Capturing complex processes of human performance

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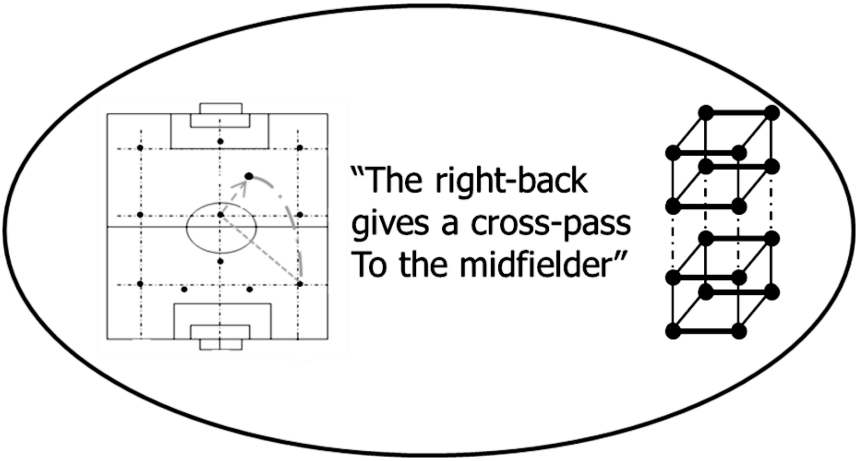
Chapter 2: Characterizing Expert Representations During Real Time Action: A Skill Theory Application to Soccer



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Abstract

In various domains, experts are found to possess elaborate domain-specific representations they developed over years. In this study, we provide the first systematic attempt to characterize short-term representations among individuals with different expertise levels. We showed videos of soccer game plays to expert, near-expert, and non-expert soccer players, and asked them to describe the actions taking place. Verbalizations were coded based on Fischer's Skill Theory. Monte Carlo permutation tests revealed that players with higher expertise constructed representations of higher complexity (regardless of their specific content). Taking the content of the representations into account, we found that higher-expertise soccer players relatively more often included high complexity levels of actions not including the ball and (moving) players on the field. These findings improve our understanding of perceptual-cognitive expertise, by demonstrating how actors with different levels of expertise integrate the information they perceive to construct their representations in real time.

2.1 Introduction

Within the domains of sports (Williams, 2000), medicine (Ericsson, 2004), and physics (Chi, Glaser, & Rees, 1982), experts are found to possess more domain-specific knowledge of facts and memories that they have developed over the years. While stored knowledge and memories refer to constituents of long-term representations, representations are also formed on the short-term (see Allan & Bickhard, 2013; Van Geert & Steenbeek, 2013). Such representations would, for example, refer to “reading” the game during a soccer match (e.g., Bjurwill, 1993), or the formation of scientific concepts during science class (e.g., Van der Steen, Steenbeek, Van Dijk, & Van Geert, 2014). These short-term representations emerge from the individual’s interaction with the material (or social) environment in real time, and are thus different from how representations are constructed in long-term memory. More specifically, what occurs in a particular situation (e.g., in a class room, on a sports field) feeds into the short-term representation, which may leave memory-traces, and change the complex network of skills and knowledge that constitutes the long-term representation (Van Geert & Steenbeek, 2013).

Research suggests that the long-term representations that have developed over time lead to an increasing ability to retrieve particular situations or structures (e.g., chess play positions, players’ positions on the soccer field), and consequently enhance anticipation skills (e.g., Ericsson & Kintsch, 1995; Feltovich, Prietula, & Ericsson, 2006; Van Geert & Steenbeek, 2013). Although long-term representations, as well as their possible relationships with domain-specific expertise have been investigated for decades, no attempt has yet been made to examine whether, and how, individuals with different domain-specific levels of expertise differ with regard to their short-term representations. In the current study, we propose Skill Theory, developed by Fischer (1980), as a framework to investigate and characterize these short-term domain-specific representations. We applied the framework in sports (i.e., soccer), a research area in which key insights into perceptual-cognitive skill development have been gained in the last decades (see Ericsson & Lehmann, 1996). An additional advantage of the domain of sports is that phenomena can be studied on a small surface and/or on a relatively short time scale.

Expertise and Long-Term Representations

Early evidence for the assumption that experts have extensive long-term domain-specific representations comes from De Groot (1946/1965), who observed that master chess players outperformed lower-level players in their ability to reconstruct a chess position after being briefly exposed to it for 5 seconds. De Groot (1946/1965) concluded that master chess players possess elaborate representations of chess plays, so that they rapidly recognize, and remember, the structuring of static chess positions to which they are exposed. This finding was later replicated by Chase and Simon (1973), who also suggested that expert chess players have developed a skill to recognize the structure of the chess piece locations, due to repeated exposure to different chess board positions.

Comparable results have been found in other domains, including soccer (e.g., North, Williams, Hodges, Ward, & Ericsson, 2009; Williams & Davids, 1995; Williams, Hodges, North, & Barton, 2006). Williams et al. (2006) presented expert and non-expert soccer players with offensive soccer action sequences; half of the sequences had already been presented to the players in an earlier viewing phase. The results of their first experiment showed that expert players recognized earlier shown sequences quicker and more often than non-expert players. In their second experiment, Williams et al. (2006) displayed the players on the field as point-light formats. That is, a series of white dots depicted the players' movements on a black background. Again, relative to non-expert players, expert soccer players recognized the similarity between the point-light sequences and the earlier encountered soccer sequences quicker and more often. In their interpretation of these results, Williams et al. (2006) suggested that expert players have more extensive (long-term) representations of patterns on the soccer field (Experiment 1), in particular with regard to players' positions in relation to each other (Experiment 2).

