted  $R^2 = .20$ , in line with H1. However, there was a negative correlation between strategy and quality of final choice,  $r = -.41, p < .01$ . A median split ( $Mdn = 13$ ) was used to classify participants as spatially oriented or functionally oriented, although the positive valence of the mean and median indicates an overall bias toward functional focus.<sup>4</sup> The means of these two groups on mean number of generated options were compared, and the difference was significant,  $t(78) = 4.48, p < .01$ . Thus, functionally orientated strategies result in significantly more options generated, but lower quality of the final decisions.

#### Additional Analyses

We performed several additional analyses, some of which were done to exclude the possibility of certain contingencies in the results reported above. First, partial correlations were determined between number of generations and each of choice quality and inconsistencies,

controlling for strategy score. This should ensure that the results concerning the effect of number of generated options is not influenced indirectly by the strategy, and thus establish more precisely (to the extent this is at all possible, using correlations) the link suggested by our model. There was a decline in the correlation between mean number of generations and quality of final option ( $r = -.24, p < .05$ ), as well as between mean number of generations and amount of inconsistency ( $r = .38, p < .01$ ), but both were still in the proper direction to support our hypotheses and remained significant at an alpha level of .05. Partial correlations were also determined between strategy and quality of final option, controlling for mean number of generations, again showing slight decreases. The significant result,  $r = -.29, p < .01$ , suggests that strategy had an effect on the quality of the final option independent of the mean number of generations.

Next, we weighted the strategy scores to compensate for the fact that some strategy subsets had more items in them. This weighting was similar in motivation and procedure to the one used in the global analyses above (Table 1). Specifically, each strategy subset was given a subset weight (Table 2) according to the proportion of total items associated with the subset; these were applied before performing the summation that resulted in strategy scores. However, categories 0 (move with ball or fake movement) and 2 (unspecified pass) could not be identified spatially, and therefore these responses were not assigned to a spatial category. To avoid possible skewing caused by this difference in number of items contained in each strategy computation, the proportion used to compute the subset weight was taken from 181 (the sum of the items in the subset column in Table 2), rather than from 107 (the total number of generated options). For example, consider the spatial-right strategy subset, which contains the categories “Pass to the rear right,” and “Pass to the front right.” There were 14 generated options assigned to these categories. Thus, the subset weight given to the spatial-right category subset was  $(1 - (14 / 181)) = .92$ . The resulting distribution is slightly “tighter” and more normal than the unweighted one, with a mean of 8.80, standard deviation of 8.17, scores ranging from 32.85 to -12.57, and skewness of .22. Correlations based on this weighted strategy measure were very similar to those

computed from the original strategy scores. Furthermore, analyses on a median split ( $Mdn = 9.03$ ) of the weighted strategy measure produced similar results concerning quality of final choice and mean number of option generations.

The availability of reaction time data prompted us to perform post-hoc exploratory analyses. The time between the end of the scene and production of the first choice was calculated for each scene in milliseconds. The only significant correlation between this response time was with the quality of first choice:  $r = .32, p < .01$ . Not surprisingly, longer latencies to produce the first decision also resulted in better decisions, in congruence with the classic speed-accuracy tradeoff (Woodworth, 1899; see Svenson & Maule, 1993, for a recent treatment). However, it could also be that participants were violating task instructions, and performing some sort of screening of the options prior to naming what was supposedly their first. This could then increase quality of the first option that was recorded, as opposed to the first option that truly “came to mind.” This possible confound, which was also noted in Klein, et al. (1995), is not central to our model, but should still be treated with caution.

Finally, to facilitate comparison with the work of Klein et al. (1995), an analysis of the effect of experience was also performed. However, whereas the Klein et al. (1995) study treated experience as a dichotomous variable determined originally by a point system, we employed a continuous measure of expertise based on actual performance. Specifically, 66 of our participants played in a real handball contest, and their performance was rated by (the same) expert judges. As in the Klein, et al. (1995) study, we found that expertise did have an influence on the quality of choices. The more experienced players chose higher-quality options as their final options,  $r = .26, p < .05$ . Although our result is significant, unlike the Klein, et al. (1995) study, differences between the two studies should be qualified based on factors such as the different tasks, rating systems, analyses and sample size (16 vs. 66); the general trend of Klein, et al. (1995) was in fact replicated here. Furthermore, two separate repeated-measures ANOVAs testing expertise as a moderating factor revealed no effect on strategy,  $F(1,65) = .23, p > .10$ , or dynamic

