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Individual Differences of Action Orientation for Risk-Taking in Sports

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The goal of this article is to explain empirical risk-taking behavior in sports from an individual cognitive modeling perspective. A basketball task was used in which participants viewed four video options that varied in the degree of associated risk. The participants were independently classified by scores on the Questionnaire for Assessing Prospective Action Orientation and State Orientation in Success, Failure, and Planning Situations as action-oriented or state-oriented decision makers. The results of the experiment show that action-oriented players shoot faster and more often to the basket and that state-oriented players prefer to pass to a playmaker more often. Four versions of a computational model of decision making, Decision Field Theory, were compared to evaluate whether behavioral differences depend on the focus of attention, the initial preferences, threshold values, or an approach-avoidance interpretation of the task. Different starting preferences explained individual choices and decision times most accurately. Risk taking in basketball shooting behavior can be best explained by different preferences for starting values for risky and safe options caused by different levels of action orientation.

Key words: basketball, decision field theory, decision making, modeling

Individuals in sports differ fundamentally from one another in the degree to which they are willing and able to perform risky decisions. A popular view is that such risky decisions can be explained by differences in personality traits. We introduce a methodology for finer examination of risk-taking behavior in sports. In particular, we promote using an individual level of examination through computational modeling. Rather than simply identifying differences in risk-taking behavior between experimental conditions, we will show how our approach can additionally explore the mechanisms that might be responsible for such differences. First, differences in risk-taking behavior caused by variations in personality traits are presented as one factor that could be incorporated into an individual level of analysis. Second, we report results from a basketball task and a questionnaire to differentiate risk-taking traits as well as risk-taking behavior. Third, we use novel computational modeling techniques within a contemporary decision-modeling framework to model the data and highlight the merits of this approach. Typically, previous research has not addressed individual difference issues in this manner, although doing so may offer important insight on how individuals make decisions.

One well known individual difference in sports is the distinction of action and state orientation (Beckmann, 1994; Roth & Strang, 1994). The state-action orientation is commonly used in sports to describe the behaviors of basketball players under stressful situations (Bar-Eli & Tractinsky, 2001; Beckmann & Trux, 1991). An action orientation is attributed to players if they concentrate on a specific goal and take risks, whereas a state orientation is attributed to players if they have non-task-relevant cognitions and reduce risk-taking behavior by considering more situative considerations and future behavioral consequences. Research using this distinction for tactical decisions concluded that this personality trait results in different decision times and choice distributions. For

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example, action-oriented basketball players shoot more to the basket and score more under competition instructions (Heckhausen & Strang, 1988). Other research has revealed that state-oriented soccer players have longer decision times (Roth & Strang, 1994). Thus, in the basketball task in the current study, we predicted action-oriented players would prefer to shoot at the basket, whereas state-oriented players would prefer to pass to a teammate who would make the play (hereafter, the playmaker), *ceteris paribus*, as predicted by Beckmann and Trux (1991).

We will begin by presenting an experiment that enables us to detect individual differences in risk-taking as a personality trait as well as differences in allocation behavior in a basketball task. We will attempt to dissect the individual decision-making process into four possible components that could be responsible for these behavioral differences. First, action-oriented players may use different cues or focus their attention on task-relevant over task-irrelevant information (Beckmann, 1994). Second, action-oriented players may have a higher preference for shooting from the onset of the decision task (Raab, 2002). Third, action-oriented players may not need as much information to respond in a given situation—that is, they may have a lower threshold for acting (Kuhl, 1986). The fourth explanation we explore is that action-oriented players consider the current task an approach task (a forced choice between two beneficial outcomes), whereas state-oriented players define it as an avoidance situation (a forced choice between aversive outcomes, Sack & Witte, 1990).

Method

A laboratory-based experiment was used to test our hypothesis that, in basketball, action-oriented players shoot more to the basket, whereas state-oriented players pass more to the playmaker. Furthermore, for neutral decisions, we should not observe any differences in the behavior of state- or action-oriented players. These hypotheses were tested using planned contrasts between the choices of the risky, nonrisky, and neutral options. Testing was conducted in a laboratory setting to minimize the influence of other known relevant factors such as physical fatigue (Roth & Strang, 1994).

Participants

Participants were undergraduate students in the Department of Sport and Sport Science at the University of Bielefeld in Germany. All participants ($N = 53$) were enrolled in a handball, volleyball, or soccer course the semester the experiment occurred and are hereafter called players. The 27 men and 26 women were all novices in basketball (no club experience), but all received an introductory course in basketball before the experiment. They received course credit for participation, and all confirmed and signed informed consent to participate.

Description and Selection of Situations

The distinction of interest for the current study was the decision to either shoot at the basket or pass to one of the other three players. We used four options rather than two to extend prior results (Raab, 1996) to a more realistic option array. In addition, we wanted to offer two more neutral options between the risky and safe options to lower the equal starting probability to 0.25 for each option. The situation "rotation of the center" was selected.

