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Decision making in online fantasy sports communities

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This paper describes the forms of knowledge used by players of fantasy sports, games where players create ideal sports teams and compete to accumulate points based on professional athletes' statistical performances. Messages from a discussion forum associated with a popular fantasy basketball game were analyzed to understand how players described their decision-making strategies to their peers. The focus of the research was to understand if players use mathematical concepts such as optimization and statistical analyses when assembling their team or if they base their decisions on personal preferences, beliefs, and biases. The analyses in this paper suggest the latter, that players rely on informal, domain-specific heuristics that often lead to the creation of competitive teams. These heuristics and other forms of player discourse related to knowledge use are described. The paper also suggests ways that analyses of existing practices might provide a foundation for creating gaming environments that assist the acquisition of more formal reasoning skills.

Keywords: Online gaming, informal learning, discussion forums, decision-making, discourse analysis, fantasy sports

1. INTRODUCTION

This paper reports a study of strategies used by players of fantasy sports games. Online discussion forums associated with these games are analyzed to understand and describe how players use contextual tools, knowledge, and peer interactions to support their formal and informal decision making processes. Decision-making processes involved in games like fantasy sports are likely to be different from those visible in schools and other formal educational settings. Understanding the structure of informal decision-making in these and similar games may suggest ways to teach formal reasoning skills by building upon existing (and often implicit) gaming strategies.

Numerous sociocultural studies have characterized differences between the types of learning that occur in formal educational contexts and everyday life. For instance, studies of activities such as carpet laying, farming, candy selling (Carraher *et al.*, 1985; Saxe, 1991), shopping (Lave, 1988), and game playing (Nasir, 2002, 2005) have examined the connections between mathematics learning and cultural practices associated with activity. One important finding of such work is that the expression and use of mathematical knowledge in everyday activities rely on tools and artifacts situated in the environment, leading to norms, values, and conventions that generally look very different than those found in formal mathematics education. For example, Lave's studies of math use in grocery stores found shoppers using various heuristics to approximate price differences and avoiding formal mathematical calculations unless they were absolutely necessary (Lave, 1988; Lave *et al*., 1999).

This strand of research suggests that informal knowledge is situated and bound to the context in which it is used. Indeed, people's informal problem-solving skills are often more robust than their abilities to reason with more abstract formalisms. For instance, Lave et al.'s tests on informal and formal mathematical problem solving found that people who could accurately make price comparisons based on heuristics performed far worse when asked to do similar calculations with mathematical formulas (Lave *et al*., 1999). Nasir's studies of high school basketball players report similar results: Players often struggled to solve statistical word problems, yet they were able to generate correct solutions when the same problems were phrased in terms of basketball (Nasir, 2000).

In the best case, people would be proficient in formal and informal knowledge methods and have the capacity to apply a wide range of approaches to problems they encounter. The discrepancy between formal and informal knowledge use that Lave, Nasir, and others report suggest a need to connect the two modes of thought. Everyday cognition that is grounded in particular contexts could be used as a foundation for developing more formal, generic understandings of mathematical problem solving. This requires understanding the nature of informal knowledge use and its contextual grounding and then using such findings to create opportunities where formal reasoning can be introduced, practiced, and reflected upon.

Computer and video games provide one context for comparing differences between formal and informal reasoning. Educators have recognized that computer games have the potential to promote concept and skill acquisition in motivating and memorable ways (e.g., Bowman, 1982; Gee, 2003; Malone, 1981; Prensky, 2000). Gee (2004) further suggests that computer and video game play is a form of everyday cognition that involves highly situated knowledge use (e.g., learning the rules of PokÈmon) rather than abstract, decontextualized rules often found in formal learning environments (e.g., learning phonetic mappings between letters and sounds). His observations are focused on written literacy, but sophisticated, yet informal reasoning around mathematics may also be present in computer and video game play. For example, sporting games may provide contexts for framing and using statistical knowledge that appeal to learners who would otherwise avoid mathematics in formal settings.

In fact, sporting performances can be quantified and understood using various statistical techniques (e.g., Berri *et al*., 2006; Hollinger, 2005; Oliver, 2003). The use of such statistics may be more apparent in a recent class of sporting game, *fantasy sports*, that are played online by an estimated 15 million people (FantasySportsTradeAssociation, 2003). Players of these games act as "team managers," selecting professional athletes to become part of their ideal sports lineups. The rules vary across fantasy games, but all use statistics generated by individual athletes to accumulate points. Players choose athletes that they believe will maximize their total scores in the game. Such decision-making can be described as a preferential choice problem (Payne & Bettman, 2002) where individuals are tasked with selecting one of many alternatives, each of which has numerous attributes requiring consideration and comparison.

Preferential choice is a fundamental part of fantasy sports games, yet little is known about how players select athletes for their teams when faced with numerous alternatives. They may engage in detailed, formal statistical analyses of athletes' past performances when creating their teams. Such thorough analyses can be viewed as forms of rational decision-making, where individuals rigorously scrutinize all possible options in an attempt to maximize the expected values of their teams. Another alternative is for players to use informal heuristics that are bound to prior knowledge of sports to avoid in-depth analyses.

This paper describes some of the decision-making processes used by fantasy sports players to understand the extent of their formal and/or informal knowledge use. Messages from a discussion forum associated with a fantasy basketball game were collected and analyzed to examine how conversations between players could be used to gain insight into knowledge use and learning. Previous studies of discourse in massively multiplayer online games (MMOGs) and discussion forums associated with popular games have focused on understanding the nature of social interactions within virtual worlds (Brown & Bell, 2004; Ducheneaut & Moore, 2004; Golder & Donath, 2004). Gee (2004) and Steinkuehler (2006) have applied discourse analysis

TOTALS FOR Friday, Nov. 12														
POS	PLAYER, TEAM	OPP	MIN	FG/A	FT/A	REB	AST	TO	STL	BLK	PTS	F Brk*	AVG**	VALUE
PG	**Steve Francis**, ORL	**LAL**	41	11/23	9/11	8	9	3	0	1	32	33	22.2	20.1
SG	**Emmanuel Ginobili**, SA	**MIA**	35	8/12	8/10	7	7	4	6	1	29	40	16.8	15.8
SF	**Rashard Lewis**, SEA	**TOR**	41	6/20	0/0	7	2	3	1	2	15	10	19.3	17.4
PF	**Tim Duncan**, SA	**MIA**	40	6/14	5/14	13	6	1	2	3	17	23	28.0	21.4
C	**Shaquille O'Neal**, MIA	**@SA**	40	9/21	5/7	21	4	3	0	2	23	33	24.0	20.5
Cch	**Boston Celtics**	**CHA**	Winning Pct: 1/1 = 1.000									5	2.4	4.8
											Totals	144	**112.7**	**100.0**

Figure 1 A team in ESPN's FastBreak fantasy basketball game with a talent value of 100 (rightmost column)

to game-related discussion forums to demonstrate how such interactions lead to the acquisition of literacy skills. The aim of this research is to investigate how discussions between fantasy sports players can be analyzed to determine the influence of prior knowledge on the process of decision-making and use of mathematics during play. In particular, three aspects of fantasy sports practice are examined (Saxe, 1991): (1) social interactions between players, (2) the structure of decision-making activities, and (3) artifacts and conventions that assist decision-making.