Perceptual-Cognitive Skills in Real Time

Although the above-mentioned studies focused on recalling or recognizing earlier encountered situations (e.g., chess positions or soccer film clips), researchers have also applied methods to untangle what information experts pay attention to during real time performance, for instance, by employing visual search paradigms and verbal report protocols. In visual search studies, several authors conducted eye-movement recordings of soccer players involved in anticipation and decision-making tasks (e.g., Helsen & Starkes, 1999; North et al., 2009; Roca et al., 2011; Vaeyens, Lenoir, Williams, Mazyn, & Phillaerts, 2007). Researchers found that, compared to non-experts, experts shifted their gaze more frequently toward the positions and movements of other players, as well as areas of free space, rather than (the player in possession of) the ball. Based on these results, researchers assumed that experts are better able to structure relevant, informative game elements into meaningful units, which enhances anticipation and decision-making. However, this assumption derives from indirect evidence (gaze fixations); a characterization of the actual cognitive structuring of the game elements (i.e., the short-term representation) was not provided.

Recently, Roca et al. (2011) added a verbal report protocol to their visual search method. Soccer players were presented with life-size video clips showing an attack of the opponent from a defender viewing perspective. They were then asked to retrospectively provide verbal reports on their thought processes during the clip. The authors found that experts evaluated the situation on the field more frequently, and provided more predictions and intentions for future actions, suggesting experts have more complex domain-specific representations (for another study combining visual search and verbal reports, see McRobert, Ward, Eccles, & Williams, 2011). Comparable findings have been revealed by McPherson and colleagues, who exclusively applied verbal protocols (e.g., McPherson, 1993; McPherson, 2000; McPherson & Thomas, 1989). For instance, after each point, McPherson (2000) asked tennis players about their thoughts when playing the previous point, and next, what they were thinking about at the current moment. McPherson (2000) also found differences related to evaluation and intentions for future actions, in the sense that expert tennis players reported a greater number and variety of goal concepts (the goal structure of the game, or means to win the game), condition concepts (when or under what conditions actions should be carried out to achieve the goals), and action concepts (rules for generating patterns to produce goal-related changes). Additionally, the sophistication levels of the concepts (i.e., reported details) were higher for experts, and they reported more connections and linkages between the concepts (experts used more words like ‘as’, ‘if’, ‘then’, ‘to’, ‘so that’, etc. within single phrases). However, Roca et al.

(2011) and McPherson and colleagues (McPherson, 1993; 2000; McPherson & Thomas, 1989) did not extract a measure reflecting the structuring, or complexity, of short-term representations.

To summarize, research methods based on visual search behaviors and verbal protocols have provided insights into what kind of information experts pay attention to, as well as how expert athletes retrospectively evaluate the situation more often, and plan future actions more extensively. Yet, focusing on separate gazes (e.g., Helsen & Starkes, 1999; North et al., 2009) or frequencies/counts based on retrospective evaluations and intentions (e.g., McPherson, 2000; Roca et al., 2011) does not provide information on the cognitive structuring of what the players actually see and how they integrate this information, which is assumed to be a key characteristic of the construction of short-term representations (Van Geert & Steenbeek, 2013). Moreover, because the participants' verbal reports were provided after the task (e.g., Roca et al., 2011) or in between intermittently played points (McPherson, 2000), the results could by definition not reflect the short-term representations the participants constructed in real time. For a systematic examination of short-term representations, it is thus necessary to have a framework allowing to score verbalizations while being exposed to real time actions, and to arrive at a single measure reflecting the complexity of the short-term representation being constructed.

Toward a Measure of Short-Term Representations

An individual's short-term representation within a domain can be viewed along two dimensions: (1) The dimension of content (e.g., a passing action of a soccer player), and (2) the dimension of complexity, that is, the integration of multiple actions and/or interconnected elements of the action (Van der Steen, Steenbeek, & Van Geert, 2012). To reliably investigate short-term representations, the theoretical framework within which they are studied should be able to take both dimensions into account. In the field of cognitive development, Skill Theory (Fischer, 1980; Fischer & Bidell, 2006) is such a theory. Taking into account the continuous interaction between person and context, Skill Theory entails a framework for evaluating the cognitive complexity of the ways in which people organize their actions and thoughts (Fischer & Bidell, 2006). One of the most powerful characteristics of Skill Theory is that it can extract complexity from content, resulting in a content-independent measure of short-term representation levels. This means that the representations of the elements (e.g., player, ball, opponent in the case of soccer) and the connections between them can be assessed in a content-independent way, making it possible to evaluate the complexity of short-term representations in various fields. Because of this possibility to obtain content-independent measures, Skill Theory enables researchers to compare levels of representations across multiple time points, contexts, persons, and levels of expertise.