This situation is a standard training skill in which the center and post players change their positions, while the perimeter players (playmaker and wings) pass the ball around to set up the play. All experimental situations were attack situations, shown to players from the perspective of the attacking team through the camera angle from the right wing player. The moment when the right wing player possesses the ball is critical in this situation, defining when and how the post and center players change their positions. The right wing player's options are then to shoot at the basket, pass to the post, pass to the center, or pass to the playmaker. In the current study, the risk for these options was manipulated by controlling the distance between each passing recipient and the associated defender. Shooting to the basket was defined as risky, because, on average, a defensive player is rather close to the shooting attacker. Passing to the playmaker was nonrisky, because, on average, no defensive player was close to the playmaker. Passing to the center or the post player was considered risk neutral, because the average distance between each pass recipient and the associated defenders was between the defender distances for passing to the playmaker and shooting. The term risk neutral was also used due to the function of these passes, because neither pass resulted in a restart of the situation (like the pass to the playmaker) or a potential score (like the shot to the basket). The situation definition and the distance manipulation between attackers and defenders have been used before in studies of decision making (Raab, 2002, 2003).

The scenes were selected for the experimental task in the following manner. Six hundred plays performed by professional players were filmed. Four experts (professional coaches) then rated these scenes (using a Likert-type scale ranging from 1 to 6) and selected the 100 best scenes in terms of situation representativeness, realism, and interrater agreement (interrater reliability of $r = .85$). Of the 100 scenes chosen for each of four situations (based on the distance of attackers and defenders), 25 scenes were included in the next selection procedure. These 100 scenes were then used in a pilot study, and an item analysis was performed on player choices. Finally, as a result of this analysis, the 51 scenes for the present study were chosen to represent an approximately equal number of (expert-rated) appropriate situations for each decision option (i.e., shoot at the basket, pass to the post, pass to the center, pass to the playmaker). The scenes differed in the particular alignment of the defensive players, specifically, how close the defenders were to each offensive player.

Apparatus and Material

The virtual environment for the experiment consisted of a video screen that displayed the scenes to which players physically responded by moving to the appropriate location in the environment (see the Procedure section of this paper). The test involved 51 scenes of a natural movement and perception situation from the perspective of the right wing player—players were to assume this role. Each scene started with some passes to the left side and stopped as soon as the ball rotated back to the right side through the playmaker and was caught by the right wing player.

Decision time was measured as the players' reaction time between the time the scene stopped and their response. The decision quality was measured by the number of appropriate decisions, as judged by the expert coaches. More importantly, the number of decisions made for each option was collected as the key dependent variable; this is in line with the risk-taking literature supporting the claim that action-oriented players prefer riskier decisions than state-oriented players.

Instrumentation

To assess the state- and action-orientation of players, we used the standardized Questionnaire for Assessing Prospective Action Orientation and State Orientation in Success, Failure, and Planning Situations (a German questionnaire for assessing "HAndlungsKontrolle bei Erfolg, Misserfolg, Planung," hereafter HAKEMP; Kuhl, 1990). The HAKEMP inventory contains 36 items measuring action- and state-orientation. It has good reliability and discriminative validity (Dahme, Bleich, Jungnickel, & Rathje, 1992), and has established construct validity (Sack, 1990). An example of an item would be:

> When I need to decide something important, then
> A: I start immediately.
> B: it takes some time before I start.

Answer A is preferred of action-oriented players and answer B of state-oriented players. We interpreted an action orientation (high values, based on the number of binary answers in the direction of action-orientation) as defining risk-seeking individuals, whereas a state orientation (low values) defined those relatively more risk averse.

Procedure

The players were instructed to make a tactical decision about the development of the attack from the point when the right wing player caught the ball. In addition, in an attempt to control for speed-accuracy effects caused by our instructions, we balanced the instructions by emphasizing the importance of both. In addition, players were informed that the scenes differed in the risk to shoot or pass to specific teammates, but they were to decide what they thought was the appropriate decision in each scene presented. The procedure of balancing decision accuracy and decision time allowed for evaluating the assumption of faster deliberation time for action-oriented players compared to state-oriented players (Roth & Strang, 1994). The players were to make their decision and use their foot to activate one of four electronic mats on the floor in front of them as quickly as possible. Each mat was associated with one of the four possible decisions. Specifically designed software was used to record the decision and the time elapsed, in milliseconds, from when the scene stopped and participants activated the electronic mat. Personal data—age, gender, and sports experience—were initially collected for all players. Afterward, players were tested individually on the main task. After the test, all players completed an inventory, including the HAKEMP questionnaire.

Statistical Analyses

First, a median-split was used to group players based on the HAKEMP score. Second, to analyze decision allocations we used a chi-square analysis followed by a *t* test examining group differences in decision appropriateness. Finally, group differences in response times are analyzed with *t* tests. The response time data were corrected in the case of extreme outliers. Specifically, we excluded responses less than 1 s after the video stopped, to avoid including guessing behavior, and response times greater than two standard deviations above the mean (less than 1% of decisions overall, using both criteria). The α level was set at .05.

Results

HAKEMP Results

The HAKEMP scale is such that a higher score means greater action orientation. The median split ($Mdn = 21$, with $M = 21.2$) in this study resulted in an action-oriented group of 30 players and a state-oriented group of 23 players. The unequal size of 30 to 23 is a result of a prior decision about the five players for which 21 answers were in the direction of action-orientation. Because these cases were above the scale midpoint (18 of 36 questions), they were allocated to the action-orientation group. To ensure this decision did not influence our aggregate analyses, we reran them with the alternative allocation but found no significant differences from the results presented below.