The long-term research objective is to develop gaming environments that assist players in the acquisition of formal reasoning skills (e.g., statistical analyses). More specifically, the researchers are interested in helping individuals reflect upon and improve their decision-making skills. The study described in this paper is an initial step towards designing such supports by identifying informal strategies used during game play and comparing them to more formal methods of analysis and decision-making. Such comparisons may be useful for bridging informal and formal reasoning in future, instructional interventions.

The paper begins with an overview of fantasy sports games to illustrate the sorts of decisions required of players. This is followed by a description of two conflicting views of decision-making: Judgment and choice as a formal, rational process vs. the informal application of domain-specific heuristics. Discourse analyses of the fantasy sports discussion forum are then presented to demonstrate how players discuss their team selections and provide insights into their decision strategies. The final discussion overviews these strategies and suggests ways to use discourse analyses of chat rooms to inform the design of games where informal knowledge can be used to scaffold the development of formal reasoning skills.

2. CONTEXT: FANTASY SPORTS

In 1979, Daniel Okrent and a group of friends created a game called Rotisserie League Baseball (Colston, 1999). Players of the game acted as "owners" of fantasy teams, selecting from the list of active Major League Baseball athletes and followed their statistics during the season to compile their scores. More so, players had to make predictions about athletes' playing time, health, and expected performances that real baseball managers make on a daily basis. Rotisserie baseball became more popular as the Internet allowed team selection and scoring to be conducted online, ultimately leading to the current generation of fantasy games for most professional sports.

Fantasy sports games can be viewed as resource allocation tasks, as players must choose athletes (resources) to maximize their scores while working with limited salary and/or talent assets. For instance, ESPN's *FastBreak* basketball game assigns a talent value to each athlete, and players cannot exceed 100 talent points when assembling their teams (Figure 1). This ceiling forces players to select one or two "superstars" and additional "role athletes" to complete their rosters.

All fantasy games include a model that maps statistical attributes of an athlete's performance into a single point value. For instance, Equation 1 shows the formula used to assign points to athletes in ESPN's *FastBreak* fantasy basketball game.

Players choose athletes that they believe will maximize points for their fantasy teams while

$$Athlete\ Score = (PTS + REB + AST + STL + BLK) - ((FGA - FGM) + (FTA - FTM) + TO)$$

where:

PTS = points scored, *REB* = total rebounds, *AST* = assists, *STL* = stolen balls, *BLK* = blocked shots, *FGA* = field goals attempted, *FGM* = field goals made, *FTA* = free throws attempted, *FTM* = free throws made, *TO* = turnovers

Equation 1. The formula for calculating athlete points in ESPN's FastBreak fantasy basketball game remaining under the talent/salary maximum. Without the latter constraint, players might choose the best athletes at every position and easily maximize their scores. But limited assets force players to compare athletes and decide which ones have the best chances of maximizing points for a given night/week.

Fantasy sports have been used in formal instructional settings to teach various concepts. Students in sports marketing and communications courses are taught how to create marketing plans, promotional materials, up-to-date information on franchises, etc. Fantasy sports can be introduced into such training to provide students with opportunities to practice these skills with simulated teams and strengthen their application of marketing theories and concepts (Billings, 2005; Brown, 2005; Gillentine & Schulz, 2001). Curricula tying fantasy sports to mathematics learning have also been developed and tested in K-12 schools (e.g., Flockhart, 2005). Students learn and practice math by computing their fantasy team's scores, creating graphs to represent their results, and working on problem sets related to sports statistics.

In both cases, fantasy simulations provide ways to apply abstract concepts (e.g., marketing, mathematics) to concrete examples. In addition, instructors and curriculum structure activity in ways that help students achieve set learning objectives. The study described in this paper does not focus on instructional uses of fantasy sports games: Rather, it focuses on understanding knowledge used by fantasy sports players *without* the structure provided by formal curriculum and instruction. In this context, comparisons are made between informal and formal reasoning that can contribute to designing instructional uses for fantasy sports.

3. DECISION MAKING

Fantasy sports games involve choosing athletes, all of whom have multiple attributes that need to be evaluated. In the case of basketball, these attributes are statistical categories such as points scored, blocks made, rebounds collected, and so on. These sorts of preferential choice problems often involve conflict as no single alternative can be considered the best choice given the range of attributes (Payne & Bettman, 2002). Therefore, people need to rely on a variety of decision strategies in order to select athletes, often by accepting less of one valued attribute to achieve more of another.

One view of decision-making, expected utility theory, suggests that people choose options with higher expected values (vonNeumann & Morgenstern, 1947). That is, if athlete *X* has an 80% chance of scoring 10 points and athlete *Y* has a 70% chance of scoring 20 points, athlete Y has a higher expected value (0.7 * 20 = 14 points vs. 0.8 * 10 = 8 points). Players using this form of decision-making would compute expected values for each athlete and select those with the highest values. This implies the exhaustive consideration of each athlete's attributes, determining outcomes and their probabilities for each attribute set that can be used to compute expected values, and making final choices based on the results.

Researchers have shown that people do not always behave according to rational, expected utility theory. For instance, Tversky and Kahneman (1974) describe how decision-making is affected by the framing or wording of possible choices. Consider the complement of the example used above: Athlete A has a 20% chance of not scoring any points, and athlete B has a 30% chance of not scoring. The problem is still the same, but the wording changes from scoring to not scoring, and the probabilities are the complement of the originals. This is enough to sway decision makers to prefer the first athlete since there is more perceived risk in choosing the option with greater probability of not scoring. Again, the two problems are identical, but the wording is enough to reverse people's preferences. This perspective suggests that rational decision-making, as defined by expected value theory, is easily biased.

Tversky and Kahneman also described how people use various heuristics when making decisions. For instance, availability, basing judgments on the ease of recalling instances of similar events, is a strategy that may influence decision-making (Tversky & Kahneman, 1974). Lexicographic or "one-reason" strategies have also been identified where the alternative with the best value on the most important or preferred attribute (e.g., rebounds collected) is simply selected (Gigerenzer *et al*., 1999; Payne & Bettman, 2002). Rational and heuristic models of decision-making can be differentiated in terms of cognitive processing: The former involves exhaustive evaluation of attributes, while the latter is a form of "bounded rationality" (Selten, 2002; Simon, 1956) where decisions are made based on partial information due to cognitive limitations (e.g., time, cost).