Skill Theory characterizes skills as thinking structures formed in a specific context, which can be a science class (Van der Steen, Steenbeek, & Van Geert, 2012), or another achievement context (see Fischer & Bidell, 2006). These thinking structures (e.g., short-term representations) can be assessed on a hierarchical scale ranging from low to high levels of complexity. The Skill Theory complexity scale consists of ten levels, divided into three tiers. The first tier refers to *sensorimotor skills*: Representing simple connections of actions on objects, events, or people in the world. The second tier refers to *representations*, which are knowledge structures reflecting components that are independent of specific observable actions, although based on them. The third tier refers to *abstractions*: General non-concrete rules that also apply to other situations. Within each tier a similar structure of four levels exists, reflecting an increasing complexity of the short-term representation. The first level begins with single sets, meaning single actions, single representations, or single abstractions. On the second level, these sets are coordinated so that they form relations between sets, called mappings. On the third level, these mappings are in turn coordinated so that they form relations between mappings, called systems. On the fourth level, systems are coordinated and form a system of systems, thereby reflecting a single set of a new type, the first level of the next tier.

Skill Theory has already been applied within educational contexts. For example, Van der Steen et al. (2014) examined interactions between a 4-years old child and a teacher, while working on different air pressure tasks—e.g., connecting two syringes with a transparent tube to explore the effect of air in this system—in three separate sessions. The authors showed that, compared to session 1 and 2, the child's answers in session 3 more often reflected higher complexity levels. Furthermore, Yan and Fischer (2002, 2007) used a Skill Theory coding system to study how adults' representations changed when learning to use a computer program. They found that the participants' representations moved from fluctuating low complexity levels to higher complexity levels. These studies thus suggest that higher complexity levels of real-time representations emerge when developing expertise. However, to arrive at such a conclusion, two important steps remain to be undertaken: (a) conducting a systematic comparison of the construction of Skill Theory complexity levels between individuals with different levels of expertise, and (b) show that the relation between expertise and complexity is applicable to other contexts (i.e., outside of education).

The Current Study

In the current study, Skill Theory was applied in a sports context (i.e., soccer). The aim was to examine whether soccer players with different levels of expertise can be distinguished on the construction of their short-term game representations, as reflected by their scores on the Skill Theory complexity scale. In addition, we aimed to explore the complexity levels of the specific contents (i.e., type of soccer actions such as passing, and game elements such as the players). Therefore, a soccer-specific coding system based on Skill Theory was designed to code the verbalizations of soccer players while they watched soccer game plays (cf. Van der Steen et al., 2014; Van der Steen, Steenbeek, Wielinski, & Van Geert, 2012; Yan & Fischer, 2002; 2007). We used the coding system to identify the complexity levels of three groups of soccer players. These three groups participated in different leagues (i.e., professional league, national amateur league, and regional amateur league) that require different levels of expertise. Hence, soccer players participating in the professional leagues were considered as experts, whereas the national amateur league players were considered as near-experts, and the players from the regional amateur league as non-experts (cf. North et al., 2009; Roca et al., 2011; Williams et al., 2006). Given the suggestion that complexity levels of representations increase when developing expertise (e.g., Yan & Fischer, 2002; 2007), we expected that soccer players with higher levels of expertise would construct representations of higher Skill Theory complexity levels. Furthermore, since short-term representations not only have a complexity dimension, but also a content dimension, we examined content-specific differences among the three groups. That is, we assessed whether the higher complexity levels of players with higher expertise were particularly related to specific types of actions (e.g., actions of a player with the ball, such as outplaying, or actions not including the ball, such as a player's off-the-ball movements), and game elements (e.g., moving elements, such as the team members, or static elements, such as the goal). In this way, we explored additional factors distinguishing expert soccer players from those with less expertise.

2.2 Method

Participants

The participants were 28 Dutch male soccer players, aged 20-34 (M_{age} = 25.65, *SD* = 3.75), each belonging to one of the following groups: Experts, near-experts, and non-experts. The group of experts consisted of seven *professional* players (M_{age} = 27.71, *SD* = 4.75), who were active in their respective professional leagues in The Netherlands for 7.14 years (*SD* = 4.34). Four players were members of two different teams in the highest professional soccer league, and three players were part of a team in the second-highest professional league in the Netherlands. These three players also played in the highest national league in the years before the data collection, and their current team was ranked first in the second-highest league, which resulted in a promotion to the highest professional league a few weeks after the data collection. The group of near-experts consisted of 11 *national amateur* players (M_{age} = 23.90, *SD* = 3.88) from two teams of the highest amateur league in the Netherlands. On average, these players were active in this league for 5.00 years (*SD* = 3.92), and none of the players had ever played in a professional league. The group of non-experts consisted of 10 *regional amateur* players (M_{age} = 26.00, *SD* = 2.11) from two teams participating in the lower three amateur leagues in the Netherlands. These players were active in their current league for 4.90 years (*SD* = 2.23), and none of these players had ever played in the professional or national amateur leagues.

Participants were provided with an informed consent, and were free to withdraw from the study at any stage. Participation was voluntary, and participants were assured their contributions would be treated confidentially.