Decision Test Results

The distribution to the four options differed between action- and state-oriented players in the expected direction, as follows. No differences of appropriate choices (p >. 05) were found between the state- and action-oriented players for the more neutral options of passing to the post (13.9%, SD = 4.4, and 13.8%, SD = 4.9, respectively) and passing to the center (9.5%, SD = 4.4, and 8.8%, SD = 4.1, respectively). However, action-oriented players shot more to the basket (41.9%, SD = 4.3, $p < .05$) and passed less to the playmaker (28.3%, SD = 4.4, $p = .07$) than the state-oriented players (35.3%, SD = 2.7, and 32.7%, SD = 4.2, respectively). The analysis of the frequency of allocations to the four options revealed significant differences only for the shoot option for the action-oriented group, χ^2 (1, N = 30) = 28.79, $p < .05$, and state-oriented group, χ^2 (1, N = 23) = 16.93, $p < .05$. Figure 1 shows the average frequency of risky and nonrisky decisions for state- and action-orientation players. Note that these numbers do not sum up to 51 (number of scenes), because decisions related to the neutral options, as expected, did not differ between the groups and were excluded from further analyses. Specifically, the chi-square analyses reveal that the number of choices for post and center players did not deviate significantly from chance (post option: χ^2 (1, N = 53) = 8.26, $p >$ .05; center option: χ^2 (1, N = 53) = 5.00, $p > .05$) supported also by a Monte Carlo simulation based on 10,000 sample tables generated within the range of the empirical data (p > .05, with a confidence level of 95%).

To determine if risk-taking behavior explained this distribution, we checked whether players chose the option compatible with their respective orientation, when it was the appropriate choice (i.e. for action-oriented players to shoot more and state-oriented players to pass to the playmaker more) of action based on the defender distances. The difference in appropriate decisions between action- and state-oriented groups was significant for the low-risk playmaker option: $t(52) = 3.17$; $p < .05$, indicating that state-oriented players passed more to the playmaker compared to action-oriented players when the situation called for it. Also, the difference between these groups in their tendency to opt for the appropriate high-risk option (shoot to the basket) occurred in the expected direction, with action-oriented players choosing this option more when the situation called for it: $t(52) = 2.16$; $p = .06$. The negative correlation between the number of passes and the HAKEMP scores (r = -.28, $p > .05$) and the positive correlation between number of shots and the HAKEMP score (r = .14, $p > .05$) were nonsignificant. However the direction of the correlations indicates that increasing action-orientation (high HAKEMP scores) is associated with a decrease in the number of passes compared to shots.

Next, we compared the action- and state-oriented groups in terms of their mean decision times for each of the four options. This revealed that differences between action- and state-oriented players were significant only in the options to shoot (difference between group means of 283 ms) and pass to the playmaker (difference of 319 ms), whereas the mean differences were small and nonsignificant for the options to pass to the post (47 ms) and to the center (198 ms). In addition, it should be mentioned that decision time for passing to the playmaker was significantly longer than for shooting to the basket (see Figure 2). Finally, regarding decision time, the action-oriented players were on average faster than the state-oriented players, $t(52) = 2.27$, $p < .05$; see Figure 2. The

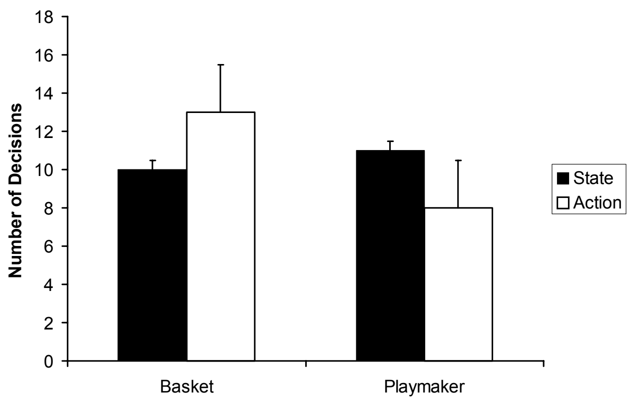

Figure 1. Number of decisions for high-risk (shoot to Basket) and low-risk (pass to Playmaker) responses for action-oriented (Action) and state-oriented (State) players in the basketball task. Lines on the bars represent standard errors.

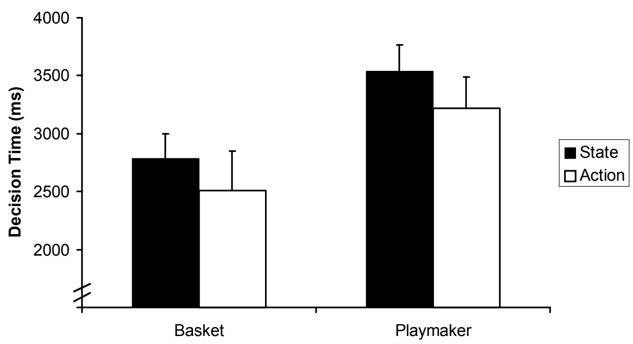

Figure 2. Decision time for high-risk (shoot to Basket) and low-risk (pass to Playmaker) responses for action-oriented (Action) and state-oriented (State) players in the basketball task. Lines on the bars represent standard errors.

Pearson product-moment correlation between HAKEMP score and decision time was $r = -0.38$, $p < .01$, indicating that higher action orientation was associated with significantly faster decisions. The Spearman correlation between decision accuracy and decision time was $r = 0.27$, $p < .01$, indicating that higher decision accuracy was associated with significantly slower decisions.