Bounded rationality often implies the use of domain-specific heuristics that exploit the regularities of particular environments (Gigerenzer & Selten, 2002). For instance, existing knowledge of basketball may guide the use of certain heuristics when creating fantasy rosters. Domain-specific decision strategies may be learned over time as players gain more experience and reflect on the efficiency and effectiveness of past choices (Rieskamp & Hoffrage, 1999). Heuristic judgments may lead to choices that are less than optimal, especially when compared to solutions generated by expected utility theory (Tversky & Kahneman, 1973). But they often lead to the same choices that would result from exhaustive computation with less cognitive effort (Gigerenzer *et al.*, 1999).

The study described below seeks to understand how fantasy sports players make preferential decisions. Do they make judgments based on normative decision models such as expected utility, or do they use domain-specific heuristics to create their teams? If they do use heuristics, are they making sensible choices in the context of fantasy sports? Does the use of heuristics lead to competitive rosters in fantasy sports games?

Fantasy sports are interesting contexts for studying decision-making because they involve the sorts of ill-defined problem solving common to real-world tasks (Gigerenzer *et al.*, 1999; Klein, 1999), yet they ultimately have well-defined outcomes. There is inherent uncertainty and risk during the process of creating fantasy rosters. Players can use numerous strategies to select their athletes, but unexpected injuries, suspensions, and poor performances can derail the best intentions. However, once decisions are made and scores are compiled, there is a "right answer" that can be used to evaluate the success or failure of a player's strategies.

The combination of uncertainty during decision-making and a well-defined solution after the fact allows player strategies to be evaluated for their accuracy. That is, naturalistic studies can be conducted to understand the richness of decision-making as it occurs. Those decisions can then be examined in terms of their effectiveness, their contribution to the players' selection of athletes and the accumulation of points.

Table 1 Discussion threads in the fantasy basketball forum by size, quantity, and percentage of total threads

Thread Length	Number of Threads	% of Total Threads
<4	16595	74.3%
5-9	4013	18.0%
10-15	1149	5.1%
>15	587	2.6%

4. METHODS

Cognitive ethnography (Hutchins, 1996), the description of cultures in order to understand their cognitive practices, was selected as the primary research methodology since the goal was to examine players' strategies and interactions with environment, tools, and other players *in situ*. The researchers collected and analyzed the texts of online discussion forums where players gathered to discuss their teams. Specifically, a discussion forum associated with a popular fantasy basketball game (ESPN's *FastBreak*) was studied between October 15, 2004 (the start of the 2004-2005 NBA season) and February 18, 2005 (the beginning of the NBA All-Star break). Approximately 55,500 people were registered for the game during this period, and 1344 of those used the chat room, contributing 82,104

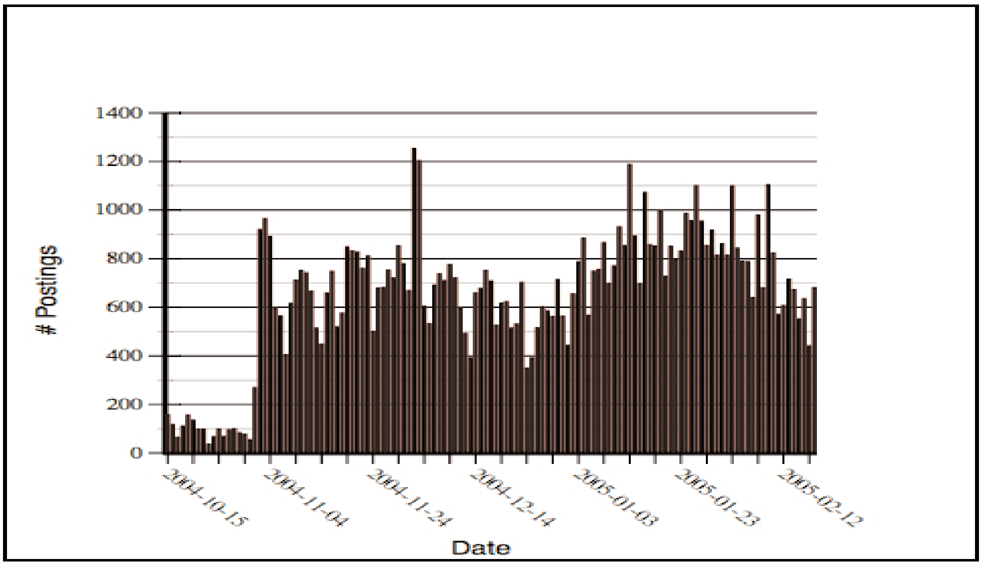

Figure 2 Number of messages posted per day on the ESPN Fastbreak discussion board between October 15, 2005 and February 18, 2005

messages (Figure 2, μ=55.33, σ=316.06). At the low end, 536 players contributed a single message, while the top contributor posted 7253 messages.

Data analysis and coding were conducted by a group of eight researchers over a year. To avoid bias, individual researchers coded separate units of data and then convened within the group to discuss and refine codes that emerged through individual analysis. Thus, the patterns presented below are the result of refinement and categorization over multiple units of data and multiple researchers. The qualitative analyses began with a broad examination of the patterns of communication over the course of the basketball season. Analyses focused on discussion threads, consecutive messages posted about a particular topic. Messages receiving the most discussion (i.e., thread length) were a small percentage of all discussion threads (7.7%, see Table 1). The majority of the threads consisted of singleton messages that went unanswered by other participants or short bursts of discussion. Analyses of the discussions focused on threads with 10 or more responses as those indicate sustained discussions, potentially containing more information relevant to fantasy sports decision making.

Initial analyses consisted of open coding, which involves reading and comparing individual data units so as to label similar units into categories (Strauss & Corbin, 1990). Open coding can be applied to any meaningful unit of data (Flick, 2002), and on the discussion boards, individual discussion threads were chosen as the smallest coherent data unit that would facilitate data classification and sequencing. This phase attempted to differentiate and categorize threads based on their intent within the fantasy game environment. For example, a thread with the title "Please join my group," was easily classified as related to recruitment, while threads with titles such as "Roster for tomorrow" or "Why not Dwayne Wade today?" were categorized as discussions about teams and athletes. As data were examined over the course of the season, it was observed that discussions during the first two weeks of primarily focused on recruiting players for the fantasy teams. After the initial recruitment phase, discussions began to focus on the game: Players discussed and compared athletes' statistics and team lineups, etc. These latter discussions, ranging from November 1, 2004 to February 18, 2005, were analyzed in more detail since they provided rich evidence of strategy use.