Procedure

The protocol of this study was approved by the Ethical Committee of the Department of Psychology, University of Groningen. The players targeted for the study were contacted either directly or through their clubs, and asked whether they would be willing to watch and describe some soccer game plays at a time that suited them. Appointments were made with the players who agreed to participate at their home soccer club. Participants were seated in front of a laptop, on which the video sequences were played. A video camera was placed at a 45° angle behind the participant to record his verbal reports. The participants were asked to watch three soccer game plays, and to describe (aloud) the actions taking place on the field. The researcher did not give any additional clarifications or points of attention, in order to keep the responses as authentic as possible.

Before the three game plays were shown, participants watched one practice sequence to check whether they (only) described the actions that took place on the field. A request to focus exclusively on the game-related actions was given to participants who described irrelevant elements, related to the supporters in the stadium (e.g., “there are many empty seats”), or the weather conditions (e.g., “it’s cloudy”) for example. After the practice sequence, the three soccer game plays were played successively with a break of 5 s between them, and were presented in a randomized order. Subsequently, all utterances were transcribed to facilitate the coding procedure.

Materials

The three videos to which the participants were exposed consisted of offensive game plays of 22 s, 17 s, and 34 s, which ended in a goal. The game plays were retrieved from matches played at the highest level in Ireland (IFA Premier League). They were recorded using a high-definition camera from an overview perspective (i.e., above the field), thereby providing a clear view of the field and the actions taking place. Only natural surrounding sounds of the game were broadcast, such as the indefinable noise from the players, crowd, and ball-kicking sounds.

None of the participants were familiar with the game plays or players, thereby ensuring the absence of familiarity advantages, such as knowing the outcome of the match or characteristic movements of particular players.

The Coding System

Based on Skill Theory, we developed a soccer-specific coding system for verbalizations consisting of seven complexity levels of game play representations (see Table 2 for an illustration of the different levels, from 1—single sensorimotor characteristics—to 7—single abstractions).[1]

We proceeded from the fact that the game of soccer consists of game elements (e.g., player, ball, team member), which are combined to form specific actions (e.g., the player passes the ball to the team member), and which are in turn combined to form specific game plays (e.g., combinations of passes and other actions in the offensive game play). A higher Skill Theory complexity level can be considered to be an increased, more complex representation of the interactions between the game elements and actions that unfold during the game play.

The verbalizations of the participants were coded in eight short phases. In the first phase, described soccer actions were separated, to form the basis for further analyses. Actions were chosen as unit of analysis, because game elements are usually meaningfully connected in actions. Actions were indicated by verbs representing a specific act (e.g., shooting, heading, passing), state (e.g., standing, having, looking), or occurrence (e.g., covering, getting). For instance, the following description, which we will use as an example, consists of four actions: "*Goal kick of the goalkeeper* (1: Kicking)*, Heads it through* (2: Heading)*, Puts it in front of the goal with the inside of his right foot* (3: Putting (the ball)), *And header into the goal* (4: Heading)".

[1] The levels 8-10 were not taken into account, because these levels go beyond single abstractions, which is virtually impossible for this specific task (i.e., describing single game plays does not require linking multiple abstractions).

In the second phase, each of these separate actions was given a label. Out of the seven types of actions that could be distinguished, two types do not include the player with the ball: off-the-ball movements—a player who walks, stands, or runs on the field without the ball—(L), and defending actions (D). Four types of actions do include the player with the ball: Individual actions of a player with the ball—not including a team member or opponent—(B), passing actions—a player plays the ball to a team member—(P), actions of a player to individually outplay his opponent(s) (U), and scoring actions—a player attempts to score the goal—(S). The last category includes all other actions, such as looking or asking (O). The above-mentioned action description would thus be coded as follows: "*Goal kick of the goalkeeper* (B), *Heads it through* (P), *Puts it in front of the goal with the insight of his right foot* (P), *And header into the goal* (S)".

In the third phase, the game elements involved in each action description were labeled. Three types of game elements refer to the players on the field: The player (S), the player's team member(s) (M), and the player's opponent(s) (T). Two other game elements refer to the "static" elements that are present, which are the goal (D) and the field (V), and the sixth game element is the ball (B). The example would be coded as: "*Goal kick of the goalkeeper* (S,B), *Heads it through* (S,B,M), *Puts it in front of the goal with the insight of his right foot* (S,B,M,D), *And header into the goal* (S,B,D)".

In the fourth phase, we counted the number of actions that were related or coupled in the action descriptions. This is the case when a relation is made between two actions taking place at the same time (e.g., "<u>The striker heads back</u> (1) to the <u>incoming midfielder</u> (2)"), or when two actions are related that follow each other in time (e.g., "<u>The player moves in front of the defender</u> (1), so that <u>he can score</u> (2)"). When two or more actions were coupled, a higher complexity level was assigned, because this coupling represents a more comprehensive view of the action (cf., McPherson, 2000; McPherson & Vickers, 2004). Our example description does not include such a coupling between actions.

In the fifth phase, a score was given for the complexity of each action based on the Skill Theory complexity scale (Fischer, 1980). Actions, such as scoring, can be described in a relatively simple way (e.g., "a shot"), but also in a more specific way indicating the position of the foot while shooting the ball (e.g., "an instep kick"), or indicating the movement(s) of the body while shooting (e.g., "a volley"), or a combination of these two, including an indication of how this influences the path of the ball (e.g., “a chip”). Mentioning one or two extra observable details was considered level 2 or 3, respectively (sensorimotor system levels), whereas statements indicating an understanding of not directly observable relations were considered level 4 (single representation level), or higher. In our example, all action descriptions involved directly observable details: “*Goal kick of the goalkeeper* (1), *Heads it through* (1), *Puts it in front of the goal with the insight of his right foot* (2; the insight of the right foot provides an extra observed detail of the way the ball was passed), *And header into the goal* (1)”.