Discussion

The results show that in risky situations action-oriented players shot more at the basket than state-oriented players. In addition, the action-oriented players were generally faster in making decisions, and the action- and state-oriented players did not differ on risk-neutral decisions. The question remains as to *why* action-oriented players made faster and more risky decisions, and how this can be modeled more precisely. In an attempt to answer this, we now turn to modeling the individual decisions dependent on the player type.

Computational Modeling of Individual Differences

Decision Field Theory. Any of the four possible components described in the introduction can explain differences in individual choices. Although considering all possible combinations would ultimately seem fruitful in identifying any interactions among these variables, we restricted ourselves in the current study for simplicity. Specifically, we manipulated these parameters independently (holding all others constant) to understand which, if any, may have predictive value. Furthermore, because competing explanations may make similar predictions regarding choice probabilities, it would be helpful to derive predictions for response time as well. Decision Field Theory (DFT; Busemeyer & Townsend, 1992, 1993) allows us to derive both choice and time predictions, while incorporating the possible influences identified above. The mathematical formulation and an elaboration of the following short overview can be found in the Appendix.

In essence, DFT assumes that at each moment during a task, attention focuses on a particular feature (e.g., probability of losing the ball) of the choice alternatives (e.g., shoot, pass). Each alternative is then assessed depending on its relative advantage on the focal feature, and this assessment is added to an initial preference for the alternative. Greater initial preference would tend to increase the choice probability for an alternative but not always. For example, if one has an initial preference for passing, but the probability of losing the ball is high due to defenders' proximity, the preference for passing will be reduced whenever attention is on losing the ball. As attention shifts between different features over time, the preference for each option continues to shift accordingly. The more important a feature is—either subjectively for the individual or objectively, based on the situation—the more likely it is to receive attention at each moment. Also, the magnitude of the preference at each moment can fluctuate, depending on the approach-avoidance assessment. For example, if a player with the ball thrives on being in the situation (approach), the preference will build up stronger. Once the player accumulates enough information to favor an alternative, this deliberation process ends and the favored option is chosen. If a player requires more information to make a decision, then the response time and choice probabilities may change as well.

Parameter Representation of Possible Cognitive Differences

To predict individual choices and decision times, we modeled four DFT parameters using independent evaluation data—the HAKEMP score—rather than the data collected in the experiment. These parameters represent four possible underlying causes of the choice and time differences in the experimental task: decision thresholds, attentional focus, the approach-avoidance nature of the decision task, and initial biases in preference. Because of their importance in sports, these properties have previously been analyzed with DFT to some degree (Raab, 2002). Detailed parameter interpretations and transformations can be found in the Appendix; following, we describe the essence of the parameter manipulations and their consequences.

Explanation 1: Threshold. The threshold parameter represents how much information a decision maker needs before choosing an option. If action-oriented players are not as inclined to require a firm and decisive preference for a particular option before acting (Kuhl, 1986), we would expect their decision threshold to be lower, and they were modeled accordingly. Lower values represent more impulsive behavior, in which the strength of an option need not be high before it is chosen, and high thresholds indicate the opposite.

Explanation 2: Approach-Avoidance. The approach-avoidance parameter is included to represent the nature of conflict in decision making—such as the high degree of conflict that can be expected from having to choose one of two desirable options and the low conflict involved in choosing between one good and one poor option (Busemeyer & Townsend, 1993). If differential perception of the situation causes individual differences (i.e., that action-oriented players perceive shooting as an approach task, whereas state-oriented players perceive it as avoidance), then the model runs manipulating the approach-avoidance parameter should best predict the results.

Explanation 3: Attention Weight. To examine the effects of differential weighting by individuals, an attention weight parameter was also included to reflect how much relative attention is afforded each attribute in a decision context. This parameter represents the proposition that different players may have different attentional focus (Beckmann, 1994). That is, if a decision maker hypothesizes one attribute (or cue) to be more important, the attention to this attribute (and, thus, the probability of thinking about it in making a decision) is increased in DFT. Modeling this possibility for individuals resulted in increased weight given to the first (benefit) dimension with increases in the HAKEMP scores—that is, action-orientation was positively related to heavier weighting of the benefits of an option, as opposed to the safety of the option.

Explanation 4: Initial Preference. Finally, we explored manipulations of the DFT parameter that represent the initial preference bias. Perhaps, when faced with decision situations, individuals have preexisting preferences for one option before even considering the information about each option. In the current (basketball) context, one may think of players called "ball hogs" by their peers, who have a predisposition to keep (or shoot) the ball regardless of the situation. So, for this manipulation, the initial bias parameter was set to reflect the possibility that more action-oriented players had a higher initial preference for shooting (Raab, 2002).

Model Predictions

The four DFT parameters were manipulated independently, and the mathematical predictions of the model are reported below (for details, see Busemeyer & Townsend, 1992). For each manipulation, the parameter of interest was determined for each individual based on linear transformations of the recorded HAKEMP scores—the simplest possible (and parameter-free) way to bring scores into the range of valid values for DFT. The remaining parameters were reset to their default values to avoid confounds, when they were not being examined (see the Appendix for transformations and default values). DFT predictions for the situation consisted of choice probabilities and mean response times for each option for each individual. However, for illustrative purposes, we focused on the players with the highest HAKEMP score (hereafter, action player) and the lowest score (hereafter, state player). Table 1 shows DFT predictions for the action and state players for all four parameter manipulations, in addition to the choice and response time data for these two individuals.