These longer threads were extracted and filtered to focus on citations of statistics or numbers and evidence of strategic conversations (i.e., comparisons of teams or athletes, descriptions of strengths or weaknesses of specific lineups or athletes, etc.). Open coding was continued to extract more detailed comparisons of strategies, but the unit of data analysis became more minute to include individual words, phrases, and sentences within the threads. Interactions within the thread were also considered to understand how players posed questions and responded to each other as they discussed game and team strategies. The analyses also focused on the presentation of numerical and statistical data and players' specific mentions of strategies or reasoning for team and athlete selection. As instances of these discourse forms were compiled, the researchers refined the categories illustrated by the conversations. For example, the researchers noted many instances where player statistics were presented without any discussion of the numbers and these instances were compiled and labeled as "speaking in statistics," since there was no deeper discussion involved. Data analyses are ongoing, but initial patterns that emerged from the early phases of open coding are described below. These patterns can be viewed as informal heuristics for game playing adopted by players in the fantasy games environment.

5. ANALYSES

While a number of the analyzed threads contain information peripheral to fantasy sports decision making (e.g., players' personal lives, "trash" talking), there are also numerous instances of players cooperating and sharing information in the discussion forum. This is somewhat surprising given the competitive nature of fantasy sports. However, peer collaboration is often mentioned as motivation for playing the games (Shipman, 2001). Players may find sharing their winning teams engaging: It is a way to display a competitive edge, but it also exposes potentially good strategies to others in the forum.

The open sharing of team information allowed the researchers to find recurring patterns of discourse. These include the presentation of statistics to discuss lineups, the use of informal heuristics to guide decision-making, and reflections on game rules and strategy use. Each of these is discussed below.

5.1 Speaking in statistics

Players often describe their fantasy lineups in terms of statistics displayed in the game's interface. For instance, Cam's message below asks for feedback about his current team.

Cam: I've kept my mind on this Lineup since this morning. Any comments to edit this roster? I just chose NO as coach cause I needed room.

CURRENT ROSTER

Pos	Player, Team	Mkt	Lock	OPP	FB PTS
PG	Dwyane Wade, MIA	19.4	19.4	BOS	27.6
SG	Kobe Bryant, LAL	22.1	22.1	NO	26.1
SF	Rashard Lewis, SEA	17.9	17.9	IND	17.9
PF	Antawn Jamison, WAS	17.8	17.8	@TOR	23.8
C	Brad Miller, SAC	19.0	19.0	MIN	21.2
Cch	Hornets, NO	3.6	3.6	@LAL	0.5
Team Values		99.8	99.8		

It appears that players copy and paste their teams from game tables (e.g., Figure 1), providing not only their chosen athletes but also associated, and potentially valuable, statistics. Although the numbers often appear in threads, participants in the discussions rarely comment on them. Even when statistical data are discussed, their use does not resemble formal discussions of descriptive or inferential statistics.

In the argument below, Griller presents Andrei Kirilenko's statistical averages to argue that he is an underrated athlete. Notice that the numbers are offered without justification or explanation, almost as if the author assumes that other players will be able to meaningfully interpret the data.

PFreak33: Don't get me wrong hes a good player but an all star? Come on please

Griller: HAVE YOU SEEN KIRILENKO'S STATS FOR THE SEASON
PTS 16.5
REB 8.1
AST 3.1
STL 1.9
BLK 2.8
THAT'S SOME GOOD ALL AROUND GAME, SHOW ME A GUY WHO DIDN'T MAKE THE ALL STAR TEAM WITH BETTER STATS

PFreak33: ummmmm…Cormello!!!

Griller: IM TALKING WEST, ANYWAY **** CARMELLO ALL HE HAD WAS MORE POINTS AND MORE ASSISTS, CARMELLO HAD NO D HE IS ALL O KIRILENKO HAS GREAT D AND STILL GIVES YOU 16 PTS

A more mathematical explanation would include these averages as well as standard deviations, statistical comparisons of athletes, and so on. Such explanations were not found in the discussion texts, although numerical data were frequently mentioned.

However, many of these messages suggest that players are considering numbers during their decision-making. In the first example above, Cam says, "I just chose NO <New Orleans Hornets> as coach cause I needed room." "Room" in this context refers to the salary cap imposed on players: Cam implies that he used the majority of his salaries on athletes and had to seek a coach that would fit into his remaining funds. Although players showed no evidence of using numbers to conduct statistical analyses, they often demonstrated their use in basic resource allocation tasks.

5.2 Fast and frugal heuristics

The infrequent use of numerical/statistical analyses in the discussions suggests that players use less formal strategies to guide decision-making. That is, players may rely on "fast and frugal heuristics" (Gigerenzer & Selten, 2002) – strategies that may be successful because they exploit domain-specific knowledge. Knowledge of the structure of a domain or environment constrains decision making, as some choices will either seem obvious or nonsensical. The heuristics described in this section demonstrate how fantasy sports players use basketball knowledge to select their teams without relying on extensive cognitive processing that would be consistent with more formal, rational decision-making.

One characteristic of expert problem solving is the tendency to first try to understand the nature of the problem qualitatively (e.g., Paige & Simon, 1966; Voss & Post, 1988). Some of the strategies identified during the analyses use qualitative comparisons of various attributes to infer relevant relationships for decision-making. For instance, players often consider how one athlete will defend another:

hal: I'm thinking of taking paul pierce for tomorrow, will he be defended bij ron artest?

DTD: not for sure, but I would say so, that's why I passed on him

Statistical comparisons are not made in this exchange, but informed players know Ron Artest's reputation as a good defender. Similarly, athletes that might ordinarily be chosen are often excluded from fantasy rosters when facing certain teams.

Ian: Thoughts please. Do you think he <Kobe Bryant> will play well?

Duncan: no man the D is going to be up him and he gets personal Defense from Bowen and under the ring is Duncan waiting for him, and if Bowen gets tired we have Ginobili

```
Booger: he will still get at least 20 fast-
   breaks, but there could be better tomorrow.
Rico: I think Kobe has almost gained KG status
   by losing Shaq (It's always asking for dis-
   aster to not pick him), but I think that the
   Spurs can stop him from being too productive.
   I have decided to not pick him.
Jason: he will still get at least 20 fastbreaks
   wtf!? Most TEAM doesn't even get 20 fastbreak
   point a game (Lakers have 19 and 13 in their
   last two), and you think Kobe's gonna have AT
   LEAST 20 fastbreaks agianst the Spurs, one of
   the better defensive team in the league?
```

Comparisons of athlete vs. athlete and athlete vs. team appear frequently in the discussion boards. Such messages show how player knowledge of NBA basketball is used to make quick decisions about athletes. Predictions based on this knowledge may be more or less accurate. The first prediction above was correct: Ron Artest defended Paul Pierce and forced him into a low scoring game. Booger was correct in the second example: Kobe Bryant collected 20 *FastBreak* points despite his opponents' defensive efforts. However, three other athletes exceeded Bryant's *FastBreak* score, validating Rico and Jason's decisions to exclude him from their lineups.