In the sixth phase, a score was given for the number of (connected) game elements in each action description. Descriptions of actions including more game elements indicate a more comprehensive view of the action, and were rewarded with a higher score. “*Goal kick of the goalkeeper* (2 elements; S,B), *Heads it through* (3; S,B,M), *Puts it in front of the goal with the insight of his right foot* (4; S,B,M,D), *And header into the goal* (3; S,B,D)”.

In the seventh phase, a Skill Theory complexity score was given for the way game features were described in each action description. For example, a “player” can be described as “the player on the left”, which gives extra (yet observable) information about the player’s position on the field, and was therefore assigned a sensorimotor mapping (level 2) score. On the other hand, the term “the left wingback” reflects an understanding about the player’s position that is not directly observable, but derived from information about the player’s position on the field in relation to the positions of other players. Statements like these were assigned a single representation (level 4) score. In our example, all game elements were described at level 1 (simple, observable information).

In the eighth phase, a final Skill Theory complexity level was assigned to each full action description. This overall complexity level consisted of the highest complexity level scored in the previous phases. However, if within an action description the same level was used twice, this would indicate a qualitatively higher understanding of the action, which was rewarded with a higher complexity level. For example, if within a single action description a level 4 (single representation) was given twice (e.g., “rebound” to indicate the type of action, and “number 10” to indicate a player; see Table 3), this would mean that the player described the action using a mapping of representations (level 5). This did not occur in our example, thus, based on the different coding phases, the actions were assigned the following overall complexity levels: "*Goal kick of the goalkeeper* (2), *Heads it through* (3), *Puts it in front of the goal with the insight of his right foot* (4), *And header into the goal* (3)". Finally, to represent the complexity of the entire game play description, we calculated the mean of the action descriptions. This number, representing the way in which all the actions and game elements were integrated, served as the main unit of analysis.

Reliability of the Coding System

Based on several pilots with soccer players of different levels, a researcher with experience in designing Skill Theory coding books constructed the coding system together with a soccer player. The reliability of the coding system was assessed using a percentage of agreement [(number of same findings) / (number of same findings + number of divergent findings)] between two coders. They coded nine descriptions given by participants, chosen randomly from among the 84 described videos. The agreement rate was 97.96% for the types of described actions; 91.84% for the complexity levels of the soccer actions; 100% for the number of (connected) game features; 98.68% for the types of game features; 93.88% for the complexity levels of the game features; and 93.88% for the overall complexity levels of the game play descriptions.

Table 2. Illustration of Skill Theory complexity levels in soccer.

Complexity level	Description
1: Single sensorimotor characteristics	Single observable characteristics of game features or actions that are not related to any other game feature or action *(The player runs)*.
2: Sensorimotor mappings	Observable relations between game features or actions *(The player kicks the ball)*.
3: Sensorimotor systems	Observable causal relations between game features or actions *(The player passes the ball to his team member)*.
4: Single representations	Not directly observable characteristics of game features or actions *(The player gives a cross pass)*.
5: Representational mappings	Relations between not directly observable characteristics of game features or actions *(The player gives a cross pass to the left wingback)*.
6: Representational systems	Relations between three or more not directly observable characteristics of game features or actions *(The left wingback gives a cross pass to the striker)*.
7: Single abstractions	Holistic inference of the interactions between the actions and game features during the game play *(They play kick and rush soccer)*.
0: Error	"Wrong" game features or actions in the game play *(The striker shoots;* while it was the left forward that placed the shot).

Data Analysis

To test whether soccer players with higher levels of expertise would construct short-term representations of higher Skill Theory complexity levels, participants of each of the three groups (i.e., experts, near-experts, and non-experts) were given a score for overall Skill Theory complexity level over the three game play descriptions.

Differences in complexity levels between the groups were tested with Monte Carlo permutation tests. Monte-Carlo tests outperform traditional parametric (e.g., ANOVA) and nonparametric tests (e.g., Kruskal-Wallis) in the case of relatively small sample sizes and/or unbalanced data sets (e.g., Ludbrook &

Dudley, 1998; Manly, 1997; Roff & Bentzen, 1989; Todman & Dugard, 2001; Van Geert, Steenbeek, & Kunnen, 2012). Contrary to ANOVA, the non-parametric Monte-Carlo procedure does not assume any underlying distribution or a minimum sample size, and one of its characteristics is that it has great discriminatory value in the case of smaller sample sizes and different group sizes in the study (e.g., Good, 1999; Lundbrook & Dudley, 1998; Manly, 1997; Todman & Dugard, 2001; Van Geert et al., 2012). The Monte Carlo test determines the probability that an observed result is caused by chance alone, by simulating that chance. To test whether experts have a more complex representation than near-experts, who in turn construct a more complex representation than non-experts, we shuffled the scores of all participants' overall complexity scores to obtain a redistributed set of scores; this was repeated 10,000 times. Then, we determined the probability (combined *p*-value; higher complexity for experts than for near-experts, *and* higher complexity for near-experts than non-experts) that the randomly redistributed scores would show results equal to, or more extreme than, the results we observed. If the *p*-value was low ($p < .05$), we could conclude that the observed results were unlikely to be caused by chance alone. To determine the magnitude of the observed outcome, we provided an estimate of the effect size by calculating Cohen's *d* (observed result divided by the pooled SD). According to the guidelines of Cohen (1988), a *d*-value of .2 to .3 is considered as small, around .5 as medium, and .8 or higher as large.