Parameter 1: Threshold. First, we will report the results of the threshold parameter manipulation based on individuals' HAKEMP scores. Within an individual, this manipulation showed no differences in response time or choice predictions for the safe (passing) option versus the risky (shooting) option. The manipulation did, however, predict differences between the action player and state player, showing that the former should have faster response times for both options. This predicted relationship was not supported by the response time data for these two players. Furthermore, the predictions from this parameter manipulation are such that both the action player and state player should have choice probabilities of 0.5 for these two options, which was clearly not the case for the action player. Although the threshold manipulation supported the fact that the action player was faster overall than the state player, this parameter did not correctly predict choices or response time by choice interactions.

Parameter 2: Approach-Avoidance. The second manipulation, of the approach-avoidance parameter, made predictions qualitatively similar to the threshold parameter, as can be seen in Table 1. Because this manipulation did not explain the behavior of these two extreme individu-

Table 1. Experimental data and Decision Field Theory predictions for extreme players

		Experimental data		Threshold		Approach-avoidance		Attention weight		Initial preference	
		Choice	Time (ms)	Choice	Time (ms)	Choice	Time (ms)	Choice	Time (ms)	Choice	Time (ms)
Action player											
HAKEMP = 35	Shoot	0.89	2,211	0.50	1.00	0.50	1.97	0.99	0.69	0.75	1.14
	Pass	0.11	3,673	0.50	1.00	0.50	1.97	0.01	0.69	0.25	2.45
State player											
HAKEMP = 7	Shoot	0.55	2,851	0.50	3.24	0.50	1.96	0.11	1.48	0.36	2.28
	Pass	0.45	2,053	0.50	3.24	0.50	1.96	0.88	1.48	0.64	1.53

Note. The column headings indicate which Decision Field Theory parameter was manipulated to obtain the associated predictions; choice values are given as probabilities of choosing the associated option from only the two options used in the model predictions; Decision Field Theory time data are not defined external to the model but could be scaled to represent milliseconds; Action player = extreme action-oriented player; state player = extreme state-oriented player; HAKEMP = Questionnaire for Assessing Prospective Action Orientation and State Orientation in Success, Failure, and Planning Situations.

als, it suggests that the explanation of different approach-avoidance views of the task was also probably incorrect.

Parameter 3: Attention Weight. The third parameter manipulated the attention weight corresponding to the first attribute, benefit of outcome. This realization assumed that action-oriented players would pay more attention to the outcome benefit of an option, whereas state-oriented players would pay more attention to the safety of an option. One can see in the third column of Table 1 that, unlike the previous two manipulations, this parameter did produce plausible choice probabilities for the two options for the action player. That is, the model predicted that the action player would shoot much more than he or she passed and that the state player would pass much more than he or she shot, which was not the case. This manipulation correctly predicted that the action player would be faster than the state player, but it did not correctly predict the interaction between choice and response time—that the action player is quicker to shoot than to pass and vice versa for the state player. Thus, while this manipulation seems more informative than the previous two, it did not fully support the notion that differential attribute weighting is the best explanation for the different behaviors of action-oriented and state-oriented players.

Parameter 4: Initial Preference. The results of the final manipulation, of the initial preference parameter, are shown in the last column of Table 1. Unlike the previous treatments, manipulation of this parameter produced different predictions for both choice probabilities and response times, within and between the individuals. In particular, DFT predicted that the action player would have a greater tendency to shoot and the state player would have a greater tendency to pass, with the former tendency greater in magnitude than the latter. These are appropriate predictions for the action player, but again the model overestimated the passing tendency of the state player. Most importantly, this parameter produced the correct predictions for the choice by response time interaction, with the action player quicker to shoot than to pass, and the state player quicker to pass than to shoot. In fact, it even predicted correctly between individuals that the state player would be quicker to shoot than the action player would be to pass—perhaps a result (empirically) of the tendency to score in game situations. These predictions make sense when considering the DFT Equations (1) through (3) in the Appendix. Because of the initial preference in a certain direction, both the choice probabilities and response times should be biased in that direction. The other parameters do not directly affect both choice probability and response time predictions in this manner.

Based on these parameter manipulations, it seems that the most likely *single* explanation for the differences between action- and state-oriented players—at least between the extreme players illustrated here—is due to initial preferences for the risky and safe alternatives, respectively. Figure 3 shows the prediction results for the initial preference parameter manipulation separately for all individuals for shooting, and Figure 4 shows prediction results for passing to the playmaker. **[F3, F4]**

With these figures, one can see the general trends in choice probability and response time implied by the initial preference parameter manipulation. Increasing this parameter, which corresponds to a move from action to state orientation by Equation (7) in the Appendix, decreases the probability of choosing the shooting option while increasing the response time for it and vice versa for the passing option. This suggests negative correlations between the parameter and both probability of shooting ($r = -.19$, $p > .05$) and response time of passing ($r = -.25$, $p > .05$) and positive correlations between this parameter and both probability of passing ($r = .26$, $p = .07$) and response time of shooting ($r = .43$, $p < .01$). Note that these figures show predictions that illustrate mathematical dependencies of the model (hence, the apparent reflection of the choice distribution in producing the response time distribution).

General Discussion

We argued that individual differences identified in action- and state-oriented players can cause risk-taking behavior in sports. An experiment using basketball showed that action-oriented players are faster in general and shoot more often to the basket (risky choice), whereas state-oriented players pass the ball more to the playmaker (safe choice). Four interpretations of these differences attributing them to differences in the initial preference, attention, threshold definition, or task perception were analyzed in a DFT computational model. The results show that the difference of the initial preference for each option, which was set differently depending on a personality trait (action orientation), could explain the differences in decision time and the option distribution. We have gone beyond experimentation by making specific predictions about the underlying process then testing these predictions in a mathematical, process-oriented model. Furthermore, we deviated from conventional model-fitting by specifying our model parameters on an independent measure (HAKEMP), rather than using the experimental data we were trying to predict.