These sorts of comparisons are likely based on experiences watching and tracking the progress of NBA athletes. Statistical analyses could be used to discover similar information, but experienced fantasy basketball players seem to bypass mathematical evaluations, relying more on experiential knowledge of athlete performances.

It was also apparent that domain-specific knowledge use differed between novice and expert players. For instance, novice players often relied on the following strategies when creating their teams.

Recognition: The recognition heuristic (Goldstein & Gigerenzer, 1999) suggests that people will choose known objects if other choices are not recognized. In fantasy sports, this translates into choosing athletes by virtue of name recognition (e.g., superstars like Shaquille O'Neal).

Inexperienced fantasy players (e.g., those new to the game and/or lacking knowledge of professional basketball) are more likely to create their teams using the recognition heuristic. Experienced players are able to use additional knowledge to choose athletes. Indeed, some players explicitly stated that they did not rely on athlete names when building their teams.

```
Mmerg: …I've been thinking that by just trying
   to maximize FBs against player values from
   the data available on the selection page, one
   could come up with pretty good rosters with-
   out even having heard the names of any play-
   ers. I am reassured that my assumption is
   true because FG% comes even before names in
   this game
jd: when i pick a guy the name is the last thing
   i look at,true i look at the besy fbpt aver-
   age for its value,then i sacrafice lower guys
   to get higher scoring guys in another posi-
   tion
```

Team Loyalty: Some players simply choose athletes from their favorite NBA Teams without considering their statistical performances. For instance, Houston Rockets fans might always select players from that team out of sheer devotion rather than looking closely at statistics to find athletes who might accrue higher point totals.

```
Ian: I'M GOING WITH T MAC AND YAO AGAIN!!!!!
   They're gonna feel the URGENCY to win tomor-
   row and BOTH will have a BREAKOUT GAME!!!!
   GOOOOOOOOOOOOOOOOOOOOOO ROCKETS!!!!! I can
   see Ice shaking his head in disappointment
   right now...... sorry man... Hey... at least
   I didn't pick Yao yesterday! That's a GREAT
   START ..... right?
```

Such decisions are primarily based on loyalty to a city/team, yet they may be effective when players choose franchise athletes with a reputation for producing high scores.

Recognition and team loyalty strategies are most likely to be used by novices. More experienced players tended to compare athlete attributes around more sophisticated heuristics. Some of the identified heuristics are described below.

Selfish Reputation: Some players avoid athletes who have reputations for not sharing the ball. The message below discusses Kobe Bryant's reputation as a selfish player.

```
eBear: why dirk you ask 1) he all around play-
   er unlike kobe 2) he understands team ball 3)
   he doesnt let his EGO destroy a franchise
   JUST my opinion to call kobe great is way
   OVER ESTIMATING his talent look at record of
   lakers without shaq! Sure without shaq kobe
   will score more but rest of his game will
   suffer! GREAT players understand how to make
   there teams better kobe doesnt understand
   that he plays for his own stats. LIKE i said
```

```
just my opinion id much rather have any of
the players i listed as my franchise player
over just a SCORER like kobe.
```

These types of discussions are often emotionally charged. Emotions are often seen as obstacles to rational decision-making, yet they can also provide effective ways to limit search spaces (Gigerenzer & Selten, 2002). That is, strong feelings about selfish athletes may lead to their exclusion from fantasy teams, reducing the number of athletes that need to be considered during decision-making.

Step Up: NBA athletes occasionally become ineligible to play due to injuries or suspensions. Fantasy players occasionally choose other athletes believing that they will "step up" and improve their games due to unpredictable absences.

For instance, when Richard Jefferson (RJ) of the New Jersey Nets was injured, players discussed if others on the Nets' squad could be counted on to score points in his absence. In this case, Jason Kidd and Rodney Buford are mentioned as the likely athletes to choose due to Jefferson's injury.

```
LakerFan: RJ IS OUT FOR THE SEASON!. Yahoo News
   Article.
Mike: so now we have Marion and noone else to
   choose from at SF; gonna have to watch Nets
   to see who is gonna pick up the slack, maybe
   Kidd will start to take a few shots
Ian: Rodney Buford will pick up the slack....
   he was doing well for the Nets before
   Vinsanity came in town. Is RJ left handed
   shooter? just curious
```

Blow Out: On nights when great teams are guaranteed to "blow out" their competition, fantasy players may avoid choosing star athletes from the former squad since it is likely that they may not play as many minutes or exert maximum effort.

```
John: …what if since it is a blowout, speedy
   sits too? dont starters usually hit the bench
   in a blowout and they put in scrubs? mcinnis
   has been decent tho speedy in 37 mins vs bob-
   cats got 8 vgms.. thats hella lame man wat u
   think
Rob: Yea... that is a concern. But it seems like
   they are one of those teams that always plays
   to the level of their competition, and thats
   it. They rarely blow out teams, so I think
   they will allow GS to hang with them for the
   most part.
```

Back-to-Back: NBA teams often play games on two consecutive nights (back-to-back, or "b2b" games). A common belief is that athlete performances will decline on the second night due to fatigue. Below a player asks for suggestions and notes that one of his alternatives is playing a back-to-back game.

```
Tiger:
  PG  Kirk Hinrich, CHI  18.3  18.3  GS 17.3
  SG  Kobe Bryant,  LAL  24.1  24.1 @MIN 24.7
  SF  Luol Deng,     CHI  13.3  13.3  GS  12.7
  PF  Kevin Garnett, MIN  25.5  25.5 LAL 34.6
  C   Marc Jackson, PHI   14.7  14.7 POR 14.3
  Cch  Bulls, CHI          3.7  3.7  GS  2.1
  Team Values            99.6  99.6
or Patterson/Curry? Patterson is on a b2b.
```

Statistical analyses suggest variations in athlete performances on the second night of back-to-back games: Some do suffer from fatigue, but others are able to perform at high levels (McCallum, 2005). Regardless, many fantasy players believe the former and avoid players on the second night of consecutive games.

The differences between novice and expert heuristics are worth noting. Recognition and team loyalty strategies are based on familiarity with athlete names. Expert heuristics examine deeper features of the attribute set, comparing athletes in terms of their abilities rather than their names/popularity. But all of these heuristics are rooted in domain specific knowledge, allowing players to reach decisions without extensive information gathering and mental processing associated with the mathematical reasoning of rational decision-making.