Regarding the exploration of complexity levels of specific contents of the game play, we focused on the separate actions and game elements. First, we calculated the proportion of *representations* per type of action (complexity levels 4-6) for each group to assess whether players with higher levels of expertise described particular types of actions (e.g., player with the ball, actions not including the player with the ball) relatively more often at high complexity levels. Second, we assessed whether players with higher levels of expertise described particular game elements (e.g., the players on the field) relatively more often at high complexity levels. Therefore we calculated a proportion score for representations per type of game element for the participants in each group. Again, differences between the groups were tested with Monte Carlo permutation tests.

2.3 Results

Preliminary Results

First, we examined differences among the three groups on other variables than the leagues in which they were playing. We found no significant differences with regard to age ($p > .05$). In addition, the groups did not significantly differ in terms of the number of active years in their current league ($p > .05$).

Skill Theory Complexity Levels

Table 3 displays three examples of a game play description of one soccer player from each group (expert, near-expert, and non-expert). This table also illustrates how we constructed a (final) complexity level for game play descriptions based on the different coding phases, and independent of the specific content of the descriptions. Based on this procedure, taking the mean complexity levels of all participants in each group into account, we found that the complexity level of expert players ($M = 4.03$, $SD = .23$) was higher than for near-experts ($M = 3.89$, $SD = .24$), who scored higher than non-experts ($M = 3.48$, $SD = .30$). The Monte Carlo results showed that the combined p-value was significant ($p_{combined} < .001$, $d = 1.66$). These results support our hypothesis, and indicate that it is highly unlikely that the results we found—complexity level of experts is higher than of near-experts, who in turn score higher than non-experts—can be caused by chance alone.[2] In line with the guidelines of Cohen (1988), the effect size (> .8) can be considered as large.

[2] Earlier researchers particularly analyzed the number of described actions or contents involved in game plays (e.g., McPherson, 2000; Roca et al., 2011). The counts of described actions and game elements also revealed significant differences between the three groups in the current study, although less striking than the differences in the complexity scores.

Table 3. Illustrations of three game play descriptions; how the complexity levels are constructed and analyzed according to their real time expressions; and the overall complexity levels based on the structuring of the game elements and actions during the game play.

Phase:	1	2	3	4	5	6	7	8
Expert player	Long goal kick of the keeper [type of pass] to the side of the field	P	SBMV	1	4	4	1	5
	Conquered by the striker	B	SBT	1	1	3	4	4
	Rebound by number 10	P	SBM	1	4	3	4	5
	Plays it to the striker on the side	P	SBMV	1	1	4	4	5
	Striker puts it in front of the goal	P	SBMD	1	1	4	1	4
	And number 10 can head in	S	SBD	1	1	3	4	4
								4.50
Near-expert player	Long goal kick [type of pass] of the goalkeeper	P	SBM	1	4	3	1	4
	Defense at one line	V	SM	1	4	2	1	4
	Rebound	P	SBM	1	4	3	1	4
	Plays it through	P	SBM	1	1	3	1	3
	At the second post, a player is uncovered	L	SD	1	4	2	4	5
	Heads into the goal	S	SBD	1	1	3	1	3
								3.83
Non-expert player	Goal kick of the goalkeeper	B	SB	1	1	2	1	2
	Heads it through	P	SBM	1	1	3	1	3
	Puts it in front of the goal with the inside of his right foot	P	SBMD	1	2	4	1	4
	And header into the goal	S	SBD	1	1	3	1	3
								3.00

Note. Phase 1 = separating actions; phase 2 = labeling actions (P = passing, B = individual action with the ball, S = scoring, V = defending, L = off-the-ball); phase 3 = labeling game elements (S = player, B = ball, M = teammate, V = field, T = opponent, D = goal); phase 4 = number of (coupled) actions; phase 5 = skill theory level assigned to the action; phase 6 = number of game elements within the action; phase 7 = skill theory level of game elements; phase 8 = final complexity level of each action description, and calculating mean complexity level (in bold).

Separate Actions and Game Elements

Figure 1 displays the within-group proportions of high complexity levels (level 4 or higher) for each specific action. The figure shows that the higher the level of expertise of a player, the higher the proportion of high-complexity descriptions that contain the actions excluding the player with the ball (off-the-ball-movements and defending actions), and consequently, the lower the proportion of descriptions that contain a player in possession of the ball (action of player with ball, passing, outplaying and scoring). Specifically, the mean of proportion score for 'off-the-ball-movements' and 'defensive actions' together was highest for experts (M_{prop} = .37) and lowest for non-experts (M_{prop} = .18); the near-experts scored in between (M_{prop} = .24). Monte Carlo analyses revealed that the differences among the three groups were significant ($p_{combined}$ < .001).