Some limitations of the current study are due in part to the novelty of our approach. For example, it seems that interaction among the various parameters may be the most plausible description of differences in player types. Manipulating two or more parameters (derived from a single scale, HAKEMP) in generating model predictions could likely show the relative influence of each and better predict the empirical data. In addition to the variables we used in our investigation, it is necessary to search for other potential variables within the focus of personality traits as well as outside the constraints we set for this paper (e.g. task or situational variables). Generalization issues are also of concern when considering the results reported here. For example, our use of novices requires caution when generalizing to more experienced populations, which often have different behavior patterns (Bar-Eli & Tractinsky, 2001) and may, thus, be modeled differently.

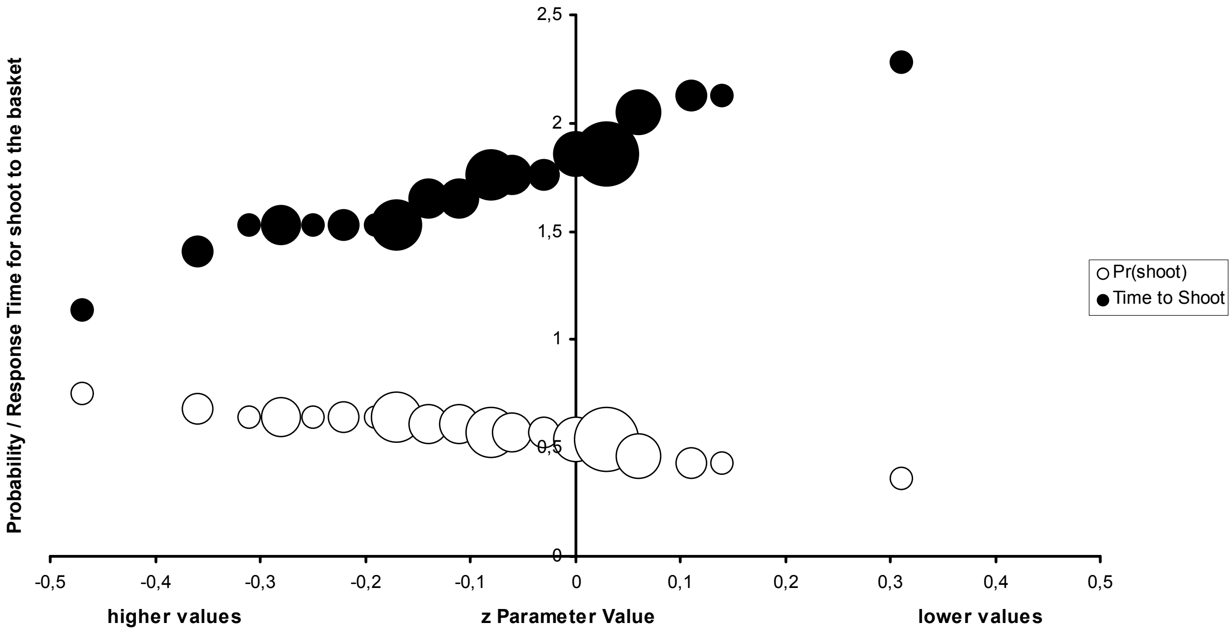

Figure 3. Results of the initial preference parameter manipulation for all individuals, showing the distribution of choice probabilities and response times for the shooting option. Bubble sizes represent frequency of players modeled by each parameter value. The largest bubble represents eight players; the smallest bubble represents one player.