5.3 Reflections on the game

Although most of the discussion threads dealt with the specifics of roster selection, there were moments when players described their strategies and how these were determined by the game rules. The following thread started as a discussion about Philadelphia 76ers' star athlete, Allen Iverson. Many players had chosen Iverson for their rosters, and his poor performance the night before resulted in diminished fantasy scores. The participants ultimately discussed the impact of skill vs. luck in fantasy games.

```
King: How can you say it's not luck. Iverson
   could of just as easily gone 18-28 instead of
   8-28. This game is based on picking the right
   guys on the right day. 33% skill 66% luck.
```

```
    Believe me I'm having my worst year ever at
    238 and it's not that i'm not good, I'm just
    have'nt had the luck!
eBear: your correct it takes knowledge some-
    what, takes checking injury reports also. but
    my point example webber killed clipps few
    days ago so to lots he looked like great pick
    but today he doing nowhere near as good, it
    shows why knowledge is involved so is lots
    of luck. no matter what player ya take they
    could fail
Will: in the short term it is luck, but over the
    long haul of the season it is not luck. the
    best vgm's find their way to the top.
```

These discussions appear less frequently than arguments associated with selecting athletes, yet they are powerful examples of players reflecting on their beliefs and decision-making habits. Although strategies are not explicitly mentioned, players are willing to engage in discussions about their decision-making.

6. DISCUSSION

If fantasy sports games are viewed as examples of preferential choice problems, one can imagine players using a variety of techniques to evaluate and choose athletes, ranging from rational applications of expected value theory to more informal uses of heuristics. The chat room conversations analyzed in this research showed few (if any) instances of formal decision-making relying on extensive computation. Most players seem to create their rosters by relying on domain-specific knowledge of NBA athletes and applying this knowledge in various ways. These heuristics may lack the precision of formal analysis methods, but heuristic approximations may be enough to be competitive in fantasy sports. For instance, 11 of the top 15 players of the ESPN fantasy basketball game were also regular participants in the discussion forum and displayed the use of fast and frugal heuristics in their messages. In short, heuristic approaches to decision-making often lead to sensible choices in fantasy sports games.

This does not mean that more formal approaches would not lead to better choices. The ultimate goal of this research is to help players become more competitive by developing formal knowledge of probability and statistics and reflecting on their decision-making strategies. Future studies will examine formal and informal decision strategies to compare their effects on game outcomes. How informal strategies are developed by individuals and adopted by other players also requires further exploration.

6.1 Design implications

This initial study is part of a larger effort to understand how informal knowledge use in computer and video game play can be characterized and used as a foundation for the acquisition of more formal reasoning skills. Gee states that games are *generators* of content that create opportunities for people to access and interact with content through *portals* like discussion boards (Gee, 2004). Discourse studies of these portals provide a window into players' strategic knowledge, but they also suggest ways that games might be enhanced to increase reflection and the acquisition of robust, transferable skills. In particular, the discourse patterns described above suggest potential directions for creating fantasy sports games to facilitate further learning.

6.1.1 Statistical analyses

Players in the discussion forum appear to create their rosters using singular evaluation approaches (Klein, 1999). That is, they may be adding athletes to their roster one at a time based on their merits rather than seeking "the best" athletes by making extensive comparisons. This form of satisficing (Simon, 1956), selecting the first option that works, is more efficient than seeking optimal choices. Surveys of players suggest that 45% spend less than an hour per week managing fantasy basketball teams (FantasySportsTradeAssociation, 2003). Limited time resources may be responsible for more satisficing, less optimizing.

However, players may lack statistical knowledge that could be applied to the process of team selection. Many people find it difficult to understand how variability in data can be expressed through means and standard deviations (Mokros & Russell, 1995; Pollatsek *et al.*, 1981). Misconceptions about the probabilistic laws of chance and randomness may also lead people to perceive patterns in independent sequences (e.g., hitting multiple shots in basketball) that do not truly exist (Gilovich *et al.*, 1985). Greater understandings of probability and statistical concepts may be useful when making choices in fantasy sports games. More so, players may be motivated to learn and use such concepts if they can see their value during game play.

It is interesting to note that statistical data from the game's interface are often copied and pasted into discussion messages. Players do this when comparing their teams and rarely discuss the statistics. Yet their presence presents opportunities for designing discussion environments to support their use in conversations and decision-making. For instance, the data could be visualized in ways that encourage analysis. Existing tools like Tabletop (Hancock, 1995), TinkerPlots (KeyCurriculum Press, 2005), and Fathom (KeyCurriculumPress, 2000) allow people to study variability by dynamically manipulating data and discovering relationships among attributes. An important function of these tools is to provide ways to analyze and describe data that can aid decision-making (Hammerman & Rubin, 2004). Similar visualizations could be provided in fantasy sports games, allowing statistical data to be explored and incorporated into team creation. One goal of the analyses described in this paper is to inform the design of visualizations that could assist statistical analyses yet remain playful enough to motivate their use.

6.1.2 Fast and frugal heuristics

Heuristics that players use to build their fantasy teams may or may not lead to competitive outcomes. For instance, statistical data from the NBA season were analyzed to understand the effectiveness of simply choosing well-known athletes (the recognition heuristic). The ten most popular athletes during the 2004-2005 season were chosen for the analysis. Table 3 shows how often these athletes appeared in the top five scorers using ESPN's *FastBreak* point model (Equation 1).

Although these ten athletes were among the best in the 2004-5 NBA season, Kevin Garnett is the only one who appeared in the top five fantasy scorers in more than half (59.8%) of the games he played in. The recognition heuristic might appear to be a sound heuristic for many players, but the percentages in Table 3 suggest that more information is needed to select athletes. For instance, Kobe Bryant was one of the best-known athletes during 2004-5, yet he only appeared as one of the top five fantasy scorers 24 times out of 67 games played (35.8%).

Players might benefit from understanding how their decision processes influence fantasy sports outcomes. Fantasy gaming environments could include ways for players to revisit the history of their team selections and learn from prior mistakes and successes. A reasonably intelligent system might examine athlete selection over time and warn players if they are biased towards ineffective strategies. Such monitoring and prompting by a computational agent could be useful for helping players reflect on their strategies.