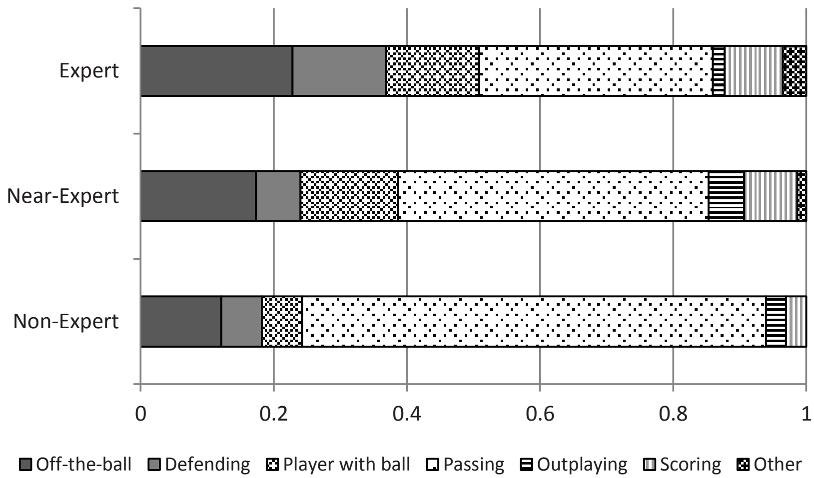

Figure 1. Proportions for high complexity levels (level 4-6) of the different types of described actions, according to level of expertise. The solid filled sections correspond to action categories excluding the player with the ball.

Figure 2 displays the within-group proportions of high-complexity descriptions (level 4 or higher) for the separate game elements. The figure shows that players with higher expertise described particular game elements relatively more often at high complexity levels. That is, the higher the level of expertise of a player, the higher the proportion of high-complexity descriptions for the “moving” game elements, i.e., the players on the field (player, team members, and opponents), and the lower for “static” game elements (goal and field). Monte Carlo tests indicate that the proportion of high-complexity descriptions for the (moving) players on the field was higher for experts (M_{prop} = .74), than for near-experts (M_{prop} = .67), who had a higher proportion than non-experts (M_{prop} = .23). Monte Carlo analyses revealed that the differences between the groups were significant ($p_{combined}$ < .001).

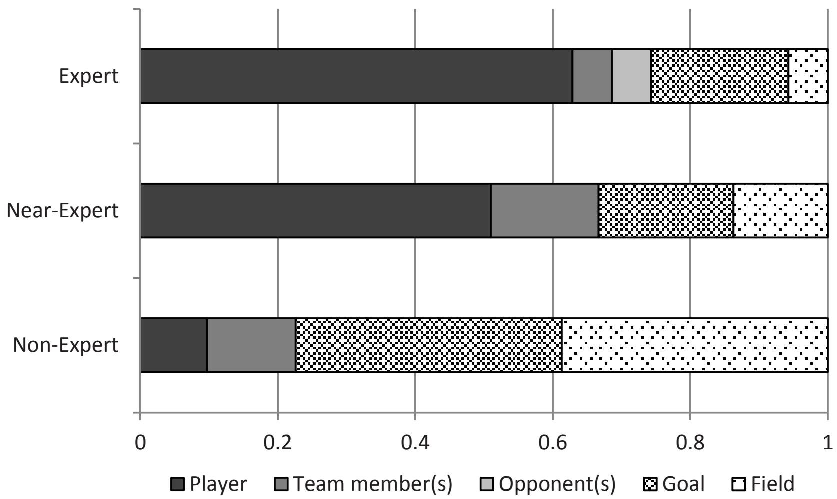

Figure 2. Proportions for high complexity levels (level 4-6) of the different types of described game elements, according to level of expertise. The solid filled sections correspond to the moving game elements (the players). High complexity levels for the ball were not included in the graph, because a ball is always described at sensorimotor level (i.e., a directly observable characteristic, often just “the ball”).

2.4 Discussion

The aim of this study was to examine short-term representations as constructed in real time, and in particular whether increasing levels of soccer expertise would accompany higher complexity levels of soccer-specific game representations. To answer this question, verbal reports of soccer sequences generated by expert (professional), near-expert (high amateur), and non-expert (low amateur) soccer players were compared, using a coding system that distinguishes different complexity levels of short-term representations. In this way we were able to demonstrate at what complexity level players with different levels of expertise integrate, or structure, the actions and elements they pay attention to.

Skill Theory (Fischer, 1980; Fischer & Bidell, 2006) provides a useful framework to examine the constructions of real-time representations, regardless of the specific content of the representations. Based on our soccer-specific coding system, we found that higher levels of expertise were associated with higher Skill Theory complexity levels of short-term representations. Thus, the short-term game representations of soccer players with higher levels of expertise are reflected in their ability to integrate the information on the field at higher complexity levels. This is in line with the claim that cognitive expertise involves a process of increasing complexity (Fischer & Bidell, 2006). Moreover, this indicates that players with high levels of expertise not just extract more (task-specific) information from the game play than low-skilled players, as was found in previous studies (cf., McPherson, 2000; Roca et al., 2011), but that they also structure this information differently, at higher complexity levels.