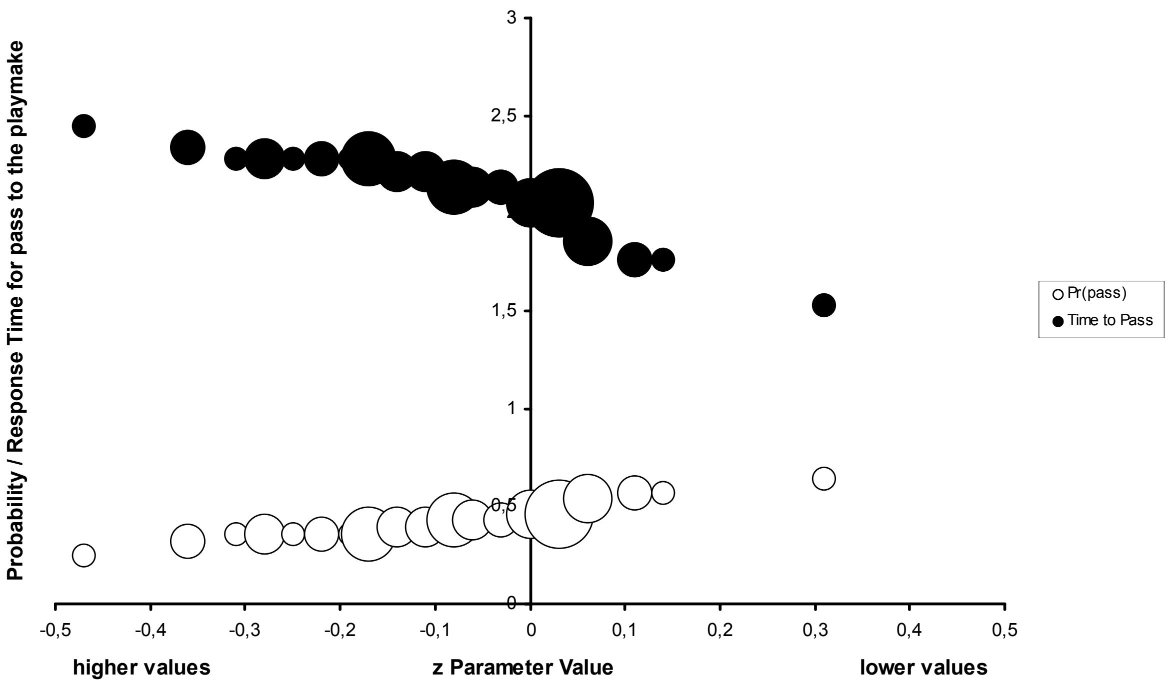

Figure 4. Results of the initial preference parameter manipulation for all individuals, showing the distribution of choice probabilities and response times for the passing option. Bubble sizes represent frequency of players modeled by each parameter value. The largest bubble represents eight players; the smallest bubble represents one player.

There are many other uses for this line of work. Within the risk-taking domain, further parameter manipulations could test hypotheses regarding the effects of time pressure (Raab, 2002). Also, the merit of the presented approach goes beyond our task, and it may be easily applied to other risk-taking behaviors, such as extreme sports and car racing or other domains completely. Note that we do not propose DFT is the only model capable of benefiting from this procedure. Other decision-making models in sports (Alain & Sarrazin, 1990) could use this approach to more finely specify what their parameters represent as well as how they function. The assumptions of the model used to generate the predictions constrains the explanatory power of any parameter set. However, this paper did not intend to be a broad comparison of different decision-making models but to offer an initial example of the utility of the methodology. These implications should be considered as a guide for future research in decision making in sports. Regardless of the environment in which it is applied, or the model chosen to represent the process, it appears that using individual analyses and a priori specification of parameter values based on personality can add fruitfully to understanding sports behavior.

We also would like to encourage testing potential implications of these results in more realistic and applied settings. For instance, from our results—with all the caution mentioned above—it can be concluded that action- and state-oriented players decide differently. Knowing the orientation of the players, coaches may use this information for deciding ball allocation strategies depending on the situation. Decisions about replacing players, when fast and risky decisions are required versus when slow and nonrisky decisions are wanted, seems another candidate for an application. We have only just begun to understand how decisions are made and, therefore, understand ourselves a little better.

References

Alain, C., & Sarrazin, C. (1990). Study of decision-making in squash competition: A computer simulation approach. *Canadian Journal of Experimental Psychology, 15*(3), 193–200.

Bar-Eli, M., & Tractinsky, N. (2001). Criticality of game situations and decision making in basketball: An application of performance crisis perspective. *Psychology of Sport and Exercise, 1*(1), 27–39.

Beckmann, J. (1994). Volitional correlates of action and state orientations. In J. Kuhl & J. Beckmann (Eds.), *Volition and personality: Action and state orientation* (pp. 155–166). Seattle, WA: Hogrefe & Huber Publishers.

Beckmann, J., & Trux, I. (1991). Wen lasse ich wo spielen? [Who plays what position?] *Sportpsychologie, 5,* 18–21.

Busemeyer, J. R., & Townsend, J. T. (1992). Fundamental derivations from decision field theory. *Mathematical Social Sciences, 23,* 255–282.

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review, 100,* 432–459.

Dahme, G., Bleich, C., Jungnickel, D., & Rathje, H. (1992). Some encouraging results concerning the reliability and some discouraging outcomes concerning the construct validity of the HAKEMP: Data from a field study. *Zeitschrift für Differentielle und Diagnostische Psychologie, 13,* 139–160.

Heckhausen, H., & Strang, H. (1988). Efficiency under record performance demands: Exertion control, an individual-difference variable? *Journal of Personality and Social Psychology, 55,* 489–498.

Kuhl, J. (1986). Human motivation: From decision making to action control. In B. Rehmer, B. Jungermann, P. Laures, & G. Sevon (Eds.), *New directions in research on decision making* (pp. 5–28). Amsterdam: North-Holland.

Kuhl, J. (1990). *Instructions for questionnaire HAKEMP Version 1990.* Munich, Germany: Max Planck Institute.

Raab, M. (1996). Einflussfaktoren taktischer Leistungsfähigkeit [Factors of tactical performance]. In F. Dannenmann (Ed.), *Volleyball 1995. Congress of the German Volleyball Association* (pp. 127–140). Hamburg: Czwalina.

Raab, M. (2002). T-ECHO: Model of decision making to explain behavior in experiments and simulations under time pressure. *Psychology of Sport and Exercise, 3*(2), 151–171.

Raab, M. (2003). Decision-making in sports: Influence of complexity as a factor in implicit and explicit learning. *International Journal of Sport and Exercise Psychology, 1, 406–433.*

Roth, K., & Strang, H. (1994). Action versus state orientation and the control of tactical decisions in sports. In J. Kuhl & J. Beckmann (Eds.), *Volition and personality. Action versus state orientation* (pp. 467–474). Göttingen, Germany: Hogrefe.