Table 3 Statistical analyses of the recognition heuristic: Percentage of times the ten most popular NBA athletes were ranked in the top five scorers in ESPN's *FastBreak*

Athlete	% in top five scorers
Kobe Bryant	35.8
Vince Carter	21.0
Tim Duncan	35.4
Kevin Garnett	59.8
Grant Hill	7.7
Allen Iverson	24.3
LeBron James	43.6
Tracy MacGrady	23.1
Yao Ming	13.8
Shaquille O'Neal	25.7

6.1.3 Reflection

Indeed, helping players reflect on their use of strategies may be a critical component of shifting fantasy sports from leisure activities to environments for learning. At times, players debated the rules of the game and how their teams were affected by luck and/or skill. Reflection is generally considered as a process conducted by individuals (Dewey, 1910; Schön, 1983), but it is also a social act (Lin *et al.*, 1999), as players seek feedback and modify their teams based on others' critiques.

In general, individuals tend to encounter difficulties in sustaining reflection over extended periods of time (Harri-Augstein & Thomas, 1991) without direct elicitation or external support for the process. Initial analyses support this conclusion, since proportionally, very few reflective discussions were apparent. Thus, including designed supports for reflection could enhance players' abilities to learn from own and others' prior strategies. For instance, fantasy sports games might prompt players to explicitly state their decision strategies and/or provide examples of expert strategies that players can compare and contrast with their own processes.

7. CONCLUSION

Approaches to teaching decision-making skills to children and adults (e.g., Baron & Brown, 1991; Glasspool & Fox, 2005; Pliske *et al.*, 2001; Ross *et al.*, 2005) acknowledge the role of practice when learning effective decision strategies. Computer and video games may provide useful contexts for such practice since players are motivated to engage with them for extended periods and learn new strategies to remain competitive. Analyses of conversations between players could serve as a baseline for understanding current decision-making processes in gaming environments and how those could be used to facilitate further learning. For example, players could be provided with tools to help them conduct statistical analyses to confirm their heuristic judgments. The researchers hope to design tools that assist the development of decision-making skills by building on players' existing strategies and their utility as identified in analyses of discussion forums and personal interviews.

The work described in this paper focuses on fantasy sports, but there may be broader implications for researchers studying knowledge acquisition and use in computer/video gaming. Ethnographic studies of gaming communities and their discourse can inform researchers about the ways that individuals participate in social interactions, express identity, and engage in knowledge use and learning (Steinkuehler, 2004). The data presented in this paper are one example of the forms of knowledge use and learning that can be identified through discourse analyses of online communities associated with popular games.

Finally, many games (especially strategic and tactical games) can be viewed as preferential choice problems because they require players to assess and act on alternatives that have complex relationships between multiple attributes. Player activities in these games might involve exhaustive consideration of attributes and/or simpler strategies that rely on the structure of the gaming environment and domain-specific knowledge. Considering gaming activities as a continuum between optimal decision-making and the use of fast and frugal heuristics may be a useful theoretical lens for investigating learning and knowledge use.

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REFERENCES

Baron, J. and Brown, R. V. (Eds.). (1991). *Teaching Decision Making to Adolescents*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Berri, D. J., Schmidt, M. B. and Brook, S. L. (2006) *The Wages of Wins: Taking Measure of the Many Myths in Modern Sport*. Palo Alto, CA: Stanford University Press.

Billings, A. (2005) Fantasy football as a tool for teaching sports communication. *Paper presented at the 26th Annual Conference of the North American Society for the Sociology of Sport*, Winston-Salem, NC.

Bowman, R. F. (1982) A Pac-Man theory of motivation: Tactical implications for classroom instruction. *Educational Technology*, 22(9), 14–17.

Brown, B. and Bell, M. (2004) CSCW at play: 'There' as a collaborative virtual environment. In J. Herbsleb & G. Olson (Eds.), *Proceedings of the 2004 ACM Conference on Computer Supported Collaborative Work* (pp. 350–359). New York: ACM Press.

Brown, R. S. (2005) Fantasy football as a tool for teaching sports information. *Paper presented at the 26th Annual Conference of the North American Society for the Sociology of Sport*, Winston-Salem, NC.

Carraher, T. N., Carraher, D. W. and Schliemann, A. D. (1985) Mathematics in the streets and in schools. *British Journal of Developmental Psychology*, 3, 21–29.

Colston, C. (1999) Revisiting Roto's Roots [Electronic Version]. USA Today Baseball Weekly. Retrieved June 10, 2006 from http://www.usatoday.com/sports/baseball/bbw/v96/bbw9605.htm.

Dewey, J. (1910) *How We Think*. Boston, MA: D.C. Heath & Co.

Ducheneaut, N. and Moore, R. J. (2004) The social side of gaming: A study of interaction patterns in a massively multiplayer online game. In J. Herbsleb & G. Olson (Eds.), *Proceedings of the 2004 ACM Conference on Computer Supported Collaborative Work* (pp. 360–369). New York: ACM Press.

FantasySportsTradeAssociation. (2003) 2003 *Generalized Comprehensive Fantasy Sport Consumer Behavior Results*. St. Louis, MO: Fantasy Sports Trade Association.

Flick, U. (2002) *An Introduction to Qualitative Research*. Thousand Oaks, CA: Sage Publications.

Flockhart, D. (2005) *Fantasy Basketball and Mathematics*. Fortuna, CA: Fantasy Sports and Mathematics.

Gee, J. P. (2003) *What Video Games Have to Teach us About Learning and Literacy*. New York: Palgrave Macmillan.

Gee, J. P. (2004) *Situated Language and Learning: A Critique of Traditional Schooling*. New York: Routledge.

Gigerenzer, G. and Selten, R. (2002) Rethinking rationality. In G. Gigerenzer & R. Selten (Eds.), Bounded Rationality: *The Adaptive Toolbox* (pp. 1–12). Cambridge, MA: The MIT Press.

Gigerenzer, G., Todd, P. M. and TheABCResearchGroup (eds.) (1999) *Simple Heuristics that Make Us Smart*. New York: Oxford University Press.

Gillentine, A. and Schulz, J. (2001) Marketing the fantasy football league: Utilization of simulation to enhance sport marketing concepts. *Journal of Marketing Education*, 23(3), 178–186.