The credibility of these results and the sensitivity of our method are strengthened by the fact that all participants were soccer players participating in official competitions, and that we did not only include experts and non-experts, but also a group of near-experts. In contrast, other studies examining representations typically involved only pronounced differences in expertise between groups. For example, in the study by McPherson (2000), a group of experts was included, consisting of players with outstanding junior tennis rankings, and a group of non-experts containing novices participating in a beginner's tennis class.

Another interesting finding that emerged from our analysis is that players with higher levels of expertise described actions not including the player with the ball relatively more often at high levels of complexity than players with lower levels of expertise. This result can be considered in line with earlier findings from visual search paradigms, showing that expert soccer players more frequently shift their gaze away from (the player in possession of) the ball to other cues, such as the positions and movements of other players and areas of free space (e.g., Helsen & Starkes 1999; North et al., 2009; Roca et al., 2011; Vaeyens et al., 2007). However, our results also extend these findings by addressing *how* players with higher levels of expertise oversee, or integrate, the off-the-ball movements and defending actions. That is, visual search results indicate which actions participants attended to, but they do not reveal whether, and how, players with different levels of expertise integrate relationships between multiple sources of information to form their representation of the actions they notice. Using the Skill Theory complexity scale, we could specifically account for this (e.g., noticing that a player "sprints"—sensorimotor level—does not mean that a participant sees that the player "chooses position"—representational level).

Furthermore, we found that, relative to players with lower levels of expertise, players with higher levels of expertise described the players on the field relatively more often at high complexity levels. High complexity levels for players on the field mainly correspond to positional indications based on the orientations of the (described) player in relation to other (moving) players. Researchers working on recall and recognition tasks have already suggested that experts generally use relational information more effectively in the decision-making process, such as the players' positions on the field and/or the relative movements between the players (e.g., North et al., 2009; Williams et al., 2006; Williams & Davids, 1995). Our results support these authors' view that the ability to integrate relational information is an important characteristic of experts.

Theoretical and Practical Implications

While early researchers (Chase & Simon, 1973; De Groot, 1946/1965) already assumed the importance of cognitive expertise in terms of stored (long-term) representations, no attempts have been made to measure complexity levels of short-term representations as they are constructed in real time. In this study, we showed that higher levels of expertise accompany higher complexity levels of representations formed when players are exposed to soccer game plays. These insights can have significant implications for future approaches to perceptual-cognitive skills. In achievement contexts (whether in education or sports), decision making and anticipation also take place in real time. Rather than relating decision making and anticipation skills to representations stored in long term memory, which is the dominant approach (e.g., Ericsson & Kintsch, 1995; Helsen & Starkes, 1999; McPherson, 2000; North et al., 2009; Roca et al., 2011), the direct mechanism, or process, underlying superior anticipation and decision making of experts may be their superior ability to notice the patterns of ongoing interactions among the various elements during game plays. This suggestion could be further explored in future research.

Zooming in on the contents of the short-term representations, the results on the complexity levels of specific action or game element descriptions extend earlier results of visual search studies, as well as recall and recognition studies. That is, the results reveal at what complexity level players with different expertise integrate, or structure, particular action(s) and elements they pay attention to.

From an applied perspective, our outcomes may also have direct implications. We showed that characteristics of short-term representations can well be examined within the framework of Skill Theory. Part of this theory's appeal is that designing and applying a Skill Theory coding system is inexpensive and relatively easy. Indeed, its user friendliness has already been evidenced in the field of education, where a percentage of agreement of over 75% was observed between researchers and untrained teachers (see Dawson-Tunik, 2006). Furthermore, it can be applied using recordings of natural situations, without placing any burden on the recorded participants (Van der Steen, Steenbeek, & Van Geert, 2012). This is a great advantage compared with more time-consuming and costly techniques used in the domain of perceptual-cognitive expertise, such as eye-movement recordings, which are also hard to employ in natural situations.

Limitations and Future Directions

The way participants (or people in general) are exposed to information could influence the way they construct their representations. For instance, it has been suggested that expert soccer players pay even more attention to their team members and opponents when they are presented with a player (ground level) viewing perspective (Mann, Farrow, Shuttleworth, and Hopwood, 2009), as opposed to the aerial viewing perspective that we used in this study. To advance insights into the ongoing construction of short-term representations, future research could therefore examine participants' representations using different viewing perspectives, including the actual player perspective.

Another interesting point for future research is to examine how the complexity of short-term representations develops over time, e.g., from a non-expert pattern to an expert pattern. Related to this, it would be fruitful to test how feedback from the coach, teacher, or manager affects individuals' construction of real-time representations. Fischer and colleagues already identified developmental ranges for domain-specific representations. Such a developmental range entails that the highest complexity level of a person under low support conditions (functional level) can be extended several steps upward when support of an expert is offered in the form of a social scaffold offering suggestions (optimal level) (e.g., Fischer & Bidell, 2006; Van Geert & Steenbeek, 2005).

Finally, as explained in the introduction, short term representations that are constructed during real-time action may leave memory-traces, and change the knowledge base (i.e., long term representations) that constitutes the long-term representation (Van Geert & Steenbeek, 2013). While long-term representations have been used as a causal mechanism for anticipation and decision making, future research should explore whether, in real time, anticipation and decision making emerge directly from the perception of interacting game elements during game plays.