inconsistency,  $F(1,65) = 1.48$ ,  $p > .10$ . This suggests expertise was not a key moderating variable in the analysis reported above. Due to this and the fact that we do not make specific predictions about expertise, we do not elaborate further on these findings, although perhaps work on the organization of experts' memory (e.g., Chase & Ericsson, 1982; Ericsson & Kintsch, 1995) could ultimately explain such differences within the context of our model.

### Discussion

We presented a model of option generation in ill-defined tasks and a resulting heuristic for these situations. Our primary hypothesis concerning strategy use, that different strategies would result in generation of different types of options, was operationalized and confirmed. Differences were also found in the number of options generated for each strategy (H1). Subsequently, these generated options resulted in differences in choice quality, per the “less-is-more” effect (H2): the serial position of a generated option was inversely related to its quality, and an increase in generated options reduced the quality of the final choice. Finally, the increase in number of generated options resulted in an increase in the dynamic inconsistency between the first (fast) and final (best) choice (H3). The correlations supporting these conclusions are summarized in Figure 3.

INSERT FIGURE 3 ABOUT HERE

Strategy was a key determinant in the number of options generated and explained 20% of the variance. Overall, those using a functional strategy generated more options, which resulted in higher dynamic inconsistency and lower quality of the final option, compared to those using a spatial strategy. Strategy did not significantly correlate to dynamic inconsistency, which suggests that increases in dynamic inconsistency were not due to the strategy per se, but due to the different number of generations by each strategy. Because both strategy and number of

generations were correlated with the quality of the final choice, partial correlations were computed that supported the significance of the effects of each measure independently. The result showing a clear serial position effect (Figure 2) was also predicted by our model, based on the “less-is-more” effect. Also, our results support previous work in the degree of dynamic inconsistency in decision making (Johnson & Busemeyer, 2001). Furthermore, it extends the explanation of why such inconsistencies occur, based on the positive relationship between the amount of inconsistencies and the increasing “distance” between the first and final choice. While this could be simply a failure of memory (i.e., remembering what the first choice was), it seems more likely that a larger generated set of options may be some sort of “signal” that introduces doubt, as mentioned earlier. Future work could elicit confidence ratings from participants to explore this explanation. We should note, also, that we recognize the danger in using correlations to presumptuously support causal relationships, rather than just covariance. However, not only did our model predict the proper connections, but the nature (timing) of the task supports such a causal relationship also. For example, considering the correlation between number of generated options and quality of final option, it would be difficult to interpret the latter as the cause of the former, due to the temporal relationship—the final option is selected after options are generated.

As mentioned in the introduction, the most closely related previous (empirical) work is that of Klein et al. (1995), but they focused primarily on establishing option-generation patterns based on experience—this variable is not central to the current study. We did find that participants who performed better in real situations (our expertise measure) chose final options of higher quality, the same trend as was found in the Klein, et al. (1995) and Engelmann and Gettys (1985) studies. Another primary goal of the Klein et al. (1995) study was to show that options were not randomly generated, and our results replicate this finding as well, providing possible strategies responsible. While they refer to a model (the Recognition-Primed Decision Model) of decision making that explains their results, they rely on experience to guide behavior without specification of the mechanisms. Gettys, et al. (1987) found that the majority of their

participants, even if they did not produce a large total number of high-quality options, did at least produce one of the top options. However, they did not report analyses concerning the serial position of such actions. The current findings complement and extend these two research programs, and subsequent studies could attempt to consolidate the approaches—our heuristic, the Klein and colleagues' focus on expertise, and the empirical base of Gettys and colleagues—into a coherent unifying framework. Other related work could also offer contributions for future research, such as testing specifically the strategies proposed by Keller and Ho (1988), or considering how work on the functional fixedness phenomenon may relate.