Gilovich, T., Vallone, R. and Tversky, A. (1985) The hot

hand in basketball: On the misperception of random sequences. *Cognitive Psychology*, 17, 295–314.
Glasspool, D. W. and Fox, J. (2005) Knowledge, argument, and meta-cognition in routine decision making. In T. Betsch & S. Haberstroh (Eds.), *The Routines of Decision Making* (pp. 343–359). Mahwah, NJ: Lawrence Erlbaum Associates.
Golder, S. A. and Donath, J. (2004) Hiding and revealing in online poker games. In J. Herbsleb & G. Olson (Eds.), *Proceedings of the 2004 ACM Conference on Computer Supported Collaborative Work* (pp. 370–373). New York: ACM Press.
Goldstein, D. G. and Gigerenzer, G. (1999) *The recognition heuristic: How ignorance makes us smart*. In G. Gigerenzer, P. M. Todd & TheABCResearcGroup (Eds.), *Simple Heuristics that Make Us Smart* (pp. 37–58). New York: Oxford University Press, Inc.
Hammerman, J. K. and Rubin, A. (2004) Strategies for managing statistical complexity with new software tools. *Statistics Education Research Journal*, 3(2), 17–41.
Hancock, C. (1995) Tabletop. Cambridge, MA: TERC/Broderbund Software.
Harri-Augstein, E. S. and Thomas, L. F. (1991) *Learning Conversations: The Self-Organized Way to Personal and Organizational Growth*. New York: Routledge.
Hollinger, J. (2005) *Pro Basketball Forecast*: 2005-06. Dulles, VA: Potomac Books.
Hutchins, E. (1996) *Cognition in the Wild*. Cambridge, MA: The MIT Press.
KeyCurriculumPress (2000) Fathom™ Dynamic Statistics™ Software (Version 1.0). Emeryville, CA: Key Curriculum Press.
KeyCurriculumPress (2005) TinkerPlots™ Dynamic Data Exploration (Version 1.02). Emeryville, CA: Key Curriculum Press.
Klein, G. (1999) *Sources of Power: How People Make Decisions*. Cambridge, MA: MIT Press.
Lave, J. (1988) *Cognition in Practice: Mind, Mathematics, and Culture in Everyday Life*. Cambridge: Cambridge University Press.
Lave, J., Murtaugh, M. and delaRocha, O. (1999) The dialectic of arithmetic in grocery shopping. In B. Rogoff & J. Lave (eds.), *Everyday Cognition: Development in Social Context* (pp. 67–94). Cambridge, MA: Harvard University Press.
Lin, X., Hmelo, C., Kinzer, C. K. and Secules, T. J. (1999) Designing technology to support reflection. *Educational Technology Research and Development*, 47(3), 43–62.
Malone, T. W. (1981) Toward a theory of intrinsically motivating instruction. *Cognitive Science*, 4, 333–369.
McCallum, J. (2005, February 14). Double whammy. *Sports Illustrated*, 102, 50–54.
Mokros, J. and Russell, S. J. (1995) Children's concepts of average and representativeness. *Journal for Research in Mathematics Education*, 26(1), 20–39.
Nasir, N. S. (2000) "Points ain't everything": Emergent goals and average and percent understandings in the play of basketball among African American students. *Anthropology and Education Quarterly*, 31(3), 283–305.
Nasir, N. S. (2002) Identity, goals, and learning: Mathematics in cultural practice. *Mathematical Thinking and Learning,* 4(2&3), 213–247.
Nasir, N. S. (2005) Individual cognitive structuring and the sociocultural context: Strategy shifts in the game of dominoes. *The Journal of the Learning Sciences*, 14(1), 5–34.
Oliver, D. (2003) *Basketball on Paper: Rules and Tools for Performance Analysis*. Dulles, VA: Brasseys, Inc.
Paige, J. M. and Simon, H. A. (1966) Cognition processes in solving algebra word problems. In B. Kleinmuntz (Ed.), *Problem Solving* (pp. 119–151). New York: Wiley.
Payne, J. W. and Bettman, J. R. (2002) Preferential choice and adaptive strategy use. In G. Gigerenzer & R. Selten (Eds.), *Bounded Rationality: The Adaptive Toolbox* (pp. 123–145). Cambridge, MA: The MIT Press.
Pliske, R. M., McCloskey, M. J. and Klein, G. (2001) Decision skills training: Facilitating learning from experience. In E. Salas & G. Klein (Eds.), *Linking Expertise and Naturalistic Decision Making* (pp. 37–53). Mahwah, NJ: Lawrence Erlbaum Associates.
Pollatsek, A., Lima, S. and Well, A. (1981) Concept or computation: Students' misconceptions of the mean. *Educational Studies in Mathematics*, 12, 191–204.
Prensky, M. (2000) *Digital Game-Based Learning*. New York: McGraw-Hill.
Rieskamp, J. and Hoffrage, U. (1999) When do people use simple heuristics, and how can we tell? In G. Gigerenzer, P. M. Todd & TheABCResearchGroup (Eds.), *Simple Heuristics that Make Us Smart* (pp. 141–167). New York: Oxford University Press, Inc.
Ross, K. G., Lussier, J. W. and Klein, G. (2005) From the recognition primed decision model to training. In T. Betsch & S. Haberstroh (Eds.), *The Routines of Decision Making* (pp. 327–341). Mahwah, NJ: Lawrence Erlbaum.
Saxe, G. B. (1991) *Culture and Cognitive Development: Studies in Mathematical Understanding*. Hillsdale, NJ: Lawrence Erlbaum.
Schˆn, D. A. (1983) *The Reflective Practitioner: How Professionals Think in Action*. New York: Basic Books.
Selten, R. (2002) What is bounded rationality? In G. Gigerenzer & R. Selten (Eds.), *Bounded Rationality: The Adaptive Toolbox* (pp. 13–36). Cambridge, MA: The MIT Press.
Shipman, F. M. (2001) Blending the real and virtual: Activity and spectatorship in fantasy sports. *Paper presented at the Fourth International Digital Arts and Culture Conference*, Providence, RI.
Simon, H. A. (1956) Rational choice and the structure of environments. *Psychological Review*, 63, 129–138.
Steinkuehler, C. (2004) Learning in massively multiplayer online games. In Y. B. Kafai, W. A. Sandoval, N. Enyedy, A. S. Nixon and F. Herrera (eds.), *Proceedings of the Sixth International Conference of the Learning Sciences* (pp. 521–528). Mahwah, NJ: Lawrence Erlbaum.
Steinkuehler, C. (2006) Massively multiplayer online video gaming as participation in a discourse. *Mind, Culture, and Activity*, 13(1), 38–52.
Strauss, A. L. and Corbin, J. (1990) *Basics of Qualitative Research: Ground Theory Procedures and Techniques*. Newbury Park, CA: Sage Publications.
Tversky, A. and Kahneman, D. (1973) Availability: A heuristic for judging frequency and probability. *Cognitive Psychology*, 5, 207–232.
Tversky, A. and Kahneman, D. (1974) Judgment under uncertainty: Heuristics and biases. *Science*, 185,

1124–1131.

vonNeumann, J. and Morgenstern, O. (1947) *Theory of Games and Economic Behavior*. Princeton, NJ: Princeton University Press.

Voss, J. F. and Post, T. A. (1988) On the solving of ill-structured problems. In M. T. H. Chi, R. Glaser and M. J. Farr (eds.), *The Nature of Expertise* (pp. 261–285). Hillsdale, NJ: Lawrence Erlbaum.

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