Sack, P. M. (1990). Eine revisierte Skala zur Messung von Handlungskontrolle [A revised scale for assessing action control]. *Zeitschrift für Differentielle und Diagnostische Psychologie, 11,* 233–241.

Sack, P. M., & Witte, E. H. (1990). Untersuchung zur Konstruktvalidität des HAKEMP 85 von J. Kuhl [Construct validity of HAKEMP 85 from J. Kuhl]. *Zeitschrift für Differentielle und Diagnostische Psychologie, 11,* 17–26.

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Appendix A: Decision Field Theory

The essence of Decision Field Theory (DFT) as applied to the present task can be interpreted from Equations (1) – (3).

$$\mathbf{V}(t) = \mathbf{CMW}(t) \quad (1)$$

$$\mathbf{P}(t) = (1 - c) \cdot \mathbf{P}(t - h) + \mathbf{V}(t) \quad (2)$$

$$\mathbf{P}(0) = z \quad (3)$$

Note that these terms are matrices (or vectors) that contain the corresponding information for all alternatives and attributes in a given situation. These matrices can be interpreted as follows: W*(t)* is a 2 x 1 vector of attribute attention weights; M is a 2 x 2 matrix containing the value on each of two attributes for each of the two alternatives (e.g., shoot, pass) in a task; C is a symmetric contrast matrix used to weight the value of an option relative to the value of the other option; P(t) defines the preference for each alternative at time *t*, where P*(0)* = *z* shows the initial bias for each alternative; *h* is a time-scaling parameter; and *c* represents approach-avoidance. Equation (1) shows how the valence V*(t)* is computed at each moment in time. At any given moment, DFT assumes that one's attention shifts in an all-or-none manner to a given attribute. This process is stochastic but driven by the importance weights (*w*) given to each attribute (for derivations, see Busemeyer & Townsend, 1992). As a result, at any given time, the W*(t)* vector contains a 1 for the corresponding attribute, and the other value is 0. This determines which corresponding values of the M matrix are used at that moment, and the valence for each option is computed as a contrast, by C.

DFT was originally formulated for comparisons of two options possessing two attributes each, for which choice probabilities and decision times are easily derived (Busemeyer & Townsend, 1992). Because only the choice options and response times of "shooting at the basket" and "passing to the playmaker" showed significant relations to player orientations (see the Results section of this paper), they were used as the two options. In this situation, the exact attributes are not clearly defined, and, so, operational definitions must be introduced. For simplicity, these values were set to 30 on Dimension 1 and 10 on Dimension 2 for the option of shooting, and 10 on Dimension 1 and 30 on Dimension 2 for the option of passing, for all predictions. These values on the attribute dimensions can be interpreted as, for example, the benefit and safety of the option, respectively. Regardless of the interpretation, the key point is simply, if the attributes are weighted equally, then neither option would appear more beneficial. For the current application, Equation (1) then becomes:

$$\begin{bmatrix} \mathbf{V}_{\mathbf{pass}}(t) \\ \mathbf{V}_{\mathbf{shoot}}(t) \end{bmatrix} = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \times \begin{bmatrix} 10 & 30 \\ 30 & 10 \end{bmatrix} \times \begin{bmatrix} W_a(t) \\ W_b(t) \end{bmatrix};$$

where $W_a(t) = 1$, $W_b(t) = 0$, or vice versa; and $\Pr(W_a(t) = 1) = w$.

In simple terms, the value for an option at a certain time is determined by how good that option is perceived, relative to the other option, on the single attribute under consideration. This momentary valence is added to a modified (depending on approach-avoidance, *c*) trace of the previous preference state, resulting in a vector P*(t)* of preferences for each alternative at each time. An alternative is chosen when the preference for that alternative exceeds some threshold value, denoted θ, that the individual considers "sufficient" for making a decision.

Transformations of HAKEMP Questionnaire to Parameter Values

The linear transformations from HAKEMP (Questionnaire for Assessing Prospective Action Orientation and State Orientation in Success, Failure, and Planning Situations) to DFT parameters were performed using Equations (4)–(7):

Threshold, θ = (72 – HAKEMP)/36 (4)
Approach-avoidance, *c* = (HAKEMP – 18)/36 (5)
Attention weight, *w* = HAKEMP/36 (6)
Initial preference, *z* = (18 – HAKEMP)/36 (7)

For example, the two most extreme individuals (in terms of HAKEMP score) were characterized by the following parameters for θ, *c*, *w*, and *z*, respectively: 1.03, 0.47, 0.97, and -0.47 for the most action-oriented individual (action player) and 1.81, -0.31, 0.19, and 0.31 for the most state-oriented individual (state player). The default values eliminated the parameters not under direct manipulation from exerting an influence. Also, sensitivity analyses (further predictions generated from around the parameter space) showed that modifying the default values across the range of valid values (with step size 0.1) did not affect the results reported. A default value of zero for *c* and *z* keeps these parameters from biasing the probabilities and decision times in either direction, a default value of 0.5 for *w* equalized the likelihood of attending to either dimension, and a default value of 1.41 for θ reflected the mean of the distribution of HAKEMP-transformed variables. Note that the transformations were chosen to restrict the maximum possible range to the default value ±0.5, based on the HAKEMP scale, which scores from 0 to 36. The only slight exception is the distribution of θ, because the default value was based on the transformation. Finally, the time step parameter (*h*) was set to 0.01 to closely approximate a continuous (rather than discrete) deliberation process.