Our approach could more broadly be applied to other types of generation processes by translation of our variables to other domains. For example, in preference or inference tasks, it is conceivable how our model could be used to explain the cue generation process; that is, in what order cues are accessed and employed in these tasks. Also, our distinction between the “first” and “final” choices of participants relates to the framework of Wilson and Schooler (1991) that distinguishes between “intuitive” and “reflective” processes, respectively. This interpretation has also been studied recently in the sports domain by Halberstadt and Levine (1999). Finally, our model could be applied to even more creative generation processes, when novelty (in the sense of surprise for the defense team) is considered an important decision variable (as opposed to quality alone).

Our model could be modified to reflect processes in other creative contexts, as well. In these situations, a different measure to drive the spreading activation component of our model would be more appropriate. In particular, it seems that in creative situations one may attempt to generate as many distinct options as possible, which would suggest that dissimilarity drives the spreading activation within the same associative network. This coincides with research in brainstorming and creative generations, and the model predictions would need to be closely examined. In brainstorming literature the opposite proposition is made from the “less-is-more” effect we predicted and discovered in the present work. This is discussed by Kramer, et al.

(1997), who state that prevalence of the opposite effect—a direct relationship between idea quantity and idea quality—has been “unequivocal” in brainstorming research. Although they are one of the few to directly test decision quality (as opposed to idea quantity and/or quality), their results did not support the hypothesis that more is always better. The relation of our model to this domain and the replication of their results are other possible avenues for future work. This, and those mentioned above, seem intriguing and are certainly not exhaustive.

Our confirmatory preliminary results, in conjunction with slight limitations in the current design, encourage future work that is more carefully designed to test our specific hypothesis. Due to the fact that this study was conducted as a part of a larger study with a broader scope, perhaps all of the necessary experimental controls were not in place. For example, certain scenes in the experimental task may have drawn attention to a particular strategy, or strategy subset—e.g., perhaps in a particular scene the most viable courses of action were all different passes to the left side. Although summing subsets to arrive at an overall strategy score was intended to account for this, it still may have introduced some minor artifacts to the data. Since the scenes were not originally chosen to balance this aspect of the task, future studies could easily be developed to give more control in testing our predictions. Additionally, simulations and other methods could provide further insight into the performance of different option-generation strategies, including the different interpretations and manipulations proposed in the preceding paragraph. Finally, the heuristic has been presented here in a study to illustrate how using “Take The First” can result in good decisions. However, like much of the initial work on simple heuristics, this does not prove that such heuristics are in fact used by people in experimental tasks or actual situations. Although the use of this heuristic is supported by the fact that people did choose the first option generated in around 60% of cases, and did not exhaustively generate options but rather just a few (2.3, on average) on each trial, future studies could also clarify this descriptive question.

In conclusion, the current work has two primary consequences. First, it demonstrates the potential of fast and frugal heuristics, as opposed to, e.g., maximization algorithms, beyond induction or prediction tasks. Within the realm of option generation, heuristics not only can produce good choices but also can illustrate counterintuitive suggestions based on how they operate. Here, we showed how “Take The First,” a heuristic for option generation that is fostered by the associative structure of memory, the use of “leverage points,” (Klein & Wolf, 1998), and repeated familiar “decision cycles” (Connolly, 1999) can predict human behavior and result in high-quality choices. Furthermore, we saw how the “less-is-more” effect that has become a theme of fast and frugal heuristics can also play a role in option generation. As a result, prudence should be taken when promoting the use of, for example, brainstorming techniques that are supposed to result in generating myriad solutions to a task with the aim of improving decision quality. In contrast, it may often be appropriate in ill-defined problems to “Take The First:” our model could even be thought of as one possible formalization of a candidate mechanism of intuition. Second, we have illustrated how option generation should be included as a key part of theoretical models of decision making. While many experiments concerned with decision making seek to control for individual differences in option generation by presenting explicitly all of the available options, we do not feel the two processes should be so easily detached. For instance, we found that the number of generated options, but not the strategy, was related to dynamic inconsistency in choices. Therefore, without exploring the option-generation process this characteristic may have been overlooked. We believe this may be the case with respect to other choice variables in decision-making studies. Finally, one can draw a number of connections to possible prescriptive applications of the present work across domains, such as sports, business, and so on. By making researchers and decision makers alike more aware of the option-generation process, and its associated payoffs and pitfalls, we can achieve not only more realistic experiments, but perhaps more productive real-world decisions.

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## Endnotes

<sup>1</sup> Although we assume here that similarity is the guiding variable for many problem solving tasks like the ones presented here, this need not always be the case. Tasks where creative or novel options are preferred, for example, would seem to imply instead a dissimilarity measure as the driving mechanism.

<sup>2</sup> This can in fact be inferred simply from applying statistics to the preceding serial position claim: if a final option is chosen randomly from the ones generated, and quality decreases with serial position, then as more options are generated the “expected value” of the final option decreases. This explanation would not likely explain the occurrence of this effect, however, since we do not find it plausible that participants will select from among the generated options randomly.

<sup>3</sup> It could be argued that this small standard deviation is due to the increase of adjustments (or “fine tuning”), because in cases of no majority of three judges for best or appropriate options, they had to discuss a solution. Separate calculation of the standard deviations for the first or last half of the scenes does not support this explanation for the appropriate options (scenes 1-15: SD = .57; scenes 16-31: SD = .56) and only to a small degree for the best option (scenes 1-15: SD = .56; scenes 16-31: SD = .43).

<sup>4</sup> This bias in sports domains towards functional strategies (Gerard, 1978) necessitated a median split due to the grossly unequal sample sizes (78 vs. 6, respectively) that would have resulted from a split at zero into “purely” functional and spatial strategies.

## Tables

Table 1.Summary of Frequency and Type of Option Generations.

Response category	Mean generations (SD)	Total frequency	Items in category	Weighted frequency	Relative frequency
0. Move/Fake	.42 (.19)	1112	25	852.2	.09
1. Shoot	.90 (.36)	2375	24	1842.3	.19
2. Pass	.28 (.22)	741	8	685.6	.07
3. Pass WL	.19 (.15)	493	7	460.8	.05
4. Pass HL	.42 (.33)	1111	7	1038.3	.11
5. Double Pass	.45 (.34)	1193	8	1103.8	.11
6. Pass CF	.54 (.30)	1431	14	1243.8	.13
7. Pass HR	.68 (.31)	1784	6	1684.0	.17
8. Pass WR	.34 (.21)	898	8	830.9	.09

Note. Response categories are defined as (see Figure 1 for explanation of abbreviations): (0) Move with ball or fake movement; (1) shoot at the goal; (2) unspecified pass; (3) pass to front left, WL; (4) pass to rear left, HL; (5) double pass, (6) pass to center-front, CF; (7) pass to rear right, HR; (8) pass to front right, WR. Mean generations are per participant, per trial. Weighted frequency is determined by  $[1 - (\text{items in category} / \Sigma \text{ items in category})]$ , to compensate for the different number of response items in each response category. Relative frequency is (weighted frequency /  $\Sigma$  weighted frequency).

Table 2.Summary of Strategy Classification.

Strategy	Strategy subset	Response categories in subset	Items in subset	Subset weight
Spatial	Left	3, 4	14	.92
	Center	1, 5, 6	46	.75
	Right	7, 8	14	.92
Functional	Keep	0, 5	33	.82
	Shoot	1	24	.87
	Pass	2, 3, 4, 6, 7, 8	50	.72

Note. Response categories in subset are defined as in Table 1, Response category. Subset weight is determined by  $(1 - (\text{items in subset} / \Sigma \text{ items in subset}))$ , to compensate for the different number of response items in each strategy subset.

### Figure Captions

Figure 1. Typical position of the offensive players in the handball scene, at the point where it was “frozen” to begin each trial. Triangles represent offensive (attack) players, circles represent defensive players. CB = center back; WR = wing player on the right; WL = wing player on the left; HL = half-back player on the left; HR = half-back player on the right; CF = center-front (pivot) player at the six-meter line; long solid line = goal; short solid line = six-meter line (defense zone); dotted line = nine-meter line.

Figure 2. Frequency of “appropriate” decisions, as rated by experts, summed over participants and trials, for the generated options in each serial position, with standard error bars.

Figure 3. Summary of significant correlations, for key variables in hypotheses. The reported correlations use the unweighted strategy scores.





